# The effects of social support on self-regulation in physical exercise

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A thesis submitted for the degree of Doctor of Philosophy

Trinity 2018



**Acknowledgements**

This project was a big part of my life over the past four years, and quite a few different aspects of myself went into bringing it to fruition. So, I feel like I should thank the many people that helped me directly with the project and also those that helped give me the skills and curiosity needed to (enjoyably) produce a 100,000-word (sorry in advance) thesis that will make this acknowledgement section look short. Those of you who don't know me need not read this. It's long not because I think I have done some epic thing, but because I want to express how lucky I feel to have these people in my life.

I'll start with my family, childhood friends, and teachers and coaches back in Winona, Minnesota and at South Dakota State University (SDSU). Thank you for creating an environment where asking questions was fun and rewarding, and for teaching me that hard work is a process that can be enjoyed. Specific shout-outs go to: my parents, Wendy and Alan Davis, my uncle, Gavin Stevens, my Nona and Yeye, Edith and Jim Stevens, Todd Stearns, Mat O'Brien, and my childhood friends, Thomas O'Brien, Adam Cloeter, Helder Lobato, Jake Walther, Chris Jack, Devon Grossell, Cliff Kaehler, Katy Quirk, Kelly Brandon, Rachel Wolfe, and Chelsi Larson, my coaches and teammates on the SDSU track and field team, specifically, Tyg Long, Lyndon McDowell, J.J. Brinkmann, and Evan Bunkers, and my academic mentors at SDSU, Dr Tim Nichols and Dr Zeno Wicks III.

Moving on to Oxford, I would first just like to say that coming here has been a very transformative experience; I have learned so many invaluable things (not including which utensils to use at a formal dinner) and that is because of the people I have met during my time here. Specifically, I need to thank my friends, my roommates at 5 Hurst St., and my teammates at the Oxford University Athletics Club. You gave me a fun environment in which I could clear my mind, be myself, and get some exercise-induced endorphin and endocannabinoid highs. Specific shout-outs go to: Dr Anna Hushlak, Dr Iliana Cardenes Trujillo, Nicolas Raab Ramm, Zoë Saunders, Bella Coutts, Claudia Hill, Daria Jensen, David Korczynski, Dr Nina Yancy, Tim Haskett, Abby D'Cruz, and Kiah Rutz.

Now, on to my academic colleagues and collaborators, who I am very lucky to say are also my friends! I've learned a lot about how to think from you all, and I am very grateful for that, but I am even more grateful that you made my work something that I enjoyed doing every day. Thank you to Dr Bahar Tunçgenç, Megan Jefferies, Dan Schofield, and Adam Kenny, my fellow DPhil students at the Institute for Cognitive and Evolutionary Anthropology (ICEA), University of Oxford, for helping me think my ideas through. Special thanks to Hristo Hristov for all your coding and statistics help, and for giving me a very personal Stack Overflow experience. Also, thank you to ICEA staff, Dr Susana Carvalho, Dr Oliver Curry, Dr Iain Morley, and the Rev Dr Jonathan Jong, for your time spent reading and thinking about my work, and for your careful critiques and advice. To my collaborators, Dr George Nicholson, Dr Ben Crittenden and Dr Pádraig Mac Carron (of the University of Oxford's Department of Statistics, Nuffield Department of Clinical Neuroscience, and Department of Experimental Psychology, respectively), I am deeply grateful for your help with designing, implementing, and analysing the studies presented in Chapter 4 and Chapter 6 of this thesis. To Cole Robertson and Jacob Taylor, we've been best friends since we met during our ICEA MSc course, and I can't express how grateful I am to have learned with you and from you over the years. Thank you for the love, understanding, and good times – I'll keep those memories with me as long as possible (same for everyone mentioned here).

Most importantly, I want to express my gratitude to my two supervisors. Chiefly, Dr Emma Cohen, but also Dr Bronwyn Tarr, who filled in for Emma when she was on maternity leave. You far exceeded what is expected of a DPhil supervisor in Oxford, both in your intellectual contributions to my work and also in the friendship you have given me. It is no exaggeration to say that this thesis would not be what it is without your help.

I would also like to thank the Clarendon Fund from Oxford University Press and Wolfson College, Oxford for awarding me a Clarendon Scholarship, which paid for my fees and living expenses during my studies. I would not have been able to finish (or even begin) this work without their support.

Finally, thank you to my internal examiner, Dr Laura Fortunato, and my external examiner, Dr David Raichlen of the University of Arizona, for your thoughtful reviews of this thesis. The *viva voce* was a very memorable and fulfilling experience, and I feel lucky to have had my work critiqued by such reflective and knowledgeable people.

**Abstract**

Cross-culturally, humans come together to move together, with physical exertion in the form of sport and exercise often being a social endeavour. Findings from disparate fields of research suggest that social environments can play an important role in moderating self-regulatory processes, such as pain and fatigue, that govern outputs and experiences during physical exertion. This, along with ethnographic and observational research linking supportive social environments with improved outcomes in sport and exercise, suggests that social support during strenuous physical exertion may facilitate physical outputs. However, the link between social support, outputs, and experiences during strenuous physical exercise is yet to be tested empirically. This thesis aims to do this, using a variety of methods to test the hypothesis that the presence of supportive, cohesive social environments change activity in neurobiological mechanisms involved in the self-regulation of strenuous physical exercise, leading to reductions in pain and fatigue and/or increases in physical outputs. The theoretical and empirical underpinnings of this hypothesis are established in Chapter 1 and Chapter 2, which link proximate and ultimate explanations of self-regulatory processes to social environments, focusing on the extent to which social support, cohesion, and integration influence human experiences and outcomes in everyday life, and in sport and exercise more specifically. Chapter 3 reports the results of an experimental manipulation of social support in everyday exercisers. Results showed that socially supported exercisers produced greater initial physical outputs, with steeper declines in these outputs over time, and that these effects were moderated by a personality trait related to how individuals appraise support from others. Chapter 4 and Chapter 5 use both 'big data' and survey methods to investigate the effects of the presence of close social relationships, perceptions of social support, and social integration at a community-based 5 km run. Results suggest that runners produce faster 5 km runs when in the presence of close, supportive others, and that these effects may be mediated by enhanced feelings of energy. Chapter 6 reports the results of an fMRI-compatible experiment that compared the effects of a cue to social support and a placebo treatment on exercise performance. Results showed significant, performance-enhancing social support effects on physical outputs, and that these effects were strongest in exercise trials with more difficult output targets. In Chapter 7, these results are summarised as a whole, and discussed with a focus on their limitations as well as their implications for current research. Covering research ranging from psychological investigations of social support, to clinical studies of endogenous analgesia, to literature on the neurobiological underpinnings of the self-regulation of physical outputs, this thesis integrates diverse bodies of work in providing a novel theoretical and empirical account of how and why social environments affect outputs and experiences during strenuous physical exertion.

**Table of Contents**

**Acknowledgements**

**Abstract**

**Introduction** **1**

**Chapter 1 – Self-regulation and social buffering** **8**

1.1 Introduction 10

1.2 Self-regulation 10

1.3 Social summertime? 11

1.4 Social buffering and support in humans 15

1.5 Conclusion 40

**Chapter 2 – Social support and cohesion effects in sport and exercise** **43**

2.1 Introduction 45

2.2 Social support effects in sport and exercise 45

2.3 Summary of literature to date 69

2.4 Thesis outline 72

2.5 Implications 74

**Chapter 3 – The effects of social support on anaerobic exercise bouts** **76**

3.1 Introduction 78

3.2 Methods 82

3.3 Results 88

3.4 Discussion 92

**Chapter 4 – Social support and cohesion effects at parkrun: a 'big data' study** **101**

4.1 Introduction 103

4.2 Data wrangling and creation 108

4.3 Software and methods used for inferential statistics 111

4.4 Analysis A 111

4.5 Analysis B 118

4.6 Analysis C 124

4.7 Discussion 134

**Chapter 5 – Social support and cohesion effects at parkrun: a survey study 150**

5.1 Introduction 152

5.2 Methods 156

5.3 Results 159

5.4 Discussion 174

**Chapter 6 – Comparing ergogenic placebo and social support effects 186**

6.1 Introduction 188

6.2 Methods 195

6.3 Results 209

6.4 Discussion 217

**Chapter 7 – General discussion 226**

7.1 Overview 228

7.2 How does social support affect strenuous physical exercise? 231

7.3 Limitations and future directions 241

7.4 Contributions to the literature 247

7.5 Broader implications and generalisability of findings 255

7.6 Conclusions 257

**Appendix A 259**

**Appendix B 294**

**Appendix C 314**

**Appendix D 361**

## Introduction

Throughout their lifespan, humans depend upon the relationships they build with others to meet not only their most basic needs, but also to acquire the cultural resources that allow them to flourish. This dependence on conspecifics appears to be an evolutionarily ancient trait; the ancestors of modern humans relied upon one another for purposes ranging from predation deterrence to raising young and acquiring nutrient-rich food sources (Hrdy, 2007; Tomasello, Melis, Tennie, Wyman, & Herrmann, 2012; Van Schaik, 1983). The strong correlation between social relationships and evolutionary fitness suggests that humans have evolved to respond to their environments in ways that depend on the social context within which they are embedded.

Social buffering refers to the phenomenon whereby the presence of conspecifics – and especially familiar, bonded conspecifics – helps individuals to better confront and recover from experiences of distress (Kikusui, Winslow, & Mori, 2006). Social buffering has been documented in many social species, ranging from rodents to primates (Hennessy, Kaiser, & Sachser, 2009; Liu & Yuan, 2016; Sanchez, Mccormack, & Howell, 2015), and it is extremely prevalent in humans, for whom social variables moderate outcomes ranging from physical activity levels to morbidity and mortality (Barkley, Salvy, & Roemmich, 2012; Holt-Lunstad & Uchino, 2008). Against a backdrop of growing levels of individualism in post-industrial societies (Putnam, 1995), a disparate body of research has shown that human health and well-being remains linked to the presence of strong, supportive social relationships. Research on social support, which can be defined as the "psychological and material resources provided by a social network to benefit an individual's ability to cope with stressful events" (Cohen, Janicki-Deverts, Turner, & Doyle, 2015, p. 135), has shown that socially integrated and supported individuals are less susceptible to physical pain, less likely to fall ill (while recovering more quickly when they do), and even live to older ages (Coan, Schaefer, & Davidson, 2006;

Holt-Lunstad, Smith, & Layton, 2010; Kulik & Mahler, 1989; Miller, Chen, & Cole, 2009).[1] While direct help and care from friends and family undoubtedly facilitate health and well-being, research is beginning to show that it is individuals' *perceived* social support, rather than received social support, that is the more consistent predictor of health outcomes (Holt-Lunstad & Uchino, 2008; Wills & Shinar, 2000). This may explain why even subtle cues of the presence (or absence) of supportive social relationships can have substantial psychophysiological effects (e.g., Eisenberger et al., 2011).

In humans, social buffering and support effects are likely based on adaptations that arose to calibrate self-regulatory processes to individuals' social worlds. Primate studies linking group living with protection from predators (Van Schaik, 1983), and archaeological evidence of care for the sick and elderly in *Homo erectus* (Lordkipanidze et al., 2005), suggest that social support and integration have correlated positively with safety and resource abundance dating back millions of years in human evolution. This evolutionarily ancient dependence on social relationships likely selected for mechanisms that account for perceptions of the social world in determining optimal self-regulatory strategies, which should depend on both internal (the state of the individual) and external (the state of the environment) conditions (Trimmer, Marshall, Fromhage, McNamara, & Houston, 2013). An adaptationist approach predicts that the availability of social support alters the optimality of a variety of self-regulatory strategies related to health and well-being, such as those involved in the governing of resource use and responses to threats.

This adaptationist perspective thus offers an explanation of findings from research on social

[1] Social buffering and social support are concepts that are often used interchangeably within the literature, although some distinctions may be helpful. Social support can be seen as a type of social buffer, whereby supporters offer resources (either psychological or material) that help supportees cope with stressors; researchers have thus described social support as buffering individuals from stress (e.g., Cohen & Wills, 1985). Social buffering is a more general term that is more commonly used when describing effects in non-human animals. Social buffering refers to reductions in stress that result from the mere presence of conspecifics (Kikusui et al., 2006), and not necessarily any psychological or material resources provided by these conspecifics. Using these definitions, then, it can be said that all social support effects are social buffering effects, but not all social buffering effects are social support effects.

support. It gives a theoretical framework – based on adaptive self-regulation – to address, for example, why socially supported individuals are less sensitive to painful stimuli and recover more quickly from injury and illness (Cohen et al., 2015; Kulik & Mahler, 1989); when safety is cued, the protective, self-regulatory function of pain is diminished, and when the replenishment of resources is likely, more liberal uses of bodily resources for healing are favoured (Trimmer et al., 2013). Indeed, the corpus of research on social support has shown that while its effects are extensive and varied, they are confined to phenomena related to self-regulation (Holt-Lunstad & Uchino, 2008). Social support alters activity in self-regulatory mechanisms that protect the body and govern the use of its resources, such as those involved in pain perception, immunity, healing, and both appraisals of and responses to stressors (Cohen et al., 2015; Heinrichs, Baumgartner, Kirschbaum, & Ehlert, 2003; Kulik & Mahler, 1989; Schnall, Harber, Stefanucci, & Proffitt, 2008).

This thesis will focus on understanding social support effects in an activity that is particularly susceptible to social influences and self-regulatory processes; strenuous physical exertion. Physical outputs during strenuous physical exertion are governed largely by the inhibitory, neurologically overlapping influences of pain and fatigue[2] on central motor drive (Noakes, 2012; Pollak et al., 2014). In sports and exercise contexts, pain and fatigue function as protective mechanisms against overexertion and injury, working to reduce physical outputs well before individuals reach the limits of their physiological capacities (Noakes, Gibson, & Lambert, 2005). Disparate bodies of evidence suggest links between social variables and physical outputs in sport and exercise. Anecdote, and ethnographic and observational research suggest that social variables, such as support and cohesion, play an important role

[2] Henceforth, I will use the following definition of pain: “an unpleasant sensory and emotional experience associated with actual or potential tissue damage, or described in terms of such damage” (Merskey & Bogduk, 1994, p. 210). I will also use the definition of fatigue from Pollak et al. (2014): “the perception of tiredness or heaviness” that occurs “during and after muscle contractions or in certain pathological conditions” (p. 369).

in moderating performance and competitive outcomes in sport and exercise (Carron, Colman, Wheeler, & Stevens, 2002; Gotaas, 2012; Kraus, Huang, & Keltner, 2010). From supporter songs in stadiums and pre-game rituals among teammates (such as the New Zealand All Blacks' *Ka Mate* haka) to words of encouragement from exercise class instructors, cues to support and team cohesion form a core part of normative practice and culture in sport teams and exercise groups. These practices perhaps function in part to alter (unconscious) assessments of exercisers' and athletes' external environments, thereby moderating the self-regulatory processes involved in governing physical outputs.

Evidence from distinct bodies of literature in clinical medicine, sport and exercise physiology, and primate bonding and sociality implicate the mechanisms through which perceptions of social support and cohesion could affect experiences of pain, fatigue, and energy during sport and exercise. A large body of clinical and placebo research has shown that the endogenous opioid and endocannabinoid systems play a crucial role in endogenous analgesia (Benedetti, Amanzio, Rosato, & Blanchard, 2011; Wager, Scott, & Zubieta, 2007) and in the regulation of physical exercise (Amann, Proctor, Sebranek, Pegelow, & Dempsey, 2009; Boecker et al., 2008; Raichlen, Foster, Gerdeman, Seillier, & Giuffrida, 2012). Importantly, both systems are also involved in the formation of primate social bonds, and in signalling their presence (Dunbar, 2012; Inagaki, Ray, Irwin, Way, & Eisenberger, 2016; Trezza, Baarendse, & Vanderschuren, 2010).

This suggests that perceptions of social support and cohesion could work through endogenous, self-regulatory mechanisms in reducing perceptions of pain and fatigue, ultimately enhancing physical outputs. Cues to social environments where support, safety, and resources are abundant reduce the potential risks (costs) involved with strenuous physical exercise: when resources are likely to be replenished and injuries likely to be cared for the body may be able to release the protective, self-regulatory 'brakes' of pain and fatigue, allowing for greater outputs for longer periods of time. This novel claim extends research that has focused largely on clinical outcomes (e.g., reductions in pain, recovery from illness) to the

everyday context of physical exercise and exertion, while offering a testable explanation of the pervasiveness of social support and cohesion cues in sport and exercise cultures.

To date, no studies directly assess the claim that social support and cohesion can enhance physical outputs through acting on self-regulatory mechanisms. Some evidence from sport psychology is suggestive, however. A relevant and important concept within sport psychology is team cohesion, defined as "a group dynamic process that is reflected in the tendency of a group to stick together and remain united in the pursuit of instrumental objectives and/or for the satisfaction of member affective states" (Carron, Brawley, & Widmeyer, 1998, p. 213). Perhaps unsurprisingly given its definition, perceptions of group cohesion have been shown to predict perceptions of social support (Burke, Carron, & Shapcott, 2008). Meta-analyses have shown a positive effect of team cohesion on outcomes in sport (Carron et al., 2002; Filho, Dobersek, Gershgoren, Becker, & Tenenbaum, 2014) and on positive experiences and adherence to exercise programmes (Burke et al., 2008; Christensen, Schmidt, Budtz-Jørgensen, & Avlund, 2006; Spink & Carron, 1994). Some work has also shown positive effects of perceptions of social support on self-efficacy[3] and performance outcomes (Freeman & Rees, 2010; Rees & Freeman, 2010; Rees, Hardy, & Freeman, 2007; Schnall et al., 2008). However, outcomes targeted in research to date are more dependent on technical skill and fine motor performance (e.g., putting in golf), than on changes in self-regulatory mechanisms relevant to physiological outputs, overexertion, and injury.

Some work on teams of elite athletes offers more direct clues. In separate experimental studies with elite rowers and rugby players, it was found that interpersonal, synchronous movement can increase pain thresholds during aerobic tests (Cohen, Ejsmond-Frey, Knight, & Dunbar, 2010) and performance in anaerobic tests (Davis, Taylor, & Cohen, 2015)[4].

[3] Self-efficacy is described as an individual's belief in their innate ability to complete a task or achieve a goal (Bandura, 1982).

[4] This research was conducted by myself and my co-authors as part of my MSc thesis (2014) at the Institute of Cognitive and Evolutionary Anthropology, University of Oxford.

Synchrony is thought to operate as a signal of cooperative, cohesive groups (Julien, Brault, Chartrand, & Bégin, 2000; Lakens & Stel, 2011; Wheatley, Kang, Parkinson, & Looser, 2012). Although this suggests an effect of socio-environmental cues – and perhaps social support and cohesion – on physiological self-regulation, this relationship is yet to be tested directly, and with more standard (i.e., social psychological) conceptions of social support and cohesion.

This will be the main objective of this thesis; to produce empirical tests of the hypothesis that cues to the presence of supportive, cohesive social environments change activity in neurobiological mechanisms involved in the self-regulation of strenuous physical exercise, as evidenced by reductions in self-reports of pain and fatigue and/or improvements in measures of physical outputs (e.g., power outputs or distance running times). The thesis consists of seven chapters. Chapter 1 introduces the general theoretical framework, core concepts, and arguments of the thesis, drawing links among self-regulation and social environments, and focusing on the extent to which social support, cohesion, and integration influence human experiences and outcomes. This chapter aims to offer a novel theoretical account of the links among (adaptive) psychophysiological self-regulation, social behaviours, and human culture. Chapter 2 narrows the focus to review social support and cohesion effects in sport and exercise, further laying the theoretical foundation for the specific empirical focus of this thesis. Following these chapters, I will present four empirical tests that aim to elucidate the mechanisms through which social support and cohesion affect outputs and experiences during physical exertion in sport and exercise. Chapter 3 reports the results of an experimental manipulation of social support in everyday exercisers. Results show that socially supported exercisers produced greater initial physical outputs, with steeper declines in these outputs over time, and that these effects were moderated by a personality trait related to how individuals appraise support from others. Chapters 4 and 5 report observational research on social support and cohesion effects at a community-based 5 km run, parkrun, using both ‘big data’ and survey methods. Analyses of the parkrun big data set indicate that individuals run faster over 5 km when social environments are likely to be supportive. Survey results suggest

that the performance-enhancing effects of these social environments are underpinned by increases in felt energy. Chapter 6 reports the results of an experiment – employing a design compatible with functional magnetic resonance imaging (fMRI) – that compared the effects of cues to social support and placebo treatments on exercise performance. Results showed ergogenic (performance-enhancing) effects of receiving cues to social support on hand-grip strength and endurance, with self-reports suggesting that these effects may be underpinned by reductions in perceptions of pain and fatigue. In Chapter 7, these results are summarised and discussed, with a focus on their limitations as well as their implications for and contributions to current literature.

## Chapter 1 – Self-regulation and social buffering

**Abstract**

This chapter focuses on the theoretical, empirical, and mechanistic links between self-regulatory processes and socio-cultural environments, discussing the extent to which social support, cohesion, and integration influence human experiences and outcomes. An adaptationist perspective is first used to explain social buffering as a self-regulatory process. Following this, the implications of the unique trajectory of human evolution are discussed, focusing on how humans are likely to respond to cues of support from close others and the social group. A variety of human behaviours and cultural symbols, rituals, and practices are then considered in relation to social buffering. It is argued that these behaviours and cultural items function to elicit social buffering effects, altering individuals' responses to illness, injury, and social and physical threats more generally. This chapter thus provides a novel account of the links among psychophysiological self-regulation, social behaviours, and culturally dependent practices and norms.

## 1.1 Introduction

Organisms evolve adaptive responses to their environments. In social species, where evolutionary fitness is closely linked to connection with the social group, these responses often depend on the presence of conspecifics, which can signal relative safety and resource availability (Van Schaik, 1983). The stress-attenuating effects of conspecific presence in social species has been called social buffering (Kikusui et al., 2006). In humans, who depend on social relationships for their most basic needs, the presence of support from others has strong and pervasive social buffering effects, ranging from improvements in immunity to reductions in perceptions of pain and more optimistic interpretations of potential challenges (Coan et al., 2006; Cohen et al., 2015; Holt-Lunstad & Uchino, 2008; Schnall et al., 2008).

## 1.2 Self-regulation

A basic principle of evolutionary theory is that organisms evolve to survive and reproduce in the environments in which they live. Even in environments that vary over time and space, there is selection for the capacity of organisms to adapt to changing conditions, from moment-to-moment fluctuations in light and temperature to longer-term variations in resource abundance. Via these adaptations, environmental, psychophysiological, and behavioural states mutually respond to one another across short and long timescales in an individual's life. These mechanistic adaptations are thought to operate via tacit cost-benefit analyses that produce optimal responses to specific environments (Trimmer et al., 2013). Research has shown that adaptive cost-benefit analyses influence psychophysiological self-regulation from immune function, to stress levels, to the higher-order emotions and motivations that govern behaviour in response to stressors (Coan et al., 2006; Cohen et al., 2015; Holt-Lunstad & Uchino, 2008; Schnall et al., 2008).

A particularly instructive example of how environmental cues can affect self-regulation comes from a study on immune activity in Siberian hamsters (*Phodus sungorus*). The study involved placing hamsters in conditions mimicking summer (long daylight hours in cage) or winter (short daylight hours in cage). After a period of acclimatisation, the hamsters were injected with an

endotoxin (a biological indicator of bacterial infection) that elicits strong immune responses in animals. Results showed that, compared to those in the winter condition, the hamsters in the summer condition showed increased immune activity; a response to the endotoxin that required more bodily resources (Bilbo, Drazen, Quan, He, & Nelson, 2002). Seasonally dependent immune responses displayed by Siberian hamsters are hypothesised to be the result of adaptations in self-regulatory mechanisms involved in governing immune function: cues to summertime and the resource abundance with which it correlates trigger self-regulatory changes that result in more liberal immune resource use. In other words, summertime infections permit a less conservative approach to resource use during infection than do wintertime infections. Resources spent fighting infections are more likely to be replenished during the relative abundance of summertime, compared to the relative scarcity of wintertime, where difficult-to-replenish resources must be conserved to protect against future vulnerabilities (Humphrey & Skoyles, 2012).

### 1.3 Social summertime?

The findings of Bilbo et al. (2002) are illustrative because they give a clear example of how environmental cues can moderate adaptive, self-regulatory processes involved in responses to stressors. In social species, where, to varying degrees, the presence of certain conspecifics correlates with safety and resource abundance, social environments act as a sort of *social summertime*. Research on social buffering in non-human animals supports this idea, generally showing that the presence of conspecifics can attenuate cautious responses to threatening stimuli. For example, among rodents (*Rodentia*) the presence of bonded conspecifics, such as cage mates, has been shown to reduce pain behaviour (e.g., writhing) in responses to noxious stimuli (Kikusui et al., 2006), fearful withdrawal from potential threats (Davitz & Mason, 1955), and cortisol secretion (an indication of the stress response; Stanton, Patterson, & Levine, 1985). Similar effects have been shown in humans. On the one hand, the presence of close social others reduces stress levels, inflammation (a response to bodily harm), and pain sensitivity (Coan, Kasle, Jackson, Schaefer, & Davidson, 2013; Eisenberger, Taylor, Gable,

Hilmert, & Lieberman, 2007; Hughes et al., 2014). On the other hand, cues to isolation and social distress more generally lead to a “short-term preservation mode” (Cacioppo, Cacioppo, & Boomsma, 2014, p. 1467) that includes increases in anxiety, sympathetic nervous system and hypothalamus-pituitary-adrenal (HPA) axis activity (implicated in the fight-or-flight response), inflammation, attention to negative stimuli, and pain sensitivity (Cacioppo, Capitanio, & Cacioppo, 2014; Chiang, Eisenberger, Seeman, & Taylor, 2012; Eisenberger, 2013a; Eisenberger, Jarcho, Lieberman, & Naliboff, 2006; Shintel, Cacioppo, & Nusbaum, 2006).

The diverse range of observed social buffering and support effects have been shown to be underpinned by changes in DNA transcription and activity in the oxytocin, endocannabinoid, and endogenous opioid systems (Barrot et al., 2005; Ebner, Bosch, Krömer, Singewald, & Neumann, 2005; Panksepp, Herman, Vilberg, Bishop, & DeEskinazi, 1981). In addition to regulating stress, fear, and pain responses, these systems are involved in the formation, maintenance, and signalling of social bonds (D'Amato & Pavone, 1996; Ebner et al., 2005; Kalin & Shelton, 1989; Zubieta et al., 2005), and researchers have theorised interactive processes among these systems and the dopaminergic reward system in motivating affiliation with bonded conspecifics and bringing about social buffering effects (Dunbar, 2012; Inagaki et al., 2016; Trezza et al., 2010; Winslow, Noble, Lyons, Sterk, & Insel, 2003). Isolation from conspecifics, and particularly highly bonded conspecifics (e.g., kin, cage mates, or friends) leads to negative affect and behavioural responses that aim to reduce this negative affect, for example, through seeking the neurological reward produced by affiliation with bonded conspecifics (Eisenberger & Lieberman, 2004; Krahé, Springer, Weinman, & Fotopoulou, 2013).

An adaptationist approach is useful in understanding social buffering effects and affiliative motivations. Psychophysiological responses like stress, fear, inflammation, and pain can prepare organisms for defensive, adaptive behaviour (fight or flight, increased vigilance, withdrawal from noxious stimuli, reductions in movement, etc.), but can also incur costs in, for

example, missed foraging and mating opportunities, and negative health outcomes resulting from chronic stress (De Kloet, Joëls, & Holsboer, 2005; Krahé et al., 2013; Panksepp, Bean, Bishop, Vilberg, & Sahley, 1980). It is generally accepted that, in social species, conspecifics are motivated to congregate as a means of predator deterrence, as the social group represents relative safety (Rubenstein, 1978; Van Schaik, 1983). To the degree that conspecifics signal safety, the presence of conspecifics reduces the optimality of defensive responses against potential dangers and threats. In line with this, research has shown that the buffering effects of conspecific partners are diminished when these partners do not signal safety, such as when they are also displaying a stress or fear response (Kiyokawa, Kikusui, Takeuchi, & Mori, 2004).

Here, it should be emphasised that the social buffering account put forth in this thesis is an adaptationist argument, and not necessarily an argument about adaptive behaviour. Psychophysiological responses that are classified as instances of social buffering (attenuated pain and stress responses, enhanced immunity, etc.) are likely adaptations to specific social environments. Given the costs of protective psychophysiological states (e.g., immobility from the pain), it is likely that natural selection has occurred for adaptations that lead to the attenuation of protective or conservative psychophysiological states when the costs outweigh the benefits, such as when social environments signal relative safety or resource abundance. Like all adaptations, those adaptations which lead to social buffering effects have arisen via natural selection as a result of their adaptiveness (that is, their association with increased fitness). However, social buffering effects are adaptive only to the extent to which the signals that evoke them are true. If social signals of safety and resource abundance are inaccurate, then consequent social buffering effects might lead to maladaptive outcomes, such as suboptimal responses to physical threats or overly-liberal uses of resources.

Both within and between-species comparisons suggest that social buffering effects occur in response to social signals. As reviewed above, within species (for example, in baboons and macaques; *Papio hamadryas* and *Macaca sylvanus*), the presence of strongly bonded

conspecifics (or tighter social networks) predicts both higher levels of support (e.g., aid in conflict) and larger attenuations in physical and social stress responses (Crockford, Wittig, Whitten, Seyfarth, & Cheney, 2008; Wittig, Crockford, Langergraber, & Zuberbühler, 2014; Wittig et al., 2008; Young, Majolo, Heistermann, Schülke, & Ostner, 2014). Further, the mere presence of stress causes individuals to affiliate with (stress-reducing) conspecifics at higher rates, suggesting adaptations that encourage affiliation when threatening environmental cues invoke a stress response (Boogert, Farine, & Spencer, 2014; Hennessy, Deak, & Schiml, 2014). Between species, there is a positive relationship between the importance of interdependent social relationships for individuals' evolutionary fitness and the size and diversity of observed social buffering effects (Kikusui et al., 2006; Tomasello et al., 2012). In a review of social buffering of the stress response, Hennessy et al. (2009) conclude that observed patterns of social buffering across species can be "accounted for by the social organization of the species" (p. 473), with socially interdependent species (i.e., those in which conspecifics rely on one another for protection or resources) displaying stronger and more diverse patterns of social buffering than species characterised by more solitary, independent living. For example, in sheep – which exhibit strong social adhesion to fellow flock members – the presence of conspecifics can have strong social buffering effects, whereas in goats – which show much weaker grouping tendencies – this form of social buffering is absent (Lyons, Price, & Moberg, 1993). Similar between-species patterns have been shown species ranging from rodents (e.g., *Cavia porcellus* and *Cavia tschudii*) to monkeys (e.g., *Callicebus moloch* and *Saimiri cassiquiarensis*), with the social order and interdependence of relationships predicting when social buffering effects occur (Hennessy et al., 2009; Hennessy, Mendoza, Mason, & Moberg, 1995). Although more direct research on the ultimate function of social buffering is needed, these cross-species comparisons offer preliminary evidence for the hypothesis that social buffering effects occur as a result of social signals that change individuals' tacit forecasts of safety and access to resources (Hennessy et al., 2009). If social buffering is largely about what conspecifics signal, it follows that stronger and more diverse social buffering effects will be observed in species with high levels of social interdependence.

### 1.4 Social buffering and support in humans

A diverse body of evidence provides support for the idea that social buffering effects in humans arose as a result of an evolutionarily ancient dependence on bonded conspecifics for ensuring relative safety and resource access. Research indicates shared social dependencies within the primate order (e.g., Sanchez et al., 2015), suggesting that social relationships had important fitness consequences dating far back into human evolution, perhaps to (at least) the last common ancestor of extant primates. This research has shown that individuals with a relatively high number of close social bonds have higher levels of coalitional support, increased longevity, and greater reproductive success (Dunbar, 1980; Silk et al., 2010). It is hypothesised that these effects can be explained by a combination of the chronic-stress-reducing effects of close social bonds, and the protective, instrumental social support offered by bonded partners during conflict (Schülke, Bhagavatula, Vigilant, & Ostner, 2010; Silk, Alberts, & Altmann, 2003).

The important role of conflict in determining fitness outcomes in extant non-human primates suggests that both inter and intra-group conflict (e.g., territory or social hierarchy disputes) played an important role in *hominidae* evolution. Lethal aggression from conspecifics is a major fitness-relevant risk in non-human primates (Boesch et al., 2008; Watts & Mitani, 2001). Coalitionary support during these conflicts is an important predictor of both the likelihood of possible conflict and the outcome of actual conflict (Boesch et al., 2008; Samuni et al., 2016). In baboons (*Theropithecus gelada*), for example, the likelihood of an individual coming to the aid of another when it is being attacked is positively related to the pairs' degree of bondedness (Datta, 1983; Dunbar, 2010). This 'predictable social support' has similarly been reported in chimpanzees (*Pan troglodytes*), where the presence of bonded partners is associated with reduced stress hormone levels in extreme situations (potentially dangerous inter-group encounters) and everyday life (Wittig et al., 2016). Given that heightened levels of these hormones prepare animals for to fight (Sapolsky, Romero, & Munck, 2000), and that bonded pairs give agonistic support to one another, Wittig et al. (2016) concluded that the presence

of bonded others actually increases safety levels during inter-group encounters, thus making buffered stress responses adaptive in these situations.

It is thus likely that the human lineage has undergone selection for social buffering effects related to the threats of conflict and predation more generally. Inter-group violence and predation would have been a major threat to hominin survival (Choi & Bowles, 2007; Van Schaik, 1983), eliciting strong psychophysiological stress responses. As previously discussed, these responses are costly in terms of missed opportunities in the short term and health consequences in the long term, and are therefore better avoided when social environments can buffer against danger. Consequently, socially buffered individuals with stress responses that responded optimally to variations in support and safety would have been at an evolutionary advantage.

The unique social evolutionary trajectory of *Homo* may have further led to selection for social buffering effects that are novel in both their strength and cause. Humans display an evolutionarily ancient and pervasive dependence on social relationships in a variety of fitness-relevant contexts, ranging from child rearing and food acquisition to care during illness and protection from predators and hostile conspecifics (Hrdy, 2007; Tomasello et al., 2012). Without direct care in childhood, for example, and access to the corpus of culturally transmitted knowledge about the world around them (including the resources this knowledge produces), human survival becomes dubious at best (Henrich, 2015). In this sense, human fitness is uniquely associated with membership in a cohesive social group and social support received from close relationships (although this is likely a quantitative rather than qualitative difference from other primate species, which, as discussed, also depend on social relationships in a variety of contexts). Human dependence on social ties is likely to have led to adaptations that function to both ensure the availability of social support and respond to its presence.

There is a great deal of evidence for cognitive adaptations in humans that function to create, monitor, and maintain positive social relationships. For instance, humans seem unique in their

abilities to predict and respond to the thoughts and intentions of others[5], and to cooperate and share resources (Hrdy, 2007; Tomasello et al., 2012). In addition to these cognitive adaptations, humans have a suite of emotional adaptations that also encourage the maintenance of social ties. For example, research suggests that oxytocin and vasopressin play an important role in inducing emotional states that support sociality and pair bonding (Carter, Grippo, Pournajafi-Nazarloo, Ruscio, & Porges, 2008), such as feelings of calmness and general well-being (Ishak, Kahloon, & Fakhry, 2011). The 'brain opioid theory of social attachment' also points to the emotional states of interpersonal warmth, calmness, well-being, and even 'euphoria' (Machin & Dunbar, 2011), but instead proposes that such emotions are mediated by endogenous opioid activity. These positive emotional states are thought to form the foundations upon which cognitive relationships of trust, care, attachment, and reciprocity can be built (Dunbar, 2012). More generally, research has shown that associating with close, supportive others is motivated by (dopaminergic) neurological reward (Acevedo, Aron, Fisher, & Brown, 2012; Inagaki et al., 2015).

Negative emotions may also be involved in motivating the maintenance of social ties. It has been proposed that neural pathways (connections between neurons that allow for signals to be sent from one area of the nervous system to another) involved in physical pain were co-opted by natural selection to react to and prevent social separation (Eisenberger & Lieberman, 2004; Panksepp, 2004). These selective pressures are thought to have arisen during the evolution of social species as a result of correlations between social isolation and risk of bodily harm and decreased access to resources and care (Eisenberger & Lieberman, 2004; Panksepp, 2004). The proposed role of endogenous opioids in forming and signalling social bonds, and in regulating perceptions of pain, gives credence to the idea that social separation

[5] Of course, in addition to helping predict the intentions of others during cooperative activities, mind reading capabilities may have also evolved for more Machiavellian purposes (Lyons, Caldwell, & Shultz, 2010).

is neurologically linked to physical pain. Indeed, there is evidence of significant correlations between sensitivity to physical pain and sensitivity to social pain (resulting from social rejection or isolation), as well as research showing that variables which increase social pain also increase physical pain, and vice versa (Eisenberger, 2012a, 2012b). Neuroimaging research has shown that similar neural regions, such as the dorsolateral anterior cingulate cortex (dACC) and anterior insula (AI), are involved in the negative affect of both physical and social pain (Eisenberger & Lieberman, 2004; Eisenberger, Lieberman, & Williams, 2003). Thus, there is evidence suggesting that humans experience social pain via the same mechanisms through which they experience physical pain[6], and that this functions to encourage the seeking and maintenance of beneficial social ties (Eisenberger & Lieberman, 2004). The negative affect and desire to affiliate that stems from social rejection and isolation causes humans to seek out close social connections and the social support that is often provided by these relationships.

In humans, social support can take a variety of forms, ranging from emotional appeasement to instrumental acts, such as food sharing and care during illness. Although costly in terms of lost time and resources, *giving* social support may also lead to adaptive outcomes. Research has shown that those individuals who give social support are more likely to have large social networks from which they can receive social support (Power, 2017). Cooperative networks of social support may thus allow humans to achieve adaptive outcomes by enhancing access to resources and increasing safety and future certainty (Hruschka, 2010). Humans thus live in interdependent worlds where many aspects of daily life are conditional on supportive

[6] There is a considerable amount of scholarly debate around these findings, with researchers arguing that shared neural pathways between physical and social pain are better explained by processes such as conflict detection or salience processing (Iannetti, Salomons, Moayedi, Mouraux, & Davis, 2013; Somerville, Heatherton, & Kelley, 2006). Eisenberger (2015) offers a rebuttal to these claims based on, among other things, reappraisals that integrate findings from recent research and the failure of competing predictive models to explain the neural overlap between physical and social pain.

interactions with others, thereby leading to self-regulatory psychophysiological strategies and fitness outcomes that are contingent on social cues.

### 1.4.1 Contrary evidence to social buffering and support accounts in humans

Regarding the possibility of contrary evidence to the accounts presented here on social buffering and support effects, it should be noted that, although perceptions of social support have been described as “one of the most universally positive constructs in the relationship literature,” it has consistently been shown that individuals may not always benefit psychologically from the actual *receipt* of social support (Ryon & Gleason, 2018, p. 1). These findings form the basis of the most common objections in the literature to claims about the ubiquity and strength of social buffering and support effects (Holt-Lunstad & Uchino, 2008).

Research has shown that social support effects can be moderated by how social support is given, the context of the relationship in which it is given, and recipients’ personality factors. Social support can have null or deleterious effects if it lowers recipients’ self-efficacy and independence, leading them to view situations as more threatening and stressful (Gleason, Iida, Bolger, & Shrout, 2003). Further, inequalities in the provision and receipt of social support between individuals can lead to perceptions of an inequitable relationship and consequent feelings of distress (Ryon & Gleason, 2018). Relationship quality more generally has been shown to moderate social support effects, with relationships of higher quality (less distress, stronger perceived bonds, etc.) being shown to have stronger positive effects on health outcomes such as morbidity and mortality (Holt-Lunstad & Uchino, 2008). Research also suggests that those individuals who have relatively low levels of perceived social support in their daily lives are more sensitive to manipulations of social support, compared to those scoring relatively high on this variable (Rees & Freeman, 2010). Those with relatively high levels of perceived social support may be insensitive to specific acts of social support, as they are able to draw on pre-existing supportive relationships during times of stress, whereas those with relatively low levels of perceived social support might find specific acts of social support particularly salient and useful in dealing with stressors (Uchino, 2009). Finally, personality

factors have been shown to moderate social support effects. For example, highly neurotic individuals are more likely to respond to the receipt of social support with concerns about the necessity to reciprocate such acts (Park et al., 2013), and individuals with low self-efficacy may view social support as an indication of their own incompetence (Bolger & Amarel, 2007). More directly, 'need for social assurance' – a construct related to individuals' desire for companionship, affiliation and social connectedness – may also affect how social support is received, with those scoring relatively high on this variable being more responsive to social support (Lee & Robbins, 1995). This research demonstrates that these personality-dependent responses can ultimately dampen or eliminate the positive effects of social support (Bolger & Amarel, 2007; Park et al., 2013). Differences in social support effects according to recipients' personality types suggest that responses to social environments may be ontogenetically adapted to environments of support or deprivation (Figueredo et al., 2005; Frankenhuis, Panchanathan, & Nettle, 2016).

These findings have implications for the types of individuals and situations in which positive social support effects are likely to be observed. They also stress the necessity of distinguishing received social support from what researchers have identified as perceived social support, which relates to "perceptions of availability of emotional, informational, tangible, or belonging support *if needed* [italics added]" (Holt-Lunstad & Uchino, 2008, p. 184). Empirical research has shown that these two constructs correlate only moderately (Wills & Shinar, 2000). Importantly, this work has revealed that perceived support is a better predictor of buffering effects and positive mental and physical health outcomes than is received social support. As mentioned above, received social support does not always lead individuals to feel more supported (Holt-Lunstad & Uchino, 2008; Uchino, 2009; Wills & Shinar, 2000). Nevertheless, this literature leaves open the possibility (yet untested empirically) that an individual could react negatively to received social support, perhaps feeling indebted and anxious as a result, yet still benefit from overall increases in perceptions of social support. Regardless, it is likely that it is individuals' perceptions of social support (both tacit and explicit), rather than the

amount of social support that they actually receive, that is most relevant to explaining how social environments can act as buffers to stress (Holt-Lunstad & Uchino, 2008).

Thus, it is important to consider the social relationships and personality types that are not conducive to social buffering and support effects, and to understand whether or not a lack of these effects in certain contexts provides evidence that is contrary to the broader claims of this thesis. This thesis claims that social support and buffering effects are brought about by social cues that signal to individuals that they are in relatively safe and/or resource abundant environments. This is congruent with findings suggesting that it is individuals' perceptions of social support – and not the actual amount of social support they receive – that predicts social buffering and support effects; individuals must interpret environmental cues (either tacitly or consciously) as ones of safety and/or resource abundance for these positive effects to occur. It is thus unsurprising that personality factors and relationship styles play a role in determining a social environment's effect on an individual.

The possibility of other types of contrary evidence must also be addressed. Such evidence would suggest that social buffering and support effects do *not* result from social environments that increase perceptions of relative safety and/or resource abundance. Potential findings could exist in a variety of contexts, but the following (interrelated) possibilities either have been tested or will be tested in this thesis: (1) findings of no positive correlation between the closeness and quality of a relationship (correlates of likely material or emotional support) and the size of its social buffering and support effects, (2) evidence that social buffering and support effects can be brought about by stimuli that have no relationship to safety and our resource abundance, (3) evidence for a confounding variable that is related to both the predictors and outcome measures of social buffering and support effects. To my knowledge, this contrary evidence does not yet exist in the literature.

Regarding the link between relationship quality and social buffering and support effects, research across multiple contexts has consistently found that closer and higher quality

relationships have stronger buffering effects than do strangers, looser social ties, or distressed or burdensome relationships (Coan et al., 2006; Eisenberger et al., 2011; Holt-Lunstad & Uchino, 2008; Robles, Slatcher, Trombello, & McGinn, 2014). Several studies have tested whether stimuli that have no relationship to safety and our resource abundance can lead to buffering or support effects; all have found that such stimuli (e.g., a chair) have buffering effects that are significantly smaller than those evoked by close social others, but that are not significantly different from those evoked by control conditions (e.g., fixation crosshairs) or complete strangers (Coan et al., 2006; Eisenberger et al., 2011; Master et al., 2009). The possibility of confounding variables is, of course, context dependent, but none have been raised as serious objections to the social support literation reviewed in this chapter and in Chapter 2. However, the specific context in which this thesis tests social support effects – during strenuous physical exercise – does lend itself to the related confounds of competition and costly signalling. It has been shown that competition can enhance physical performance (Corbett, Barwood, Ouzounoglou, Thelwell, & Dicks, 2012; Konings, Schoenmakers, Walker, & Hettinga, 2016; McCormick, Meijen, & Marcora, 2015; Tomazini et al., 2015), thus making it possible that effects ascribed to social support and its facilitating effect on physical outputs (see Section 2.2, p. 45, for a full account) are actually the result of increased motivation due to competition (Hettinga, Konings, & Pepping, 2017), which itself has been construed as a costly signal of physical fitness to potential rivals and mates (De Block & Dewitte, 2009; Miller, 1999). The confound of competition is addressed throughout the empirical chapters of this thesis, which present studies that attempted to control for competition (with varying degrees of effectiveness). The possibility of competition as an alternative explanation for the results presented in this thesis is discussed in Section 7.3.2 (p. 242).

### 1.4.2 Adaptationist accounts of social buffering and support effects in humans

In this thesis, I argue that high levels of social dependency in the *Homo* lineage likely shaped a range of adaptations that function to calibrate psychophysiological states to particular social environments, and that a subset of these adaptations are what underpin the social buffering

and support effects that I review, test, and present. Crucially, as discussed in Section 1.3 (p. 11), these adaptations need not always lead to psychophysiological states that are adaptive; false social cues to safety and resource abundance could lead to suboptimal responses.

However, Humphrey and Skoyles (2012) have argued that homeostatic or 'baseline' psychophysiological states in extant humans are overly conservative (e.g., levels of pain sensitivity that are too high, regulation of immune resources that are too cautious, etc.) given evolutionarily unprecedented levels of safety and resource abundance in (the vast majority of) modern populations (Pinker, 2019). If this is true, then it is likely that the majority of social buffering and support effects reported in the literature are also adaptive, as they bring psychophysiological states in line with modern reality; this is consistent with well-established research linking social support to reductions in morbidity and mortality in modern populations (Cohen et al., 2015; Eisenberger, 2013b; Gleason & Iida, 2015; Holt-Lunstad & Uchino, 2008). On the contrary, responses to social rejection and isolation may be particularly maladaptive in modern populations, given that the mechanisms underpinning these responses likely evolved in environments where social isolation correlated much more strongly with scarcity and threats from predators and conspecifics (Cacioppo, Cacioppo, et al., 2014). It therefore seems likely that, despite a shift toward lifestyles that are less directly dependent on close social relationships (especially in industrialised populations; Putnam, 1995), humans maintain adaptations (reviewed in Section 1.4.2, p. 22, and in Section 2.2.3, p. 53) that evolved to respond to particular social environments with particular psychophysiological states, and that these responses may exhibit some evolutionary mismatch[7] with modern environments (Li et al., 2018; Tooby & Cosmides, 1990).

[7] Li, van Vugt, and Colarelli (2018) define evolutionary mismatch as "the adaptive lag that occurs if the environment that existed when a mechanism evolved changes more rapidly than the time needed for the mechanism to adapt to the change" (p. 1). In this case, the mismatch is between the importance of close social relationships for safety and resource acquisition in environments where the adaptations underpinning social buffering and support effects evolved, and the importance of close social relationships for safety and resource acquisition in modern times.

However, as is the case with other adaptationist accounts (Gould & Lewontin, 1979), directly testing the adaptationist hypotheses put forth in this thesis will likely prove difficult (and this is not the objective of this thesis). Hennessy et al. (2009) have suggested examining how the diversity and frequency of social buffering effects might differ across cultures according to varying levels of interdependence (e.g., depending on religion, subsistence style, or population density). To date, however, this research is yet to be conducted. Although there is a lack of direct evidence for adaptationist hypotheses on social buffering and support in humans, the comparative, non-human data reviewed in Section 1.3 (p. 11), as well as the diversity and ubiquity of findings in humans presented in this chapter and in Chapter 2, are certainly congruent with adaptationist accounts of these effects.

The vast majority of this research focuses on the proximate mechanisms of social buffering and support effects in humans, with only a small fraction of researchers providing ultimate, evolutionary explanations for these effects[8]. Thus, ultimate accounts of the effects discussed in this thesis represent a largely original intellectual contribution to bodies of literature that have otherwise focused on describing when and how (at the proximate level) social environments affect psychophysiological responses to stressors.

Examining the literature described in this thesis with an ultimate, evolutionary perspective offers several benefits. The evolutionary account that I provide extends previous research that has attempted to give ultimate accounts of psychophysiological responses to social cues of support, cohesion, or isolation (Cacioppo, Cacioppo, et al., 2014; Hennessy et al., 2014; Hennessy et al., 2009). Through taking a broad, evolutionary perspective in explaining why specific psychophysiological responses to specific social environments exist – as a means of attuning behavioural strategies to levels of safety and resource abundance cued by social environments, it is argued – this thesis provides a framework to reinterpret a multitude of

[8] To my knowledge, only Hennessy et al. (2009), Hennessy et al. (2014), and Cacioppo, Cacioppo, et al. (2014) offer extended, direct discussions of the ultimate functions of psychophysiological changes stemming from social cues.

findings that have not yet been given ultimate explanations. Specifically, this perspective facilitates the identification of self-regulatory mechanisms that are likely to be responsive to social cues (more detail on these mechanisms is provided in Section 2.2.3, p. 53). Further, the remainder of Section 1.4 (as well as Section 2.2.2, p. 45) gives an account of how a diverse set of human behaviours, cultural norms, and practices – ranging from mere companionship to synchronised group movement – provide social cues of safety and resource abundance that lead to a variety of changes in psychophysiological mechanisms that respond to stressors such as pain, injury, illness, and social and physical threats more generally.

### 1.4.3 Companionship and touch

Research on non-human animals suggests that companionship and touch are evolutionarily ancient buffers that signalled relative safety and access to resources in the daily lives of human ancestors (Kikusui et al., 2006). In modern humans, cross-cultural norms and practices of companionship and touch function in a similar way, as they often surround painful and stressful experiences. Even though supportive others are often unable to offer instrumental support (e.g., providing medical care), they may be able to induce buffering effects by signalling emotional support and thereby influencing recipients' tacit assessments of safety and resource availability.

Intimate physical touch, such as handholding and hugging, is thought to be a universal signal of support, empathy, and care (Cohen et al., 2015; Goodwin, 2017). Cross-cultural similarities in touch behaviours and meanings may be grounded in evolutionarily ancient responses to touch in the context of bonded relationships. In *hominidae*, intimate touch has likely been associated with close social relationships that provide both protection and access to shared resources (Dunbar, 2010; Seyfarth & Cheney, 2012; Silk et al., 2003). Researchers have speculated that "hugging is a behaviour that may be manipulated to provide the beneficial effects associated with support" (Cohen et al., 2015, p. 145). Indeed, touch and companionship more generally are often critical components of social interactions during stressful events; norms around companionship and supportive touch have been documented

cross-culturally in the context of hospital visits, childbirth, sport, and exercise, as well as healing, tattooing, and circumcision rituals (Holmes, 1958; Kaptchuk, 2011; Kulik & Mahler, 1989; Sanders & Vail, 2009).

Research suggests that, although practices of companionship and touch do not act directly on stressful stimuli to prevent them from occurring, they still can have positive effects for those under stress. Randomised control trials (RCTs) have shown that just the presence of close others during childbirth can reduce women's use of pain relief medication, and that touch and massage, in addition to reducing pain, can also reduce anxiety levels in women giving birth (Chang, Wang, & Chen, 2002; Field, Hemandez-Reif, Taylor, Quintino, & Burman, 1997; Kennell, Klaus, McGrath, Robertson, & Hinkley, 1991). Other research has shown that those individuals whose spouses visit them in the hospital while they are recovering from surgery require less pain medication and heal more quickly than those who receive fewer spousal visits (Kulik & Mahler, 1989). The amount of hugs an individual receives on a daily basis has also be shown to be negatively correlated with risk of infection and objective signs of illness, most likely because perceptions of social support reduce the pathogenic, immunity-supressing effects of stress (Cohen et al., 2015).

Research is beginning to show that these effects are underpinned by neurobiological changes in systems involved in the pain and stress responses. Generally, the presence of close others has been shown to reduce stress levels (Karremans, Heslenfeld, Van Dillen, & Van Lange, 2011). Holding the hand of a spouse can reduce activity in brain areas involved in both the emotional and behavioural threat responses. Interestingly, in this scenario, the attenuation of the neural threat response was moderated by marriage quality, with higher marriage quality correlating with less activity in brain areas involved in the threat response (Coan et al., 2006). Other research suggests that touch and the presence of close, supportive others can lead to the activation of the endogenous opioid system, which has analgesic effects and can contribute to the self-regulation of stress (Dunbar, 2010; Inagaki et al., 2016; Weller & Feldman, 2003; Zubieta et al., 2005). As will be discussed in Chapter 2, physical outputs are

also governed by activity in the endogenous opioid system. This suggests the possibility that companionship and cohesion signalling touch also affect sport and exercise performance through reducing athletes' perceptions of pain and fatigue (Amann et al., 2009; Kraus et al., 2010).

### 1.4.4 Care from others

While many of the social buffering effects found in humans – such as those resulting from companionship and touch – are likely to exist in other highly social species, the unique evolutionary trajectory of humans may have also led to species-specific forms of social buffering, and this may have in turn affected human evolution itself. A quantitatively, if not qualitatively, unique characteristic in humans is the practice of caring for the ill and injured. Archaeological evidence dating back to 1.77 million years ago suggests that *Homo* individuals with (otherwise life-threatening) disabilities were able to survive for long periods as a result of care from others (Gracia et al., 2009; Hublin, 2009; Lordkipanidze et al., 2005; Trinkaus & Villotte, 2017; Trinkaus & Zimmerman, 1982; Wu, Schepartz, Liu, & Trinkaus, 2011). If care of this nature was available for such a large portion of human evolution, it is likely to have affected adaptive responses to illness and injury. Just as biannual variations in resource abundance have led to adaptations for seasonal-dependent immune responses (Bilbo et al., 2002), it may be that variation in socially acquired resources has led to adaptations that are sensitive to the quality of social relationships and the possibility of care from others.

Greater availability of care would have favoured the evolution of psychophysiological responses to illness and injury that took additional resources provided by others into account (Humphrey & Skoyles, 2012). Where care was available, recovery would not necessarily be wholly or primarily dependent on resources intrinsic to the individual (e.g., immune system functioning, energy reserves, etc.). Rather, recovery would be partially outsourced to others and their ability to provide additional care and healing resources (Humphrey & Skoyles, 2012). Therefore, insofar as social support from others led to changes in recipients' access to resources and ability to heal, selective processes would have favoured self-regulatory

responses to illness and injury that led to more liberal uses of healing resources when social support was cued.

Links among social support, resource availability, and healing capacities may have also selected for increased sensitivity to, and motivation toward, sources of extrinsic care. Indeed, it seems likely that humans have also evolved adaptations that encourage seeking out socially supportive relationships when ill or injured. Wall (1999) has argued that physical pain is a 'need state' – similar to hunger or thirst – that motivates reductions in negative affect through 'consummatory acts' such as receiving care and attention from others. New empirical research supports this claim. Using a novel experimental paradigm, Inagaki et al. (2015) gave participants a low dose of an endotoxin that induces an inflammatory response. They found that, compared to those who received a placebo, participants who received an endotoxin expressed a greater desire to be around a 'support figure' (someone they go to for help and comfort), and that this effect was mediated by activity in a brain area (the striatum) involved in motivation for reward which is also activated when viewing close others (Acevedo et al., 2012). This experimental evidence corroborates observations that sickness increases approach behaviour (i.e., clinging and general preferences for proximity to caregivers) in infants (Bowlby, 2008) and supports research concluding that chronic pain leads to increases in anxiety as a result of heightened concerns over social rejection (Macdonald & Kingsbury, 2006).

#### 1.4.4.1 Social support and placebo effects in medical contexts

Placebo effects are beneficial, biomedically meaningful outcomes that result from conditioning and/or beliefs and expectations about the receipt of a putatively effective medical treatment (Benedetti, Carlino, & Pollo, 2011; Moerman, 2002). Many different types of placebo effects are known to significantly affect medical outcomes – they have been shown to, for example, reduce pain and depressive symptomology, and to ease symptoms of Parkinson's Disease (Benedetti, 2013; Benedetti et al., 2016; Colloca & Benedetti, 2005; Kirsch & Sapirstein, 1998). Crucially, placebo effects are distinct from those effects arising from active medical treatments

(Benedetti, 2009). Thus, placebo effects can arise due to a variety of factors, including previous experience, ritual practices surrounding medical treatment, and practitioner-patient relationships (Benedetti, 2009). As such, placebo effects can occur in tandem with medically effective treatments, or in their absence, as long as patients believe or expect a treatment to be effective.

Viewed from a broader perspective, many types of placebo effects are actually responses to social environments (Davis, Hettinga, & Beedie, 2019). Medical treatments almost always entail receiving the support of practitioners and, more generally, the support of medical institutions (and the healing power and knowledge associated with them). Experiencing or seeing successful healing as a result of engaging with these medical institutions may lead patients to associate treatments embedded in these contexts with safety, care, and resource abundance. Learned associations of medical treatments with these outcomes may allow the symbols, practices and rituals of medical institutions to have buffering effects that are similar to the buffering effects of close, supportive relationships. In other words, these processes may allow the cultural items surrounding medical treatments to fill the role of traditional support figures in activating the neurological circuitry involved in buffering effects (Bowlby, 1969; Eisenberger et al., 2011). Indeed, studies using fMRI have shown that placebo analgesia is partially contingent on cognitive evaluations that lead individuals to perceive stimuli as being less likely to cause them harm (Wager et al., 2004). Due to the support and relative safety that they signal, putatively effective treatments can cause stressors to be evaluated as less serious and threatening, leading to a buffering of distress (Trimmer et al., 2013).

Given ancient dependencies on social relationships in the human lineage – and the existence of adaptations that arose as a result – the prospect of care from others is likely to have substantial effects on self-regulatory, psychophysiological responses to illness and injury. If individuals expect that the care they are receiving will aid them in overcoming an illness, for example, this may alter the forecasted costs and benefits of (slightly riskier) strategies involving deployments of finite immune resources. Care from others can reduce the potential

costs of immune resource deployment, since individuals are more likely to be able to replenish these resources in supportive social environments, and it can also increase the potential benefits, since (biomedically effective) care from others enhances the likelihood that immune responses will actually lead to recovery from the illness (Evans, 2003; Humphrey & Skoyles, 2012).

As patients came to believe in the effectiveness of care, healers may have begun to use more and more elaborate forms of treatment as a means of signalling the presence of care and impending psychophysiological improvements. While some of these treatments would have been effective because of their biomedical effects, others would have been effective simply because of the self-regulatory changes they led to. Through these processes, and the gradual build-up of cultural items that signalled the presence of competent care from others, the first placebo effects were born.[9]

#### 1.4.4.2 Placebo effects – social and cultural cues

Studies on the placebo effect in clinical settings may provide the most understood and documented example of how socio-cultural cues can affect human psychophysiological responses to stressors (Beedie & Foad, 2009; Benedetti, 2013; Evans, 2002, 2003; Humphrey, 2002, 2013). A recent study on placebo responses in RCTs investigating neuropathic pain suggests that patients' responses to treatments depend largely upon the social context within which they are administered (Tuttle et al., 2015). The study found that

[9] In this sense, placebo effects are effective in as much as they lead to biomedical improvements (e.g., reductions in pain, enhanced immunity, etc.). However, placebo effects are not always *adaptive*. Humphrey and Skoyles (2012) argue that human self-regulatory processes are over-conservative given modern levels of safety and resource abundance, leading to, for example, levels of protective pain or immune resource conservation that are maladaptive. In relatively safe, resource rich environments, less conservative strategies are more adaptive. Thus, when placebo effects lead to reductions in pain in a hospital setting, they will likely lead to adaptive outcomes, since pain and associated stress levels have been shown to be negatively correlated with wound healing (Woo, 2012). However, if a placebo effect led to pain reductions that caused individuals to be overly active, thereby causing an injury to reoccur or preventing it from healing in the first place, it would lead to maladaptive outcomes. Similarly, if a placebo effect led to enhanced immune resource use in the absence of adequate replacement resources, this could lead to maladaptive outcomes where individuals are left vulnerable to future infections due to depleted immune resources (which would have been conserved in the absence of the placebo treatment).

placebo responses have increased over time, and that this increase occurred only in the United States, where, compared to Europe, trials have become larger, longer, and more expensive over time (Tuttle et al., 2015). In explaining these results, the authors point to the fact that longer trials typically involve more, and hence richer and more attentive, interactions between patients and care providers, suggesting that patients in longer trials have higher levels of perceived support (Dunlop et al., 2012; Tuttle et al., 2015). Supporting this conclusion is a study demonstrating a positive correlation between patient-practitioner face-to-face interactions (which increases with trial length) and placebo responses (Vase, Nørskov, Petersen, & Price, 2011). It may also be that the larger, longer, and more expensive trials in the United States also include greater investment in presentation (newer equipment, treatment rooms, hospitals, etc.) – a cue to patients which suggests greater investment from medical institutions in treating their pain. These studies highlight how social context and cultural cues can lead to medically meaningful effects on patient outcomes.

On the importance of the practitioner-patient relationship, Kaptchuk (2002) claims that “the practitioner-healer must expertly play the role of heroic rescuer to facilitate a placebo effect” (p. 818). Research has shown, for example, diminished placebo analgesia following putatively effective self-administered treatments compared to the same treatments received from practitioners (Hashish, Hai, Harvey, Feinmann, & Harris, 1988). While these results could be explained by patients’ beliefs about the efficacy of the self-administered treatments, Hashish et al. (1988) and other researchers have pointed to the importance of an active role of the practitioner in bringing about the observed pain reductions (Evans, 2002; Steinkopf, 2015). A similar finding comes from a study using a placebo acupuncture intervention, which varied the ‘intensity and quality’ or practitioner-patient interactions (Kaptchuk et al., 2008). Compared to conditions in which patients received no treatment or treatments with ‘business like’ interactions with the practitioner, those patients who had long, ‘supportive and empathetic’ interactions with their practitioners experienced the greatest amount of symptom relief (Kaptchuk et al., 2008). Meta-analyses have agreed with this finding, showing that the

practitioner-patient relationship has significant, and medically meaningful, positive effects on healthcare outcomes, such as pain and stress levels (Di Blasi, Harkness, Ernst, Georgiou, & Kleijnen, 2001; Kelley, Kraft-Todd, Schapira, Kossowsky, & Riess, 2014). These studies highlight the importance of what has been called “performative efficacy” (Kaptchuk, 2002, p. 817) in generating placebo effects. Performative efficacy relies upon patients’ associating medical symbols, rituals, and practices with support and impending psychophysiological improvements.

Indeed, cues to caring, supportive environments seem to be used cross-culturally as a means of bringing about patient improvements. Curing the ill and injured, especially in cultures that do not practice Western medicine, often involves treatment rituals that require the participation of friends, family, and the broader community. Among the !Kung, curing ceremonies are community endeavours that involve women singing and clapping a rhythm while male curers circle around a fire in short, synchronous steps (Marshall, 1976). Similarly, in northern Malawi, the entire community is expected to take part in healing ceremonies, and even the sick join in singing, dancing, and clapping with the collective whole (Friedson, 1996). Navajo “chantway” healing rituals also involve the participation of the sick and their family, friends, and members of the broader public (Kaptchuk, 2011). While patients likely derive spiritual meaning from these ceremonies, it is noteworthy that, across cultures, patients’ support networks (e.g., their friends and family) are often participants in these rituals. Their participation may signal the availability of a large and caring social network, leading to the positive health effects (e.g., enhanced immunity and healing) associated with placebo treatments and perceptions of social support more generally (Cohen et al., 2015; Kulik & Mahler, 1989).

As such, social and cultural buffering effects may underpin many types of placebo responses. Across cultures, medical treatments involve patients “perceiving a field of symbols [or cues] created in whatever manner by a shaman, herbalist, psychiatrist, or other practitioner” (Moerman, 2002, p. 60). These symbols, such as the doctor’s white coat in Western cultures, along with the correct performance of culturally prescribed behaviours, allow practitioners to

associate oftentimes ambiguous procedures with care, support, and years of learning about the effectiveness of a medical institution. In other words, these cultural items allow treatments to be "embedded in an authoritative cultural truth" (Kaptchuk, 2011, p. 1,849) about care, healing, and the effectiveness of medical treatments. Through norms of behaviour associated with these 'cultural truths,' practitioners are able to signal to their patients that they are receiving the support of effective treatments, practitioners, and medical institutions more broadly.

### 1.4.5 Friendship

Companionship and care in times of need are also central to the norms, expectations, and behaviours that characterise human friendship. Although diverse in form and practice, friendship is a human universal (Brent, Chang, Gariépy, & Platt, 2014). Cross-culturally, friendships consistently entail norms of mutual aid, such as caring, making sacrifices, and looking out for the interests of one another, especially during times of need (Hruschka, 2010). In fact, mutual aid is the most frequently cited descriptor of friendship in the ethnographic record; a review of 60 of the world's societies found reference to norms of mutual aid in 56 cultures, and this norm was never disconfirmed (Hruschka, 2010).

Although norms of mutual aid characterise friendship universally, the value placed on friendships varies within and across cultures, and this variation has been shown to be positively related to future uncertainty and risk (Hruschka, 2010). Support provided by friends is most useful in times of threat and stress, and people seem to be most drawn to friends – and their buffering effects – when a threat is imminent (Inagaki et al., 2015).

Indeed, mutual aid seems to be a cross-cultural universal in human friendships, and, in most cases, it cannot be explained by traditional theories of reciprocity (Hruschka, 2010). Traditional explanations of altruistic behaviour among non-kin have focused on reciprocal altruism, and, in particular, the 'tit-for-tat' strategy, in which initially cooperative individuals attempt to balance the receipt and allocation of altruistic acts through reciprocating the prior behaviour of their

partners (Axelrod & Hamilton, 1981). However, cross-cultural research suggests that friendships are not characterised primarily by tit-for-tat strategies (Falk, Fehr, & Fischbacher, 2008; Hruschka, 2010; Nash, 1970; Tsang, 2006). Instead, this research has pointed to a sort of 'generalised reciprocity,' based on positive affect and a robust 'habitual urge' to help friends in need, regardless of specific tallies of past altruistic behaviours. In fact, strict tit-for-tat accounting of altruistic behaviour is often viewed as unacceptable among friends, where imbalances in received help resulting from differing fortunes are completely acceptable (Hruschka, 2010). Friends build a relationship "from one where the largest risk is exploitation by a partner to one where the largest risk is losing a mutually beneficial friend" (Hruschka, 2010, p. 209). This process is theorised to result in friends that are willing to sacrifice not because of past favours or expected reciprocation in the future, but because of positive affect, habit, and the desire to maintain mutually beneficial relationships (Hruschka, 2010).

The result is that human friendships form a social niche of abundant mutual aid[10], which provides safety and resources in the face of environmental stressors and threats. Thus, friendship – and the norms and institutions that govern its formation and maintenance – can be seen as a culturally derived buffer, the assurance of which potentially changes the psychophysiological responses humans have to environmental stressors. Empirical work suggests that this is the case. Those who report their daily interactions to be more supportive show attenuated stress responses (Eisenberger et al., 2007), and the stress-reducing effects of close relationships such as friendships have been shown to strongly influence health outcomes – lacking close social connections increases the risk of mortality more than obesity,

[10] Of course, (unreciprocated) aid is also expected among kin (Hamilton, 1964), and humans are likely to benefit from social buffering effects derived from relationships with genetically related others (Holt-Lunstad & Uchino, 2008). In fact, genetic kin will often times be central to individuals' social support networks, and their presence has been shown to have strong buffering effects in a variety of situations (Coan et al., 2006; Holt-Lunstad & Uchino, 2008; Kulik & Mahler, 1989). However, these relationships will not be specifically reviewed in this section, as its aim is not to be a comprehensive account of the (cultural) forms of social buffering in humans, but to offer some examples of behaviours and norms that lead to social buffering effects.

physical inactivity, alcohol abuse, and (moderate) cigarette smoking (Holt-Lunstad et al., 2010; Holt-Lunstad & Uchino, 2008).

### 1.4.6 Acting as one

Cross-culturally, humans often surround stressful events with cultural practices that entail coming together as a group to move and act as one. These collective activities, such as dancing, singing, chanting, and marching, blur the lines between participants' individual identities and the identity of the larger group (McNeil, 1995; Pearce, Launay, & Dunbar, 2015; Tarr, Launay, Cohen, & Dunbar, 2015a; Weinstein, Launay, Pearce, Dunbar, & Stewart, 2015). Like the support signalled by companionship, touch, and care, highlighting individuals' membership in a cohesive social group may signal that individuals will not deal with challenges alone, but with the aid of their group as a whole (Fessler & Holbrook, 2014).

A common feature of these practices is the synchronisation of physically exertive activities. Synchronised exertion can lead participants to experience a 'collective effervescence' (Durkheim, 1912/1965), while becoming "absorbed in the unified community" (Radcliffe-Brown, 1922, pp. 252 – 253). These feelings of ecstatic oneness may help to explain findings of increased similarity, liking, trust, social unity, and prosociality after synchronous, exertive movements (Launay, Dean, & Bailes, 2013; Reddish, Fischer, & Bulbulia, 2013; Tarr, Launay, Cohen, & Dunbar, 2015b; Valdesolo, Ouyang, & DeSteno, 2010; Weinstein et al., 2015). At the mechanistic level, the effects of synchrony and exertion have been hypothesised to result in part from activation of the endogenous opioid and endocannabinoid systems, which can reduce pain and stress, and underpin feelings of pleasure, well-being, and self-transcendence (Boecker et al., 2008; Dietrich & McDaniel, 2004; Tarr, Launay, Benson, & Dunbar, 2017). When these feelings are experienced in a group context, they are hypothesised to lead to a prosociality-increasing 'social high' (Reddish, Bulbulia, & Fischer, 2013; Tarr et al., 2015b).

However, it is also possible that, by increasing *perceptions* of bondedness and cohesion, collective behaviours serve as a cue to the presence of close, supportive relationships among

fellow in-group members. Individuals who work together to synchronise behaviours must engage in the sharing of mental representations of one another's intentions (Tomasello, Carpenter, Call, Behne, & Moll, 2005). The sharing of intentions – which occurs not just in synchronous activities, but in collaborative activities more generally (such as non-synchronous dance, music making, and ritual participation) – is thought to lead participants to "experience each other as co-active, similar and cooperative members of a group" (Kirschner & Tomasello, 2010, p. 362). By facilitating a sense of acting and belonging together as a single unit, these activities may cue the presence of a cohesive, cooperative, and supportive group (Reddish, Fischer, et al., 2013).

The positive relationship between evolutionary fitness and levels of integration and support from one's social group suggest that, for the ancestors of modern humans, membership in a cooperative, supportive social group was crucial not only to surviving, but also to thriving (e.g., Hawkley & Capitanio, 2015; Page et al., 2017). It is thus likely that the enhanced perceptions of bondedness and connectedness brought about by collective behaviours such as song and dance change participants' tacit evaluations of their current and future environments. Since bonded relationships with individual group members and connection to the group as a whole likely increased access to resources such as food, protection, and care from others, cues to these social group environments may change the predicted costs and benefits of a variety of psychophysiological responses to stressors.

Like the well-established social buffering effects of loved ones, culturally constructed forms of synchronous, exertive movement have been shown to have analgesic effects (Tarr et al., 2015b; Tarr, Launay, & Dunbar, 2016; Weinstein et al., 2015). Some cultural practices and rituals seem to be at least tacitly based on this principle. For example, ethnographic accounts of Māori tattooing rituals describe how male participants are surrounded by relatives who sing songs that are "supposed to sooth him and enable him to bear the pain with equanimity" (Best, 1924, p. 555). Similarly, after young Mbuti boys are circumcised, they join their companions in song as a means of easing their pain (Turnbull, 1962).

There are similar effects on the physical pain and discomfort associated with strenuous physical labour – “the practice of working in company, the songs and choruses so often heard in primitive working parties... all have a palliative influence, tending to soften the harsh actuality of the laborious task” (Firth, 1959, p. 239). For example, ‘chain gangs’ – which involve prisoners being chained together during forced labour – are thought to have synchronised repetitive movements to reduce feelings of physical discomfort and fatigue (Fritz et al., 2013), perhaps through increasing perceptions of group entitativity and support. Some have argued that music making exists in these contexts as a means of distracting singers from the discomfort of difficult work (e.g., Boutcher & Trenske, 1990). Although this may explain some of the effects of music on physical discomfort and strenuous physical exertion, recent experimental evidence suggests that music making reduces perceptions of physical exertion, and that this effect is not mediated by a simple distraction from proprioceptive feedback (Fritz et al., 2013). This allows for the possibility that music making is an emotionally-charged means of creating positive affect and reducing perceptions of exertion that highlights spiritual and cultural themes and singers’ shared membership in a supportive cultural group. Indeed, increases in pain thresholds and measures of social bondedness following group music making have been attributed to activity in the endogenous opioid system (Weinstein, Launay, Pearce, Dunbar, & Stewart, 2016). Given the involvement of the endogenous opioid system in reducing perceptions of pain and physical fatigue (Amann et al., 2009; Wager et al., 2007), these findings offer a means through which the social environments signalled by synchronised movements and music making could affect mechanisms involved in the self-regulation of pain, fatigue, and stress.

If song, dance, and coordinated movement are cultural signals to group cohesion and support, they may have buffering effects that extend beyond pain and physical fatigue. As discussed previously, violent conflict with other groups has been a continued source of threat and consequent stress throughout human history (Pinker, 2011; Walker, 2001). Many aspects of the cultural practices surrounding inter-group conflict may work to reduce stress levels among

participants by signalling social support. For example, a common feature of military life is synchronous marching, or 'keeping together in time' (McNeil, 1995). Despite changes in military technology that make marching an anachronistic means of preparing for battle, it remains a part of military drills across cultures. Other forms of keeping together in time, such as synchronised singing and dance, form part of many pre-combat rituals across cultures (Edgerton, 1989; Gearing, 1962). These include the war dance of the Cherokee, which involved groups of warriors dancing in step on the eve of battle (Gilbert, 1978), and that of the Tsonga, which included patriotic chants, synchronised movements, and simulated combat moves (Junod, 1927a, 1927b). In describing the feeling of 'oneness' brought about by Zulu battle dances, Mitford (1883) offers the unique perspective of a 19th century British anthropologist:

> "The earth shakes beneath the thunder of their feet as they bring them to the ground like one man. They clash their knob-kerries and shields together, they roar like wild beasts; but never for a moment do you lose the modulation of fantastic harmony, the rhythm of the strange, fierce, thrilling chant to which you feel yourself unconsciously beating time; and the irresistible longing comes over you to seize a Kerrie, throw yourself into the rout, and stamp and howl with the best of them" (pp. 287 – 288).

These rituals may serve to indicate the presence of a cohesive, bonded group, cueing to participants that they will not face combat alone, but with the support of a larger whole. Marching in step leads individuals to perceive threatening others as less formidable (and thus less stress-inducing), presumably because of the "coalition size, solidarity, and capacity for coordination" (Fessler & Holbrook, 2014; p. 1) signalled by synchronous movement with others. Further, research has indicated that synchronous group movement increases feelings of unity and trust, which in turn enhance the likelihood of future cooperative behaviours (Reddish, Fischer, et al., 2013). Through signalling the presence of the ability and desire to successfully coordinate and cooperate, these pre-battle rituals may dampen participants' forecasts of impending danger and threat. While research on humans in these situations is

lacking, research on non-human primates has shown that the presence of bonded conspecifics leads individuals to display attenuated stress responses when facing the prospect of (potentially life threatening) inter-group conflict (Wittig et al., 2016).

The evidence presented here links coordinated group behaviours and rituals with reductions in stress, pain, and fatigue. To date, however, researchers have described collective rituals involving coordinated song and dance as functioning to either increase social bonding among participants (reviewed above) or to signal coalitional strength to out-group members through showcasing a groups' ability to coordinate and cooperate (Hagen & Bryant, 2003a). Explanatory theories which argue that these collective rituals function solely to bring about social bonding must consider why they so often occur during, immediately before, or immediately after highly stressful events, and why they are practised by already highly bonded groups. Those suggesting coalition signalling must consider why these rituals often occur in situations where no out-group members are present. Family members singing to sooth loved ones during painful rituals (e.g., Best, 1924), and warriors dancing on the eve of battle (e.g., Gilbert, 1978), occur without the presence of out-group members to signal to, and within what are likely already highly bonded and cohesive groups. A buffering account offers an explanation that links social support with stress attenuation, providing a novel understanding of a ritual form that has been studied in different contexts by anthropologists for over a century (Durkheim, 1912/1965). Nevertheless, bonding, signalling, and buffering accounts of collective, coordinated rituals are all likely valid in certain instances, and they are not exclusive of one another. Although more research is needed, these disparate bodies of work suggest that acting together as one during coordinated group movement can enhance participants' perceptions of group cohesion and social support, thereby altering responses not only to pain and fatigue, but also to impending stressors more generally. Considering the importance of cultural symbols, norms, and practices in bringing about social buffering effects, it is possible that processes of cultural evolution have led to the spread and maintenance of these cultural items within cultural groups, resulting in a suite of *cultural buffers*: symbols, norms, and

practices that signal the presence of cohesive, supportive social environments where safety, resource abundance, and care from others are relatively likely.

## 1.5 Conclusion

Evolutionarily ancient dependencies on close, supportive social relationships in the human lineage have resulted in adaptations that not only encourage social integration and bonding, but also alter psychophysiological states in response to current and predicted social environments. Theoretical research suggests that psychophysiological changes stemming from social cues are a result of changes in self-regulation (Humphrey & Skoyles, 2012; Trimmer et al., 2013). Different social environments favour different self-regulatory strategies; when a social environment signals relative safety, resource abundance, and support and care from others, less conservative self-regulatory strategies become more optimal. In these scenarios, bodily resources are used in a more liberal fashion, and activity in protective mechanisms, such as the pain and stress response, is attenuated. In other words, these environments act as a (social) buffer against current and future stressors.

The empirical research reviewed in this chapter gives evidence for widespread social buffering and support effects in humans. These effects have been shown to reduce perceptions of pain, enhance immunity and healing, and attenuate the stress response more generally (Coan et al., 2006; Cohen et al., 2015; Eisenberger et al., 2011; Kulik & Mahler, 1989). A variety of social cues can lead to these effects, with research demonstrating that social buffering effects in humans can be brought about by a wide array of stimuli, extending beyond touch and conspecific presence, which are prevalent in many species (Kikusui et al., 2006). Humans provide one another with aid in the form of care during injury and illness, and coalitionary

support during times of inter-group and interpersonal conflict[11], and these behaviours can result in, for example, reductions in stress, pain perception, and wound healing times (Klaus, Kennell, Robertson, & Sosa, 1986; Kulik & Mahler, 1989; Lepore, 1992).

Further, human capacities for norm-following, language, and symbolic culture more generally have allowed for unique forms of social buffering and support effects. For example, many placebo effects stem from social information that is conveyed in culturally-dependent ways; patient-practitioner interactions – and the way practitioners present themselves (dress, hospital design, ritualistic procedures, etc.) – are predicated on a set of norms, symbols, and practices that situate treatments and practitioners within a set of cultural truths about healing, care, and social support (Kaptchuk, 2011). Friendship norms and practices, across cultures, work to promote mutual aid between individuals, creating social environments in which friends can depend upon the support of one another in times of need (Hruschka, 2010). At the group level, collective rituals (e.g., song and dance) that increase participants' perceptions of group cohesion and the potential for future cooperation (Reddish, Fischer, et al., 2013; Weinstein et al., 2015) often surround stressful events, such as painful initiation rituals, difficult physical labour, and inter-group conflict. Research suggests that, in these instances, these collective rituals function to buffer pain, fatigue, and stress (Best, 1924; Fritz et al., 2013; Turnbull, 1962).

This chapter has presented theoretical and empirical evidence for the widespread existence of social and cultural buffering effects and the psychophysiological mechanisms that underpin them, creating a framework for understanding relationships among psychophysiological self-regulation, social interactions, and relevant cultural symbols, practices, and norms in humans. Across a range of contexts and via a diverse set of socio-cultural signals, these social and

[11] Regarding the uniqueness of these human behaviours, coalitionary support during both intra and inter-group conflict is well documented in non-human primates (primarily), but also in other group-living, social species (Brent et al., 2014; Datta, 1983; Wittig et al., 2016). Instances of non-human animals helping sick, injured, or disabled conspecifics are less common in the literature, although they have been observed in primates, elephants, and cetaceans (de Waal & Suchak, 2010). Nevertheless, the rarity with which these behaviours are observed in non-human animals suggests that humans are at least quantitatively unique in this regard.

cultural buffers signal safety and the availability of social support, and the psychological, material, and cultural resources that come with it. Chapter 2 will narrow the contexts in which these effects are examined, focusing on how social and cultural cues to the presence of cohesive, supportive social environments can alter both experiences and outputs in sport and exercise.

Cues to support and team cohesion – ranging from cheering fans and encouraging exercise class instructors, to pre-game rituals and in-game daps and high-fives – are a fundamental component of normative practice and culture in sports teams and exercise groups. Research suggests that physical outputs are highly variable within individuals, and depend largely on self-regulatory mechanisms involved in physical fatigue and its neurobiological correlate, pain, which is itself highly influenced by social variables (Kikusui et al., 2006; Noakes, 2012; Noakes et al., 2005). Evidence for a mechanistic link between social environments and the self-regulation of physical outputs is corroborated by ethnographic, observational, and (nascent) experimental research which suggests that supportive, cohesive social environments can improve outputs, outcomes, and experiences in sport and exercise. Chapter 2 aims to further investigate these claims, reviewing the current state of findings in relevant bodies of research, and providing a theoretical and empirical basis for the hitherto untested hypothesis that cues to the presence of supportive, cohesive social environments change activity in neurobiological mechanisms involved in the self-regulation of strenuous physical exercise, as evidenced by reductions in self-reports of pain and fatigue and/or improvements in physical outputs.

# Chapter 2 – Social support and cohesion effects in sport and exercise

**Abstract**

This chapter narrows the focus of Chapter 1, giving a theoretical and empirical account of social support effects in sport and exercise. After a brief overview of extant literature and observations, the implications of considering the role of social environments in the evolution of group physical activities in humans, such as long-distance hunting, are discussed. Sport and exercise in modern humans are then considered, and current evidence is provided for the effects of social environments on outputs and experiences during strenuous physical exertion. Theoretical and empirical evidence on the emotional and neurobiological basis of self-regulation during exercise is presented next. I link this research to findings on social support-based endogenous analgesia and the neurobiological underpinnings of social buffering and bonding in providing an account of when and how social environments are likely to affect experiences and outputs during strenuous physical exertion. This is followed by a discussion of the few studies that have manipulated social environments and measured outputs and experiences during strenuous physical exertion. After addressing gaps in the current literature, I provide an outline of the empirical studies presented in this thesis, which are aimed at informing and extending current understandings of how socially supportive environments affect experiences and outputs during strenuous physical exertion.

## 2.1 Introduction

Cultural norms and practices in sport and exercise often cue the presence of supportive relationships and cohesive groups. These range from norms having to do with supporting and encouraging others during group exercise classes to ritualised pre-game warm-ups and routines that signal the presence of a highly coordinated, cooperative, cohesive team. Although supportive, cohesive relationships are integral to many forms of sport and exercise, little work has been done to understand how these social environments affect the self-regulatory processes that govern physical outputs in these contexts. Building on foundations developed in Chapter 1, I will further develop an account that explains these phenomena. I will extend clinical research on endogenous analgesia and self-regulation more generally, marrying it with literature on the mechanistic underpinnings of pain, fatigue, and outputs during physical exertion. The literature reviewed here underpins the central hypothesis of this thesis: that social support and cohesion can increase physical outputs via reducing perceptions of pain and fatigue during strenuous physical exertion.

## 2.2 Social support effects in sport and exercise

From the reliance of human ancestors on social hunting and foraging (Tomasello et al., 2012) to the modern cultural phenomena of sport and group exercise, humans have long come together to move together. This movement often involves high amounts of physical exertion, which can lead to both pain and its neurological correlate, fatigue (Noakes, 2012). Pain and fatigue function in the context of physical exercise as mechanisms that protect against potential injury and vulnerability resulting from overexertion and exhaustion (Noakes, 2012). However, ethnographic, observational, and experimental research suggests that, in the context of strenuous physical exertion, cues to safe, caring, resource-abundant environments may lead to adaptive reductions in pain and fatigue (Cohen et al., 2010; Davis et al., 2015; Gotaas, 2012; Kraus et al., 2010; Stevinson, Wiltshire, & Hickson, 2014). Where safety and support are relatively more assured, the potential harms of overexertion and exhaustion are reduced. This potentially lifts the protective ‘brakes’ of pain and fatigue on physical outputs,

allowing individuals to push their bodies harder and for longer. Converging evidence from disparate fields is beginning to suggest that sport and exercise performance is highly dependent on context, with environmental cues, and, in particular, social cues, affecting activity in a variety of psychophysiological mechanisms that have downstream effects on both objective and subjective performance outcomes (Davis & Cohen, 2018; Davis, Hettinga, & Beedie, in press; Hettinga et al., 2017; Lane, Terry, Beedie, Curry, & Clark, 2001; Pollo, Carlino, & Benedetti, 2011).

### 2.2.1 Implications for human evolution: ethnographic and archaeological evidence

In modern contexts, sport and group exercise are often accompanied by cheering fans and encouraging partners or instructors, but strenuous physical exertion and its attendant signals of support have their beginnings long before professional sporting events and fitness classes. Ethnographic evidence for the use of social support as a performance-enhancer comes from a variety of contexts and cultures. Anthropologists have written of the apparently ancient practice of log racing among the Payacú of the Amazonian basin (Numuendaju, 1979). Log races involved running along cleared paths – up to a mile in length – while carrying heavy logs. When runners could no longer bear the weight, they would pass the log on to a teammate. An important aspect of the ritual surrounding these races was the participation of the spectators and the support they showed the participants. The evening before the race, villagers would sing good-luck songs “while whipping up team spirit as a group” (Gotaas, 2012, p. 110; Numuendaju, 1979). On the day of the race, the teams would sing and stamp in unison as a means of warming up. Once the race began, villagers would scream encouragement at the participants while running along the track with them. The Tarahumara of Mexico had similar practices in their famed long-distance foot races. As runners began giving up in exhaustion, the cheering increased from the spectators – “rarely in the world have there been such active spectators” (Gotaas, 2012, p. 112).

If these rituals can be taken as any indication of the cultural practices of Early Stone Age (ESA) hominins, they may shed light on the importance of cues to social support in facilitating

transitions in human ancestral subsistence patterns. It has been argued that human capacities for endurance running stem from adaptations that arose as a result of selection for those individuals able to exploit the calorie and nutrient-rich resources available in animal carcases (Carrier et al., 1984). Fossil records indicate that meat eating occurred among hominins (here, *Australopithecus afarensis*) as early as 3.39 million years ago (McPherron et al., 2010; Semaw et al., 2003), and it is thought that long-distance running as a means of both scavenging fresh carcasses (long-distance scavenging) and pursuing prey to exhaustion (persistence hunting) dates back to at least one million years ago, based on adaptations evidenced in the skeletal remains of *Homo erectus* (Bramble & Lieberman, 2004). Although successful long-distance scavenging and persistence hunting has been documented across a range of modern (i.e., since the beginning of the ethnographic record) hunter-gatherer populations – see Lieberman, Bramble, Raichlen, and Shea (2007a) for a brief review – it is a relatively rare practice in extant groups. However, present-day hunter-gatherers offer a limited and sometimes biased picture of the hunting and scavenging practices of ESA hominins; the advent of agriculture and projectile weapons (such as the bow and arrow and throwing spears, which favour solitary ambush hunts) have reduced the relative efficacy of long-distance scavenging and persistence hunting as a means of acquiring calories (Lieberman et al., 2007a; Marlowe, 2005). This suggests that ESA hominins would have been more reliant on cooperative, endurance-based foraging strategies than would otherwise be suggested by the current ethnographic record, which encompasses human groups with technologies and ecological niches that are unlikely to be representative of ESA hominins.

Given their relative reliance on cooperative, endurance-based foraging, these hominins may have taken advantage of the buffering effects of supportive, cohesive social environments as a means of facilitating long-distance scavenging and persistence hunting. By surrounding what would have been an important means of dietary supplementation with rituals that build and signal cohesion to in-group members (e.g., song and dance), they may have reduced the forecasted costs associated with physical overexertion and exhaustion. Thus, social

environments could have led to self-regulatory changes in pain and fatigue, allowing individuals to put forth greater and riskier physical efforts during long-distance pursuits. In modern humans, many groups participate in pre-hunt dances that involve highly collaborative choreographies, synchronised movements, and harmonious arousal (Edgerton, 1989; Grinnell, 1889; Turnbull, 1965). All of these activities can elevate participants' experiences to that of the greater whole, and perhaps signal to them the safety of maximum physical effort within the context of their supportive social group.

Research in modern sport and exercise contexts corroborates ethnographic accounts and evolutionary speculations in illuminating the connection between group cohesion and enhanced physical performance. Many practices, rituals, and symbols within sport function not only to bond individuals together, but also as signals to team cohesion and the broader communities that support them. It is likely that these cultural items are meant to signal cohesion to both out-group members – as coalition signalling hypotheses would claim – *and* fellow in-group members (see Section 1.4.6, p. 35). Perhaps the most famous of these practices is the *Ka Mate* haka, a world-renowned, collective Māori ceremonial dance and challenge performed by the starting 15 of the New Zealand All Blacks rugby union team following the national anthem at international matches. The haka consists of a synchronised set of words and body movements, which players describe as aiding them in reaching their goals as a team and in building both their physical and spiritual capacities (Lardelli, Mauger, & Mealamu, 2007).

The All Blacks haka may be the most famous cohesion-signalling team practice in sport, but it does not stand alone. American football teams have adopted modified versions of the haka (Yeoman, 2015), thus adding to an already rich tradition of practices focusing on team and community cohesion. This includes a variety of pregame rituals, dances and chants, including, for example, the University of Auburn's "Tiger Walk", which involves players walking to their home stadium on a path lined by up to 20,000 fans offering pre-game high-fives and words of encouragement (Gumprecht, 2003; Yeoman, 2015). During games and matches, traditions of

supportive anthems, songs, and chants are ubiquitous across sports and fan bases (Whannel, 1995). These practices are often mirrored by intra-player cues to cooperative relationships and group cohesion, such as words of encouragement, hugs, pound hugs, high-fives, secret handshakes, and daps (Kraus et al., 2010). Team colours, slogans, and pre-game rituals further foster and maintain a sense of a highly-cohesive social environment within and around sporting teams and clubs.

Similar processes seem to be at play in group exercise. Yoga, CrossFit, fitness gyms, and running groups often involve cooperation, coordinated movement, and encouragement. Participants report that these social aspects of group exercise are important motivators in their attendance and performance (Stevinson et al., 2014). These aspects of group exercise may help to explain why, despite the convenience of engaging in the same or similar activities individually, people so often exercise with others.

Taken as a whole, these findings suggest an evolutionarily ancient relationship between social ties and physical exertion. Diverse forms of exercise and sport contain highly social, cooperative elements[12]. The cross-cultural ubiquity of (social) long-distance running in modern contexts (Gotaas, 2012) perhaps highlights the importance of evolved neurobiological mechanisms (such as the endogenous opioid and endocannabinoid systems) that facilitate and reward habitual, voluntary exercise (Boecker et al., 2008; Raichlen et al., 2012; Raichlen, Foster, Seillier, Giuffrida, & Gerdeman, 2013). These mechanisms also respond to social cues (Inagaki et al., 2016; Machin & Dunbar, 2011; Trezza et al., 2010), allowing for the possibility that certain social environments further facilitate and motivate physical exertion, especially in endurance settings (see Section 2.2.3.2, p. 57, for a more detailed account of how these systems might interact with social environments during exercise). The highly social nature of

[12] The lone exception to this might be exercise practices in highly individualistic, post-industrial societies, where individuals often exercise on their own. However, the popularity of running clubs, parkrun, CrossFit, and group exercise and yoga classes in these societies highlight continued human preferences for social forms of exercise.

many forms of modern sport and exercise thus offers some support for the idea that the presence of close social relationships – and the resources they signal – played a crucial role in facilitating and encouraging the cooperative, endurance-based foraging behaviours, such as long-distance scavenging and persistence hunting, that are thought to have arisen in ESA hominins (Bramble & Lieberman, 2004; Lieberman, Bramble, Raichlen, & Shea, 2007b).

### 2.2.2 Observational and experimental evidence

Observational research also suggests a positive link between perceptions of support and cohesion and performance in sport and exercise. This work has not yet begun to investigate how self-regulatory pain and fatigue mechanisms might be altered by social environments, or how these alterations might affect endurance (aerobic) or power (anaerobic) outputs. Nevertheless, this research gives credence to ethnographic and anecdotal support for a link between social support and physical performance, in as much as the cultural practices and symbols described above can be seen as cues to supportive, cohesive group environments.

Cohesion in sport is construed as the ability of a collection of individuals to be united in the pursuit of group goals and individual needs (Carron et al., 1998). Thus, social cohesion can be understood as a form of social support that is dependent on individuals' perceptions of their relationships to the group as a whole (Burke et al., 2008). Two meta-analyses examining athletes' perceptions of team cohesion have shown a positive link between cohesion and both subjective (e.g., athlete self-reports) and objective (e.g., scores, winning percentage, etc.) performance measures (Carron et al., 2002; Filho et al., 2014). While cohesion studies generally rely upon survey-based methods to assess cohesion levels (e.g., measures assessing team members' perceived belongingness, unitedness toward a common goal, etc.; Carron, Widmeyer, & Brawley, 1985) more ecologically valid measures of cohesion have a similar relationship with performance. For example, Kraus et al. (2010) showed that National Basketball Association (NBA) teams with greater amounts of early-season cooperation-signalling touch were more successful later in the season (i.e., they won more games). In football, team-oriented scoring celebrations where shown to predict higher finishes in league

standings at the end of the season (Bornstein & Goldschmidt, 2008). Both of these measures – cooperation-signalling touch and team-oriented goal celebration – can be seen as indicators of team cohesion, thus giving ecologically valid support to the idea that social cohesion is positively associated with sport performance.

Research on perceptions of cohesion in group exercise has yielded similar results, with higher levels of perceived cohesion predicting positive affect, attendance to group sessions, and overall adherence (Burke et al., 2008; Spink & Carron, 1994). Hypotheses on the mediating factors in the relationship between perceptions of cohesion and exercise affect and adherence have posited that beliefs about mutual support during exercise activities are important in enhancing group members' feelings of self-efficacy toward exercise (Christensen et al., 2006). These claims have been corroborated by research on parkrun, "a fast-growing international network of free, weekly, timed 5 km runs in public spaces" (Stevinson et al., 2014, p. 171). In semi-structured interviews, participants cited "feeling accepted and integrated" and "encouragement received" as important factors sustaining their participation in parkrun (Stevinson et al., 2014, p. 172). Indeed, 31% of sampled participants cited "social togetherness" as one of the most important aspects of parkrun, leading Hindley (2018) to attribute the event's popularity to it being a 'home away from home' that provides "psychological comfort, warmth, and mutual support" (p. 16).

In sport, perceptions of social support correlate with perceptions of group cohesion (Carron et al., 2002; Filho et al., 2014), and, like in group exercise, social support can have positive effects on objective outcome measures. Observational studies have demonstrated that perceptions of instrumental and emotional social support are associated with successful performance among Olympic athletes, tennis players, and amateur golfers (Freeman & Rees, 2010; Gould, Guinan, Greenleaf, Medbery, & Peterson, 1999; Rees & Hardy, 2004; Rees et al., 2007; Scheffer, 1704). Survey-based work suggests that some of these effects could be explained by increases in self-confidence, as perceived social support from teammates is positively related to constructs of self-confidence (Freeman & Rees, 2010). Experimental work

has corroborated these findings, although it is difficult to extrapolate what the results imply beyond skill-based performance (e.g., what their implications are for physical performance related to self-regulation). For example, in a two-by-two, between-participants study on putting in golf, social support was manipulated in groups of participants with either low or high levels of perceived social support in their daily lives. The social support manipulation involved those in the support condition (but not the control condition) reading a note from the experimenters stating that they were “very capable sportspeople” and that the experimenters would “be here throughout the task, so please feel free to ask for our help at any time” (Rees & Freeman, 2010, p. 337 ). Putting performance results revealed main effects of both pre-experiment perceived social support in participants’ daily lives and the social support manipulation. Those with higher levels of pre-experiment perceived social support performed better than those with low levels of pre-experiment perceived social support, and those in the social support condition performed better than those in the control condition. Also, participants with low pre-experiment perceived social support performed significantly better in the social support condition, suggesting that these ‘lonely’ individuals were particularly sensitive to cues of social support (Rees & Freeman, 2010).

Thus, research has examined the effects of perceptions of group cohesion and social support on both objective and subjective performance outcomes in a variety of sports and exercises. Although this work is informative in terms of effective social support manipulations, it has major gaps. Despite a substantial amount of observational research linking perceptions of cohesion and social support to success in sports requiring high levels of both aerobic and anaerobic performance, this literature is yet to test this link experimentally, or to address the neurobiological mechanisms through which these effects might occur. Nevertheless, research on the psychological and neurobiological mechanism involved in sport and exercise performance more generally – while not related directly to social support or cohesion – does shed some light on potential mediators of the relationships among perceptions of social

support and cohesion, endogenous self-regulation, and aerobic and anaerobic physical outputs.

### 2.2.3 Mechanisms

The mechanism by which perceptions of social support and cohesion might affect sport and exercise performance vary depending on the activity and the cognitive and physiological systems involved. Here, I will focus on mechanisms most relevant to the main hypothesis of this thesis; that cues to the presence of supportive, cohesive social environments change activity in neurobiological mechanisms involved in the self-regulation of strenuous physical exercise, as evidenced by reductions in pain and fatigue and/or improvements in physical outputs. I will first review the role of emotion and self-construal (how individuals perceive themselves and the world around them) in determining physical outputs. I will follow this with a detailed description of the neurophysiological mechanisms involved in the endogenous regulation of pain, fatigue, and physical outputs. Throughout, I will highlight how perceptions of social support and cohesion could affect activity in these mechanisms, with the knock-on effect of enhanced performance via reductions in perceptions of pain and fatigue.

#### 2.2.3.1 Emotions and self-construal

In an impactful essay on the influence of emotion in competitive sport, Lazarus (2000) argued for the importance of a cognitive-motivational-relational theory of emotion in explaining sport performance (Lazarus, 2000). The theory – widely cited in sport psychology literature on the proximate emotional mechanisms that affect performance[13] – proposes that emotions are dependent on a 'core relational theme' that represents the relationship between the environment and the individual. Similar to theories on emotions from evolutionary psychology (e.g., Cosmides & Tooby, 2000), a key premise of Lazarus' (2000) theory of emotion in

[13] There is also a broader field known as exercise physiology, but work in this area has tended to focus less on psychological factors (that could be related to social and cultural buffering) and more on the physiological aspects of exercise. Some of this research, on how emotions can affect the development of fatigue (e.g., Beedie, Lane, & Wilson, 2012), will be reviewed later in this section.

competitive sport is that emotions are adaptations that lead organisms to behave in context-dependent, fitness-enhancing ways. It is argued that each emotion has a biologically derived 'action-tendency' – an innate response state involving psychophysiological mechanisms that predisposes the organism to act in a manner that is adaptive to the stimuli that caused the emotion (Cosmides & Tooby, 2000; Lazarus, 2000). The action tendency for anger, for example, is "a powerful impulse to counterattack in order to gain revenge" (Lazarus, 2000, p. 243). Emotions thus function to "prepare the organism to respond adaptively to environmentally recurrent stimuli" (Shariff & Tracy, 2011, p. 395). As such, emotions can have both positive and negative effects on sport and exercise performance and motivation. The general rule proposed in the sport psychology literature is that the more an emotion's action tendencies align with the task demands of an activity, the more the activity will be facilitated (Rathschlag & Memmert, 2013); the fight-or-flight response may facilitate performance in boxing, but have detrimental effects on the fine motor control needed in an archery competition, for example.

Research has generally supported a cognitive-motivational-relational theory of emotion in competitive sport, as findings have shown that action tendencies are important in predicting relationships between emotions and performance (Kavanagh & Hausfeld, 1986; Rathschlag & Memmert, 2014; Woodman & Hardy, 2003). For example, Rathschlag and Memmert (2013, 2014) demonstrated that happiness and anger – compared to 'neutral' emotional states – lead to increased jumping heights, faster sprinting, and higher ball-throwing speeds, arguing that the action tendencies of anger ('lashing out') and happiness ('approach') facilitated these activities. Moreover, anxiety (action tendency: 'inaction and withdrawal') has been shown to lead to a less efficient use of bodily resources through increased levels of oxygen use, muscle tension, and ventilation (Beedie et al., 2012; LeDoux, 1998; Rathschlag & Memmert, 2014; Wilson, Lane, Beedie, & Farooq, 2012), and poorer physical performance in sport in both experimental (Rees & Freeman, 2010) and observational studies (Rees & Hardy, 2004). The physiologically 'tense' and cognitively demanding aspects of anxiety are thought to lead to

decreased efficiency (due to muscle tension) and performance-diminishing cognitive interference (Beedie et al., 2012; Lazarus, 2000; Rees & Freeman, 2010).

Social environments often influence the emotions described above. For example, time series analyses have shown that team and individual happiness – correlates of team cohesion – are positively associated with performance (Totterdell, 2000). Further, as discussed in Section 1.4 (p. 11), social support has anxiety-reducing effects (Coan et al., 2006; Kikusui et al., 2006; Roberts, Klatzkin, & Mechlin, 2015), and studies suggest that these effects can have a downstream influence on both cognitive interference and the use of bodily resources (Linden, Chambers, Maurice, & Lenz, 1993), two areas in which high levels of anxiety negatively affect performance. Further, the positive link between social support and self-efficacy (Christensen et al., 2006) may also lead to higher energy levels. Energy has been described as "positive feelings about the capacity to complete mental or physical activities" (O'Connor & Puetz, 2005, p. 229). Social support can therefore boost energy levels – and perhaps physical outputs – by enhancing self-efficacy. However, it should be noted that some research outside of sport and exercise has shown that inappropriate forms of social support (such as those interpreted as overly paternalistic) can have detrimental effects on recipients' perceived competence and self-efficacy (Gleason & Iida, 2015; Ryon & Gleason, 2018), which could lead to lower levels of energy, motivation, and physical outputs in the context of sport and exercise. Nevertheless, research in sport and exercise generally suggests a positive link between perceptions[14] of social support and positive emotions and beliefs, such as enhanced feelings of happiness, positive mood, self-efficacy, and energy (Christensen et al., 2006; Filho et al., 2014; Stevinson et al., 2014). These findings may help to explain higher exercise participation and adherence levels in individuals who feel more socially supported or who feel they are part of a cohesive exercise group; these perceptions may increase levels of self-efficacy and energy, which

[14] See Section 1.4.1 (p. 19) for a discussion of the difference between perceived and received social support.

make attendance and adherence more likely (Hindley, 2018; Spink & Carron, 1994).

Conversely, decreased activity levels have been linked to ostracism, loneliness, and depression in recent research. Experimentally, it has been shown that children who experience ostracism (v. inclusion) in a virtual ball-tossing game (Cyberball) displayed reduced physical activity levels in a subsequent 30 min period where they were given the opportunity to engage in either active or sedentary play (Barkley et al., 2012). This was thought to result from feelings of social rejection and sadness in children in the ostracism condition of the experiment (Barkley et al., 2012). This finding is in accordance with observational research showing that, whereas positive interactions with peers are linked to increased physical activity levels in children, negative interactions have effects in the opposite direction (Rittenhouse, Salvy, & Barkley, 2011). These findings are likely underpinned by emotional changes resulting from positive or negative social interactions. In a quasi-experimental set up, children's depression levels were assessed before a test of their exercise motivation and performance; more depressed children set easier goals for themselves and performed less well on a running task lasting either 12 min or for 3800 m, depending on the test location (Lane et al., 2001). Relating these findings back to children's social environments, depression is a strong correlate of loneliness, or a perceived lack of close, supportive relationships (Nangle, Erdley, Newman, Mason, & Carpenter, 2003). Observational studies in adults reveal similar patterns; lonely individuals are less likely to engage in physical activity (Hawkley, Thisted, & Cacioppo, 2009). 'Depressive symptomology' is an action tendency of loneliness, rejection, and isolation more generally, which includes negative affect, loss of interest, and low energy levels (Cacioppo, Capitanio, et al., 2014). Thus, perceptions of social support and group cohesion seem to affect energy and depression levels, two related constructs that appear to influence both exercise performance and adherence.

Of particular relevance to performance, research has also shown that social support influences cognitive assessments of the difficulty of exercise. In a quasi-experimental design, Schnall et al. (2008) showed that participants who were accompanied by a friend estimated a

nearby hill to be less steep than did those who were on their own (Schnall et al., 2008). Follow-up experimental studies showed that just thinking of a supportive friend (v. a neutral or disliked person) also led to estimations of the slope as being less steep (Schnall et al., 2008). This offers evidence that perceptions of support (and perhaps group cohesion) can affect cognitive estimates of variables related to the difficulty of impending exercise. Given the known links between psychological expectations and physiological self-regulation, it seems likely that negative appraisals will engender more conservative and cautious self-regulation compared to positive appraisals, which may ultimately lead to differences in performance.

These findings point to possible cognitive and emotional constructs that mediate the effects of social support on physical outputs during sport and exercise. To date, however, researchers have not considered whether or how these cognitive and emotional processes affect activity in the neurobiological mechanisms involved in the self-regulation of pain, fatigue, and physical outputs during exercise.

#### 2.2.3.2 Neurobiological systems involved in the regulation of physical outputs

Research on the emotional regulation of physical outputs has not drawn heavily from the primary literature on relevant mechanisms at the neurophysiological level. Research on the neurobiological underpinnings of self-regulation during strenuous physical exertion has shown that pain and fatigue are extremely important mechanisms in determining intra-individual variability in physical outputs during sport and exercise (Pollak et al., 2014). Fatigue has been described “principally as an emotion, part of a complex [self-]regulation, the goal of which is to protect the body from harm” ( Noakes, 2012, p. 6). As fatigue levels increase, central motor drive, positive affect, and motivation to continue physically exertive activities decrease (Amann et al., 2009). Both pain and fatigue function to protect the body from harm, and they exhibit a great deal of neurological overlap; both occur during physical exertion when skeletal muscle contraction leads to the release of a variety of muscle metabolites (such as lactate, ATP, and protons) and cytokines (Pollak et al., 2014; Robson-Ansley, Milander, Collins, & Noakes, 2004). At low concentrations (found with moderate physical exertion) these muscle

metabolites evoke sensations commonly described as fatigue, whereas high concentrations (found with intense physical exertion) evoke sensations commonly described as pain (Pollak et al., 2014). In other words, pain and fatigue can be seen as occupying ranges on a single spectrum of physical discomfort: "the same combination of metabolites that evokes sensations of fatigue at low concentrations evokes pain at higher concentrations" (Pollak et al., 2014, p. 377).

Similar findings exist for pro-inflammatory cytokines. In an experimental study, the administration of interleukin-6 (IL-6) – a pro-inflammatory cytokine that is a common component of responses to both physical and social stressors (Chiang, Eisenberger, et al., 2012; Chiang, Saphire-Bernstein, Kim, Sherman, & Taylor, 2012) – led to significantly slower 10 km time trials in trained runners (Robson-Ansley et al., 2004). Compared to the placebo condition, participants reported higher levels of fatigue, 'heaviness in legs,' depressed mood states, and reduced ability to concentrate after IL-6 administration (Robson-Ansley et al., 2004). These findings are perhaps unsurprising in light of the known associations between the inflammatory response and hyperalgesia (increased sensitivity to painful stimuli) and between strenuous physical exertion and the release of pro-inflammatory cytokines (Carmichael et al., 2006).

Pain and fatigue during physical exertion can be conceptualised as self-regulatory emotions that function to protect against physical harm resulting from overexertion. This is highlighted by the fact that exhaustion (resulting from extreme levels of fatigue and then pain), in most if not all but the most life-threatening situations, develops long before complete recruitment of skeletal muscle or any sort of breakdown in whole body homeostasis[15] (Noakes, 2012; Noakes et al., 2005). Exhaustion from prolonged exercise in recreational athletes occurs when

[15] Here, I use whole body homeostasis to mean a set of internal conditions, optimal for bodily functioning, that exist in a dynamic state of equilibrium.

only ~30% of available motor units[16] are active; elite athletes improve upon this by no more than 10 – 20% (Noakes et al., 2005). This has led researchers to the logical conclusion that "if there is skeletal muscle reserve at the point of physical exhaustion, then fatigue cannot be caused by peripherally-based control but must result from CNS [central nervous system] regulation of skeletal muscle motor unit recruitment" (Noakes et al., 2005, p. 121). Of course, CNS control is based on a response to feedback from physiological systems, but the point is that the ultimate determinant of fatigue lies within the CNS (Stein, Collins, Daniels, Noakes, & Zigmond, 2007). It is this conclusion – that fatigue is governed by the CNS – which led Noakes et al. (2005) to call fatigue a sensory perception and emotion.

Taken as a whole, this body of research suggests that fatigue is a self-regulatory emotion that occurs well before individuals reach their physiological limits (i.e., the full capacity of their locomotive system in a given context). This has led placebo researchers to coin the term 'headroom' to describe the discrepancy between the point at which athletes cease physical exertion due to fatigue (colloquially, 'exhaustion') and their true physiological maxima (C. Beedie, personal communication, June 21, 2017). The adaptive function of headroom is clear; individuals need to maintain some locomotive resources in case of emergency (i.e., the appearance of a predator). Thus, fatigue sets in before locomotive resources are completely spent. The idea of headroom suggests that environmental cues that lead to changes in the CNS's regulation of strenuous physical exertion could lead to enhanced outputs in everyday exercisers and athletes alike. Indeed, research in the sport and exercise sciences has shown that individuals' fatigue levels and maximum physical outputs are not constant, but dependent on a host of individual[17] and environmental factors. For example, the competitive motivations or the receipt of a (placebo) medical treatment can affect when fatigue sets in and, ultimately,

[16] Motor units have been defined as "the group of muscle fibers innervated by a single motor axon" (Devanandan, Eccles, & Westerman, 1965, p. 359).

[17] For example, compared to amateur athletes and everyday exercisers, professional athletes may have relatively smaller 'headroom' due to years of training and experiences that allow them to produce outputs that are closer to their physiological maxima.

individuals' physical outputs (Hettinga et al., 2017; Pollo et al., 2011). Crucial to the hypotheses of this thesis, these effects are mediated by neurobiological pathways that are involved in both pain and fatigue perceptions *and* the signalling and maintenance of close social relationships.

Given that pain and fatigue represent different areas on a spectrum of physical discomfort (Pollak et al., 2014), research on pain perception can inform the comparatively underdeveloped body of research on fatigue. Research on placebo analgesia has implicated the endogenous opioid and endocannabinoid systems in the self-regulation of pain and fatigue. Using a variety of methods, such as fMRI and pharmacological blockades, research on placebo analgesia has shown that self-regulatory reductions in pain perception are underpinned by opioid and endocannabinoid activity in the brain (Benedetti, Amanzio, et al., 2011; Bingel & Tracey, 2008; Wager et al., 2007). Participants' beliefs and expectations of pain relief from putatively analgesic medical treatments are hypothesised to initiate activity in a 'descending pain modulatory network' in the brain, involving prefrontal cortices (generation and integration of beliefs and expectations), the anterior cingulate cortex (ACC; sensory and affective perceptions of pain), and subcortical structures, such as the periaqueductal gray (PAG; endogenous opioid transmission) and striatum (endocannabinoid transmission) (Bingel & Tracey, 2008; Colloca, Klinger, Flor, & Bingel, 2013; Eippert, Finsterbusch, Bingel, & Büchel, 2009; Hutchison, Davis, Lozano, Tasker, & Dostrovsky, 1999). This descending pain modulatory network – which, through a diverse set of research, has emerged as an explanatory framework for endogenous analgesia – is thought to lead to reductions in perceptions of pain through inhibiting afferent (incoming) pain signals from nociceptive systems[18], which ultimately leads to reductions in activity in brain areas associated with sensory and affective responses to noxious stimuli (Bingel & Tracey, 2008; Ossipov, Dussor,

[18] Nociception is the sensory nervous system's response to particular harmful stimuli, which involves the stimulation of nerve cells that sense, for example, cutting, crushing, or heat. When stimulated, these nerve cells send signals through the spinal cord for processing in the brain (Wall & Melzack, 2004).

& Porreca, 2010; Pollo, Carlino, & Benedetti, 2008). Both the endogenous opioid and endocannabinoid systems have been shown to underpin the analgesic effects of the descending pain modulatory network (Benedetti, Lanotte, Lopiano, & Colloca, 2007; Bingel & Tracey, 2008)

Perceptions of pain have also been shown to be modified by social variables. For example, the presence of a supportive individual, and the receipt of active social support, led to diminished pain reports during a cold pressor task, which requires participants to keep their hand submerged in ice water for an extended period of time (Brown, Sheffield, Leary, & Robinson, 2003). Further, holding the hand of a (romantic) partner has been shown to reduce self-reports of the unpleasantness of experimentally induced pain (Coan et al., 2006), and even *cues* to the presence of these partners (i.e., simply viewing photos of the partner) have been shown to have analgesic effects (Master et al., 2009).

Data from similar studies (Coan et al., 2006; Eisenberger et al., 2011) suggest that these analgesic effects stem from attenuation of activity in regions related to the neural response to physical threats, such as the ventral anterior cingulate cortex (vACC), and activation of safety-signalling brain regions – specifically, the ventromedial prefrontal cortex (vmPFC). These experiments used holding the hand of a loved one and photos of romantic partners as cues to social support. Compared to control conditions (e.g., holding the hand or viewing a photo of a stranger), individuals in these social support conditions displayed relatively less activity in brain areas related to feelings of threat and relatively more activity in brain areas associated with feelings of safety. These patterns of brain activity further predicted reduced activity in pain-related neural regions, such as the dACC and AI. Further, reduced activity in pain-related neural regions corresponded with reductions in self-reports of pain unpleasantness (Coan et al., 2006; Eisenberger et al., 2011). Although not investigated specifically by these studies, Eisenberger et al. (2011) speculate that these endogenous analgesic effects were underpinned by opioid signalling. In fact, Wager et al. (2004) have suggested that opioid-dependent analgesic placebo responses are partially contingent on participants' evaluations

of the potential harm a stimulus can cause; their studies showed that activity in brain areas involved in cognitive evaluations of potential harm and safety were related to placebo analgesia. Taken together, these findings suggest that, by activating the endogenous opioid and endocannabinoid systems, cues to reduced threat or safety – such as the presence of a close, supportive other – can alter perceptions of experimentally induced pain.

Like pain, perceptions of physical fatigue are moderated by activity in endogenous opioid and endocannabinoid systems. Both systems have been implicated in the 'runner's high,' an analgesic, anxiety-reducing state of positive affect, that can occur both during and after prolonged aerobic exercise (Boecker et al., 2008; Raichlen et al., 2012; Raichlen et al., 2013). Raichlen et al. (2012) propose that, in species with "high-intensity running behaviors" (p. 1,335), selection for the neurobiological basis of the runner's high occurred to both facilitate and encourage what would have been an important means of resource acquisition. Activation of these systems has been shown not only to enhance mood and reduce pain perceptions, but also to regulate perceptions of fatigue and discomfort during physical exertion. For example, one study showed that administration of naloxone, an opioid antagonist (i.e., a substance which blocks the effects of opioids), led to decreases in total cumulative work and exercise time (i.e., quicker fatigue and exhaustion) and increases in perceived exertion in a cycle ergometer test to exhaustion (Sgherza et al., 2002). Interestingly, heart rate and ventilation measures were similar at the final common workload in both conditions, leading Sgherza et al. (2002) to conclude that "peak exercise capacity was limited by individual's PE [perceived exertion], which can be attenuated by endogenous opioids, rather than by physiological fatigue" (pp. 2,027 – 2,028). Conversely, opioid agonists (i.e., substances that enhance the effects of opioids) reduce perceptions of fatigue, doing so in much the same way as in perceptions of pain; by binding to opiate receptors in the spinal cord and attenuating

ascending activity in nociceptive and metaboreceptive (activated by muscle metabolites) nerve fibres (Almeida, Roizenblatt, & Tufik, 2004; Amann et al., 2009)[19].

The cortical projection of these nerve fibres increases with the release of pro-inflammatory cytokines and metabolites from fatiguing muscles, which seems to have the effect of reducing central motor drive (Adreani, Hill, & Kaufman, 1997). Experimental research has shown that administering the opioid agonist, fentanyl, can block these afferent nerve signals. In a 5 km ergometer cycling time trial, administration of fentanyl led to greater outputs during the first half of the trial (v. placebo), but, eventually, greater levels of fatigue and lesser outputs during the second half of the trial (Amann et al., 2009). Effectively, the fentanyl-based opioid blockade caused the brain to be 'blind' to afferent nerve signals of peripheral pain and fatigue, leading the CNS to push peripheral muscles past their regular limit (i.e., the limit established by the feedback system when signals of fatigue are not blocked). The result of this was greater initial outputs in the first half of the trial, but, as a consequence, greater levels of muscle fatigue and lower outputs at the end of the trial, compared to the placebo condition. Therefore, after fentanyl administration, athletes 'overshot' optimal output levels at the beginning of the trial, causing relatively worse outputs at the end of the trial. The researchers further reported observations of "severely impaired locomotor functioning" (Amann et al., 2009, p. 280) following trials in which fentanyl was administered, with athletes needing assistance in walking to post-trial assessment areas. This was attributed to the extremely high levels of muscle fatigue resulting from the absence of inhibitory feedback during the fentanyl trials (Amann et al., 2009).

Thus, it seems that ascending neural pathways not only affect perceptions of pain and fatigue, but also have inhibitory effects on areas of the CNS involved in motor drive, "thereby

[19] Research on how the endocannabinoid system regulates perceptions of pain and fatigue during physical exercise in humans is less developed than that on endogenous opioids, but research on rodents suggest that increases in endocannabinoid levels underpin exercise-induced reductions in pain sensitivity (Galdino et al., 2014). More generally, research in humans has shown that exercise – which can lead to the release of endocannabinoids (Raichlen et al., 2013) – reduces perceptions of pain (Cook & Koltyn, 2000; Dietrich & McDaniel, 2004).

contributing to the conscious and/or subconscious determination of the magnitude of central motor drive during high-intensity endurance exercise" (Amann et al., 2009, p. 279). The more signals of pain and fatigue that reach the CNS, the 'harder' it becomes to maintain motor drive, perhaps in a manner similar to the experience of keeping one's hand on a hot plate despite the pain it causes; the stronger and more persistent the pain, the more difficult it becomes to resist retracting one's hand. More generally, afferent signals from peripheral muscles likely contribute to (tacit) cost-benefit analyses of optimal central motor drive, facilitating maximal performance while maintaining adequate reserves for post-exercise locomotor function. It has been argued that fatigue symptoms rise in a manner inversely related to the amount of continued physical exertion that "can be safely sustained at that particular exercise intensity *under those specific conditions* [italics added]" (Noakes et al., 2005, p. 122). The fact that regulation of central motor drive is to some degree condition-specific means that fatigue is susceptible to top-down processes that are dependent on environmental information, including social information.

Relevant research on placebo effects in sport has shown that, as with perceptions of pain, socio-environmental cues can have a large impact on fatigue levels and, ultimately, physical outputs. In two experiments, Pollo et al. (2008) showed that administration of placebo caffeine following verbal suggestion (experiment one) and conditioning plus verbal suggestion (experiment two) led to increases in mean muscle work and decreases in perceived muscle fatigue, leading the researchers to suggest "a powerful top-down modulation of muscle performance by placebo" (p. 383). Using a conditioning paradigm, Benedetti, Pollo, and Colloca (2007) gave recreational athletes a placebo (believed by participants to be morphine) in a simulated sport competition (a leg extension exercise to voluntary fatigue) after a two-week training procedure in which they were conditioned to expect pain reductions and performance enhancement resulting from the morphine administration. Compared to control groups (who either did not undergo morphine conditioning or did not receive a placebo on the day of the competition), the group that received the placebo 'morphine', and had done the two-

week training/conditioning period, showed enhanced physical performance (a higher number of leg extensions) via increased levels of pain and fatigue endurance. Thus, simply expecting the effects of morphine during the competition reduced perceptions of pain and fatigue and enhanced performance. However, a separate study showed that this placebo response could be almost completely blocked by administering the opioid antagonist naloxone. This strongly suggests that the significant effect of placebo administration on participant pain endurance and physical performance was mediated by endogenous opioid activity (Benedetti, Pollo, et al., 2007). The fact that naloxone did not completely block ergogenic responses to placebo morphine responses suggests that non-opioid processes – such as those involving the endocannabinoid system – could have also contributed to the observed ergogenic placebo response (Benedetti, Pollo, et al., 2007). These findings offer a mechanism that may help to explain placebo effects in a variety of sporting contexts, ranging from increases in professional weight-lifting performances (Ariel & Saville, 1971; Maganaris, Collins, & Sharp, 2000) to improvements in aerobic cycling trials (Beedie, Stuart, Coleman, & Foad, 2006).

To summarise, several strands of research have shown overlap in the neurobiological mechanisms involved in pain and fatigue, and have implicated these mechanisms in regulating outputs and experiences during strenuous physical exertion. The bodies of literature on the neurobiological pain-fatigue overlap, and on the importance of pain and fatigue in determining outputs during strenuous physical activities, provide part of the foundation of this thesis' hypotheses on the effects of social support on experiences and performance during exercise, as a variety of socio-environmental cues have been shown to alter pain perception (e.g., Coan et al., 2006; Eisenberger et al., 2011; Master et al., 2009). While the research reviewed in this section offers valuable insight into how beliefs (both conscious and sub-conscious) about internal environments (i.e., having received an ergogenic drug) can influence neurobiological systems involved in regulating physical outputs and experiences, it is yet to investigate how external social environments – integral to most forms of physical activity in humans – might

have similar effects. The next section considers how social factors can affect mechanisms involved in the self-regulation of pain, fatigue, and physical exertion.

### 2.2.4 Cohesion, social support and performance in strenuous physical exertion

Although not directly related to exercise psychology and physiology, other fields of research have shown that, like perceptions of pain, perception of fatigue and reliant physical outputs are highly dependent on contextual cues. As reviewed in Section 2.2.3.2 (p. 57), beliefs about the receipt of a performance enhancing drug can, by themselves, lead to reductions in fatigue and performance enhancement during physical exertion. Considering results linking social support to endogenous analgesia (e.g., Eisenberger et al., 2011) and the neural overlap between pain and fatigue (Noakes et al., 2005), I hypothesise that 'beliefs' (or innate, subconscious expectations) about social environments are likely to have similar fatigue-reducing and performance-enhancing effects (Cohen, 2015, 2017; Davis & Cohen, 2018; Davis et al., 2015). As discussed in Chapter 1, cohesive, supportive social environments are associated with resource abundance, safety, and care. In these environments, exhausted or injured individuals would be cared for and able to replenish bodily resources. Dipping into physiological reserves of reducing one's headroom, so to speak, would be less risky given such assurances. Speaking in terms of self-regulation, there would be greater activity in endogenous systems involved in reducing perceptions of fatigue and increasing physical outputs when social environments indicate safety, care, and resource abundance.

This account may explain links between the cohesion-signalling touch identified as a predictor of team success in the NBA (Kraus et al., 2010), for example, and performance in sport more generally. Studies have shown that positive social interactions and touch activate the body's endogenous opioid system (Dunbar, 2010, 2012), offering a means by which positive, cooperation-signalling touch could affect pain and fatigue perception, and, ultimately, performance.

Considering experimental research, some studies have used synchronous movement to induce either endogenous analgesia or performance enhancement during exercise. Synchronous movement has been construed as a cue to social cohesion and desire to affiliate (Julien et al., 2000; Lakens & Stel, 2011; Wheatley et al., 2012). Furthermore, synchronous movement – relative to non-synchronous group activities – can increase measures of both self-reported social bonding, and prosocial behaviour, with research indicating that prosociality effects are mediated by endogenous opioid activity (Lang, Bahna, Shaver, Reddish, & Xygalatas, 2017; Reddish, Bulbulia, et al., 2013; Reddish, Fischer, et al., 2013; Tarr et al., 2015a, 2015b; Tarr et al., 2016; Wiltermuth & Heath, 2009).

The first of study to manipulate synchrony during group exercise showed that synchronous group rowing trials (compared to individual rowing trials with equivalent physical output levels) led to significant increases in pain thresholds from pre to post exercise in a competitively elite, highly trained, university boat crew (Cohen et al., 2010). A series of follow-up studies, again using samples of experienced university and club-level rowers, corroborated these findings, indicating that synchronous group rowing with strangers also leads to heightened pain thresholds, compared to individual rowing (Sullivan & Rickers, 2013). In another study, synchronous rowing was again shown to increase pain thresholds compared to solo *and* anti-phase synchronous rowing, leading the authors to conclude that the increases in pain thresholds were due to in-phase synchrony and not solely to the presence of strangers (Sullivan, Rickers, & Gammage, 2014). The descending pain modulatory network identified in the ergogenic placebo studies described in Section 2.2.3.2 (p. 57) might also explain these results, as the researchers speculated that endogenous opioid activity explained the observed increases in pain threshold. Indeed, through using the opioid antagonist naltrexone, Tarr et al. (2017) confirmed that endogenous opioid signalling underpins pain threshold increases resulting from synchronous movement.

None of these studies investigated performance effects, instead opting to explicitly control for output levels. To date, only one study – published by myself and colleagues – has examined

synchrony effects on physical performance outputs. This study used a synchronous warm-up manipulation – akin to the New Zealand All Blacks haka – in a team of competitively elite university rugby players. In a within-subjects design with three conditions, athletes first warmed up either on their own, non-synchronously with a teammate, or synchronously with a teammate. After the synchronous warm-up with their teammates, athletes ran significantly faster times (compared to the non-synchronous condition) in a maximum effort, solo anaerobic conditioning test, and these improvements were competitively meaningful (Davis et al., 2015).

Although non-synchrony is typically construed as a control condition in these studies, there may be effects specific to non-synchrony that also relate to perceptions of cohesion. The lack of any observable increases in pain threshold and physical performance during or following non-synchronous movement may result from lower perceptions of working together as a cohesive unit. Non-synchrony is not merely the absence of synchrony. Anti-phase synchrony may even work to highlight self-other boundaries, thus reducing perceptions of group cohesion (Davis et al., 2015).

Contrarily, working to move in synchrony may increase perceptions of group cohesion and social support. According to the Reinforcement of Cooperation Model (Reddish, Fischer, et al., 2013), synchronous movement can increase perceptions of successful cooperation and social unity, which in turn increase trust and confidence that future successful cooperation is likely. In the experiments described above, working together to produce synchronous movement may have highlighted the presence of cohesive, supportive relationships where future aid in meeting individual needs is likely (Hruschka, 2010; Wheatley et al., 2012). Like social support during experimentally induced pain (Coan et al., 2006), these perceptions may have worked to increase pain and fatigue thresholds, thereby enhancing performance. In sum, then, research on synchronous movement both before and during exercise suggests that cues to cohesive, supportive social environments can have pain-reducing and performance-enhancing effects among experienced athletes.

### 2.2.5 Contexts for social support effects in sport and exercise

The research reviewed in this chapter suggests that social support effects during strenuous physical exertion work through mechanisms involved in perceptions of pain and fatigue. Pain and fatigue are neurobiologically related emotions that function to protect the body from overexertion and injury (Noakes, 2012; Pollak et al., 2014). As such, pain and fatigue are more likely to affect physical outputs the closer individuals get to their physiological maxima, and the point at which exertion can no longer be safely sustained (Noakes et al., 2005). Since social support effects are likely to alter outputs during strenuous physical exertion through acting on perceptions of pain and fatigue, it follows that these effects will be strongest when pain and fatigue are playing an important role in governing outputs: when individuals are nearing their physiological maxima.

It is important to account for motivations when considering the situations in which individuals will perform nearest their physiological maxima. For example, extrinsic rewards, such as winning a major competition, are likely to play a crucial role in determining individuals' motivations to produce (perceived) maximum physical outputs. These motivations likely interact with social environments in determining pain and fatigue levels. Tacit, self-regulatory calculations will take into account potential rewards (e.g., Olympic gold medals) and potential costs (e.g., overexertion and injury) in determining levels of perceived pain and fatigue and the physical outputs they govern. Through changing the potential costs of overexertion and injury (both are less costly when supportive others make care and resources more likely), social support may alter when protective pain and fatigue perceptions begin to attenuate potentially dangerous levels of physical exertion.

## 2.3 Summary of literature to date

Broadly, research has shown that performance outcomes involve self-regulatory systems that are heavily dependent on environmental cues. In humans, a species in which individuals depend on bonded conspecifics for safety and access to resources (Tomasello et al., 2012), social environments play a large role in determining activity in self-regulatory mechanisms

(Kikusui et al., 2006). Exercise motivation and performance has been shown to be governed by an endogenous self-regulatory system that modulates perceptions of both pain and fatigue, which are signalled through overlapping neurobiological pathways (Noakes et al., 2005; Pollak et al., 2014). Research has shown that endogenous analgesia resulting from activity in this self-regulatory system is dependent on environmental cues, such as (placebo) medical treatments (e.g., Bingel & Tracey, 2008; Colloca et al., 2013) and the presence of bonded, supportive others (e.g., Coan et al., 2006; Eisenberger et al., 2011; Master et al., 2009). Given the overlap in the self-regulatory neural pathways involved in pain and fatigue, the extensive literature on analgesic social support effects, and evidence of placebo effects on perceptions of fatigue and physical outputs (Benedetti, Pollo, et al., 2007), it seems likely that social environments will also affect perceptions of fatigue and the physical outputs it governs. Indeed, both anecdote and ethnographic and observational work suggest that social support and cohesion in sports teams and exercise groups leads to enhanced motivation and performance (Filho et al., 2014; Gotaas, 2012; Kraus et al., 2010). However, to date, research is yet to thoroughly investigate what follows from these diverse bodies of literature; that perceptions of social support and group cohesion reduce perceptions of pain and fatigue and enhance performance among both ordinary exercisers and professional athletes.

### 2.3.1 Gaps in the literature

There is little empirical work testing the effects of perceptions of social support on pain, fatigue, and performance during strenuous physical exertion. What does exist in the sport psychology literature looks mostly at skill-based performance, such as putting in golf (Rees & Freeman, 2010; Rees et al., 2007), rather than outcomes based on the endogenous self-regulation of fatigue, such as aerobic and anaerobic outputs (Amann et al., 2009; Pollo et al., 2008). Research on how social environments relate to aerobic and anaerobic outputs is either observational in nature – looking at exercise class adherence, for example (Spink & Carron, 1994) – or can only be seen as a test of the effects of social support in a specific subset of the population (experienced athletes) and to the extent that behavioural synchrony can be

construed as a cue to supportive, cohesive social groups (Davis et al., 2015; Sullivan & Rickers, 2013; Sullivan et al., 2014). As reviewed in Section 2.2.4 (p. 66), synchrony-induced increases in pain threshold during exercise likely result at least partially from heightened endogenous opioid activity (Tarr et al., 2017), which can also influence physical outputs (e.g., Amann et al., 2009). Further, the mechanisms by which other social environments (e.g., cohesive teams, encouraging exercise class instructors) might affect strenuous physical exertion are not well understood. Some research in sports psychology on the role of emotions is relevant (e.g., Beedie et al., 2012), but this work has not yet been related to research on the neurobiology of self-regulation during strenuous physical exertion. Further, although brain imaging technologies – such fMRI and positron emission tomography (PET) – have been used to investigate opioid-based endogenous analgesia (Wager et al., 2013; Wager et al., 2004; Wager et al., 2007) and runners' highs (Boecker et al., 2008), they have not been used to identify the neural pathways involved in self-regulation during exercise. Given the neurobiological overlap in pain and fatigue, investigating these neural pathways may help to connect research on how social environments influence self-regulation during exercise to the more developed bodies of literature on self-regulation during experimentally induced pain (i.e., that on endogenous, placebo-based analgesia) and on emotion in sport and exercise. Finally, despite observational and ethnographic work suggesting ergogenic social support effects on physical outputs during sport and exercise (Gotaas, 2012; Hindley, 2018; Kraus et al., 2010; Stevinson et al., 2014; Wiltshire, Fullagar, & Stevinson, 2018), there is no research that empirically tests whether this is the case using constructs and manipulations of social support consistent with those presented in sport and social psychology literature (e.g., Heinrichs et al., 2003; Rees & Freeman, 2010). In sum, there is currently a lack of empirical work – both experimental and observational – that tests the hypothesis that, during aerobic and anaerobic exercise, social support affects experiences and outputs through endogenous pain and fatigue mechanisms.

## 2.4 Thesis outline

Given the lack of research in this area, the goal of this thesis is to initiate a programme of research that tests the hypothesis that cues to the presence of supportive, cohesive social environments change activity in neurobiological mechanisms involved in the self-regulation of strenuous physical exercise, leading to reductions in perceptions (and self-reports) of pain and fatigue and/or improvements in outputs. This hypothesis can be tested at the behavioural (physical outputs) and mechanistic (reports of pain and fatigue, activity in neurobiological self-regulatory systems) levels. Logistically, tests of the hypothesis should first investigate physical outputs and self-reports of pain and fatigue, before potentially proceeding to more focused examinations of proposed neurobiological pathways (e.g., using brain-imaging techniques). This order of research allows for relatively inexpensive 'proof of concept' studies that will form the basis for more expensive research, such as studies using fMRI. Studies using fMRI technologies would help to directly test the hypothesis that social support during strenuous physical exercise increases activity in endogenous opioid and endocannabinoid-based self-regulatory mechanisms that govern physical outputs through their effects on perceptions of pain and fatigue. Although these methods will not be employed in this thesis, I will provide a research paradigm that is consistent with and amenable to future studies that could do so.

The section below provides an overview of the empirical contribution of this thesis, in which I use diverse methods across four separate studies to test the hypotheses developed above. Full abstracts can be found at the start of each chapter.

### 2.4.1 Summary of Chapter 3

Chapter 3 presents the first direct, experimental test of the hypothesis that social support enhances outputs during strenuous physical exercise through its effects on perceptions of pain and fatigue. Social support was manipulated between participants in a manner consistent with manipulations of the variable in social and sport psychology research (Heinrichs et al., 2003; Rees & Freeman, 2010; Roberts et al., 2015). Primary outcome measures of interest were exercise outputs over a series of four anaerobic stationary cycling trials, a commonly

used measure of anaerobic performance (Greer, McLean, & Graham, 1998; Zupan et al., 2009), and participants' reports of physical exertion (Borg, 1982) and discomfort (Eisenberger et al., 2011) during the cycling trials. Results revealed that, compared to controls, participants in the social support condition produced greater initial outputs and steeper declines over time. This effect was moderated by participant neuroticism; an important predictor of how individuals react to social support.

### 2.4.2 Summary of Chapter 4 and Chapter 5

These chapters describe a two-pronged, observational approach to empirically test the hypothesis that social support affects participant run times and experiences at parkrun, a free, timed, community-based 5 km run that happens across the United Kingdom (UK), and internationally, every Saturday morning. Chapter 4 consists of an analysis of a big data set, obtained from parkrun's publicly-accessible website, containing information on over nine million runs at parkrun over the past seven years. From this data set, several social networks were created. These networks represented parkrunners' social ties. The presence of 'close' social relationships were then used in multilevel models to predict parkrunners' run times. Chapter 5 consists of a survey analysis of a subset of parkrunners recruited from sites around the Oxford, UK area. The survey took repeated measures, over a five-month period, of variables related to participants' running experiences and sociality while at parkrun. Measured variables were then used to test whether the presence of close others (i.e., family and friends), perceptions of social support, or pre-run sociality predicted participants' run times and perceptions of fatigue while at parkrun. Results from the big data study suggest that social integration and the presence of close running partners predict faster run times. The survey study results add nuance to these findings, showing that the presence of close others, perceptions of social support, and pre-run sociality predict greater levels of felt energy, and that felt energy mediates the ergogenic effects of these social predictor variables on 5 km run times.

### 2.4.3 Summary of Chapter 6

Chapter 6 presents a study that employs an fMRI-compatible, within-subjects, 2 × 2 × 3 factorial design to test the effects of ergogenic placebo treatments and cues to social support (a photo of a support figure) on performances and experiences during repeated trials of a hand-grip exercise that varied in difficulty (conducted at either 40%, 50%, or 60% of participants maximum hand-grip strength). This study allowed for comparisons of social support and ergogenic placebo effects in exercise, and developed an experimental paradigm that can subsequently be used to investigate neural mechanisms. Results revealed that the social support cue led participants to produce greater hand-grip outputs, at similar (and, in some instances, non-significantly lower) levels of reported difficulty. Further, the effects of social support became significantly stronger as the difficulty of the trials increased.

## 2.5 Implications

This research will offer the first experimental and observational tests of the hypothesis that cues to social support change activity in neurobiological mechanisms involved in the self-regulation of strenuous physical exercise, eventually leading to reductions in pain and fatigue and/or improvements in outputs. In addition to the primary theoretical and empirical contributions of the research, the methods I develop will offer new tools for diverse fields of study. Chapter 3 presents an experiment that builds upon past manipulations of social support (e.g., Heinrichs et al., 2003), making them viable in an exercise setting and eliminating confounds of social facilitation. Through the social network analyses of the community run data described in Chapter 4, I demonstrate a novel way in which social support effects could be tested in a variety of contexts, including regular face-to-face exercise classes and increasingly popular online exercise networks and communities. In addition, in Chapter 6, I offer a fMRI-compatible, methodologically novel means for elucidating the neurobiological underpinnings of context-dependent changes to self-regulatory systems during exercise. More generally, this research draws from disparate bodies of literature to develop a theory that explains how and why social and cultural cues can affect self-regulatory processes – an area

of interest for academics from fields as diverse as anthropology, psychology, and epidemiology. Finally, the empirical work that this multi-disciplinary thesis has generated should be of interest to practitioners, caregivers, policy makers, and the wider public.

## Chapter 3 – The effects of social support on anaerobic exercise bouts

A condensed report of the study presented in this chapter was published in *Adaptive Human Behavior and Physiology* (Davis & Cohen, 2018).

**Abstract**

A between-subjects experimental design was used to test the hypothesis that social support increases performance outputs during anaerobic exercise bouts via altering activity in self-regulatory mechanisms involved in perceptions of pain and fatigue. Participants' perceptions of social support were manipulated prior to a series of four 30-s anaerobic exercise bouts. Measures of physical outputs and perceptions of physical discomfort and exertion were taken as the main outcome variables of interest. Analyses showed that participants in the social support condition produced greater initial outputs and steeper declines over time, compared to controls. This effect was moderated by participant neuroticism; an important predictor of how individuals react to social support. The findings are discussed in terms of proposed causal mechanisms linking supportive social environments with self-regulation and physical performance.

## 3.1 Introduction

Studies in a variety of contexts – using ethnographic, observational, and experimental methods – suggest that team cohesion and the presence of close, supportive relationships can enhance performance during sport and exercise via reductions in physical discomfort and fatigue (Davis et al., 2015; Gotaas, 2012; Kraus et al., 2010); see Section 2.2 (p. 45). However, the effects of the presence of close supportive others – an operationalised form of emotional social support (Heinrichs et al., 2003; Schnall et al., 2008) – on physical performance have not been tested experimentally. Whether and how social support affects pain and fatigue, and the physical outputs they govern, remain open questions. This study tested the hypothesis that social support influences everyday exercisers' performance during anaerobic exertion via altering activity in self-regulatory mechanisms involved in perceptions of pain and fatigue.

In social species, such as chimpanzees, bonobos (*Pan paniscus*), and baboons (*Papio*), survival and reproduction correlate positively with close, stable relationships with conspecifics, and social environments can have strong psychophysiological influences on individuals (Dunbar, 1980; Kikusui et al., 2006; Samuni et al., 2016; Silk et al., 2003; Watts & Mitani, 2001; Wittig et al., 2016). Research has shown that the safety signalled by the presence of conspecifics, and especially bonded conspecifics, can 'buffer' adverse responses to threatening stimuli, as measured, for example, by reductions in indicators of stress, fear, and pain (Kikusui et al., 2006; Kiyokawa et al., 2004). In humans, where the presence of close social relationships has for millennia correlated not only with safety, but also care and resource abundance (Tomasello et al., 2012), social support is associated with a diverse range of positive psychological and physiological effects (Hennessy et al., 2009). Perceptions of both situational and daily levels of social support can lead to reductions in stress responses and perceived pain unpleasantness, as well as improvements in healing and immunity (Cohen et al., 2015; Eisenberger et al., 2011; Kulik & Mahler, 1989; Roberts et al., 2015). The presence of social support thus seems to change the parameters of adaptive behaviour in response to a range of stressors, threats, and risks.

Evidence suggests that social support constitutes a resource that potentially reduces recipients' appraisals of threat or impending adversity in physical and social challenges, and this can have downstream effects on a variety of psychophysiological responses (Lazarus & Folkman, 1984). Physical exertion incurs costs in resource use, and it risks possible exhaustion and injury. Mechanisms modulating pain, fatigue, and predictions and perceptions of difficulty in physical challenges are thought to result from selection for adaptive exertion levels given particular internal and external environments (Humphrey & Skoyles, 2012; Noakes, 2012; Noakes et al., 2005). While pain, fatigue, and heightened perceptions of physical challenges can help to protect against overexertion and physical harm, they also come at a cost (e.g., reductions in mobility that limit foraging and mating opportunities). Here, I suggest that the presence of social support, insofar as it signals a valuable resource for aiding recovery, may therefore serve to temper the perceived challenge of physical exertion and the costs of potential exhaustion and injury. In conjunction with clearly perceived benefits of peak performance (e.g., winning an Olympic gold medal), this can lead to a lifting of the self-regulatory 'brakes' of pain and fatigue (relative to conditions of no support), ultimately enhancing performance.

Research on placebo effects has illuminated the neurobiological pathways through which environmental cues and socially derived beliefs affect physical performance (for a full review of this literature, see Section 2.2.353, p. 53). Studies have shown that placebo analgesia is mediated by endogenous opioid and endocannabinoid activity in top-down pain modulation systems (Benedetti, Amanzio, et al., 2011; Wager et al., 2007). Given the overlap in neurobiological pathways involved in pain and fatigue modulation (Davis & Bailey, 1997; Noakes et al., 2005; Pollak et al., 2014), and the importance of both as self-regulatory mechanisms that govern strenuous physical outputs (Noakes, 2012), researchers have recently investigated whether placebo performance enhancement during exercise is based on neuropharmacological mechanisms similar to placebo analgesia in clinical contexts (Pollo et al., 2008, 2011). Studies have found that placebo performance enhancement can be partially

blocked by opioid antagonists, suggesting involvement of the endogenous opioid system, but also other systems that underpin endogenous analgesia and self-regulation during physical exertion, such as the endocannabinoid system (Benedetti, Pollo, et al., 2007). Both endogenous opioids and endocannabinoids have been implicated in the formation, maintenance, and signalling of social bonds (Inagaki et al., 2016; Machin & Dunbar, 2011; Trezza et al., 2010), indicating one possible pathway through which the presence of social support could modulate pain, fatigue, and physical performance during strenuous exercise.

Responses to available social support are unlikely to be consistent across individuals, however (see Section 1.4.1, p. 19). Effects of social support on responses to stressors may be ontogenetically tuned according to developmental environments of support or deprivation. Research suggests that variation in responsiveness to social support may be explained by individuals' need for social assurance from others and whether they tend to perceive daily interactions to be supportive (Cohen et al., 2015; Lee & Robbins, 1995). Other research on the moderators of social support effects has identified neuroticism as an important personality factor that affects how social support is received. Neurotic individuals are more likely to focus on the potential social costs of receiving social support, making them less likely to experience its positive effects (Park et al., 2013). Further, the quality of the relationship between supporters and those being supported has been shown to predict the magnitude of social support effects; relatively high-quality relationships lead to larger social support effects (Coan et al., 2006).

Although research has shown that social support can influence perceptions of physical challenges and alter activity in self-regulatory mechanisms involved in governing physical outputs, it remains unclear how these purported changes in self-regulation affect performance during everyday activities such as strenuous physical exercise. Although results consistently indicate a positive effect of social support on performance, previous experimental studies have either focused on coordination and skill-based tasks (e.g., Rees & Freeman, 2010), or used synchrony as a cue to social support (Davis et al., 2015); see Section 2.2.2 (p. 50). This study

is the first to test the effects of social support – as operationalized in social psychological literature (Heinrichs et al., 2003; Rees & Freeman, 2010) – among everyday exercisers during a strenuous physical activity.

Specifically, I tested the hypothesis that social support enhances the performance of anaerobic exercise (see Table 3.1). In a between-subjects experiment, participants' social support was manipulated before a difficult physical exercise task. The social support manipulation used here was similar to those used in other studies, where social support was induced by having a close friend accompany participants while they completed a stressful task, versus having no companion present (Heinrichs et al., 2003). However, it differs in that participants in both the social support (hereafter 'companion') and control (hereafter 'solo') conditions brought a companion with them to the study; this was done to ensure that participants (hereafter 'exercisers') had similar experiences and expectations leading up to participation in the study and immediately prior to the social support manipulation.

The exercise task consisted of four 30-s, maximum effort cycling bouts; physical performance outputs and self-reports of physical discomfort and exertion were measured across the four bouts. Although an indirect measure, self-reports of physical discomfort have been shown to correlate with neurobiological activity in systems that process pain and fatigue (Eisenberger et al., 2011; Pollak et al., 2014). I therefore used pain and fatigue ratings as an initial test of my hypothesis on the effects of social support on anaerobic outputs and to inform conjectures of possible psychological and neurobiological mechanisms underlying these effects. Finally, I also measured a set of individual attributes that have been shown to alter the effects of social support – the quality of the exerciser-companion relationship, exercisers' social support in daily life, their need for social assurance, and their level of (trait) neuroticism – as these variables had the potential to moderate the effect of the social support manipulation on strenuous physical exercise (see above and Section 1.4.1, p. 19). See Table 3.1 for a full list of hypotheses.

**Table 3.1** Hypotheses

| | |
|---|---|
| **Anaerobic outputs, ratings of perceived exertion, and reports of physical discomfort** | |
| **Hypothesis 1** | Social support will enhance anaerobic performance, as evidenced by:<br>(a) greater anaerobic outputs with lower ratings of perceived exertion and lower perceptions of physical discomfort, or<br>(b) greater anaerobic outputs with equivalent ratings of perceived exertion and perceptions of physical discomfort, or<br>(c) equivalent anaerobic outputs with lower ratings of perceived exertion and lower perceptions of physical discomfort. |
| **Moderators of social support effects on anaerobic outputs** | |
| **Hypothesis 2** | The quality of the exerciser-companion relationship will moderate social support effects, such that the performance-enhancing effect of social support will be stronger for exercisers with a relatively high-quality relationship with their companion, as compared to those with a relatively low-quality relationship with their companion. |
| **Hypothesis 3** | Exercisers' perceived daily social support will moderate social support effects, such that the performance-enhancing effect of social support will be stronger for exercisers with relatively low perceptions of daily social support, as compared to those with relatively high perceptions of daily social support. |
| **Hypothesis 4** | Exercisers' need for social assurance will moderate social support effects, such that the performance-enhancing effect of social support will be stronger for exercisers with relatively high needs for social assurance, as compared to those with relatively low needs for social assurance. |
| **Hypothesis 5** | Exercisers' (trait) neuroticism will moderate social support effects, such that the performance-enhancing effect of social support will be stronger for exercisers with relatively low levels of neuroticism, as compared to those with relatively high levels of neuroticism. |

## 3.2 Methods

### 3.2.1 Participants

Participants were recruited around the city of Oxford, UK, using flyers and emails to Oxford University mailing lists for a study putatively investigating the links among personality, exercise, and cognition (see Appendix A, Figure A 1, p. 291). As such, the study did not involve deception, although details of the exact nature of the study were withheld so that participants did not guess the experimental hypotheses. To participate, individuals were required to be "at least recreationally fit," aged 18 – 49, and to bring a companion to the study. Companions

were to be “someone you feel you have a close connection with and that you can depend upon in times of need (such as a friend, romantic partner, or family member).” Exercisers and their companions were compensated £15 and £10, respectively. This study was approved by the School of Anthropology and Museum Ethnography Research Ethics Committee, University of Oxford (reference number: SAME/CUREC1A/15-045).

An initial power analysis – assuming a medium to large effect size ($\eta_p^2$ = .13) with a power of 0.8 and an α equalling .05 – generated a recruitment goal of 80 pairs of participants. In total, 81 exercisers and their companions participated in the study. Four pairs were excluded from analyses: one due to experimenter error, one for bringing an underage companion, and two for guessing the hypothesis and experimental condition. This left a total of 77 exercising participants, 53 females (69%), age range = 18 – 42 years, *M* = 23.60 years, *SD* = 5.44 years, and their companions. Additionally, two exercisers (one in each social support condition) did not finish their fourth bouts of exercise due to feeling unwell. Thus, there were missing data for their exercise outputs. These two exercisers were excluded only from the mixed ANOVAs reported below, as these models cannot accommodate missing data points, leaving a total of 75 exercising participants for mixed ANOVA analyses and 77 exercising participants for all other analyses. Data collection did not continue after data analysis.

### 3.2.2 Procedures and materials

All participants came to the study with their chosen companion. Upon their arrival, participant pairs identified themselves as either exercisers or companions. They were then sent to separate rooms to read and sign informed consent forms, which explained to them the study and timeline for their participation. Exercisers were also asked to fill out the Physical Activity Readiness Questionnaire (Thomas, Reading, & Shephard, 1992): all were cleared to exercise. From this point onwards, exercisers were fitted with a Polar H7 heart rate sensor with Bluetooth data recording. Average heart rates were calculated for each of the 30 s exercise bouts.

Immediately following this, and still in separate rooms, both participants answered a series of background questions related to their demographics and relationship with one another, though only the answers of exercisers were included in analyses, as these were the participants influenced by the social support manipulation of interest. Regarding their demographics, participants were asked to provide their age, sex, nationality, and English language proficiency (Fluent, Advanced, Intermediate, or Beginner). Participants were also asked to answer the following questions about their relationship with each other using seven-point Likert scales (1 = *Low amount*, 4 = *Medium amount*, 7 = *High amount*): "To what extent do you feel your companion is there for you when you need him/her (for example, emotionally, psychologically and/or materially)?", "Rate your overall similarity to your companion.", "Rate how connected you feel to your companion.", and "Rate how close your relationship is with your companion." Additionally, participants were asked how long they had known each other (years, months). Participants also answered the question: "How frequently are you in contact with your companion each week (whether in person, text, phone call, email, etc.)? Please indicate which of the following options best approximates the average number of times you are in contact with your companion each week" (Less than once a month, A few times a month, Every week, A few times a week, Every day, or A few times a day). An abbreviated (10-item) version of the 'Big Five' personality inventory, published by Rammstedt and John (2007), was used to measure participants' personality traits. In order to obtain estimates of exercisers' pre-experiment anaerobic fitness levels, a modified version of the Habitual Physical Activity Questionnaire was administered; as a means of gaining more information on how often participants did anaerobic exercise, they were allowed to list four sports (instead of two) as part of their regular physical activity (see Appendix A, Section 1, p. 260) (Baecke, Burema, & Frijters, 1982).

Social support was manipulated after the pre-exercise questions, creating two, between-subjects conditions – 'companion' and 'solo'. In the solo condition, exercisers (still in a separate room) were informed that their companion had left after finishing their portion of the

study. Exercisers in the solo condition were then told they would complete the rest of the study on their own. Exercisers in both conditions were then given instructions for the cycling bouts. In the companion condition, as a means of increasing exercisers' perceptions of emotional and instrumental support (Heinrichs et al., 2003; Rees & Freeman, 2010), the companion was brought into the room to listen to the instructions to "better understand" the task, and exercisers were told their companion would be waiting for them in the next room should they "need anything at all" while they completed the rest of the study. Companions were thus not present during the actual exercise portion of the experiment – they waited in a separate room. This was done to avoid any confounds from observation effects. A hypothesis-blind experimenter delivered the manipulation (see Appendix A, Section 2, p. 261) and instructions throughout the exercise portion of the experiment (see Appendix A, Section 3, p. 262).

The exercise task was based on the Wingate Anaerobic Test, a common measure of anaerobic fitness (Bar-Or, 1987; Zupan et al., 2009). It consisted of a 4-min warm-up and practice session followed by four, 30-s, maximum-effort cycling bouts (hereafter 'exercise bouts') on a Monark 874E ergometer (McArdle, Katch, & Katch, 2010). Before each of the four exercise bouts, exercisers were reminded that it was "crucial" they give maximum effort (for full exercise bout instructions, see Appendix A, Section 3.4, p. 264). Anaerobic output over the 30-s trial was calculated using the equation (McArdle et al., 2010):

$$AW\ (J) = 6g(kp)r\ (\text{in } 30\ s)$$

where AW (J) is total anaerobic work (or output) in joules, 6 is the distance travelled per pedal revolution in metres, g is gravitational acceleration in metres per second squared, kp is the resistance applied to the wheel in kilograms (6.5% of the exerciser's body mass), and r is the total number of complete pedal revolutions during the 30-s bout. Between each exercise bout there was a 3-min recovery period during which, as a means of estimating activity in pain and fatigue modulatory systems, exercisers completed measures related to how much effort they felt they were giving and their levels of physical discomfort. For estimates of physical effort,

exercisers answered the following prompt using the 14-point Borg Scale of Perceived Exertion (Borg, 1982): “Please rate your feelings of exertion (how much physical effort you felt you were giving) during your last cycling bout.” (see Appendix A, Figure A 2, p. 292). For estimates of physical discomfort, exercisers answered the following prompt using a 20-point scale adopted from previous research on experimentally induced pain (Eisenberger et al., 2011): “Please rate the physical discomfort you felt during your last cycling bout. Look at the scale and the expression and then choose a number.” (see Appendix A, Figure A 3, p. 293).

Following a final recovery period after the fourth exercise bout, participants answered manipulation-check questions and a hypothesis probe. Manipulation checks included the following questions, all answered on seven-point Likert scales: “How much did you like the experimenters?” (1 = *not at all*, 7 = *a lot*), “Do you think you could have tried harder during the cycling bouts?” (1 = *not at all*, 7 = *very much so*), “How much did you enjoy the experiment?” (1 = *not at all*, 7 = *a lot*), “Did you feel self-conscious during the exercise portion of the experiment?” (1 = *not at all*, 7 = *very much so*), “How comfortable and supported did you feel during the exercise portion of the experiment?” (1 = *not at all*, 7 = *a lot*), “How anxious did you feel both before and during the experiment?” (1 = *not at all*, 7 = *a lot*), “How did you come to the experiment (walking, biking, by car, by bus, etc.?” (text box for open response), “Did you and your friend come to the study together?” (yes or no), and “How often do you exercise with the friend you brought to the experiment?” (1 = *never*, 7 = *a lot*). The hypothesis probe was: “What do you think this experiment was about?” (text box for open response). Exercisers then answered the Multidimensional Scale of Perceived Social Support (MSPSS) (Zimet, Dahlem, Zimet, & Farley, 1988) and the Social Assurance Scale (SAS) (Lee & Robbins, 1995) using seven-point Likert scales (1 = *Disagree*, 7 = *Agree*). The 20 questions from these two scales (12 from the MSPSS and eight from the SAS) were presented in a randomised order and prefaced with: “The final set of questions concern you and how you feel generally. They are not specific to how you feel today or right now in this study.” (for a complete list of these questions, see Appendix A, Section 4, p. 266). The MSPSS measures perceptions of social

support from friends, family, and significant others in individuals' daily lives (Zimet et al., 1988), and the SAS measures individuals' needs for companionship, affiliation, and connectedness (Lee & Robbins, 1995). Thus, both measures should be generally unaffected by exercisers' experiences during the experiment, as they focus on respondents' personality characteristics and perceptions of social support in their daily lives. All questions were presented and answered on a desktop computer using a Qualtrics online survey (for a full schedule of measurements see Table 3.2).

### 3.2.3 Analysis

Mann-Whitney *U* tests (used because of non-normal distributions of condition-wise differences in the outcome variables) were conducted to check the effects of the social support manipulation and to identify potential confounds. A primary mixed ANOVA was then used to test the hypothesis that exercisers in the companion condition would produce greater total anaerobic outputs over the four 30-s exercise bouts. A secondary mixed ANOVA on peak power outputs during each 30-s bout, another commonly used output variable for Wingate Anaerobic Tests (McArdle et al., 2010), was also conducted as a means of confirming that observed patterns of results were not simply an artefact of analysing total anaerobic outputs as the main outcome variable (methods used for calculating peak power outputs are reported in Appendix A, Section 5, p. 267). Mixed ANOVAs were also used to test the effects of the experimental conditions, exercise bouts, and their interaction on exercisers' rates of perceived exertion (RPE) and reported physical discomfort, as well as their average heart rates during the 30 s exercise bouts. Finally, individual differences known to alter the receipt of social support were included in a series of four mixed ANOVAs – with Bonferroni corrected α values ($.05 \div 4 = .0125$) as a means of adjusting for multiple testing – that tested potential moderators of the effects of social support on strenuous physical exercise outputs and experiences. Moderator variable scores were tertile split (ranked and then assigned a category according to tertile); analyses excluded the middle tertile as previous research suggests that social support differentially influences those scoring relatively high or low on these variables

**Table 3.2** Schedule of measurements

| Variable | Question type |
|---|---|
| **Pre-exercise questions (both exerciser and companion)** | |
| Demographic information | Age, sex, nationality, English proficiency |
| Companion-exerciser relationship | Similarity, closeness, connectedness and how much the other is there for them in times of need, length of relationship, frequency of contact |
| Personality | 10-item Big Five personality inventory (Rammstedt & John, 2007) |
| Anaerobic fitness | Modified version of Habitual Physical Activity Questionnaire (Baecke et al., 1982) |
| **Exercise affect questions – presented after each exercise bout (exerciser only)** | |
| Rate of perceived exertion (RPE) | Borg Scale of Perceived Exertion (Borg, 1982) |
| Physical discomfort | Amount of physical discomfort (Eisenberger et al., 2011) |
| **Post-exercise questions (exerciser only)** | |
| Manipulation checks | Feelings of enjoyment, comfort, support, and anxiety during the study, liking of the experimenters, and degree to which they could have tried harder |
| Hypothesis probe | Purpose of experiment |
| Perceptions of daily social support | Multidimensional Scale of Perceived Social Support (Zimet et al., 1988) |
| Need for social support and assurance | Social Assurance Scale (Lee & Robbins, 1995) |

(Cohen et al., 2015; Park et al., 2013). All mixed ANOVAs included exerciser sex and estimated anaerobic fitness as control variables. Model assumption checks can be found in Appendix A, Section 7 (p. 269), and all data used in analyses can be found at: https://doi.org/10.6084/m9.figshare.5675392.

### 3.3 Results

Regarding the manipulation checks and potential confounds, Mann-Whitney *U* tests revealed no significant difference between the experimental (i.e., social support) conditions in exercisers' post-exercise ratings of enjoyment, liking of the experimenters, self-

consciousness, comfort and support, anxiety, or whether they felt they could have tried harder during the exercise bouts. There were also no significant between-condition differences in the exerciser-companion relationship, estimates of exercisers' self-reported anaerobic fitness, personality traits, age, or sex (see Appendix A, Table A 1, p. 276). Regarding concordance between exerciser-companion pairs in how they viewed their relationship, there was a strong correlation between the scores of exercisers and their companions on a factor extracted from the questions they answered about their relationship, $r = 0.643$, $t(75) = 7.28$, $p < .001$ (see Appendix A, Section 6, p. 268, for information on the creation of this factor).

Mixed ANOVAs (with exercise bout as a repeated measure) revealed that neither companion sex nor companion age (younger, older, or same age as companion) significant effects on exerciser's anaerobic outputs when examining both social support conditions together, and when analysing the companion and solo conditions separately (see Appendix A, Table A 2, p. 277).

A mixed ANOVA was used to analyse participants' total anaerobic outputs by experimental condition and exercise bout (Hypothesis 1). The model, which included exerciser sex and estimated anaerobic fitness as control variables, revealed a significant condition × exercise bout interaction, $F(2.09, 213) = 5.34$, $p = .005$, $\eta_p^2 = .070$ (see Appendix A, Table A 3, p. 278). Post-hoc contrasts revealed that, compared to the solo condition, the presence of companion support led to higher initial total anaerobic outputs (per bout) and steeper declines over the four exercise bouts (see Appendix A, Table A 4, p. 279). Analysing peak power outputs instead of total anaerobic outputs yielded a similar pattern of results: a significant condition × exercise bout interaction, $F(2.47, 175) = 4.36$, $p = .009$, $\eta_p^2 = .058$, which post-hoc tests revealed to be due to higher initial peak power outputs and steeper declines over the four exercise bouts in the companion condition, as compared to the solo condition (see Appendix A, Table A 5, p. 280, and Table A 6, p. 281). Another mixed ANOVA, including the same controls as above,

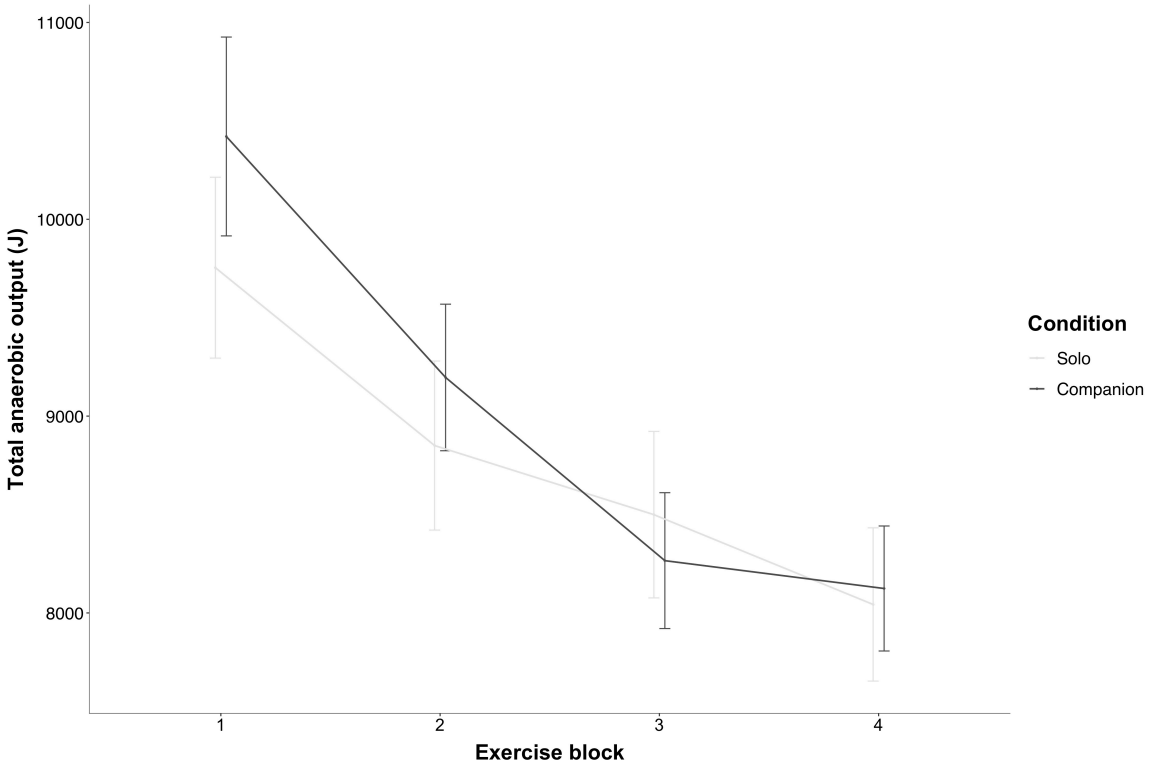



**Figure 3.1** Mean (± 1 *SE*) anaerobic outputs (joules, J) by condition.

revealed no effect of condition, bout, or their interaction on average heart rate (Appendix A, Table A 7, p. 282).

Mixed ANOVAs were also used to analyse exercisers' RPE and reported physical discomfort (Hypothesis 1). This revealed a non-significant effect of experimental condition, but a significant main effect of exercise bout, and a condition × exercise bout interaction on exercisers' RPE, $F(1.91, 139.58) = 5.34$, $p = .007$, $\eta_p^2 = .068$ (see Figure 3.2 below and Appendix A, Table A 8, p. 283). Post-hoc contrasts showed that, compared to those in the companion condition, participants in the solo condition displayed greater increases in RPE across the four bouts (see Appendix A, Table A 9, p. 284). Regarding participants' physical discomfort, analyses revealed a main effect of exercise bout only, $F(1.78,130.24) = 31.85$, $p < .001$, $\eta_p^2 = .263$; physical discomfort decreased across bouts (see Appendix A, Table A 10, p. 285).

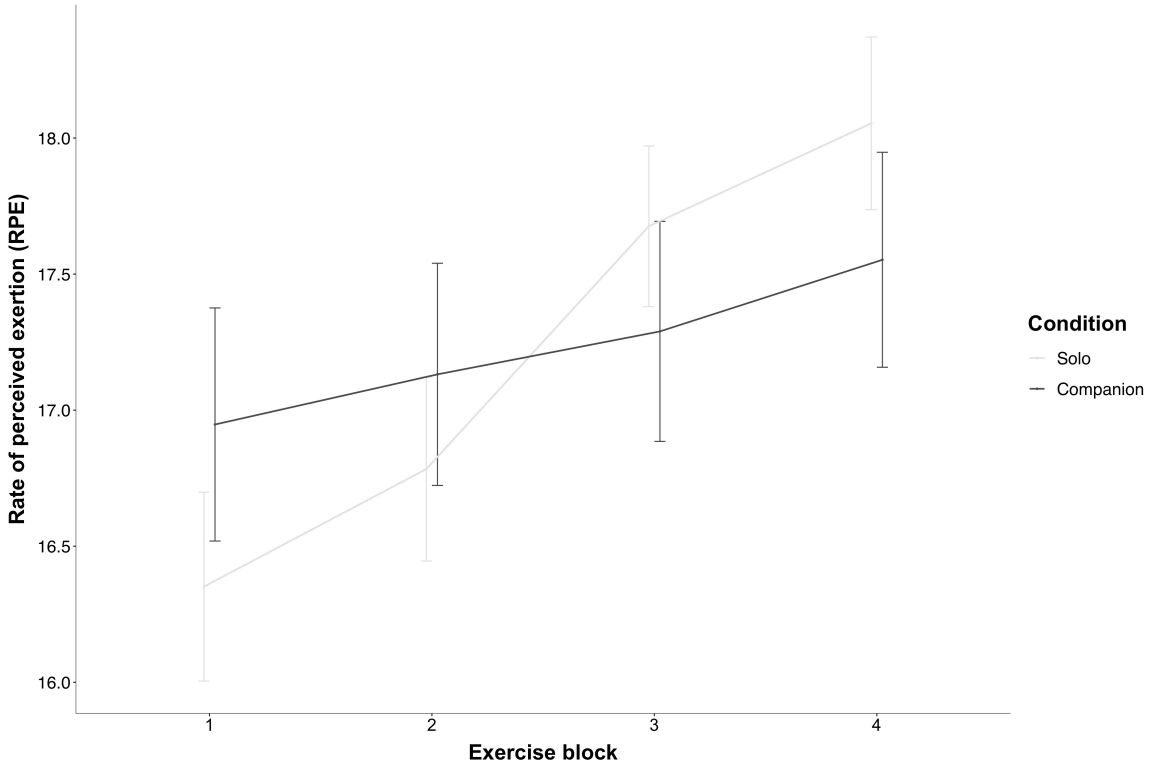



**Figure 3.2** Mean (± 1 *SE*) rate of perceived exertion (RPE) by condition.

To further explore the effects of social support on anaerobic outputs, four additional mixed ANOVAs were conducted. In addition to the control variables of participant sex and estimated anaerobic fitness, one of four hypothesised moderators of social support effects (see Table 3.1, p. 82) were also included in each ANOVA: the factor extracted from the questions on the companion-exerciser relationship (Hypothesis 2), exercisers' perceived social support in daily life (Hypothesis 3), their need for social assurance (Hypothesis 4), and their level of neuroticism (Hypothesis 5). Bonferroni-adjusted significance levels of α = .0125 (.05 ÷ 4) were used as a means of correcting for multiple testing. Results revealed non-significant condition × exercise bout × moderator interactions for all models (see Appendix A, Table A 11 – Table A 13, pp. 286 – 288) except the model including neuroticism, $F$(1.98,126) 5.69, $p$ = .005, $\eta_p^2$ = .119 (see Appendix A, Table A 14, p. 289). Compared to the solo condition, the companion condition yielded higher anaerobic outputs among exercisers low in neuroticism and lower anaerobic output among exercisers high in neuroticism (see Appendix A, Table A 15, p. 290).

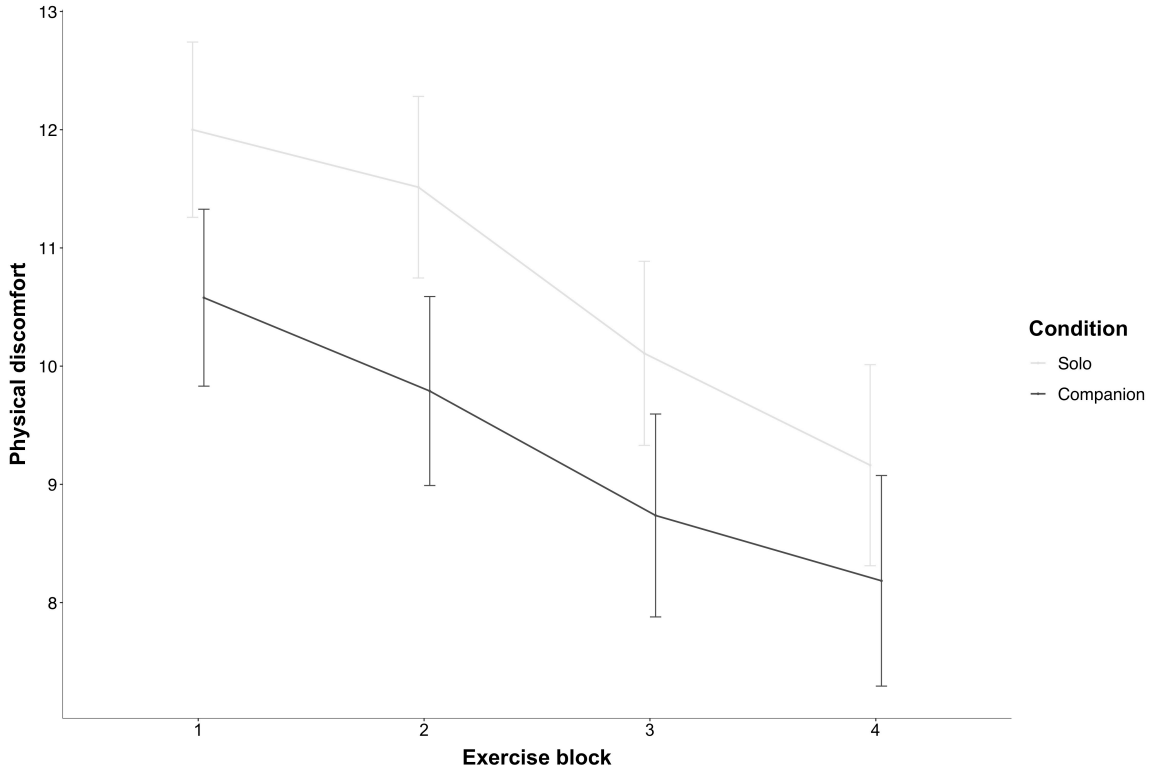



**Figure 3.3** Mean (± 1 *SE*) physical discomfort by condition.

## 3.4 Discussion

This experiment investigated the influence of social support on performance in a difficult exercise challenge. Due to non-significant between-condition effects on mean performance, RPE, and physical discomfort (i.e., when all exercise bouts were collapsed into a single mean), the null of Hypothesis 1 (no significant between-condition difference in anaerobic outputs or self-reports of RPE and physical discomfort) cannot be rejected. However, analyses revealed a condition × exercise bout interaction on exerciser outputs, with higher initial outputs and steeper declines in the companion condition, compared to the solo condition (see Figure 3.1). There was also a significant condition × exercise bout interaction for RPE, with exercisers in the solo condition displaying greater increases in RPE across the four bouts. While these results were not predicted in Hypothesis 1, the condition × exercise bout interactions observed in anaerobic outputs and RPE suggest an influence of social support on these variables.

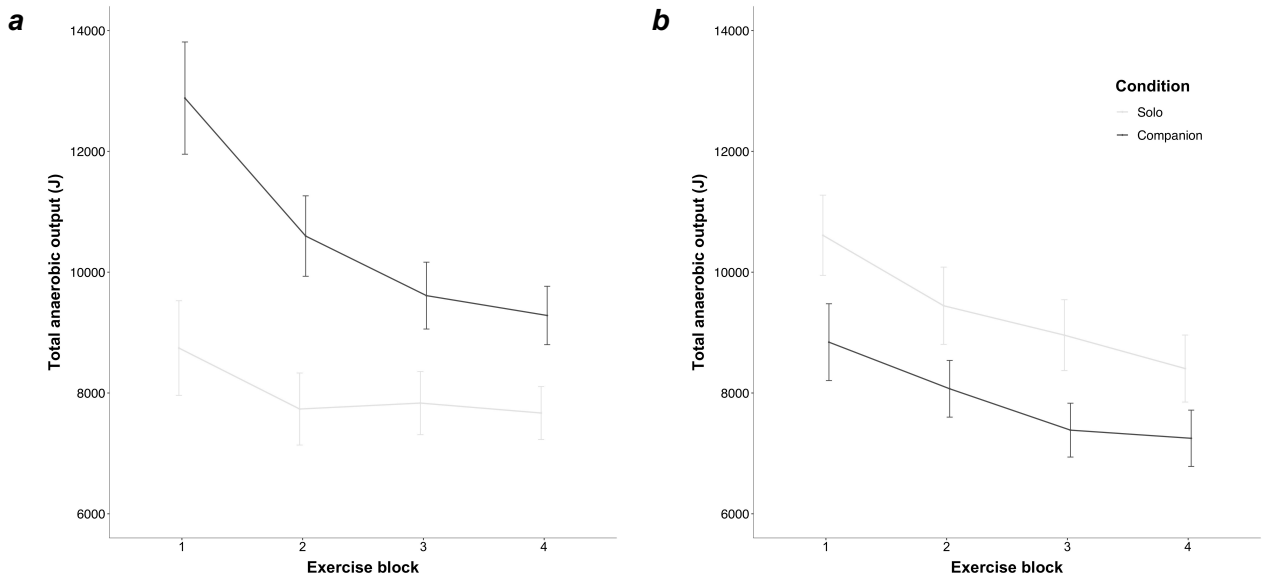



**Figure 3.4** Mean (± 1 *SE*) anaerobic outputs (joules, J) by condition for individuals (*a*) low and (*b*) high in neuroticism.

Higher initial outputs and steeper declines over time in the companion condition, compared to the solo condition, are congruent with previous findings from disparate fields of research. Within social psychology, experiments have shown that perceptions of physical and social resources and physiological capabilities can affect how challenges are assessed, altering participants' perceptions of their ability to succeed. For example, research has shown that variables that can impede physical performance – such as additional weight to carry, fatigue, or poor health – can cause distances to be perceived as greater, as they reduced perceived capacities to successfully complete physical tasks (Bhalla & Proffitt, 1999). In relation to strenuous physical exertion, social support has been shown to increase self-efficacy among exercisers (Christensen et al., 2006), which may help to explain the finding that physical challenges are perceived as less difficult when assessed in the presence of a supportive companion (Schnall et al., 2008). In the context of this experiment, supported participants may have estimated the exercise task as easier, which could have led to greater initial outputs, followed by lower outputs in later exercise bouts because of greater accrued muscle fatigue.

Nevertheless, it is important to consider why a higher level of output was not sustained in the companion condition (see Figure 3.1), given that the rationale for Hypothesis 1 was that the

presence of social support would alter activity in the neurobiological mechanisms governing pain, fatigue, and physical outputs, all of which are already known to be susceptible to environmental cues, such as ergogenic placebos (e.g., Benedetti, Pollo, et al., 2007; Eisenberger et al., 2011; Pollo et al., 2008, 2011). It is unknown whether ergogenic placebo studies would produce similar output patterns via activity levels in endogenous pain and fatigue modulation systems – to date, no studies of comparable design have been conducted. However, a related possible explanation concerns the interaction between the central and peripheral neurobiological mechanisms that govern outputs during strenuous physical exertion. Research using opioid analgesics, which I predict would have similar effects to activation of the endogenous opioid system via social reward (Panksepp et al., 1981), has shown patterns of decline similar to the anaerobic outputs of participants in the present study. Lumbar intrathecal injections of the opioid agonist fentanyl before a maximum-effort 5 km cycling trial led to increased outputs during the first 2.5 km, and decreased outputs in the second 2.5 km, compared to placebo injections (Amann et al., 2009). These results were hypothesised to result from an opioid mediated block on fatigue-signalling locomotor muscle afferents in the fentanyl condition. This block would reduce the inhibitory influence of these muscle afferents – and the pain and fatigue they signal – on central motor drive (Pollak et al., 2014), causing increased initial outputs but then also greater locomotor fatigue. Ultimately, relatively higher accumulations of muscle fatigue from increased first-half outputs in the fentanyl condition led to reduced muscle drive and outputs in the second half of the trails, relative to the placebo condition (Amann et al., 2009).

This result allows for speculation on how the presence of close, supportive others could similarly affect exercise outputs. The output profiles in the companion condition of the present study may result from processes involving heightened activation in endogenous, self-regulatory systems that reduce perceptions of pain and fatigue and that are also known to be involved in signalling the presence of social bonds (Fattore, Melis, Fadda, Pistis, & Fratta, 2010; Inagaki et al., 2016), such as the endogenous opioid and endocannabinoid systems

(Benedetti, Amanzio, et al., 2011; Panksepp et al., 1981; Wager et al., 2007). As a result of reduced pain and fatigue signalling, participants in the companion condition – who potentially also viewed the task as less challenging (Schnall et al., 2008) – may have initially 'overshot' optimum outputs, producing higher outputs in the first two exercise bouts, but lower outputs in the final two exercise bouts, due to heightened locomotor fatigue. Future research should explore the interplay between central motor drive, afferent inputs from locomotor muscles, and endogenous pain and fatigue modulating systems using manipulations involving both ergogenic placebos and social support (Tanaka & Watanabe, 2012).

Performance outputs can also be interpreted with consideration of other direct physiological and self-report measures. In the present experiment, between-condition differences in output profiles were not reflected in heart rate data, which showed no significant effects of experimental condition or exercise bout. Furthermore, in the solo condition, RPE increased across bouts in parallel with decreased outputs, while in the companion condition, RPE remained relatively constant (see Figure 3.2). This could be explained in a variety of ways – all speculative – including reduced metabolic costs and perceived effort in socially supportive conditions. In the companion condition, these effects may have been underpinned by lower levels of negative affect (Lane, Wilson, Whyte, & Shave, 2011) and reduced locomotor muscle feedback owing to an endogenous opioid-based blockade of signals from muscle afferents; exercisers in this condition may have thus experienced reduced sensitivity to variation in RPE (Amann et al., 2009). Ultimately, however, overall differences in RPE profiles between the two conditions were small, with responses varying by only one to two points on the 14-point RPE scale.

Other factors may account for the overall observed results (i.e., when ignoring the tertile split based on neuroticism scores). For example, relatively steeper output declines in the companion condition are also potentially attributable to a decrease over time in the perceptual salience of social support, which was manipulated only at the beginning of the exercise bouts. Over time, the availability of emotional social support may have decreased for exercisers in

the companion condition because they were not reminded of the presence of their companion after the social support manipulation. This suggestion is in line with non-significant differences between the two conditions in reported comfort and support during the exercise trials, which was measured after the exercise bouts. It should also be noted, however, that the effects of support on self-regulation are not necessarily contingent on explicit awareness and appraisal of support, but rather by implicit cognitive processes that access levels of threat, safety, and resource availability within a given environment (Coan et al., 2006). Future studies could also incorporate additional cognitive measures that have robust associations with the presence or absence of perceived social support, such as participants' assessments of the difficulty of impending physical challenges (Schnall et al., 2008).

The non-significant differences between the companion and solo conditions in reported comfort and support also suggest the possibility that a variable separate from social support was responsible for the observed differences in physical output profiles between the two conditions, although suggestions of alternative variables would be entirely speculative. The study design aimed to control for competition, social facilitation, reputation management, and distraction, for example. Companions waited in a separate room during the exercise portion of the experiment, and, as such, it would have been clear to them that their companion could not know about or observe their performance. Given this, it is unlikely that competition, social facilitation, reputation management (i.e., exercisers 'showing off' to companions), or distraction varied significantly between the companion and solo conditions. It is, however, possible that variables such as competition and reputation management were influenced by the presence of the experimenter, who was in the room observing the exercise trials, although there is no reason to think that this would occur more in the companion condition, as compared to the solo condition. Nevertheless, future studies could be conducted using covert video monitoring, thereby removing any effects resulting from experimenter observation.

Future work could also aim to improve the study's social support manipulation, while still eliminating these potential confounds. Firstly, adding reminders of companion support during

or between the exercise bouts could enhance the salience of the presence of social support. Additionally, changing the nature of the social support provided might lead to stronger effects. Specifically, the manipulation could focus more on enhancing exercisers' self-efficacy, as this type of social support (esteem support) may have stronger effects in the context of strenuous physical exercise than emotional social support (which was manipulated here). For example, Rees and Freeman (2010) used a social support manipulation that, in addition to providing emotional support, also attempted to increase recipients' perceived capacities; participants in the social support condition read a script that included "you are a very capable sportsperson and we fully believe that you will be able to execute this task successfully… feel free to ask for our help at any time" (p. 337), whereas those in the control condition read nothing. Results showed that those in the social support condition performed significantly better in a golf putting task than did those in the control condition (Rees & Freeman, 2010). Although this experiment investigates social support effects in a skill-based task, as opposed to a task dependent on the self-regulation of physical outputs, its findings may still be relevant here. Enhancing self-efficacy via manipulating esteem support in the experimental design of the current study could have performance-enhancing effects. As reviewed in Section 2.2.3.1 (p. 53), positive links between self-efficacy and feelings of energy have been hypothesised to be related to neurobiological systems involved in the self-regulation of physical outputs.

The effects of social support on physical outputs are likely strongest when individuals are performing closest to their psychophysiological maximum, such as when the potential benefits are high. This is because physical outputs depend most on self-regulatory processes when individuals are nearing their psychophysiological limits (Noakes, 2012), as discussed in Section 2.2.5 (p. 69). Adaptive self-regulation of physical outputs during exercise is calibrated by perceived costs and benefits, and the resources available to maximise the latter while minimising the former. For example, if social environments signal future safety, care, and resource abundance, then fatigue – as a mechanism to protect against potentially harmful overexertion and injury – may set in at a relatively later stage, allowing individuals to put forth

greater physical efforts. In the present study, exercisers where instructed to engage in a maximum-effort activity, following relevant procedures in the sports performance literature (e.g., Bar-Or, 1987; Zupan et al., 2009). However, given that our sample consisted of untrained athletes, it is possible that exercisers were not accustomed to or capable of achieving 'true' maximal effort. Learning how to overcome the neurobiological restraint mechanisms involved in strenuous physical exercise can take years of training (Noakes et al., 2005). Further, the exercise in this study was motivated by a relatively low-value goal (participants were merely told it was important they try their hardest during the exercise bouts). It could be, then, that exercisers did not put forth a level of effort for which the buffering effects of social support would be strongest. Indeed, mean responses on a seven-point Likert scale to the question "Do you think you could have tried harder during the cycling bouts?" (1 = *not at all*, 7 = *very much so*) were 3.11 and 3.08 for the solo and companion conditions, respectively. Future studies could ask additional questions about participants' motivation levels or increase participants' incentives to put forth maximal effort (e.g., through monetary rewards – this method is used in the study reported in Chapter 6), or they could use a subset of the population that is accustomed to giving maximal effort under laboratory conditions, such as trained athletes.

A final possibility suggested by the results of this study is that differences in personality (specifically, neuroticism levels) may systematically influence the support-performance relationship. As seen in Figure 3.4, and in accordance with Hypothesis 5, those participants who scored low in neuroticism had relatively higher outputs when in the companion condition (as compared to the solo condition), whereas those scoring high in neuroticism had relatively higher outputs in the solo condition (as compared to the companion condition). This is in line with previous research, which identified the personality factor neuroticism as an important moderator of the effects of social support; benefits of social support appear to be dampened in highly neurotic individuals (Park et al., 2013). In the present experiment, compared to their counterparts in the solo condition, exercisers that were low in neuroticism and in the

companion condition produced greater total anaerobic outputs across all exercise bouts (see Figure 3.4a). Exercisers high in neuroticism showed the opposite pattern; compared to their counterparts in the solo condition, these individuals produced lower anaerobic outputs across all exercise bouts when in the companion condition (see Figure 3.4b). Although the sample size following the tertile split is relatively small ($n$ = 48) for investigating a three-way interaction – and results should therefore be interpreted with caution – these differences were highly significant and the effect of the interaction was strong ($\eta_p^2$ = .119). Again, this pattern of results is in accordance with previous research, which found that the positive effects of social support vary according to neuroticism levels, with those low in neuroticism being the most susceptible to beneficial social support effects (Cohen et al., 2015; Park et al., 2013). Due to tacit or conscious preoccupations with the potential costs of receiving social support, highly neurotic exercisers may be less susceptible to the buffering effects of social support on pain, fatigue, and negative affect (Beedie et al., 2012; Cohen et al., 2015; Park et al., 2013).

Research has shown that neuroticism correlates with early life stress and fast life history strategies (Figueredo et al., 2005); relatively reduced social buffering effects among neurotic individuals may potentially be explained by behavioural strategies that are adaptively tuned during development to environments where the benefits of social support are less likely to be received. The results of the present study and others on the relationship between social support and personality tentatively suggest a reasonable modification of my hypothesis: for individuals who are sensitive to the benefits of social support (e.g. individuals low in neuroticism) companion presence has positive effects on physical performance. This interpretation has parallels in clinical placebo research, where individual differences in placebo responsiveness are well established, with, for example, neuroticism negatively predicting placebo-induced analgesia (e.g., Peciña et al., 2013).

However, other variables that were hypothesised to moderate sensitivity to the social support received in the current study – the quality of the exerciser-companion relationship (Hypothesis

2), daily perceived social support (Hypothesis 3), and need for social assurance (Hypothesis 4) – did not significantly moderate observed social support effects. While these variables have been shown to affect the receipt of social support in other contexts – such as during experimentally induced pain (relationship quality; Coan et al., 2006) and in the performance of skill-based tasks (daily perceived social support; Rees & Freeman, 2010) – they have not been studied in the context of strenuous physical exercise. It is possible that the moderating effects of these variables on emotional social support during strenuous physical exercise are weaker, and that a different kind of social support, such as one that focuses on increasing exercisers' self-efficacy, might have been more strongly influenced by these moderators. These possibilities will be discussed further in Section 7.2.2 (p. 235).

### 3.4.1 Conclusions

The hypothesis-driven approach developed here motivates new questions and directions for research that will potentially shed light on causes, incidence, and limits of social support effects occurring not just in health, but in everyday physical activity. Although the results of this experiment are promising, they should be replicated in future studies with improved social support manipulations and larger, more diverse samples. These studies should also test the specific mechanisms hypothesised to underlie observed effects; for example, through using pharmacological blocking (e.g., Tarr et al., 2017) or PET methods (e.g., Boecker et al., 2008) (see Section 7.3.3, p. 245).

Given that the present experiment employed a laboratory environment in which to study social support effects on exercise outputs, an obvious complement to this research would be to study social support effects in a more naturalistic exercise environment, as these environments may provide more robust variation in perceived social support and include exercisers with stronger motivations to perform at or near their psychophysiological maxima. In Chapter 4, I will present a study of data from parkrun, a free, weekly, community-based 5 km run. I use parkrun's extensive data set to create social networks that operationalise social support variables; I then test the effects of these variables on parkrunners' 5 km run performances.

## Chapter 4 – Social support and cohesion effects at parkrun: a ‘big data’ study

All R and Python scripts referenced in this chapter can be found here:
https://github.com/arranjdavis/DPhil_Thesis_Chapter_4_Data_Analyses

Where appropriate, these scripts acknowledge the contributions of Dr Pádraig MacCarron. Dr MacCarron helped me write the Python scripts used to scrape data from parkrun websites, he also helped me design and create (using the Python package *networkx*) the social networks employed in Analysis A and Analysis C.

**Abstract**

Observational research has shown that perceptions of social support and group cohesion positively influence exercise experiences and adherence. To date, no research has sought to understand how these variables affect the performance of voluntary physical exercise in a naturalistic setting. This study tested the hypothesis that the presence of social support leads to faster run times at parkrun, a free, weekly, community-based timed 5 km run that occurs at over 600 locations in 10 countries worldwide. Data were collected from a public, online database that parkrun has accumulated since its inception in 2004. The database contains information – including runner ID, gender, age, and run times – on over nine million runs. Social networks were created that characterised and quantified the strength of relationships between parkrunners and their running companions on a given day. This social network data was then used to operationalise variables that represent the presence of close, supportive others. These variables were used to predict parkrunners' 5 km run performances. Results indicate that when parkrunners finished their runs with a faster running partner (a parkrunner they had a consistent history of finishing with) or attended a parkrun with a travel partner (a parkrunner they had travelled to many different locations with) they ran faster over 5 km. Relatively high levels of social integration on a given day (finishing near parkrunners they had finished near before) also predicted faster 5 km run times. These results are discussed in relation to extant literature on social support effects in group exercise and sport, with a consideration of the challenges of drawing inferences from large, observational data sets.

## 4.1 Introduction

Although a considerable amount of research has been carried out on the social factors influencing exercise motivation and adherence (Barkley et al., 2012; Courneya & McAuley, 1995; Estabrooks, 2000; Estabrooks & Carron, 1999; Spink & Carron, 1994), little work has been done to measure the effects of social environments on objective outcomes of exercise performance (see Section 2.2.4, p. 66, for a review of this literature). Given this lack of research, the weekly, community-based running events collectively known as parkrun provide an extremely useful resource for naturalistic data on objective exercise outcomes. A not-for-profit organisation, parkrun is sustained through the participation of a select group of corporate sponsors and volunteer organisers, who work with their communities to organise timed, weekly 5 km runs in local parks. Stevinson et al. (2014) has described the aim of parkrun as being to "promote physical activity and community spirit, by providing supportive opportunities to exercise" (p. 171). All parkrun events report weekly run results on their website, contributing to a data set that contains information on parkrunner ID, age, gender, previous runs, and 5 km run time, among other metadata, for over nine million runs at over 600 different locations in 10 different countries (as of November, 2015). The combination of a supportive, community-based ethos, along with the availability of an extensive, longitudinal data set on 5 km run performance, makes parkrun an ideal setting in which to study ergogenic social support effects.

As discussed in Chapter 2, a diverse body of literature suggests that cohesive, supportive social environments affect exercise outcomes. For example, cues to social inclusion have been shown to affect physical activity levels, with included individuals being more physically active (moving more, in this case) than socially excluded or isolated individuals (Barkley et al., 2012; Hawkley et al., 2009). Further, perceptions of group cohesion have been shown to positively predict adherence to group exercise programmes, and shared beliefs about mutual support within the group, which enhance members' self-efficacy (Burke et al., 2008; Christensen et al., 2006). Although there is a relatively large body of research on how social

environments can affect individuals' motivations to perform exercise and adhere to exercise regimes (see Section 2.2.2, p. 50, for a more extensive review of this literature), no work has been done to understand how these variables might actually affect the performance of physical exercise. That is, no studies have measured how perceptions of social support and cohesion actually affect voluntary exercise outputs (e.g., power outputs, run times, or exercise duration). Research reviewed in Section 2.2 (p. 45) suggests that social support can affect outputs during physical exertion through reducing self-regulatory, output-attenuating perceptions of pain and fatigue. A naturalistic study on ergogenic social support effects among exercisers would offer a significant contribution to current literature; the research reported here aims to fill this gap.

### 4.1.1 Social support at parkrun

Given its highly social ethos and its extensive data set on run performance, working with parkrun offers the potential for a novel, naturalistic test of the hypothesis that social support enhances physical outputs among ordinary exercisers. Crucially, the nature of parkrun means that it is likely to produce meaningful variations in perceptions of social support, based on the presence of close social others, and integration into social networks more generally. Researchers have described parkrun as a "mass community event" and a "home away from home" that offers participants "psychological comfort, warmth, and mutual support" (Hindley, 2018, p. 10). Run by local volunteers and describing itself as a 'run and not a race' with no ability or attendance requirements, parkrun offers a welcoming, community-based setting for participants to attend as often as they please. This inclusive ethos allows parkrun to attract participants who do not identify with traditional views on competitive running, thus creating a participating population that includes a wide range of demographic categories[20] and skill levels (Hindley, 2018; Stevinson et al., 2014).

[20] While parkrun strives to create an inclusive ethos – it has a relatively even (reported binary) gender split, and all age groups are well-represented in the organisation as a whole – it must be noted that individuals from ethnic minorities and lower socio-economic groups are particularly underrepresented at parkrun, even in areas that are ethnically diverse (Stevinson & Hickson, 2013).

Social relationships are a major tenet of parkrun. Participants have reported 'social togetherness' to be the second most important aspect of parkrun, following only "getting exercise" (Hindley, 2018). Current literature and my ethnographic observations suggest that social relationships are built and solidified through conversations among parkrunners both before and after runs (Hindley, 2018; Stevinson et al., 2014; Wiltshire et al., 2018). This is especially the case among individuals of similar skill levels. Individuals report chatting while running alongside other parkrunners, and often begin casual conversations as they wait in line (ordered by finishing rank) to hand in their parkrun ID barcodes so that their run times can be recorded (this recording procedure is followed at all parkrun locations). When all runners are finished, it is common for parkrun event organisers to invite participants to a local cafe to continue socialising (Hindley, 2018). Although participants at a given parkrun location change from week to week, there is a continuity of core runners and volunteers that work to create a sense of community, which offers runners an informal network of emotional support where "even loose ties with relative strangers can be highly valued" (Hindley, 2018, p. 10).

While parkrun has an overall ethos that is supportive and not generally competitive, participants do care about their run performance, with many citing a desire to improve upon previous run times (Stevinson et al., 2014; Wiltshire et al., 2018). It is thus possible that parkrunners draw upon social support from others when pushing themselves to perform better. Indeed, participants often describe the social support they receive from other parkrunners to be instrumental in increasing their confidence levels and motivation to attend and complete runs (Hindley, 2018; Stevinson et al., 2014). To take just two examples from interviews with parkrunners:

> "Running with others is a massive motivation. The self-talk doubts don't creep in when in a group … I don't think I would run 5 km every week if I didn't have a group like this to run with" (Hindley, 2018, p. 12).

> “When people come through the finish line, you know, there’s people there and they’re all cheering you on and, you know, it just gives a real boost really; and like that first experience I had of that woman, you know, supporting me through the last little bit when I was struggling. That happens all the time” (Wiltshire et al., 2018, p. 10).

These statements are in line with the idea that belonging to the parkrun community helps to enhance runners’ self-esteem and self-efficacy through increasing their perceptions of social support (Hindley, 2018). Previous research has demonstrated a positive link between social support and self-efficacy (Christensen et al., 2006), which has itself been theorised to enhance energy levels via altering individuals’ perceived capacity to complete difficult physical tasks (O'Connor & Puetz, 2005).

Increased energy levels, along with the pain and fatigue reducing effects of social support, thus make the socially supportive, cohesive parkrun community a potential source of performance enhancement for participants (see Section 2.2.3, p. 53, for a full review of this literature). When parkrunners perceive their social environments to be safe and supportive, it may alter protective, self-regulatory processes that govern physical outputs, leading to lower levels of pain and fatigue, higher levels of energy, and greater physical outputs. Importantly, previous research suggests that social support effects are likely to be strongest when individuals are socially integrated (i.e., participating in a broad range of social relationships) and perceive support to be available from others with whom they have close, positive relationships (Coan et al., 2006; Holt-Lunstad & Uchino, 2008). In the context of parkrun, this likely means that individuals’ perceptions of social support will vary according to their integration into the parkrun social network and to the presence of close friends or family members at particular runs.

This study took advantage of parkrun’s immense amount of data on individual-specific event attendance and run times to investigate the effects of social support on performance. Using parkrun’s data, I created several social networks that gave information on parkrunners’ social

environments at particular runs. Specifically, these social networks allowed for the identification of the presence of finishing partners (pairs of parkrunners who frequently finished their runs together) and travel partners (pairs of parkrunners who travelled to many different locations together), and for measures of parkrunners' social integration on a given day. Variation in these social variables was assumed to correlate with parkrunners' perceptions of social support cohesion, and they were used to predict parkrunners' 5 km run performance.

### 4.1.2 Hypotheses

I used naturally occurring variation in social integration and the presence of close social relationships at parkrun to test the hypothesis that parkrunners will run faster 5 km times when socially integrated and in the presence of partners, close friends, or family members. The observational nature of this study required me to operationalise social support through inferring social relationships from patterns observed in social networks created from parkrun's data set. Through examining these patterns, it can be inferred when individuals were likely to feel socially supported, either from being in the presence of a close other or being highly integrated into the parkrun social network.

Thus, I created two types of predictor variables: one representing parkrunners' social integration and the other representing the presence of close others. Both variable types were constructed and measured within the constraints of the existing parkrun database. Social integration was operationalised as a function of the likely number and strength of social relationships that a given parkrunner had with other parkrunners on a given day (Holt-Lunstad & Uchino, 2008). Presence of close others was operationalised as a binary variable representing the presence or absence on a given day of co-participants that parkrunners had a robust history of co-occurrences with at past parkruns. In Analysis A, I tested whether finishing alongside a frequent finishing partner predicted run times among parkrunners who were the slower (on average) of frequent finishing pairs. Next, in Analysis B, I tested the effects on 5 km run times of being at the same parkrun event with a frequent travel partner. Finally, in Analysis C, I tested whether social integration predicts 5 km times. Together, these analyses

**Table 4.1** Hypotheses

| | |
|---|---|
| **Analysis A** | |
| **Hypothesis A** | Finishing alongside a frequent finishing partner predicts faster 5 km run times among parkrunners who are the slower (on average) of a given frequent finishing pair. |
| **Analysis B** | |
| **Hypothesis B** | The presence of a frequent travel partner predicts faster 5 km run times. |
| **Analysis C** | |
| **Hypothesis C** | The more socially integrated a parkrunner is on a given day at parkrun, the faster their 5 km run time. |

will reveal effects of different components of social support and integration on participants' running performance.

## 4.2 Data wrangling and creation

I first downloaded HTML files of parkrun finish lists that are publicly available on parkrun websites (see http://www.parkrun.org.uk/oxford/results/latestresults/ for a finish list example). Each parkrun event has its own webpage, which contains a finish list of all registered runners who participated on that date. These webpages have systematically catalogued web addresses that give information on both location and run number (and thus date); this allowed for the creation of a Python script that downloads the HTML files for all of these webpages. These data were downloaded on November 8, 2015, and include all parkrun finish lists dating back to the inaugural event on June 23, 2007.

After obtaining these HTML files, I extracted a number of variables of interest for every single run by each participant at parkrun since June 2007. These variables included the run location and run number (ordered from the first parkrun held at that location), the run date, the parkrunner's ID number, their 5 km time, their sex and age (according to parkrun's sex and age categories), and their total previous runs at all parkrun locations. Some parkrun events and individual runs were not included in the outputted data set due to corrupted HTML code. In total, this script yielded full information on 9,820,072 runs from 1,160,736 parkrunners at

70,377 parkrun events held at 671 locations from 10 different countries. Out of the nearly ten million runs, 7,091,554 were from the UK, and, out of the other nine countries, only Australia had over one million runs (1,272,452).

I then assigned a country to each parkrun location using the country code top level domains from each parkrun website URL. One location (with one finish list and one unique parkrunner) was not in the index of parkrun locations by country, and was therefore dropped from the data set. This resulted in a data set with full information on 9,820,030 runs from 1,160,735 parkrunners at 70,376 parkrun events held at 670 locations across 10 countries.

### 4.2.1 Data reduction and cleaning

Data were filtered through several criteria to facilitate inferential analyses. Some parkrun locations recorded run times of 00:59:59 for all run times over 1 hr (01:0:00); 00:59:59 appeared in the data set 6,229 times, compared to only 77 and 87 appearances for 00:59:58 and ’01:00:01, respectively). As it is not possible to know which, if any, of these data points are accurate, all run time observations of 00:59:59 were removed. The parkrun data set also contains information on individuals under the age of 18; to comply with ethical requirements, information on these individuals was also removed from the data set. The data set also contained information from wheelchair participants. Only a small percentage of locations offer a wheelchair accessible 5 km course, and the times from these participants often exceed 1 hr, and, as such, constitute an outlier set; the data from these participants was therefore removed from the data set. Additionally, two runs were excluded for incorrect age categories of “100-104” and “110-114.”

Many parkrunners in the data set had only participated in parkrun very infrequently over the recording period. Making statistical inferences from multilevel models with a low number of observations per level-two unit (i.e., parkrunner) can lead to inaccuracies and problems with convergence (Snijders & Bosker, 2012). To avoid these problems while retaining the majority of the data – those who ran 10 or more times were responsible for the majority (73%) of runs

**Table 4.2** Data reduction procedures

| Data set | Size |
|---|---|
| Original from parkrun website | 9,820,072 runs<br>1,160,736 parkrunners<br>70,377 events<br>671 locations |
| **Step 1:** Adding country data (Python) | |
| **Updated data set:** Original with country data | 9,820,030 runs<br>1,160,735 parkrunners<br>70,376 events<br>670 locations |
| **Step 2:** Remove parkrunners with a time of 00:59:59 (Python) | |
| **Updated data set:** Original data excluding ambiguous times | 9,811,031 runs<br>1,160,283 parkrunners<br>70,310 events<br>670 locations |
| **Step 3:** Remove all parkrunners with mislabelled ages, who are under the age of 18, or who used a wheelchair (R) | |
| **Updated data set:** Original data excluding ambiguous times, and parkrunners under the age of 18 or who used a wheelchair | 8,660,182 runs<br>969,464 parkrunners<br>70,310 events<br>670 locations |
| **Step 4:** Remove all parkrunners who have less than 10 runs (R) | |
| **Updated data set:** Original data excluding ambiguous times, parkrunners under the age of 18, who used a wheelchair, or with less than 10 runs | 6,485,902 runs<br>213,051 parkrunners<br>70,281 events<br>670 locations |

in the data set – and a large range of variation in run frequency (range = 10 – 417), runners with ten or fewer runs were eliminated from the data set used for analyses. Removing runs from these categories of individuals reduced the number of parkrunners from 1,160,735 to 232,301, and the number of runs from 9,820,072 to 6,485,902. Finally, the data – which were originally ordered alphabetically by parkrun event – were reordered chronologically. This final data set was used for the analyses reported below; any further changes made to the data that are specific to a particular analysis are described below in the study-specific procedures. For a full list of data reductions procedures, see Table 4.2.

## 4.3 Software and methods used for inferential statistics

The R packages *lme4* (Bates, Maechler, Bolker, & Walker, 2014) and *lmer* (Kuznetsova, Brockhoff, & Christensen, 2015) were used to carry out all the primary analyses reported below. Assumption checks were carried out in accordance with the methods suggested by Snijders and Bosker (2012), and are reported in Appendix B, Section 1 (p. 295).

## 4.4 Analysis A

This analysis tested whether finishing alongside a frequent finishing partner predicted 5 km run times. For finishing partners to finish alongside each other frequently, they need to be of similar competence level or intentionally modify their running speeds in order to finish simultaneously, as all parkrunners start their runs at the same time. It is unlikely that parkrunners are of precisely the same fitness as the friends, family members, and acquaintances they chose to (run and) finish with. Thus, the faster parkrunners in these pairs would need to slow their speed in order to finish with their slower partners. Therefore, I focused my analyses of finishing partner effects on individuals who are the slower runner of the pair, as these individuals are more likely to be performing closer to their self-regulatory limits, and thus will be most susceptible to ergogenic social support effects (see Section 2.2.5, p. 69).

### 4.4.1 Variable creation

The first step in this analysis was to identify finishing partners using the data set created by following Step 1 and Step 2 in Table 4.2. This was done through creating a social network of all parkrunner pairs who had ever finished within 2 s[21] of each other (henceforth, 'together') at the same parkrun event (i.e., on the same day). Some pairs will finish together by chance, so a frequency cut-off was established. This cut-off was based on the distribution of the amount of times each parkrunner pair in the social network finished together ($M$ = 1.12, $SD$ = 0.86,

[21] A time of 2 s was chosen because of parkrun's policy for finish lines and run time recording; the finish line is at the end of a funnel, which encourages parkrunners to cross the finish line separately, so that they can be given a number which can be matched to a particular time. Thus, parkrunners who run next to each other will not always finish at the exact same time.

range = 1 – 131, skewness = 29.73). Due to the heavy positive skew in the number of times pairs finished together, the 95$^{th}$ percentile of this distribution was used as the cut-off: 2% of parkrunner pairs had finished together three or more times (over 5% had finished with each other two or more times). Thus, to meet the criteria for being frequent finishing partners, parkrunner pairs needed to finish together three or more times.

The next step was to add to this data set variables that indicated (1) whether or not parkrunners had a finishing partner (see above criteria) present at a particular run, and (2) whether the parkrunner was the faster or slower of the finishing partner pair, determined by comparing the average time off all previous runs for each partner up to the date of the run. The data (runs) of all parkrunners who were the faster runner in a finish partner pair were removed from the data set. For example, if parkrunner A had two finishing partners, and they were slower on average than one of the partners, but faster on average than the other, all of parkrunner A's runs would be removed from the data set (since, they were faster than one of their finishing partners). Thus, only those runs from parkrunners who were *only* ever slower runners in finish partner pairs were retained for analysis (2,622,466 runs from 59,724 faster running partners were excluded from the data set). Remaining parkrunners who did not meet the criteria described in Step 3 and Step 4 in Table 4.2 were also excluded. The average total number of runs for parkrunners in the final data set, which included 538,096 runs from 13,478 parkrunners, was 39.92 (range = 10 – 299, *SD* = 29.99); 14% of these runs were with a frequent finishing partner.

In addition to creating the finish partner presence variable, I also created a 'previous runs' variable, which represents the number of previous runs a parkrunner had completed up to the date of the current run. The 'previous runs' variable was $\log_2$ transformed (to facilitate model fit) and used as a covariate in the models described below, as previous runs represent a potential confound of the finish partner presence effect on run times; it is possible that both finish partner presence and physical fitness (faster run times) increase with previous runs.

#### 4.4.1.1 Model convergence procedures

The authors of the R package *lmer* – which is used to run the multilevel regression models used in this thesis – state that when models estimated with this package fail to converge, it "typically is not due to a suboptimal estimation algorithm, but is a consequence of attempting to fit a model that is too complex to be properly supported by the data" (Bates, Kliegl, Vasishth, & Baayen, 2015, p. 1). Thus, when *lmer* models fail to converge, it is an indication of model overparameterisation, which Bates et al. (2015) have shown can adversely affect statistical inference. For this reason, when a model used in this thesis failed to converge, random effect parameters where removed (least variance first) until convergence was reached. Through this method of model simplification, I came to use the most complex random effects structure possible given the data (Barr, Levy, Scheepers, & Tily, 2013).

### 4.4.2 Results

As assumed in Section 4.4.1, faster running partners were indeed slowing down to run with their slower partner(s); they average 27 min 14 s (*SD* = 6 min 45 s) per run when finishing alone, and 32 min 2 s (*SD* = 8 min 43 s) per run when finishing with their partner(s), $t(417{,}960) = -309.47$, $p < .001$.

The model on slower running partners' logged run times revealed a significant effect of finish partner presence on 5 km run times, $b = -0.005$, $SE < .0.001$, $t(12{,}580) = -9.66$, $p < .001$, while controlling for previous runs (for full model results see Table 4.3). The presence of a finishing partner predicted a 0.50% decrease in 5 km run times (as compared to when parkrunners finished without their faster partners), or a decrease of 9.03 s for a parkrunner with a run time equal to the overall average in the data set (30 min 14 s).

#### 4.4.2.1 Follow-up analyses

In addition to the data sets created for the main analyses, additional data sets were created based on different cut-offs for identifying intentional finishing partners. This was done as a means of examining whether the model estimates of finishing partner presence reported in

**Table 4.3.** Main multilevel model testing effects of the finish partner presence variable on logged 5 km run times

| **Fixed effect** | **Coefficient** | ***SE*** | **df** | ***t*** | ***p*** |
|---|---|---|---|---|---|
| Intercept | 3.488 | 0.002 | 14,270 | 1,730.13 | < .001 |
| Finish partner presence | −0.005 | < 0.001 | 12,580 | −9.66 | < .001 |
| $Log_2$ previous runs | −0.024 | < 0.001 | 52,670 | −173.21 | < .001 |
| **Random part** | **Variance** | ***SD*** | | | |
| Intercept | 0.053 | 0.230 | | | |
| Finish partner presence | 0.001 | 0.039 | | | |
| $R^2_m$ = 0.010, $R^2_c$ = 0.979 | | | | | |

Section 4.4.2 were a result of the cut-off used for identifying finishing partners. These data sets were created using the same criteria described above; only the cut-off for identifying finishing partners was changed. This resulted in 24 separate data sets, each of which included finishing partners who had finished together a specific minimum amount of times, ranging from two or more finishes together up to 25 or more finishes together (the cut-off used in the analyses reported in Section 4.4.2 was three or more finishes together).

The resultant data sets are thus highly similar. For example, a high percentage of parkrunners included in the data set created with a cut-off of 15 finishes together are included in the data set created with a cut-off of 16 finishes together. The only difference between the two data sets is that parkrunners with exactly 15 finishes with a faster finishing partner are excluded from the data set created with a cut-off of 16 finishes together. Both data sets contain all runs from parkrunners with 16 or more finishes within 2 s of a faster finishing partner. For this reason, data sets created with similar cut-offs have a high percentage of overlap: the data set created with the cut-off of 16 includes 88% of the parkrunners (and 90% of the runs) included in the data set created with the cut-off of 15 (which, of course, contains 100% of the parkrunners and runs included in the data set created with the 16 cut-off). Although adjacent data sets are overlapping, as the cut-off used increases, the composition of finishing partners

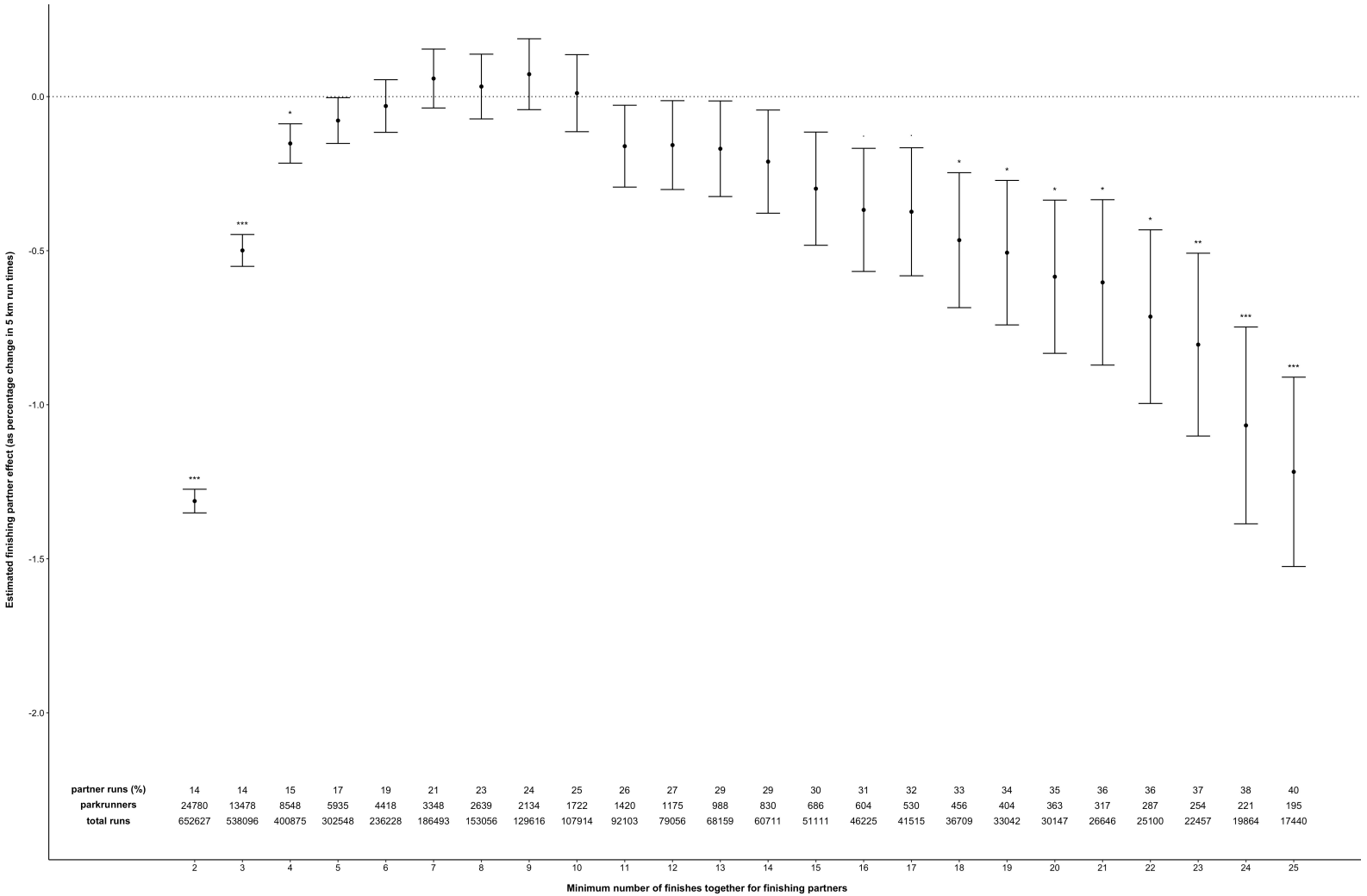



**Figure 4.1** Estimates (± 1 *SE*) of finishing partner presence effect on 5 km run times by the minimum number of times parkrunner pairs were required to finish together to be included in the data set. Estimates were based on subsets that included only those parkrunners who were the slower of finishing pairs.

*** Statistically significant at $p < .001$
** Statistically significant at $p < .01$
* Statistically significant at $p < .05$
• Statistically significant at $p < .1$

in the resultant data set will change. Pairs of parkrunners with a relatively high number of finishes together are more likely to be intentionally running together and hence have a close social relationship, while those with relatively low number of finishes together are more likely to have finished together by chance.

Figure 4.1 shows that the performance-enhancing effects[22] of finishing with a partner decreased as the cut-off for identifying finishing partners increased from 2 to 9, and then increased as the cut-off increased from 10 to 20, leading to an inverted U-shaped pattern with significant performance-enhancing effects of finishing partner presence at both relatively low and high cut-offs. It should be noted that, as the cut-off increases, so does the percentage of partner runs in the data set; 40% of runs in the data set created with a cut-off of 25 finishes together are partner runs, whereas only 14% of runs in the data set created with a cut-off of two finishes together are partner runs.

### 4.4.3 Limitations

Figure 4.1 suggests that the effect of the presence of finish partners with relatively weak relationships (i.e., those that finished with their slower partners five or less times) seemed to be caused (at least partially) by the way the variable was created. If a slower parkrunner happens to finish with a parkrunner that is faster than them (based on average run time to date) then they are, by definition, running faster than their average time. It is easy to imagine a scenario in which a parkrunner (parkrunner A) runs faster than their average time (as result of 'random' fluctuations in their run times), leading them to (unintentionally) finish within 2 s of a faster (on average) parkrunner (parkrunner B). It is also easy to imagine this happening (without intention from either runner) more than three times, especially if parkrunner A and parkrunner B consistently attend the same parkrun location over the course of multiple years.

[22] The *p*-values associated with these effects are not corrected for multiple comparisons, since Figure 4.1 is not depicting the results of multiple, independent tests of my hypothesis. Instead, the results of these hypothesis tests are dependent (they are run on overlapping subsets of the same original data set), and the analyses presented in this section are intended to illustrate how the results reported in Section 4.4.2 (p. 113) change with the cut-offs used when creating the finish partner presence variable.

Scenarios such as these appear to have given the finish partner presence variable an inflated performance-enhancing effect at relatively low cut-offs for minimum partner finishes (such as the one used in the main analysis reported in Section 4.4.2, p. 113).

As the cut-off for being counted as finishing partners increases, unintentional finish partner relationships – like that described above between parkrunner A and parkrunner B – become less likely. For example, the data set which used three or more finishes within 2 s of a faster parkrunner as the criteria for being included in the data set is much more likely to be influenced by these chance relationships than is the data set which used 18 or more finishes within 2 s of a faster parkrunner as the criteria. Looking at Figure 4.1, it appears that the effect of these chance relationships is strongest at the lowest cut-off, which identified finishing partners as those parkrunners who finished within 2 s of each other two or more times. This effect diminishes up until a cut-off of ten finishes within 2 s of each other. At this point, a different effect seems to begin influencing the data. At cut-offs above ten, where finish partner relationships are unlikely to be due to chance, the performance-enhancing effects of finish partner presence increases along with the number of times partner pairs have finished together. It is hard to imagine a scenario in which two parkrunners finish within 2 s of one another 20 times and do not have a significant social relationship.

Thus, I hypothesise that two separate effects are occurring in the data set presented in Figure 4.1. At low cut-offs (below 10), the effects of finish partner presence appear to be determined by chance relationships, such as the one described above between parkrunner A and parkrunner B. At high cut-offs (15 or above), the effects of partner presence may result more from the support signalled by the close social relationship that parkrunners have with their faster partners, who they intentionally finish with and perhaps rely upon for motivation, reassurance, and feelings of self-efficacy. As discussed in Section 4.4.2.1, the percentage of partner runs in the data set increases with the cut-off used for categorising parkrunner pairs as finishing partners, suggesting that parkrunners with a high number of finishes with their

faster partner are more dependent on these individuals (this is discussed more in Section 4.7.1, p. 136).

Aside from the inclusion of what were likely chance relationships in data sets with lower cut-offs for finish partners, this analysis had two other unideal features. First, it led to the exclusion of parkrunners who run with slower partners, thereby slowing down their pace to do so. Therefore, this analysis focused on a subset of parkrunners who (either intentionally or unintentionally) finished with a faster partner multiple times. Second, and more importantly, it likely included parkrunner pairs who intentionally ran together in order to socialise. It is common for parkrunners to chat while running alongside one another, and they report this aspect of parkrun as an important aspect of the 'togetherness' that sets parkrun apart from other forms of exercise (Hindley, 2018; Stevinson et al., 2014; Wiltshire et al., 2018). It is thus likely that some of the parkrunners included in this data set were more motivated to socialise than they were to perform near their physiological maxima, where I hypothesise that social support effects will be most likely to occur.

## 4.5 Analysis B

This analysis used a similar hypothesis to that tested in Analysis A, but this time identified running partners as those who had attended a high number of different parkruns together. Pairs of parkrunners who finished their runs together (i.e., at similar times) were excluded. This aimed to create a data set that included run data for pairs who frequented parkrun together, thereby capturing some indicator of available social support, but that excluded data from co-finishers, thereby minimising confounds of competition, and the influence on outcomes of pacing strategies (e.g., running slower in order to run together) and parkrunners who ran together in order to socialise. By not looking at parkrunners who finished together (i.e., within 2 s of one another), this analysis avoids the problems introduced by the finish partner presence variable used in Analysis A. Finally, this analysis used an expanded data set that included all parkrun locations around the world. The assumption was that parkrunners who attend different locations around the world together likely had close social ties.

### 4.5.1 Variable creation

Since it is possible that many parkrunners will, by chance, run at the same parkrun events in different locations, the first step was to make a stringent cut-off for the number of different parkrun locations partner pairs would need to run together at for it to be assumed they had a close, supportive relationship. The cut-off was based on the distribution of the number of locations that each parkrunner had run at (mode = 1, $M$ = 2.66, $SD$ = 3.85, range = 1 – 250, skewness = 14.59). Due to the heavy positive skew in the number of different locations attended, the 95$^{th}$ percentile of this distribution (eight locations) was used as the cut-off. To be included in the data set – and assumed to be a close, supportive pair – parkrunner pairs needed to attend at least 8 different parkrun locations together.

The parkrunner pairs who travel to multiple locations together are also likely to choose to run together. To avoid having to again focus only on parkrunners who are the slower individual in the pair (since faster partners are likely to need to slow their pace to run with their slower partners), I set another cut-off. Any pair of parkrunners who finished within 1 min of each other (on the same day, at the same parkrun event) would be excluded from analyses, as finishing within (around) 1 min could result from running the majority of the run together. Not excluding these pairs would have undesirable consequences for testing Hypothesis B, as explained in Section 4.5.

Thus, there are two requirements that parkrunner pairs must meet to be included in these analyses: they need to have run at eight or more locations together and not have finished within 1 min of each other (on the same day, at the same parkrun event). The assumed scenario created by these requirements is one of two parkrunners (henceforth, ‘travel partners’) – friends, family members, or partners – who travel to parkruns together but run on their own, thereby creating a situation where they are more likely to focus on performance during their runs. Although not running alongside their partner, I assume that these runs occur in an environment of social support.

Out of the 4,383,865 total pairs in the original social network (individuals can have multiple pairs), only 9,902 (< 1%) had run at 8 or more locations together. Of these, there were 8,905 unique parkrunner pairs, and 4,716 had run within one minute of each other. This left 4,189 pairs of parkrunners (henceforth, 'travel partners') for the analyses. After excluding participants based on the criteria in Step 3 and Step 4 of Table 4.2 (p. 110), the data set consisted of 488 individual parkrunners with 29,857 total runs, or an average of 61.18 runs per parkrunner (*SD* = 45.58, range = 11 – 258), 58% (*n* = 17,189) of which were runs where both parkrunners in a partner pair were present. The data set thus consisted of all of the runs from these 488 parkrunners, and I created a variable – called 'travel partner presence' – which identifies whether a particular run was a solo run or a run where a travel partner was present.

In addition to creating the travel partner presence variable for each run, I also created a 'previous runs' variable, which represented the number of previous runs a parkrunner had completed up to the date of the current run. The 'previous runs' variable was $\log_2$ transformed (to facilitate model fit) and used as covariate in the models described below, as previous runs represent a potential confound of travel partner presence effects on run times; it is possible that both the travel partner presence variable and physical fitness (faster run times) increase with previous runs.

### 4.5.2 Model selection

In order to test the hypothesis that attending a parkrun with a close, supportive partner would lead to faster run times, I ran a multilevel model on the data set described above. The outcome was parkrunners' logged (to facilitate model fit) 5 km run times. The main predictor variable of interest was travel partner presence. Covariates included parkrunners' gender, age, and number of previous runs. This model allowed for intercepts and slopes to vary by parkrunner. Slopes varied only for travel partner presence, as allowing the slopes of the covariates to vary caused the model to fail to converge; this was thus the most complex random effects structure

possible (Barr et al., 2013)[23]. The model was fit using restricted maximum likelihood (REML), as this method provides the best estimates of variance components (Maas & Hox, 2004).

### 4.5.3 Results

The model revealed a main effect of travel partner presence on logged 5 km run times, $b$ = −0.004, $SE$ = 0.002, $t(360) = -1.98$, $p = .048$ (see Table 4.4 for full model results). Running with a partner leads to a 0.37% decrease in (unlogged) run times. This translates to a 5.85 s decrease in run time for a parkrunner with an average 5 km time of 26 min 20 s (the average of all runs in the data set).

Figure 4.2 shows the random effects for each parkrunner. Random effects in this case can be thought of as travel presence partner effects for each parkrunner, adjusted for number of runs, individual-level variation, and relation to the overall effect (Snijders & Bosker, 2012). Within parkrunners, the negative effect of partner presence on run times was significant, even though overall times for solo runs ($M$ = 25 min 11 s, $SD$ = 5 min 56 s, range = 14 min 44 s – 81 min 41 s) were significantly faster than overall times for partner runs (mean = 27 min 4 s, $SD$ = 6 min 32 s, range = 14 min 38 s – 78 min 44 s), $t(27{,}683) = 25.21$, $p < .001$. This is a classic example of Simpson's paradox (Simpson, 1951), and it suggests that parkrunners who are slower on average are more likely to run with their travel partners, while faster parkrunners are more likely to run on their own. Indeed, parkrunners who were the slower of travel partner pairs ran 64% of their runs with their (faster) travel partners, whereas these faster partners ran only 50% of their runs with their slower partners, $\chi^2(1) = 596.22$, $p < .001$.This means that slower parkrunners exert a disproportionate influence on run time data for partner runs, while faster runners exert a disproportionate influence on run time data for solo runs. This leads to a slower mean time for partner runs even though parkrunners tend to run faster times when with their partners, as compared to on their own.

[23] See Section 4.4.1.1 (p. 118) for a justification and explanation of the procedures followed when a model failed to converge.

**Table 4.4** Main multilevel model testing effects of travel partner presence on logged 5 km run times

| **Fixed effect** | **Coefficient** | ***SE*** | **df** | ***t*** | ***p*** |
|---|---|---|---|---|---|
| Intercept | 3.023 | 0.013 | 1,020 | 235.76 | < .001 |
| Travel partner presence | −0.004 | 0.002 | 360 | −1.98 | .048 |
| $Log_2$ previous runs | −0.010 | < 0.001 | 26,200 | −16.73 | < .001 |
| Gender (female) | 0.275 | 1.470 | 485 | 18.72 | < .001 |
| Age | 0.024 | 0.001 | 6,976 | 17.00 | < .001 |
| **Random part** | **Variance** | ***SD*** | | | |
| Intercept | 0.026 | 0.162 | | | |
| Travel partner presence | <0.001 | 0.028 | | | |
| $R^2_m$ = 0.393, $R^2_c$ = 0.886 | | | | | |

#### 4.5.3.1 Follow-up analyses

In addition to the data set created for the main analysis, additional data sets were created based on different cut-offs for the number of parkrun locations parkrunners needed to attend together to be considered travel partners. These data sets were created using the same criteria described above; only the cut-off for the minimum number of different locations that travel partners needed to attend together to be included in the data set was changed. This resulted in twelve separate data sets, each of which included travel partners who had attended a specific minimum number of locations together (ranging from three or more locations up to 15 or more locations). As the cut-off for including parkrunner pairs as travel partners increases, the percentage of 'false positive' close, social relationships included in the data set will decrease, as individuals who do not actually know each other are more likely to run at the same parkrun locations on the same day by chance three times than, for example, ten times. As such, those parkrunners in data sets with higher minimum requirements for including travel partners are more likely to have close, social relationships with their travel partners than those with lower minimum cut-offs.

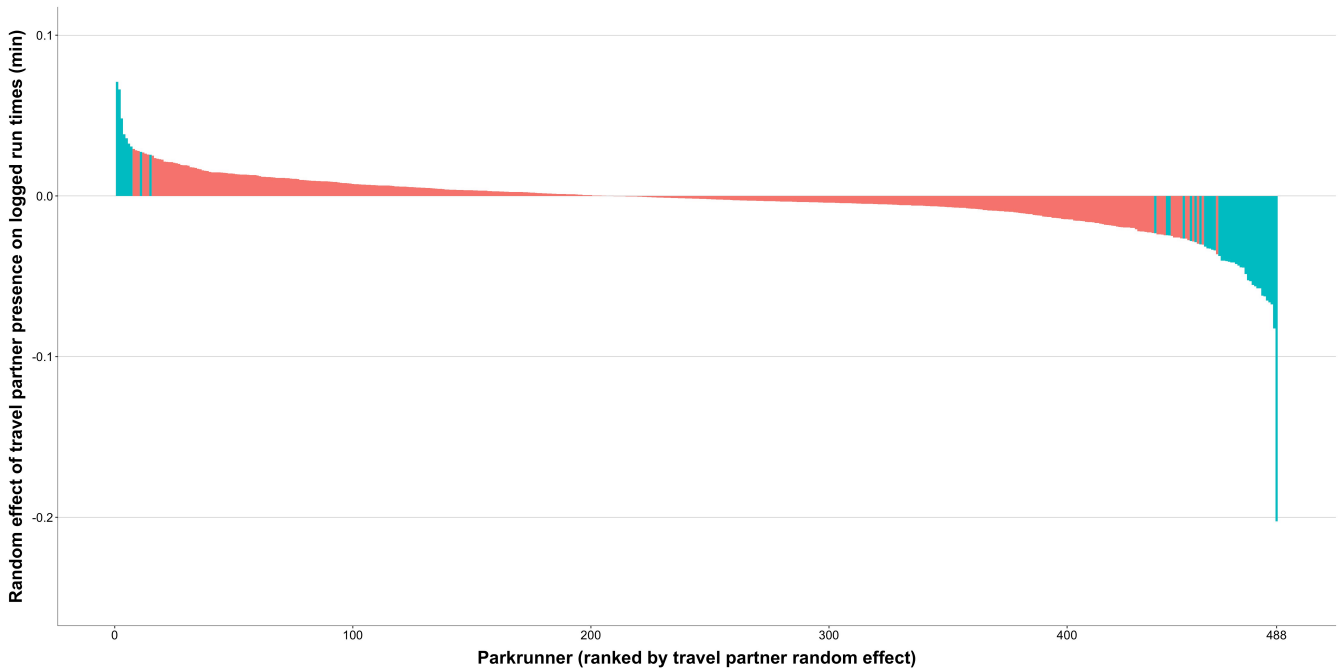



**Figure 4.2** Travel partner random effects on logged 5 km run times for each parkrunner, ordered from largest (travel partner presence predicts slower 5 km runs times) to smallest (travel partner presence predicts faster 5 km runs times). Green bars indicate that comparative posterior 90% confidence intervals for the random effect did not contain 0. Red bars have comparative posterior 90% confidence intervals for the random effect that did contain 0.

Figure 4.3 shows that, as the minimum number different locations visited by travel partners in the data set increases, estimates of the performance-enhancing effect[24] of travel partner presence on 5 km run times increase. Although the estimated effect of travel partner presence increases as the cut-offs for travel partner data set creation becomes more stringent, the effect is not estimated to be significant with relatively low and high cut-offs. In data sets with relatively low cut-offs – and a resultant higher percentage of 'false positive' close social relationships – travel partner presence has little effect on run times. In data sets with relatively high-cut-offs – and more 'true positive' close social relationships – travel partner presence has strong performance enhancing effects, but the standard errors of these estimates are large, due to

[24] Again, the *p*-values associated with these effects are not corrected for multiple comparisons, since Figure 4.3 is not depicting the results of multiple, independent tests of my hypothesis. Instead, the results of these hypothesis tests are dependent (they are run on overlapping subsets of the same original data set), and the analyses presented in this section are intended to illustrate how the results reported in Section 4.5.3 change with the cut-offs used in the creation of the travel partner presence variable.

relatively smaller sample sizes (e.g., *n* = 81 for the highest cut-off). Thus, there appears to be a cut-off 'sweet spot' where there is a high enough proportion of travel partners with close social relationships in the data set, and the sample sizes are large enough to detect significant effects.

### 4.5.4 Limitations

Both Analysis A and Analysis B focused on relatively small samples of parkrunner pairs that likely had very close social relationships with their partners. While these relationships can make up an important component of parkrunners' social environments at parkrun, research has also shown that parkrunners derive support from co-participants with whom they have relatively loose ties, such as acquaintances and friends they see on an occasional basis at parkrun (Hindley, 2018). Given this, Analysis A and Analysis B, which focused on the presence of close relationships, cannot be taken to be entirely representative of the experiences of a 'typical' parkrunner. As a means of supplementing Analysis A and Analysis B, Analysis C tested social integration at parkrun more generally, creating a variable that accounted for the presence of the more casual (yet supportive) relationships described by Hindley (2018).

## 4.6 Analysis C

As discussed in Section 4.1, parkrunners build relationships with those they are close to (in time) when they finish their runs, as they often have conversations after finishing, while they wait in a line to have their run time recorded, or after having done so. Finishing near people that are familiar might predict the amount of social support cued to parkrunners during their runs, as high scores on this variable would represent the presence of individuals with whom parkrunners are likely to have *at least* a casual, friendly relationship. Since attendance is not compulsory, and parkrunners attend as they please. individuals' social integration (and concurrent perceptions of social support) on a given day will vary according to the specific individuals that attend. On some days, either through chance or deliberate planning, parkrunners will have more social relationships present than on others. This analysis took advantage of these fluctuating social integration levels, quantifying the quality and quantity of

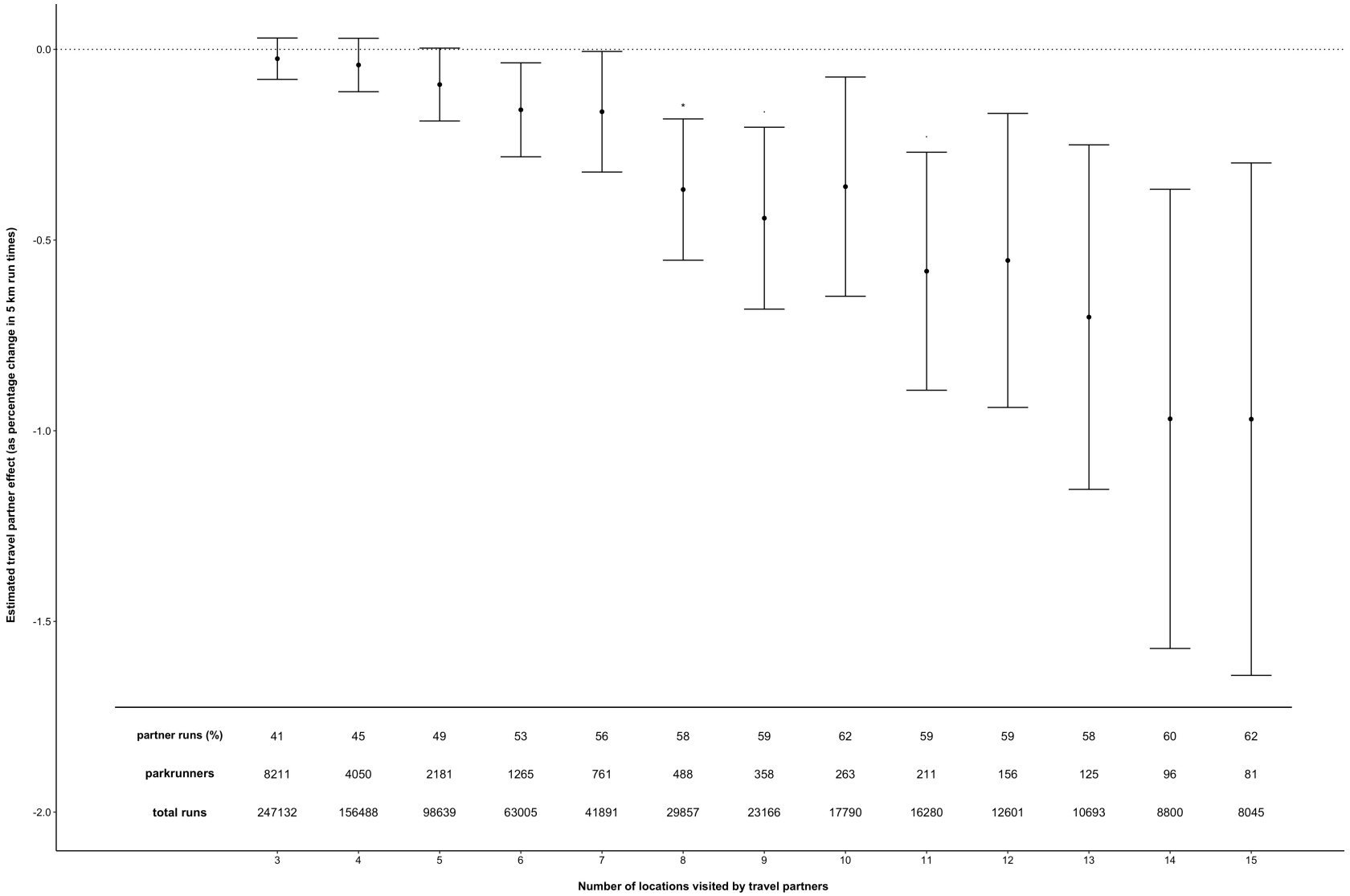



**Figure 4.3** Estimates (± 1 *SE*) of travel partner presence effect on 5 km run times by the minimum number of different locations parkrunner pairs were required to attend together to be included in the data set.

parkrunners' likely social relationships on a given day, and using this variable to predict 5 km run times.

### 4.6.1 Variable creation and further data reduction

I first created a variable that aimed to measure the strength of parkrunners' relationships on a given day – I called this variable 'finish partner relationship strength' (FPRS). I created the FPRS variable using the *networkx* package in Python. Specifically, I used *networkx* to create a graph which represents links between parkrunners who finish within 15 s of one another at a particular parkrun. This cut-off was chosen to capture those relationships that are built between parkrunners who finish near to each other in time, and then interact while or after waiting to have their time recorded. The more frequently parkrunners finish near each other in time, the greater the chance they will interact with each other, as parkrunners disperse after waiting in line to have their times recorded; parkrunners who finish 10 min apart would be unlikely to interact, for example. A shorter time interval, such as the 2 s used in Analysis A, was not used because this would have yielded social networks that were made up (largely) of parkrunners who were intentionally running next their finishing partners, thereby focusing on a subset of runners that intentionally modify their running pace (these types of runs are controlled for in this analysis; see below). Further, a 2 s cut-off would have excluded from analyses those relationships that come about not by intentionally running (and finishing) together, but through socialising post-run (as described above). The 15 s cut-off was thus used as a means of capturing relationships among parkrunners that are built through these processes of post-run socialisation.

Using this 15 s cut-off, every time a pair of parkrunners finished together at the same location on the same day a 'weight' of one was added to the links between these parkrunners in the social network. This led to a final *networkx* graph with weighted links between parkrunners that represent how many times they had finished within 15 s of each other. For example, if a parkrunner A finishes within 15 s of both parkrunner B and C on a given day, and this was parkrunner A's fourth time finishing within 15 s of parkrunner B and 23$^{rd}$ time finishing within

15 s of parkrunner C, parkrunner A's FPRS score on that day would be 27. Assuming that this was the first time that parkrunner B had finished within 15 s of parkrunner C, parkrunner B's FPRS score would be 5, and so on.

In addition to creating an FPRS score for each run, I also created a 'previous runs' variable, which represent the number of previous runs a parkrunner had completed up to the date of the current run. The 'previous runs' variable was used as covariate in the models described below, as previous runs represent a potential confound of FPRS effects on run times; it is possible that both FPRS and physical fitness (faster run times) increase with previous runs.

A variable was also created that indicated whether or not parkrunners were running with a finishing partner, as defined in Analysis A. However, the cut-off used here for identifying finishing partners was a minimum of five finishes within 2 s, instead of three, as this cut-off seemed to give a more realistic indication of the presence of an intentional finishing partner, and hence an increased likelihood of parkrunners focusing on socialising instead of performance (five finishes is where the effects that result from how the variable was created become non-significant; see Figure 4.1, p. 115). I therefore will attempt to control for these social runs in the analyses below through including as a covariate a variable representing whether or not parkrunners were running with a frequent finishing partner (i.e., a parkrunner they had finished within 5 s of at least five times). Controlling for the effect of running with frequent running partners is especially important in this data set, as it includes those parkrunners that are the faster of frequent finishing pairs, which means that they frequently slow their running pace in order to run with their slower running partners.

Finally, the model presented in Section 4.6.2 failed to converge when run on a data set containing runs from all 10 countries at which parkrun occurs. I therefore eliminated all runs from non-UK parkruns, and this led to model convergence. Removing runs from all non-UK

parkruns reduced the number of parkrunners from 213,051 to 150,725, and the number of runs from 6,485,902 to 4,821,684[25].

### 4.6.2 Model selection

In order to test the hypothesis that social integration on a given day at parkrun predicts 5 km run times I ran a multilevel model on the data set described above. The outcome was parkrunners*'* 5 km run times and the main predictor variable was FPRS. Covariates included parkrunner's gender, age, number of previous runs, and whether or not they were running with a finishing partner (i.e., whether or not they finished within 2 s of a parkrunner they had finished within 2 s of on five or more previous occasions). A natural log transformation was applied to 5 km run times, and a $\log_2$ transformation was applied to both the FPRS and previous runs variables, as their distributions were roughly log-normal. These transformations were done to facilitate model interpretation and fit (Snijders & Bosker, 2012).

This model allowed for intercepts and slopes to vary by participant. Slopes varied only for the FPRS and previous runs variables; this was the appropriate random effects structure (Barr et al., 2013). The model was fit using restricted maximum likelihood (REML), as this method provides the best estimates of variance components (Maas & Hox, 2004).

### 4.6.3 Results

The model presented in Section 4.6.2 revealed a significant negative effect of the $\log_2$ transformed FPRS variable on natural log transformed run times, $b = -0.012$, $SE < 0.001$, $t(97{,}740) = -86.42$, $p < .001$, while controlling for parkrunners' age, gender, number of previous runs, and whether or not they were running with a finishing partner (see Table 4.5 for full model results). This indicates that a doubling of social integration (as measured by the FPRS variable), leads to a 1.24% decrease in (unlogged) 5 km run times, or an improvement

[25] Removing all non-UK runs left some parkrunners in the resulting data set with fewer than 10 runs (since some of their runs came from non-UK parkrun locations). Runs from these parkrunners (12,729 runs from 5,065 parkrunners) were *included* in the final data set, because their removal led the model presented in Section 4.6.2 to fail to converge.

**Table 4.5** Main multilevel model testing effects of the $\log_2$ FPRS variable on logged 5 km run times

| **Fixed effect** | **Coefficient** | ***SE*** | **df** | ***t*** | ***p*** |
|---|---|---|---|---|---|
| Intercept | 3.140 | < 0.001 | 386,700 | 3,611.33 | < .001 |
| $\text{Log}_2$ FPRS | −0.012 | < 0.001 | 97,740 | −86.42 | < .001 |
| $\text{Log}_2$ previous runs | −0.011 | < 0.001 | 146,800 | −147.62 | < .001 |
| Partner presence | 0.093 | < 0.001 | 4,015,000 | 375.40 | < .001 |
| Gender (female) | 0.193 | < 0.001 | 151,400 | 256.30 | < .001 |
| Age | 0.019 | < 0.001 | 673,400 | 168.40 | < .001 |
| **Random part** | **Variance** | ***SD*** | | | |
| Intercept | 0.031 | 0.176 | | | |
| $\text{Log}_2$ FPRS | 0.001 | 0.035 | | | |
| $\text{Log}_2$ previous runs | < 0.001 | 0.022 | | | |
| $R^2_m = 0.272$, $R^2_c = 0.843$ | | | | | |

of 19.94 s for a parkrunner with a run time at the overall average of 26 min 53 s. The effects of the covariates were also highly significant.

#### 4.6.3.1 Follow-up analyses

In addition to the possibility that the cut-off used in creating the FPRS variable biased the model's results, there are several issues that arise when making statistical inference from large data sets (the data set used in Analysis C was especially large compared to those used in Analysis A and Analysis B, which were subsets of the data set used in Analysis C). Specifically, extremely small standard errors can lead to *p*-values being highly sensitive to very small (i.e., meaningless) effects that exist because of the inherent (unmodeled) structures present in the data set. Below, I present several follow-up analyses that attempt to address potential biases in the model used here.

#### 4.6.3.2 Different cut-offs

In addition to the model described above, which used a cut-off for the FPRS variable of 15 s, I ran three additional models with different cut-offs: 1 min, 2 min, and 3 min. As described in

Section 4.6.1, the FPRS variable tracked the amount of times parkrunners had finished within 15 s of co-participants, as parkrunners were assumed to be more likely to have built social relationships with those they finish nearby in time. Given this, I would expect the effects of the FPRS variable to diminish as the cut-off increase; parkrunners who finish within 3 min of one another are less likely to have a supportive social relationship than those who finish within 15 s of one another. Results, presented in Table B 1 – Table B 3 in Appendix B (p. 311 – 313), suggest that this is the case, with *t*-values for the FPRS effect decreasing from −86.42 (15 s) to −62.45 (1 min) to −33.56 (2 min) to −18.57 (3 min) as the cut-off increased.

#### 4.6.3.3 Permutation analysis

I ran a permutation analysis to check whether the coefficients and their associated t-values and significance levels resulted not from significant relationships between the predictors variables and run times, but instead from the size and structure of the data. I ran 1000 permutations on the run times of 15,073 randomly sampled parkrunners (10% of the total number of parkrunners from the data set used in the model reported above). I chose a random sample of 10% of the 150,725 parkrunners from the data set described in Section 4.6.1, p. 126) because running the same permutation analysis using all 150,725 parkrunners would have taken orders of magnitude longer (more than a month, by my calculations, even while employing a high amount of parallel processing). Each permutation involved running the model described in Section 4.6.2 (p. 128) on a permuted data set, where each of the 15,073 randomly sampled parkrunners' run times were randomly reordered, and reassigned a run (row) associated with the parkrunner they came from. I also ran the same model 1000 times on the (unpermuted) run times of 15,073 randomly sampled parkrunners (for each model, resampling with replacement from the data set described in Section 4.6.1, p. 126). I did this so that I could compare the distribution of model coefficients and their associated *t*-values produced by the 1000 models run on unpermuted samples to those produced by the 1000 models run on permuted samples. In permutation analyses such as these, predictor variables that do not have strong relationships with the outcome variable should show similar coefficient

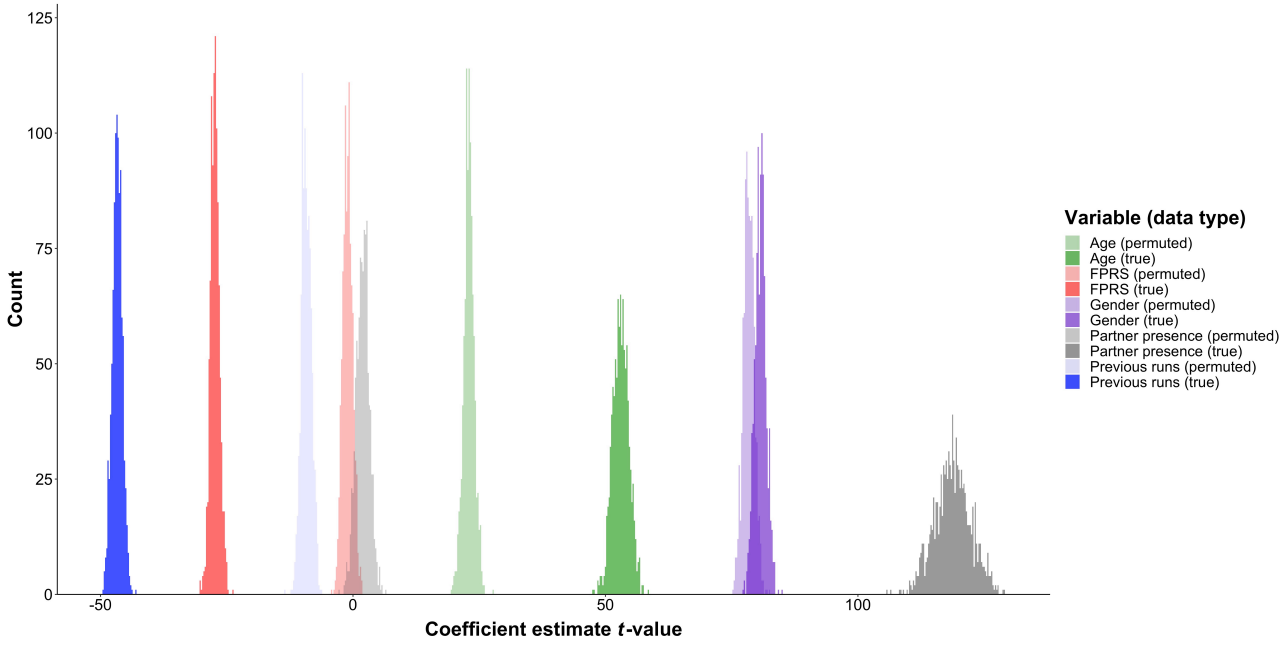



**Figure 4.4** Results of the permutation analysis. Every variable in the model presented in Section 4.6.2 has a distribution of *t*-values based off their coefficient estimates from 1,000 models run on data with permuted and true 5 km run times.

estimates and associated *t*-values when estimated on the true and permuted data, as should predictor variables that do not vary within individuals (since data was permuted *within* individuals, in this case). However, for predictor variables with strong relationships with the outcome variable, there should be large discrepancies between the coefficient estimates and associated *t*-values estimated on the true data versus those estimated on the permuted data; coefficient estimates and associated *t*-values should trend toward zero when estimated on permuted data. The models run on the true and permuted run times were identical to the model presented in Section 4.6.2 (p. 128), except that, to facilitate model convergence, the natural log (instead of $\log_2$) of the FPRS and previous runs variables were used. I also scaled these two variables, and the natural log of the run times variable. These changes will not affect interpretation of the results of the permutation analysis, since my main focus is on changes in *t*-values.

Figure 4.4 shows the differences in the distributions of *t*-values for model *b* coefficients from the 1000 models run on the actual (true) run times and on the permuted run times. Most importantly, the effect of the $\log_2$ of the FPRS variable shows a large reduction when estimated

on the permuted run times. The *t*-values from the $\log_2$ FPRS coefficients were close to zero (mean = −1.050, *SD* = 0.889) when estimated on permuted run times, but considerably higher than zero when estimated on the true run times (*M* = −27.34, *SD* = 0.097). The difference between the two distributions of *t*-values was highly significant: $t(1982.7) = 631.57$, $p < .001$, 95% CI [26.20, 26.37]. The $\log_2$ previous runs variable showed a similar pattern, *t*-value difference 95% CI [37.35, 37.53], as did the partner presence variable, *t*-value difference 95% CI [−117.03, −116.56]. The effect of age category also differed when estimated on the permuted run times, as compared to the true run times, *t*-value difference 95% CI [−30.18, −29.95]. This is likely due to the fact that participants' age categories changed over the time their data was collected. Crucially, this pattern was not observed for the gender variable, the effect of gender on run times was (comparatively) highly similar[26] when estimated on permuted and true run times, *t*-value difference 95% CI −2.22, −2.22]. This can be explained by the fact that 5 km run times were randomised *within* parkrunners; the overall effect of gender on all run times held. Finally, it is interesting to note that the distributions of *t*-values for $\log_2$ of the FPRS and previous runs variables do not have a mean of zero for the models run on the permuted run times. This is likely due to the structure of the data; relatively faster parkrunners tend to have relatively higher mean scores for the FPRS and previous runs variables. Permuting the data *within* parkrunners did not completely decompose this structure.

#### 4.6.3.4 Linear models on data without level-two structure

Given the possibility for a latent level-two structure in the data that could be driving results (i.e., faster parkrunners also having a higher mean FPRS score) I examined the relationship between the $\log_2$ of the FPRS variable and logged 5 km run times in a non-hierarchically structured data set. This was accomplished by running 1000 linear models on random

[26] Given that run times were permuted within parkrunners, one would expect the distributions of the gender variable to be the same for permuted and true run times. However, they are slightly different. This is because, when a regression model is fit, the estimate of a particular coefficient is affected by the amount of variation the other covariates explain. Permuting run times changes the amount of variance explained by the other variables, as is evident from Figure 4.4. Thus, the coefficient estimate for the gender variable is slightly different between the two data sets.

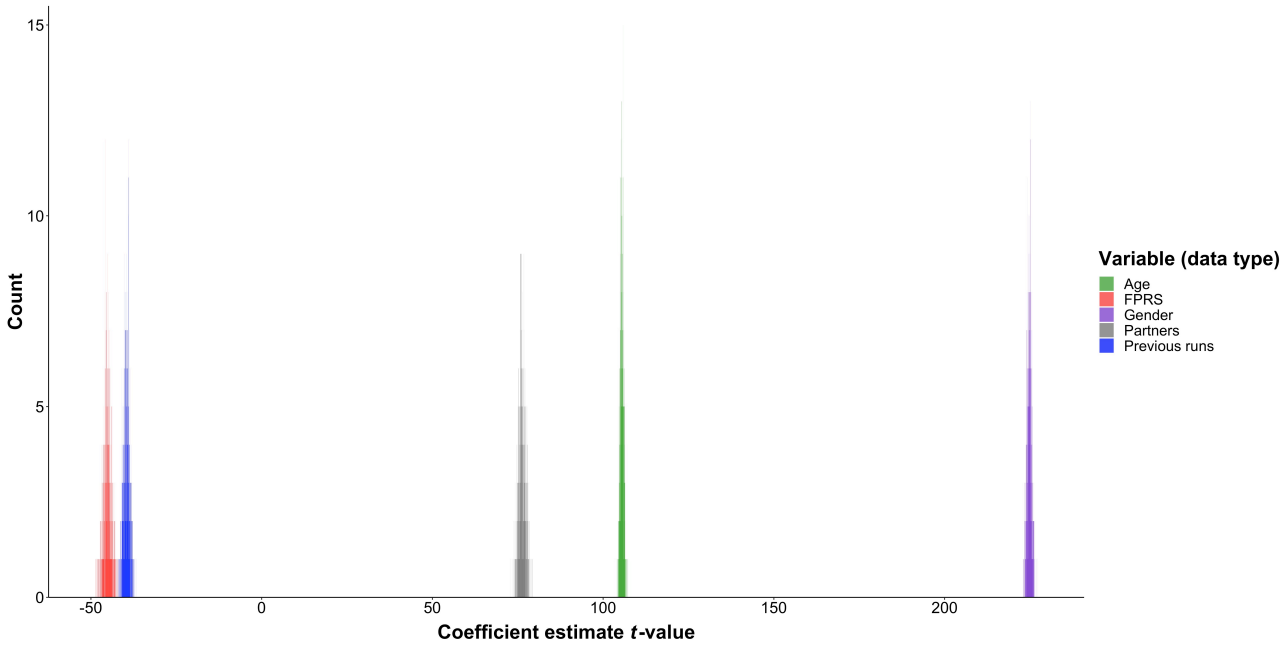



**Figure 4.5** Distribution of model coefficient *t*-values derived from running separate linear models on 1,000 random samples of one run per parkrunner.

samplings of one run from each of the 150,725 parkrunners in the data set. With the exception of the random effects, the linear models used here contained the same variables (and transformations) as those in the model presented in Section 4.6.2 (p. 128). Results, presented in Figure 4.5, suggest that the statistical significance of the variables in the main model were not the result of latent level-two structure in the data. When the level-two structure in the data was removed, the effect of the $\log_2$ of the FPRS variable on logged run times held, and became stronger than the effect of the $\log_2$ of the previous runs variable.

#### 4.6.3.5 Testing the FPRS effect on run times by location

Another means of testing the effect of the FPRS variable on run times is to examine its consistency across different parkrun locations. To do this, I ran the model presented in Section 4.6.2 (p. 128) on subsets of data consisting of every run from every location that was in the top 80% of locations ranked by total runs. Locations in the bottom 20% had less than 2,500 total runs, and models run on these data sets were prone to convergence failure. This also occurred with seven locations in the top 80%; these locations were excluded from further analyses.

This produced a distribution of $log_2$ FPRS beta estimates (see Figure 4.6); the models run on 55 out of the 285 locations estimated positive $log_2$ FPRS effects on run times (16 of these estimates were statistically significant), negative (i.e., performance-enhancing) effects of the $log_2$ FPRS variable on run times were estimated at 230 of the 285 locations (168 of these estimates were statistically significant). When controlling for partner runs, previous runs, gender, and age, the FPRS variable has a significant negative effect at 68% of locations. Further, 71% of the locations with positive estimates of the FPRS variable on run times have confidence intervals crossing 0. Locations with significant positive $log_2$ FPRS effects also have fewer total runs; when considering total runs at all 285 locations, they are, on average, in the $18^{th}$ percentile.

## 4.7 Discussion

Here, I studied social support effects at a weekly, community-based 5 km run through the use of a big data set. Specifically, I tested the hypothesis that the presence of social support is associated with faster run times at parkrun. Analysis A examined pairs of parkrunners who had finished within 2 s of each other at least five times. This analysis showed significant, performance-enhancing effects of finish partner presence on 5 km run times. Analysis B used a similar method as Analysis A, but instead used the presence of a travel partner as an indicator of social support. Results revealed that the presence of a travel partner was associated with faster 5 km run times. Analysis C created a variable – FPRS – that aimed to measure parkrunners' likely social integration at a particular parkrun. Higher scores on the FPRS variable, which represents stronger relationships with co-finishing parkrunners, predicted faster 5 km run times. Importantly, the effects in these analyses held when controlling for relevant confounds, such as previous runs. Further, the observed effect sizes are in line with the 1 – 2% increases in physical outputs typically observed in ergogenic placebo studies (Beedie & Foad, 2009).

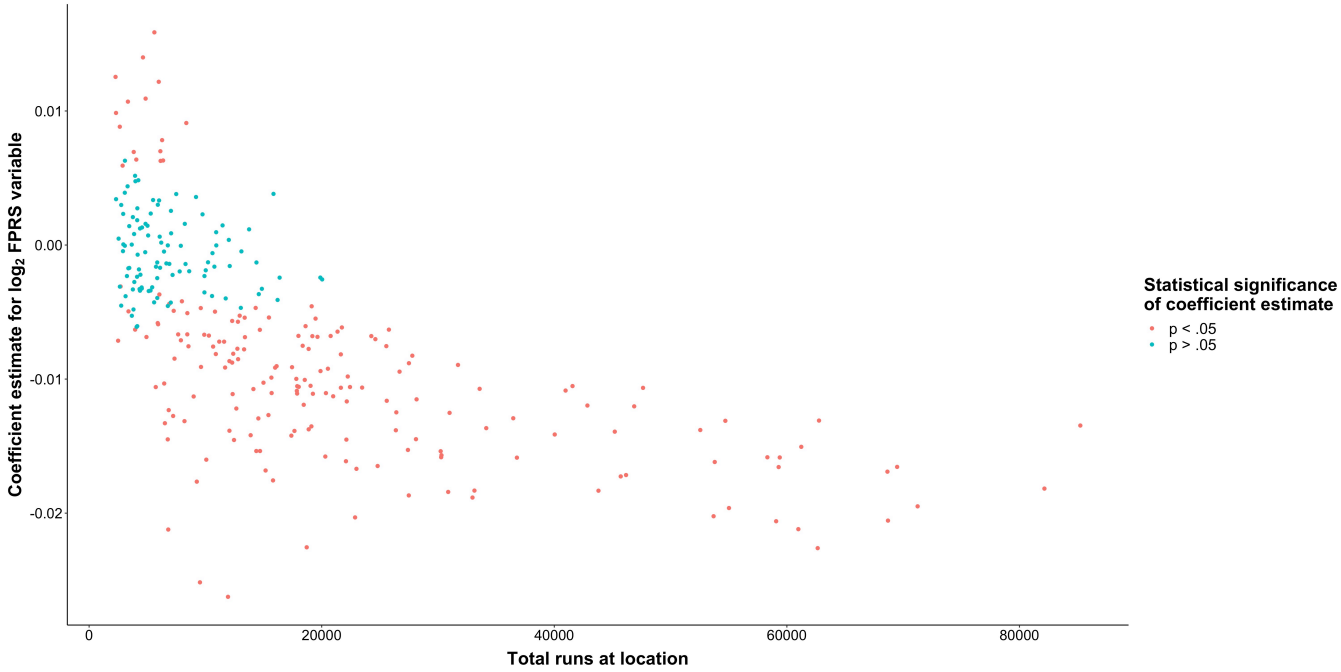



**Figure 4.6** Beta coefficient estimates for the $\log_2$ FPRS variable by total runs at UK parkrun locations. Red points represent coefficient estimates that are statistically significant at $p < .05$.

Overall, then, results of the analyses presented here support the hypothesis that parkrunners run faster over 5 km when in the presence of socially supportive others. Generally, the results of these analyses are in line with the mechanistic account of ergogenic social support effects presented in Section 2.2.3 (p. 50). Perceptions of social support – as measured by the social predictor variables used in this study – may have altered parkrunners self-efficacy as well as their perceptions of pain and fatigue. Research has shown that social support can lead to physical tasks being estimated as less difficult (Schnall et al., 2008), and to greater energy levels during these tasks via enhanced perceptions of competency and ability (O'Connor & Puetz, 2005). These effects could have led parkrunners to choose faster running paces than they would have if they were feeling relatively unsupported. Altered running paces may have further been facilitated by increased activity in endogenous self-regulatory systems involved in the regulation of pain, fatigue, and physical outputs during strenuous physical exercise (Amann et al., 2009; Benedetti, Amanzio, et al., 2011; Boecker et al., 2008; Dunbar, 2012; Inagaki et al., 2016; Raichlen et al., 2012; Trezza et al., 2010; Wager et al., 2007). However, the observational nature or this study limits the degree to which the its findings can be applied

to these mechanistic accounts. Further, as discussed in Section 1.4.1 (p. 19), social support effects depend on context. Below, I will discuss how the particular social environments investigated in this study's analyses may have increased perceptions of social support, and ultimately enhanced 5 km run performance. Of course, other explanations for the observed effects are also possible, and I will discuss these in Section 4.7.4 (p. 140) and in then in further detail in Section 7.3.2 (p. 242).

### 4.7.1 Finishing partners

A straightforward means of testing social support effects at parkrun using the present data set was to compare the effect of finishing next to a faster partner to the effect of finishing on one's own. This analysis focused on the partner who was consistently the slower of the pair, as faster partners would have to intentionally slow their running pace in order to finish with their slower partners on a consistent basis. Analyses revealed significant, performance-enhancing effects of (faster) finish partner presence on 5 km run times (around 9 s faster for a parkrunner with run times near the average, 30 min, for the data set), when the cut-off for being included in analyses was finishing together at least three times (something less than two percent of finishing partners had done).

These effects appear to vary depending on the finish partner cut-off used to generate the data set used for analysis. It appears that genuine performance-enhancing effects existed in data sets with parkrunners who had finished with their finishing partners a relatively high number of times (around 15 or more times). For data sets with relatively low cut-offs, partner presence likely predicted faster run times simply because finishing with a faster partner *by definition* meant that slower partners were running faster than their average. What was driving the performance-enhancing effects observed in data sets with relatively low finish partner cut-offs, then, was likely the large proportion of parkrunners who happened to finish next to a faster runner when they themselves were running faster than their average. In addition to these effects, it could also be that when slower parkrunners had faster target co-participants to pace themselves on (and finish next to) they were able to run slightly faster than their average time.

Indeed, parkrunners have mentioned using faster co-participants as a means of motivation and pacing (Wiltshire et al., 2018). Thus, it is possible that results are at least partially explained by both statistical artefacts and some form of competition (discussed in relation to this analyses in Section 4.7.4.2, and as it applies to the results of this thesis more generally in Section 7.3.2.1, p. 242), where slower parkrunners try to match the pace of faster co-participants who they do not have a close social relationship with.

The trend toward stronger finish partner presence effects as data sets had more stringent finish partner cut-offs and hence higher percentages of intentional finishing partners is notable. As it became more likely that finishing partners included in the analysis actually had close social relationships, the performance-enhancing effect of their presence on slower partners' run times increased. However, it should be noted that this trend was not tested statistically; instead, it should be taken as an indication of how observed finish partner effects changed with the stringency of the finish partner cut-off being used. Nevertheless, the trend is in line with Hypothesis A, which predicted that the presence of strong social relationships (in the form of a faster, frequent finishing partner) would lead to faster 5 km run times. The observed trend is also consistent with research on analgesic social support effects (e.g., Coan et al., 2006) and in social support effects more generally (Christensen et al., 2006; Holt-Lunstad & Uchino, 2008); see Section 1.4 (p. 15). Crucially, I argue that these effects are unlikely to be explained by competition, since faster partners are intentionally slowing down to run with their slower partners.

Generally, the presence of a supportive, faster (intentional) finishing partner may have increased slower partners' self-efficacy and energy (Christensen et al., 2006; Filho et al., 2014; Stevinson et al., 2014). In the context of voluntary exercise, the construct of self-efficacy is thought to represent individuals' perceived ability and competence (O'Connor & Puetz, 2005). It is possible that the presence of a more competent, faster running partner altered slower partners' self-efficacy. This may have led to increased feelings of energy, which correlate positively with both perceptions of social support and self-efficacy in exercise

settings (O'Connor & Puetz, 2005). In turn, enhanced perceptions of energy may have been underpinned by activity in self-regulatory systems involved in reducing stress levels and perceptions of pain and fatigue. These effects may be responsible for the faster running paces of parkrunners in the presence of faster frequent finishing partners. When faster finishing partners intentionally modified their pace to run at the chosen pace of their slower partners, these slower partners seem to have chosen running paces that were slightly faster than what they would have chosen on their own, thereby leading to performance-enhancing finish partner presence effects.

### 4.7.2 Travel partners

Another relatively straightforward means of identifying the presence of social support is to identify whether parkrunners were in the presence of a travel partner; someone with whom they had travelled to at least eight different parkrun locations. Given the highly selective nature of this variable – only 2% ($n$ = 488) of parkrunners have a running partner with whom they have travelled to at least eight separate parkrun locations – it is likely that it indicates the presence of a close social relationship. The random effects from the travel partner model suggest that the majority of parkrunners experience positive (performance-enhancing) effects when in the presence of a travel partner (Figure 4.2); 6 s decreases in 5 km run times for parkrunners with an average 5 km time of 26 min (the average of all runs in the data set). Further, there was a general trend suggesting an increase in the performance-enhancing effects of travel partner presence as the cut-off for classifying parkrunner pairs as travel partners became more stringent. In other words, the follow-up analyses suggest that the ergogenic effects of travel partner presence were strongest in data sets where travel partners were relatively likely to have close social relationships. Again, it should be noted that this trend was not tested statistically; instead, it should be taken as an indication of how observed travel partner effects changed with the stringency of the cut-off being used during data set creation.

Importantly, it is unlikely that these results were driven by competition, as analyses focused on travel partner pairs that did not finish with similar times. Thus, the presence of a travel

partner likely represented the presence of a supportive social environment. These supportive social environments may have altered the self-regulatory processes that govern parkrunners' performance.

### 4.7.3 Social integration at parkrun

Analysis C measured parkrunners' social integration on a given day. Results showed that a doubling of social integration (as measured by the FPRS variable) leads to a 1.24% decrease in (unlogged) 5 km run times – an improvement of around 20 s for a parkrunner with run times near the overall average of 27 min. The performance enhancing effects of FPRS-measured social integration seemed to be robust and unbiased (i.e., not a result of unmodeled structures in the data or the cut-off used in the creation of the FPRS variable).

Social integration has been shown to be a correlate of perceived levels of social support (Holt-Lunstad & Uchino, 2008). If parkrunners indeed build social relationships with frequent nearby finishers, then the presence and quality of these relationships (as measured by the FPRS variable) likely predict perceptions of social support at parkrun. Indeed, Hindley (2018) has observed that parkrunners value the social interactions and relationships they build at parkrun, even though these are often with relative strangers with whom they only have loose social ties. Relationships of this style are likely common for parkrunner pairs who finish nearby one another on a frequent basis. The effects of the FPRS variable on run times at parkrun may thus be explained by the feelings of social support that parkrunners experience when relatively well-integrated into parkrun social networks on a given day. As discussed in Section 4.1, these feelings of social support may have changed parkrunners' assessments of their impending 5 km running challenge, and their perception of pain and fatigue, ultimately leading to faster run times when they were socially integrated.

Measuring social integration at parkrun likely presents the most ambiguities, as this variable is intended to measure the quality and quantity of parkrunners' social relationships at a given parkrun event, as well as their overall sense of community identification (Holt-Lunstad &

Uchino, 2008). Estimating this from an observational data set is challenging; social integration had to be estimated entirely from the presence of social relationships inferred from parkrunners' run data. It is thus possible that social relationships that were only weak at best were included, or that strong relationships were excluded, or that observed FPRS effects are best explained by a variable orthogonal to social support. This final possibility will be discussed next.

### 4.7.4 Alternative explanations

The results presented in this chapter could be explained by several factors that are unrelated to parkrunners' perceptions of social support and cohesion. These include the possibility that the predictor variables measured something different than social support or cohesion, that these variables were confounded with competition, and that the size and structure of the big data set led to misleading inferential statistics.

#### 4.7.4.1 Inference from observational data

The observational nature of this study required me to operationalise social support through inferring social relationships from parkrunners' finish patterns. Through examining these finishing patterns, I identified when individuals were likely to feel socially supported, either from being in the presence of a close other (the finish partner presence variable and the travel partner presence variable) or being highly integrated into the parkrun social network (the FPRS variable). Assumptions about felt social support are based on research showing that social integration and the presence of close friends predict perceptions of social support (Holt-Lunstad & Uchino, 2008). Thus, to the extent that the variables used here actually measure the presence of close friends, family members, and social integration, they can be seen as proxies for perceptions of social support as, *on average*, these variables are likely to represent the presence of social support. However, the perceived social support of particular individuals at particular runs was ultimately inferred from parkrun's online database, making alternative explanations possible.

#### 4.7.4.2 Competition

Competition has been shown to be a major driver in determining physical outputs in sport. Generally, and across a wide range of sports, performance is enhanced in competitive versus non-competitive settings (Corbett et al., 2012; Konings et al., 2016; Tomazini et al., 2015). These findings are explained by increased motivation in competitive settings (e.g., McCormick et al., 2015); individuals are driven to perform better via the extrinsic goal of besting rivals. Increased motivation to perform better during competition, or when being observed, has been explained at the ultimate level in terms of costly signalling, an account that identifies physical performance in sport and exercise as a costly indicator of physical fitness to rivals and potential mates (De Block & Dewitte, 2009; Miller, 1999).

While these explanations are certainly relevant to competitive sport and exercise more generally, there is reason to believe that competition and costly signalling may not be particularly relevant to the findings presented here. Firstly, parkrun goes to great lengths to distance itself from more traditional views of running as competition, describing itself as a 'run and not a race' (Hindley, 2018). Further, I showed a social support effect using a data set that intentionally excluded head to head competition; my analysis of the 'travel partner' data set (Analysis B) excluded pairs of parkrunners who travelled to parkruns together *and* ran similar times, thus making it unlikely that direct competition is solely responsible for faster run times in the presence of travel partners. Thus, while competition might explain *some* of the effects currently being attributed to social support in the present study, it is unlikely to be the sole explanatory factor of enhanced 5 km run times. That being said, costly signalling can exist without competition, with runners putting forth greater physical effort when in the presence of potential mates, rivals, or allies. This explanation would be plausible if parkrunners were more likely to engage in costly signalling when in the presence of friends and family versus when in the presence of strangers. Some research suggests that this might be the case. For example, Barclay (2016) has argued that individuals compete in 'biological markets' for friendships and social relationships more generally, attempting to portray themselves as high-quality

cooperative partners. Given societal norms and expectations that favour physical competence and fitness (Okun et al., 2003), it is possible that, in the context of parkrun, individuals may put forth greater effort when in the presence of those they have pre-existing relationships with as a means of appearing competent or hard-working. Although these claims have not been tested in the context of exercise, they do provide a potential confound for the social support effects observed here. Nevertheless, it is possible that competition and costly signalling exist alongside perceptions of social support. For example, individuals may want to signal exercise competence to close friends, and they may also have competitive relationships with those whom they also perceive as socially supportive. In sum, there are plausible alternative explanations to the results presented here, although it seems unlikely that these alternative explanations explain *all* of the observed effects of the social support variables on 5 km run performance at parkrun.

#### 4.7.4.3 Spurious results stemming from the use of large data sets

The observational nature of this study, combined with the big data used, mean that many results could be significant not because of the proposed social support effects, but because of small standard errors of *b* estimates and arbitrarily defined social support parameters. Along with the theoretical justifications for my creation of the social support variables used, I took several steps to test the robusticity of the models reported here.

In Analysis C, I conducted a permutation analysis to test whether the statistical significance of the FPRS variable was due to the size of the data, and not the nature of its relationship with 5 km run times. The permutation analysis, which involved permuting 5 km run data within parkrunners, demonstrated that randomising the relationship between the FPRS variable and 5 km run times effectively eliminates the significant, ergogenic effects of the FPRS variable on 5 km run times. This suggests that the ergogenic effects of the FPRS variable do not result solely from the size of the data used in the main analysis of Analysis C. Through running 1000 linear models (using one randomly-sampled run per parkrunner) with the same predictor variables used in the main analysis of the FPRS variable, I also demonstrated that latent,

level-two structure in the data was not driving the significance of the FPRS variable. The effect of the FPRS variable in a non-hierarchically structured data set was relatively similar to its effect in a data set containing multiple runs per parkrunner (the data used in the main analysis of Analysis C).

I also showed that the effect of the FPRS variable held at individual parkrun locations: 168 locations replicated the overall finding of statistically significant run time-reducing effects of the FPRS variable, whereas only 16 showed statistically significant run-time increasing effects (slightly more than double what would be expected by chance at $\alpha = .05$). All of these 16 locations had relatively few total runs (see Figure 4.6, p. 135). One possible explanation of why these locations had positive estimates of the FPRS variable on run times is that, with fewer total runs, fewer runners were able to build significant social relationships that were not already pre-established. Indeed, those locations where the FPRS variable effect was estimated to significantly improve run times had a larger range for the FPRS variable (0 – 124 v. 0 – 86), and also a larger positive skew (skewness = 11.87 v. skewness = 9.54) than those locations where this effect was not observed. These differences would have led to the FPRS estimate on run times being influenced more by relatively low FPRS scores at the locations with positive estimates, as compared with those with negative estimates. It might be that the negative effect of this variable on run times is driven by relatively strong social relationships (represented by high FPRS scores), thereby explaining why models from locations with relatively small social networks (and low FPRS scores) estimate positive effects of the variable on run times. Finally, as a means of confirming that the observed FPRS effect was not an artefact of how the variable was created, I tested the effects of FPRS variables created with less stringent cut-offs. These models showed similar results to the main FPRS variable used (which was created using a 15 s cut-off for determining partner finishes); when controlling for the presence of partner runs, there was a negative overall effect of the FPRS variable on 5 km run times at all cut-offs used. Further, as the time frame increased for determining finishing partners, the performance-enhancing effect of the FPRS variable decreased. These findings

are what would be expected given the hypothesised relationship between the FPRS variable and run times; larger time frames likely included more non-significant or 'false positive' social relationships, thereby reducing the performance-enhancing social support effects captured by the FPRS variable.

### 4.7.5 Researcher degrees of freedom and cut-off procedures and justifications

The analyses presented in this chapter involved predicting 5 km run performances at parkrun with social variables that were created using relatively arbitrary cut-off points. As Simmons, Nelson, and Simonsohn (2011) argue, 'ambiguous' analytical decisions (such as the cut-off decisions made in this chapter) increase "researcher degrees of freedom" (p. 1,359) – the number of potential analyses that could be run on a data set – and high researcher degrees of freedom increases the possibility of researchers (oftentimes unintentionally) selecting analytical pathways that lead to statistical significance. The analytical procedures and justifications of this chapter must thus be considered in this light.

The predictor variables used in this study were based on identifying particularly strong social relationships in a data set. For both Analysis A and Analysis B, I wanted to identify pairs of parkrunners with particularly strong social relationships, and therefor used only parkrunners in the 95$^{th}$ percentile of finish partner runs and locations attended with partners, respectively (see Section 4.4.1, p. 111, and Section 4.5.1, p. 119). For Analysis C, I used a 15 s cut-off to identify parkrunners who finished their runs nearby one another, and who were thus likely to interact while or after waiting to have their run time recorded (Hindley, 2018). All three cut-offs used were established before inferential analyses were conducted. However, it is certainly possible to conceive reasonable justifications for the use of a different cut-off in every analysis reported in this chapter.

Following the recommendations of Simmons et al. (2011), I thus carried out follow-up analyses on each main analysis reported in this chapter. These follow-up analyses show to what degree the results of each main analysis depend on the arbitrary analytical decisions of the study (i.e.,

the cut-offs used). Generally, the follow-up analyses are in line with the hypotheses laid out in Table 4.1 (p. 108). The performance-enhancing effects of the predictor variables correlate positively with the probability that these variables represent the presence of close social relationships. However, the results of these follow-ups suggest that they should inform the cut-offs used in future analyses. For example, in Analysis A, the follow-up analyses show that, due to the way the variable was created, a more stringent cut-off should have been used so that the finish partner presence variable is more likely to represent close social relationships, instead of chance finishes within 2 s between parkrunner pairs who are not intentionally finishing together.

### 4.7.6 Follow-up research

A replication of this study could be pre-registered – following the methods of van 't Veer and Giner-Sorolla (2016) – and re-run using parkrun data from November 8, 2015 (the last day included in the data set used here) to the present. Pre-registration would establish *a priori* cut-offs for the identification of close social relationships and the predictor variables used in the main analyses. These cut-offs would be based on results reported in this chapter. With regard to the travel partner variable, parkrun geo-location could be taken into account in order to give weight to occasions where parkrunner pairs co-attend geographically distant parkrun events, since parkrunner pairs are more likely to co-attend multiple parkrun locations near their residence by chance as a result of changing locations for variety or for better running and/or weather conditions. The pre-registered design could also allow for a set of follow-up analyses similar to those reported here, which would test the sensitivity of results reported in the main analyses to changes in the *a priori* cut-offs used (Saltelli, Tarantola, Campolongo, & Ratto, 2004). Hypotheses related to exercise adherence and cross-cultural differences in social support and cohesion effects could also be investigated using these data sets (Hennessy et al., 2009).

The results from the follow-up analyses presented in Analysis A and Analysis B suggest that finish and travel partner presence affect attendance at parkrun, or ‘exercise adherence,’ as it

is referred to in relevant literature (e.g., Fraser & Spink, 2002; Spink & Carron, 1994). As the cut-offs for classifying parkrunner pairs as finish and travel partners increase, so too do the percentage of partner runs (v. solo runs) in the data set. In other words, as it becomes more certain that those parkrunner pairs included in a data set actually have close social relationships, partner runs (either with finish or travel partners) become relatively more frequent than solo runs. For example, Figure 4.1 (p. 125), shows that only 14% of runs are finish partner runs when the cut-off for including parkrunner pairs in the data set is two finishes within 2 s of one another, but that the frequency of finish partner runs increases to 40% when the cut-off for including parkrunner pairs in the data set is 25 finishes within 2 s of one another. Figure 4.3 (p. 125) in Analysis B shows a similar pattern; travel partners are present at 41% of runs in the data set created with travel partners who attended a minimum of three parkrun locations together, and 62% of runs in the data set created with travel partners who attended a minimum of 15 parkrun locations together[27]. To investigate partner presence effects on adherence, future studies could run multilevel logistic regressions using partner presence (or strength of relationship with running partner) as the predictor variable and attendance (binary) as the outcome.

Given that parkrun has data on runs from locations in 10 different countries, it would be possible to examine how ergogenic social support effects vary by country. Although tangential to the specific empirical questions of this thesis, researchers have become increasingly interested in the cultural factors that affect the receipt of social support (e.g., Hennessy et al., 2009; Park et al., 2013). The parkrun data set is thus of potential interest to this field of research, as it offers a naturalistic experiment whereby cultural factors vary at parkrun

[27] Of course, some of the differences between the percentage of partner runs in these data sets will be due to more stringent cut-offs leading to higher percentages of partner runs. However, this is unlikely to entirely explain observed differences in attendance between the data sets. For example, in Analysis B, 62% of runs were partner runs in the data set consisting of travel partners who had attended a minimum of 15 different parkrun locations together. The parkrunners included in this data set had an average of 99.32 total runs (*SD* = 61.08, range = 17 – 283). Meeting the requirement to be included in the data set (15 runs with a travel partner at separate locations) would thus only require around 15% partner runs, on average, which is far below the observed 62%.

locations across (and within) countries, while procedures remain relatively constant (all parkrun events are free, weekly, and involve a 5 km run or walk). An analysis of how social support and cohesion effects at parkrun vary by country could be done by adding an additional 'level' to the multilevel linear regression model used in Analysis C. Following the methods suggested by Snijders and Bosker (2012), this would lead to a model with runs nested within parkrunners (level-two variable) nested within the country which they occurred (level-three variable). Researchers could then examine the random effects of country on the relationship between the FPRS variable (or a different social variable) and 5 km run times.

A pre-registered, follow-up study to the analyses presented here thus offers several benefits. First, it allows for the use of *a priori* cut-offs (informed by the results of this study) for the creation of social predictor variables, which would reduce researcher degrees of freedom and the likelihood of false-positive findings (Simmons et al., 2011). Second, follow-up studies also allow for more fine-grained indicators of close social relationships (for example, taking into account the location of parkrun events that parkrunner pairs travel to). Third, such a study could also test other hypotheses related to how social support and cohesion affect attendance (adherence) at parkrun, and how ergogenic social support and cohesion effects are moderated by cultural factors that vary across countries that participate in parkrun.

### 4.7.7 Generalisability

When generalising these results, it should be noted that Analysis A and B used a highly selective subsample of parkrunners, with social relationships that are likely much closer and more supportive than the loose ties that characterise typical relationships at parkrun (Hindley, 2018; Stevinson et al., 2014). However, Analysis C tried to counter this, looking at social networks at parkrun more broadly. The results from Analysis C might thus be the most applicable to other group exercise contexts, whereas the findings from Analysis A and B are perhaps best seen as tests of the effects of social support among highly bonded pairs of exercisers.

The analyses presented in this chapter – especially Analysis A, but also in Analysis B – used follow-up analyses to identify the appropriate cut-offs for classifying relationships at parkrun as ‘close’. In this sense, the research presented in this chapter could be considered to be in what van 't Veer and Giner-Sorolla (2016) call an ‘exploratory phase’, in which “methods are tested without much prior evidence” (p. 5). Exploratory phases of research should be followed by confirmatory research that strives for “exact replications of the design and analysis that ‘worked’ in the exploratory phase” (Simmons et al., 2011, p. 1,365), as a means of reducing the likelihood of accepting false-positive results. This (future) confirmatory research is described in Section 4.7.5 (p. 144). As a result of the exploratory nature of some aspects of the research presented in this chapter, the need to confirm these results with additional research should be stressed when making generalisations about this study.

### 4.7.8 Conclusions

The supportive, community-based ethos of parkrun, combined with the availability of its large data set on 5 km run performance, made it an ideal setting in which to study the effects of social support on running performance among ordinary exercisers. I used the data set to create multiple variables meant to represent the presence of social support at parkrun. Results showed that, when their runs were not oriented towards socialising, parkrunners’ 5 km run times improved in social situations in which they were likely to have felt socially supported. Although research has shown that perceptions of social support and cohesion predict adherence to group exercise regimes (Fraser & Spink, 2002; Spink & Carron, 1994), this is the first study to suggest that these variables might also facilitate the performance of exercise.

The purely observational data used in this study mean that assumptions about parkrunners’ perceptions of social support are somewhat speculative. Further, the data analysed here does not offer any direct tests of the mechanistic accounts I have provided for ergogenic social support effects. As a means of addressing these shortcomings, Chapter 5 presents a survey study of a subset of the parkrunners studied in this chapter’s analyses. This survey was designed to gather information on parkrunners’ social environments, their perceived social

support and integration, and their motivations and experiences at particular parkrun events. The data provided by this survey thus complement the findings presented in this chapter, giving more accurate data on when parkrunners were in the presence of close, supportive others, when they felt supported by these individuals and the parkrun community more generally, and how they felt (e.g., perceived energy and fatigue) as a result during their runs.

## Chapter 5 – Social support and cohesion effects at parkrun: a survey study

All R and Python scripts referenced in this chapter can be found here:

https://github.com/arranjdavis/DPhil_Thesis_Chapter_5_Data_Analyses

**Abstract**

Results from the analysis of parkrun's big data set, presented in Chapter 4 of this thesis, suggest that parkrunners run faster over 5 km when in the presence of close social relationships (Analysis A and Analysis B) and when socially integrated (Analysis C). However, these results are observational in nature, relying on constructs of social support and integration that may be independent of parkrunners' actual perceptions. This study aimed to overcome these issues by further investigating the hypothesised effects of social support on 5 km run times and experiences at parkrun. It used a repeated-measures survey of UK-based parkrunners to gather data on the presence of close social relationships and perceptions of support and integration on a given day at parkrun. Variables hypothesised to mediate or moderate the relationship between these social predictor variables and performance outcomes were also measured. Felt energy was shown to mediated indirect ergogenic effects of the social predictor variables on 5 km run times. These findings are largely in accordance with the findings presented in Chapter 4, and with previous research linking social support to self-efficacy and feelings of energy.

## 5.1 Introduction

The results of the big data analysis of parkrun presented in Chapter 4 suggest that social integration and perceptions of social support lead parkrunners to run faster 5 km times. These findings were observational in nature, however, leading to the possibility that the social support and integration variables used to predict parkrunners' 5 km run times did not actually reflect parkrunners' perceptions. To measure behaviours and perceptions more directly, I conducted a longitudinal survey of UK-based parkrunners. The aim of this survey was to compile run-specific self-reports from parkrunners' on their pre-run sociality, perceptions of support and integration into the parkrun community, and their experiences during their runs. These data were then used to both confirm findings of the big data analyses presented in Chapter 4, and to identify potential moderator and mediators of the hypothesised relationships among social support, experiences, and 5 km run times at parkrun.

The longitudinal, survey-based approach employed here will offer a more detailed data set to complement the big data findings presented in Chapter 4. As reviewed in Chapter 4, parkrun strives to create a welcoming, supportive community that encourages participation from a wide demographic of runners (Hindley, 2018; Stevinson et al., 2014). Individual parkrunners can thus experience social support from running in the presence of friends, family, or partners, from social integration into the parkrun community, or from a combination of these factors (Holt-Lunstad & Uchino, 2008). This context provides an optimal real-world opportunity to investigate the central claims developed in this thesis. These claims are reviewed again briefly below, before the predictions and design for the current survey study are presented.

During strenuous physical exercise, cues to supportive social environments can lead to reductions in the adaptiveness of protective functions like pain, fatigue, and lethargy, owing to evolutionary associations of these environments with safety, well-being, and resource abundance (see Section 2.2, p. 45). Given their role in both exercise self-regulation (e.g., Amann et al., 2009; Raichlen et al., 2012; Raichlen et al., 2008) and in signalling the presence of bonded social relationships (e.g., Inagaki et al., 2016; Kikusui et al., 2006; Trezza et al.,

2010), the endocannabinoid and endogenous opioid systems offer two distinct yet similar pathways through which cues to social support could affect exercise outputs (see Section 2.2.3, p. 53, for a full version of this argument). Research suggests that relatively enhanced activity in these systems can lead to reductions in pain, fatigue, and lethargy, and increases in motivation, positive affect, enjoyment, and energy (Beedie & Foad, 2009; Boecker et al., 2008; Dietrich & McDaniel, 2004; Pollo et al., 2008; Raichlen et al., 2012). Through these analgesic, rewarding effects, endogenous opioid and endocannabinoid activity during strenuous physical exercise are thought to enhance motivation, positive experiences, and performance (Boecker et al., 2008; Raichlen et al., 2012).

The effects of social support on strenuous physical exercise are also likely to be moderated by several factors. In Section 2.2.5 (p. 69), I suggest that physical outputs depend most on self-regulatory processes when individuals are nearing their psychophysiological limits (Noakes, 2012). Given that the endogenous opioid and endocannabinoid systems are known to respond to social cues (Dunbar, 2012; Inagaki et al., 2016; Trezza et al., 2010), and that both are thought to be involved in self-regulation during physical exercise (Boecker et al., 2008; Dietrich & McDaniel, 2004), it is likely that social support effects are strongest when individuals are pushing themselves to produce their maximum physical outputs. As discussed in Section 1.4.1 (p. 19), research also suggests that some individuals will be more attuned to social support than others, such as individuals who rely on others at relatively high levels, or those who feel particularly socially disconnected (e.g., Lee & Robbins, 1995).

Here, I report the results of the first longitudinal study to test the effects of (self-reported) social variables on both physical performance and experiences among ordinary exercisers in a naturalistic setting. In addition to the survey, I used publicly available data from the parkrun website to acquire information on parkrunners' age, finishing rank, and 5 km run times for each time they filled out the survey. The survey provided repeated measures of the other main outcome variables of interest (i.e., in addition to 5 km run times) – participants' perceptions of fatigue and enjoyment. It also provided repeated measures of several predictor variables

related to social support – who participants attended parkrun with, their social behaviour before their runs, and how much they felt integrated in and supported by the parkrun community (this was combined into one variable, the parkrun community component, see Section 5.3.3, p. 162). Finally, the survey collected repeated measures of potential moderating (motivations for attendance, who participants ran with) and mediating (how energised participants felt, how much physical effort they put forth) variables. The survey was designed to be as comprehensive as possible while adhering to parkrun's request that the study not burden its participants (i.e., that it take less than 5 min to complete); participants filled out a 14-question survey immediately following their runs at parkrun over a four-month period.

### 5.1.1 Hypotheses

Specific hypotheses are presented in Table 5.1. Generally, I hypothesise that social support and integration at parkrun lead to reductions in perceptions of fatigue, higher levels of energy and positive affect, and, ultimately, faster 5 km run times. These effects may be shown in three ways: (a) through faster running times at equivalent levels of fatigue, (b) through reductions of fatigue at equivalent running times, or (c) through both faster running times and lower levels of fatigue (see). Given my prediction that social support and integration effects on fatigue will result from activity in the endogenous opioid and endocannabinoid systems, and that activity in both these systems has been associated with positive affect, I also expect social support to predict how much parkrunners enjoy their runs (Boecker et al., 2008; Raichlen et al., 2013). Regarding the quality of social support more specifically, and in line with previous research showing that the analgesic effects of social support are strongest in close, supportive relationships (Master et al., 2009), I hypothesise that the closest social relationships will have the strongest effects on perceptions of fatigue and 5 km run times.

I also predict that several variables will moderate and mediate the effects of social support. Regarding potential moderators, two variables may make parkrunners more susceptible to the effects of social support, as these variables indicate that participants are more tuned to social cues, or that they will find their runs to be more difficult. The moderating variable predicted to

**Table 5.1** Hypotheses

| | |
|---|---|
| | **Main effects of social predictors on 5 km run times** |
| **Hypothesis 1.1** | Coming or meeting up with friends/family (v. coming alone) predicts faster run times. |
| **Hypothesis 1.2** | Higher scores on the parkrun community component will predict faster run times. |
| **Hypothesis 1.3** | Being social (v. not being social) before the run will predict faster run times. |
| | **Main effects of social predictors on fatigue levels** |
| **Hypothesis 2.1** | Coming or meeting up with friends/family will predict lower levels of fatigue. |
| **Hypothesis 2.2** | High scores on the parkrun community component will predict lower levels of fatigue. |
| **Hypothesis 2.3** | Being social (v. not being social) before the run will predict lower levels of fatigue. |
| | **Main effects of social predictors on enjoyment levels** |
| **Hypothesis 3.1** | Coming or meeting up with friends/family will predict higher enjoyment levels. |
| **Hypothesis 3.2** | High scores on the parkrun community component will predict higher enjoyment levels. |
| **Hypothesis 3.3** | Being social (v. not being social) before the run will predict higher enjoyment levels. |
| | **Moderators of main effects of social predictors on run times and perceptions of fatigue** |
| **Hypotheses 4.1 – 4.3** | Effects of the social predictor variables (Hypothesis 4.1: coming or meeting up with friends/family \| Hypothesis 4.2: parkrun community component \| Hypothesis 4.3: pre-run sociality) on run times will be stronger among those who were primarily motivated to attend parkrun so that they could run together with other people. |
| **Hypothesis 4.4 – 4.6** | Effects of the social predictor variables (Hypothesis 4.4: coming or meeting up with friends/family \| Hypothesis 4.5: parkrun community component \| Hypothesis 4.6: pre-run sociality) on fatigue levels will be stronger among those who sped up to run with their running partner(s). |
| | **Mediators of main effect of social predictors on run times** |
| **Hypotheses 5.1 – 5.3** | Scoring high on the social predictor variables (Hypothesis 5.1: coming or meeting up with friends/family \| Hypothesis 5.2: parkrun community component \| Hypothesis 5.3: pre-run sociality) will predict higher energy levels, and higher energy levels will predict faster run times. |

affect susceptibility to social cues is how much a participant focused on the social aspects of parkrun as motivation for attendance, as individuals who look to others for support are likely to be most susceptible to social support effects (e.g., Lee & Robbins, 1995). The moderating variable predicted to be related to difficulty is whether or not participants ran faster (than their

usual pace) to keep up with a faster running partner, as participants are likely to find their runs to be more difficult when they are nearing their psychophysiological limits.

In addition to these predictions, I will examine which aspects of participants' exercise experiences mediate relationships between the social support and integration variables and parkrunners' 5 km run times. Two potential mediators of interest are how energised participants feel as a result of being with the parkrun community and how much physical effort they put into their runs. As well as being associated with positive affect, endogenous opioid and endocannabinoid activity are thought to lead to feelings of 'boundless energy' during exercise (Boecker et al., 2008; Dietrich & McDaniel, 2004). Research has described the mood of energy as "positive feelings about the capacity to complete mental or physical activities" (p. 229; O'Connor & Puetz, 2005). As such, feelings of energy, which constitute a separate psychological construct from fatigue, are an important predictor of physical performance (O'Connor & Puetz, 2005), and may therefore influence participants' run times (see Section 2.2.3.1, p. 53, for a further discussion of the concept of felt energy). Concerning physical effort, previous work has shown that perceptions of social support are important in increasing motivation at parkrun (Stevinson et al., 2014), suggesting that increases in effort might mediate the relationship between social support variables and participants' 5 km run times.

## 5.2 Methods

### 5.2.1 Participants

Participants were recruited from six parkrun sites in southern England (UK): Oxford, Abingdon, Didcot, Reading, Harcourt Hill, and Fulham Park, beginning on January 23, 2016 and ending on March 12, 2016. I attended each location at least once over this seven-week period to recruit participants. Participants were thus recruited either in person or through parkrun event webpages. After agreeing to participate and giving informed consent, participants were sent a link to the survey beginning on the first Saturday after which they had given their consent to participate and ending on May 28, 2016, thus making 18 the maximum number of survey

responses (repeated measures) from a participant. The informed consent form (read as either a hard copy at their event or online) conveyed to them that their participation in the study was voluntary and that their involvement should not affect their attendance to parkrun (see Appendix C, Figure C 1, p. 359). The form stated that participants should attend parkrun as usual during the study period (weekly, biweekly, sporadically, etc.) and respond to the survey when they did so, although it was made clear that they were not *required* to respond to the survey each time they attended a parkrun (this was done to meet the request of the parkrun Research Board that the study be as minimally intrusive as possible). In total, 188 parkrunners signed up to receive the survey link. Of these 188 potential participants, 144 filled out the survey at least once, and these participants filled out 736 usable surveys (see Sections 5.3.1, p. 159). This study was approved by both the parkrun Research Board and the School of Anthropology and Museum Ethnography Research Ethics Committee, University of Oxford (reference number: SSH_SAME_C1A_15_084). Data collection did not continue after data analysis.

### 5.2.2 Survey procedure

The parkrunners who signed up to participate in the study were given the option of receiving the link to the survey through email, text, or post (no participants chose post). Survey links were sent out at 9:45 a.m. every Saturday from January 30, 2016 to May 28, 2016, and participants were instructed to complete the survey as soon as possible after their run (all parkruns begin at 9:00 a.m.; parkrunners thus received the survey following their run).

The survey consisted of 14 questions in total and was conducted using Qualtrics' desktop and mobile platforms. Participants first entered their name and parkrun ID. This was followed by the question: "Besides other motivations you might have had for attending parkrun today, which of the following options best applies to you? I was motivated to… (a) improve my ranking; (b) improve my time; (c) run together with other people." Only one response option was permitted.

The next eleven questions were asked in a randomised order for each iteration of the survey. On seven-point Likert Scales (1 – *not at all*, 7 – *very much*), participants were asked about their experience at parkrun on the day: “How much did you feel supported by the parkrun community today?”, and “How much did you feel you were a part of the parkrun community today?” (based on the findings of Stevinson et al., 2014). Participants were also asked about their energy and fatigue levels using questions adapted to the parkrun context from the Profile of Mood States items measuring ‘Vigour-Activity’ and ‘Fatigue-Inertia’ (Grove & Prapavessis, 1992; McNair, 1971): “How much did you enjoy your run today?”, “How energising did it feel to be with the other parkrunners today?”, and “How physically fatigued did you feel during your run today?” (if participants answered with a 5 or greater on the seven-point Likert Scale for this question, they were asked, using the same scale, “How physically painful did this fatigue feel?”). As a measure of their effort levels – since parkrun accommodates runners giving whatever amount of effort they chose – participants were also asked to “Please rate your feeling of exertion (how much physical effort you felt you were giving) during your run today.”, with response options following the Borg Rating of Perceived Exertion scale (Borg, 1982) (see Appendix A, Figure A 2, p. 292).

Participants were also asked to describe certain social aspects of their run: “Please choose the answer that best describes your run today. “Today I ran… (a) on my own; (b) alongside one or more acquaintances; (c) alongside one or more friends/family members; (d) alongside a mix of acquaintances and friends/family members,” and “Which of the following best applies to you? (a) Today I slowed down for my running partner(s); (b) Today I sped up for my running partner(s); (c) Today my natural pace was pretty much the same as the pace of my running partner(s); (d) Not applicable – I ran on my own.”

Finally, participants answered two questions on their sociality before the run. “Please choose the option that best describes what you were doing just before you went to the start line today; (a) Getting ready or hanging out on my own; (b) Getting ready or hanging out with others; (c) Something else (e.g., rushing to get the start line, chatting on my phone, etc.).” and “Did you

come along with, or meet up with, anyone else at parkrun today? Please choose the answer that best applies to you. Today I came/met up with… (a) nobody else; (b) one or more acquaintances; (c) one or more friends/family members or a mix of acquaintances and friends/family members."

### 5.2.3 Data acquisition

A Python script was used to reduce the data set created in Section 4.2 (p. 108), to include only runs from recruitment locations spanning the survey dates (see Section 5.2.2).

#### 5.2.3.1 Participant age and run times

In order to supplement the survey data, I matched – again using Python – participants' parkrun ID numbers and survey dates to specific entries in the data set created above, and found their run time, finishing rank, age, and gender data[28]. Age data are grouped according to age categories pre-determined by parkrun; the data set thus contains an age category for 18 – 19 year olds, and then categories spanning four years (20 – 24, 25 – 29, etc.) up to 75 – 79.

## 5.3 Results

### 5.3.1 Survey responses

In total, there were 734 survey responses (after removal of duplicates) from 143 participants (see Figure 5.1); 49% of participants were female ($n$ = 70), and females filled out 46% of all surveys used in the analyses below ($n$ = 341). Participants filled out the survey an average of 5.09 times (median = 4, $SD$ = 4.02, range = 1 – 17). The mean age of participants (assuming participants' age was at the midpoint of their age category) was 48.27 years (median = 47, $SD$ = 11.90, range = 18.50 – 77).

[28] The script matched survey responses to runs in parkrun's online database for 617 of 765 survey responses. The unresolved 148 responses were calculated manually (31 responses were duplicates or provided an unmatchable name and parkrun ID number, and the remaining 117 were from parkrunners who ran at locations different from the recruitment locations). Duplicate responses – multiple responses from the same participant on the same day – were removed from the data set (in this case, the participant's first full response was maintained in the data set).

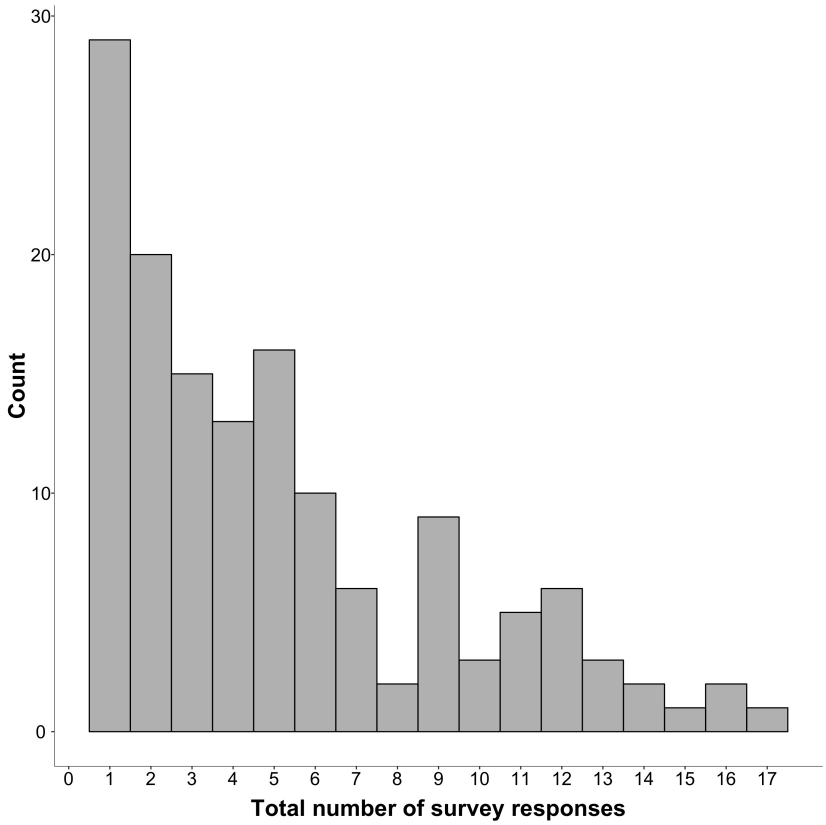



**Figure 5.1** Histogram of participants' total survey responses.

The median time taken to return completed surveys was 4 hr 32 min, meaning that a survey with the median completion time was submitted at 2:17 p.m. on the day of the parkrun. The distribution, however, was highly positively skewed (skewness = 2.98), with a range of 4 min 17 s to 166 hr 31 min, and a mean of 15 hr 32 min (*SD* = 26 hr 38 min). Of the 734 survey responses, 195 (27%) were returned within 2 hr, 585 (80%) within one day, 664 (90%) within two days, and 717 (97%) within four days (see Figure 5.2a). Regarding how long it took participants to complete the survey once starting it, the median completion time was 2 min 39 s (*M* = 14 min 41 s, *SD* = 150 min 40 s, range = 56 s – 43 hr 10 min); 87% of surveys were completed in under 5 min, and 96% were completed in under 10 min[29] (see Figure 5.2b).

[29] Of all completed surveys included in analyses, 3% took longer than 30 min to complete. This is likely due to one of two reasons, both relating to the fact that start times were derived from when participants first clicked on the link to the survey. Participants with unusually long completion times may have either clicked the link, but then delayed actually completing it, or completed the survey, but then delayed actually submitting it.

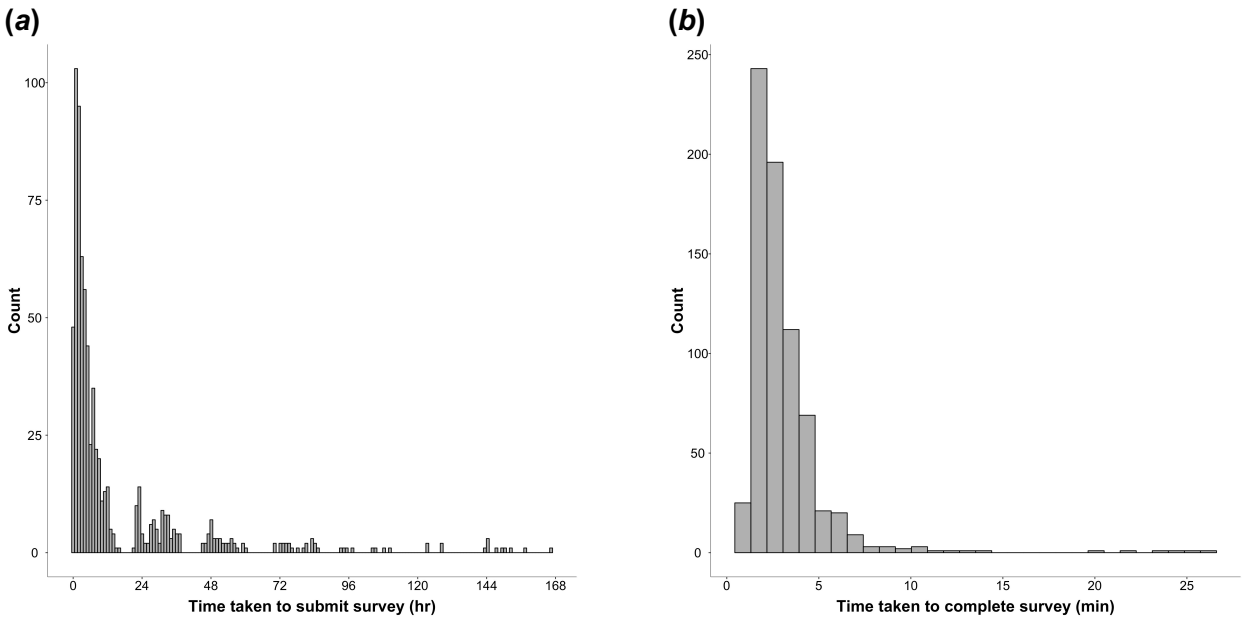



**Figure 5.2** Histograms of (*a*) time taken (from the nearest Saturday at 9:45 a.m.) to return completed surveys and (*b*) time taken to complete the survey (measured by the time participants clicked on the link to the survey to the time they submitted their final answer); all surveys that took longer than 30 min were excluded from the histogram to facilitate its interpretation (see footnote 29).

### 5.3.2 Descriptive statistics

The majority of survey responses indicate that participants were motivated to attend parkrun for social reasons, "to run together with other people" (*n* = 448, 61%), rather than competitive reasons, "to improve my time" (*n* = 268, 37%) and "to improve my ranking" (*n* = 18, 2%). The majority of responses (*n* = 497, 68%) were for runs where participants reported running without a partner or companion, followed by "alongside one or more friends/family members" (*n* = 106, 14%), "alongside one or more acquaintances" (*n* = 85, 12%), and "alongside a mix of acquaintances and friends/family members" (*n* = 47, 6%). In the majority of surveys, participants reported coming or meeting up with friends and family, or a mixture of friends, family, and acquaintances (*n* = 394, 54%), versus coming or meeting up with one or more acquaintances (*n* = 202, 28%) or coming on their own (*n* = 138, 19%). Regarding what participants were doing just before the run (henceforth 'pre-run sociality'), the response most frequently chosen was 'getting ready or hanging out with others' (*n* = 462, 63%), as compared to 'getting ready or hanging out on my own' (*n* = 189, 26%) or doing something else (*n* = 83,

11%). For the purpose of the inferential analyses reported below, I created binary categories for the variables on who participants came or met up with and their pre-run sociality: either coming or meeting up with friends/family ($n$ = 394, 54%) or not ($n$ = 340, 46%) and either being social before the run ($n$ = 462, 63%) or not ($n$ = 272, 37%).

Although informative of the survey results as a whole, this descriptive picture should be interpreted with caution when considering parkrun more generally, as it is most heavily influenced by those participants who answered the survey the most times (see Figure 5.1).

### 5.3.3 Relationship with the parkrun community

Responses to the following two questions relating directly to the parkrun community were highly correlated ($r$ = .72): “How much did you feel supported by the parkrun community today?” and “How much did you feel you were a part of the parkrun community today?”. A principal components analysis (PCA) was used to test the relationship between these two variables, based on the hypothesis that the questions on support and inclusion would load onto a component related to social support from the parkrun community. Although an assumption of PCA is independence of data, which is violated by repeated measures designs, research has shown that PCA without accounting for serial correlation is acceptable (i.e., leads to negligible biases) when there are more than 30 level-two units (participants in this case), the correlations between the variables are high, and researchers are only interested in the first principal component (Jiang & Eskridge, 2000). This is the case in this instance, as there are 143 participants, the correlations between the variables are high ($r$ = .72), and only one potential component was of interest.

Preliminary checks confirmed the usefulness of PCA in this context. Bartlett’s test was highly significant, indicating that PCA is appropriate for these variables, $\chi^2$ (1) = 533.39, $p$ < .001. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy (MSA’s = 0.5, due to there only being two variables) suggested that the sample size and data were acceptable for PCA, and the determinant of the correlation matrix was unproblematic (0.482).

The one component extracted from the two variables had a Kaiser's criterion of 1.72, explained 86% of the variance in answers to the two questions, and had a relatively high level of reliability (Cronbach's alpha = .840). I took this component as representing the perceived strength of participants' relationship with the parkrun community. I used this variable as a social predictor of the outcome variables of interest and called it the 'parkrun community component.'

### 5.3.4 Inferential statistics

The R packages *lme4* (Bates et al., 2014) and *lmer* (Kuznetsova et al., 2015) were used to carry out the primary analyses. Marginal $R^2$ ($R^2_m$ and $R^2_c$) were calculated using functions from the *piecewiseSEM* package in R (Nakagawa & Schielzeth, 2013). The R packages *mediation* (Tingley, Yamamoto, Hirose, Keele, & Imai, 2014) and *lme4* (Bates et al., 2014) were used to carry out the multilevel mediation analyses, which employed bias-corrected and accelerated (BCa) bootstrap-based confidence intervals. Assumption checks were carried out in accordance with the methods suggested by Snijders and Bosker (2012) and Bauer, Preacher, and Gil (2006), and are reported in Appendix C, Section 1 (p. 315).

### 5.3.5 Multilevel model selection

Due to the nested nature of the data (survey and run data within participants) I used a multilevel linear regression model with participants as the level-two variable, allowing maximum random effects structures when possible (Barr et al., 2013).

Studies have shown biases in slope and intercept variance estimates when the number of level-one units (here: survey responses and 5 km run data) per level-two unit (here: participants) is small (Bell, Ferron, & Kromrey, 2008). However, in a Monte Carlo study, Bell et al. (2008) showed that this does not affect fixed effects estimates: "the proportion of singletons[30] (up to .70) had no notable effect on the estimation of fixed effects for the level-

[30] In the present study, a singleton is a participant with only one survey response. Of the 143 participants included in analyses, 29 answered the survey only once (21%); see Figure 5.1 (p. 160).

one predictors, but evidenced a clear impact on the interval estimation of the parameters for the level-two predictors" (p. 4060; Bell et al., 2008). Bell et al. (2008) go on to report that:

> with smaller levels of level-two units (less than 500), increases in the proportion of singletons led to a reduction in the accuracy of the confidence intervals for level-two predictors and bias in Type I error control of the binary level-two predictor, but did not impact the accuracy of the estimates for level-one predictors (p. 4,063).

Thus, estimates for the predictor variables of interest (all at level-one) should not have been affected by the large proportion of singletons in the data set.

Models were first fit using maximal random effects structures where possible. When models failed to converge, random effects structures were simplified (eliminating random effects for covariates; smallest random effects variance first, and then the social predictor variable, if necessary) until convergence was achieved (Barr et al., 2013)[31]. Logged 5 km run times were used to improve model fits. The 5 km run times models also included as covariates participants' reported exertion levels and whether or not they slowed down to run with their running partner(s). Regarding models on participants' perceptions of fatigue, these included logged 5 km run times as a covariate. These covariates were included to control for effort and output levels, respectively.

### 5.3.6 Family-wise error rates and multiple comparisons corrections

When testing families of comparisons (hypotheses) it is necessary to control for the increased probability of making a Type I error as a result of conducting multiple hypothesis tests (Benjamini & Hochberg, 1995; Bonferroni, 1936; Field, Miles, & Field, 2012). Table 5.1 (p. 157) shows that this study has five separate families of hypotheses. These families of hypotheses test how three separate but related social predictor variables (meant to represent

[31] See Section 4.4.1.1 (p. 115) for a justification and explanation of the procedures followed when a model failed to converge.

the presence of social support and cohesion at parkrun) predict 5 km run times (1.1 – 1.3), fatigue (2.1 – 2.3), and enjoyment (3.1 – 3.3) at parkrun, and how the effects of these predictors are moderated (4.1 – 4.3 and 4.4 – 4.6) and mediated (5.1 – 5.3) by parkrunner characteristics and emotions. Since the general hypothesis underlying each family is tested three times (once for each of the three social predictor variables), there is an inflated probability of Type I error.

There are many ways to control for increased Type I error rates associated with making multiple comparisons. The most common is the Bonferroni correction (Bonferroni, 1936), although this procedure has been shown to be extremely conservative, leading to low power for detecting true relationships between predictor and outcome variables (Cribbie, 2007). Multiple alternatives to the Bonferroni correction are available. The procedures proposed by Benjamini and Hochberg (1995) are particularly useful in controlling the 'false discovery rate' (FDR) – "the expected proportion of errors among the rejected [null] hypotheses" (p. 291) – while allowing for more power to detect true effects, as compared to the more conservative Bonferroni correction. More importantly, research from Benjamini and Yekutieli (2001) suggests that this procedure will appropriately control the FDR when hypothesis tests are dependent (as they are likely to be within the hypothesis families described above – the social predictor variables will likely be correlated and they are hypothesised to have similar relationships with the outcome).

As a result of their appropriateness for this particular study, the analyses reported below will use the procedures of Benjamini and Hochberg (1995) in determining critical values for each of the three tests in the five families in Table 5.1. The procedure calls for *p*-values in a family of tests to be ranked in ascending order (e.g., 1. $P < .001$, 2. $p = .045$, etc.) and then compared to a critical value calculated as:

$$(i / m) \times Q$$

where i is the ordered rank of the *p*-value, m is the total number of tests in the family, and Q is the desired false discovery rate. In this study, m is always three (since each family consists of three hypothesis tests) and Q is always (a conservative) rate of 0.05. Thus, for this study, the critical values for each family of hypotheses are .017, .033, and .050 for the first, second, and third ranked *p*-values, respectively. Finally, critical values are compared to their corresponding *p*-values, starting with the lowest ranked (largest) *p*-value; all *p*-values lower than their critical values are accepted as significant, as are all *p*-values with ranks higher than the first *p*-value accepted as significant, even if they do not meet their respective Benjamini-Hochberg adjusted critical value (Benjamini & Hochberg, 1995).

While this procedure is relatively straightforward for the families of comparisons compromising Hypothesis 1.1 – Hypothesis 4.6, it is less clear how it applies to mediation models, which test three separate, but related, pathways; indirect effects, direct effects, and total effects (Hayes, 2013). Little research has been done on correcting for multiple comparisons when conducting (multilevel) mediation analyses (Cribbie, 2007). Given the lack of an established procedure, I will treat each type of effect (indirect, direct, and total) as a sub-family of tests when accounting for multiple comparisons for Hypothesis 5.1 – Hypothesis 5.3, as the procedures used here are essentially testing whether the social predictor variables have significant indirect, direct, and/or total effects on 5 km run times. This will lead to, for example, the three indirect (or direct or total) effects generated from the tests of Hypothesis 5.1 – Hypothesis 5.3 being subjected to the procedures of Benjamini and Hochberg (1995) described in the previous paragraph.

### 5.3.7 Main effects of social predictor variables

Multilevel models were used to test the main effects of the social predictor variables (i.e., who participants came or met up with, the parkrun community component, and pre-run sociality) on the main outcome variables of interest; participants' 5 km run times, perceptions of fatigue, and levels of enjoyment (Hypotheses 1.1 – 3.3).

#### 5.3.7.1 Hypotheses 1.1 – 1.3

First, I tested whether the social predictor variables predicted parkrunners' 5 km run times, using Benjamini-Hochberg adjusted critical values. Whether or not participants came or met up with friends/family (versus coming alone or coming or meeting up with only acquaintances), $b = -0.007$, $SE = 0.006$, $t(611.1) = -1.24$, $p = .216$, did not significantly predict run times (Hypothesis 1.1). The parkrun community component did not significantly predict run times, $b = 0.004$, $SE = 0.003$, $t(68.3) = 1.63$, $p = .108$ (Hypothesis 1.2). Finally, participants' pre-run sociality, $b = 0.002$, $SE = 0.006$, $t(607.2) = 0.33$, $p = .742$, also did not significantly predict run times. See Appendix C, Table C 1 – Table C 3 (pp. 335 – 337), for full model summaries.

#### 5.3.7.2 Hypotheses 2.1 – 2.3

I then tested, again using Benjamini-Hochberg adjusted critical values, whether the social predictor variables predicted runners' perceptions of fatigue. Coming or meeting up with friends/family (versus coming alone or with acquaintances) predicted lower levels of fatigue, while controlling for 5 km run times, $b = -0.220$, $SE = 0.108$, $t(77.5) = -2.04$, $p = .045$ (Hypothesis 2.1, Table 5.2), but not at its Benjamini-Hochberg adjusted critical value of .0167. Neither the parkrun community component, $b = 0.090$, $SE = 0.063$, $t(74.9) = 1.42$, $p = .159$ (Hypothesis 2.2), nor participants' pre-run sociality, $b = -0.006$, $SE = 0.100$, $t(289.8) = -0.06$, $p = .951$, predicted levels of fatigue (Hypothesis 2.3); see Appendix C, Table C 4 – Table C 5 (pp. 338 – 339).

#### 5.3.7.3 Hypotheses 3.1 – 3.3

Next, I tested whether the social predictor variables were related to how much participants enjoyed their runs. Whether or not participants came or met up with family/friends, $b = 0.230$, $SE = 0.086$, $t(714.2) = 2.67$, $p = .008$ (Hypothesis 3.1), the parkrun community component, $b = 0.439$, $SE = 0.039$, $t(673.6) = 11.21$, $p < .001$ (Hypothesis 3.2), and participants' pre-run sociality, $b = 0.346$, $SE = 0.100$, $t(80.7) = 3.47$, $p < .001$ (Hypothesis 3.3), all positively predicted how much participants enjoyed their runs. All effects were significant at their

**Table 5.2** Effects of who participants came or met up with on perceptions of fatigue (Hypothesis 2.1)

| **Variable** | ***b*** | ***SE*** | ***t*(df)** | ***p*** |
|---|---|---|---|---|
| Intercept | 12.523 | 1.089 | 179.64 (11.50) | < .001 |
| Came or met up with family and/or friends | −0.220 | 0.108 | −2.04 (77.49) | .045 |
| Logged run 5 km run time | −2.321 | 0.331 | −7.02 (181.31) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 104.983 | 10.246 | | |
| Came or met up with family and/or friends | 0.200 | 0.448 | | |
| $R^2_m$ = 0.126, $R^2_c$ = 0.439 | | | | |

respective Benjamini-Hochberg adjusted critical values. See Appendix C, Table C 6 – Table C 8 (pp. 340 – 342), for full model summaries.

### 5.3.8 Moderators of social predictor variables

Tests on whether certain variables moderated the main effects of the social predictor variables were carried out by adding an interaction term between the social predictor variables and categorical variables representing potential moderators. Significant interaction terms would suggest that the variable moderates the relationship between the social predictor variable and participants' 5 km run times or perceptions of fatigue.

#### 5.3.8.1 Hypotheses 4.1 – 4.3

Whether or not participants were motivated to attend parkrun for social reasons – "to run together with other people" – or competitive reasons – "to improve my time" and "to improve my ranking" – didn't moderate any of the relationships between the social predictor variables and 5 km run times. For all analyses, the interaction terms were not significant at Benjamini-Hochberg adjusted critical values (all $p > .05$); see Appendix C, Table C 9 – Table C 11 (pp. 343 – 345).

#### 5.3.8.2 Hypotheses 4.4 – 4.6

Whether or not participants sped up to run with a running partner(s) or not did not significantly moderate, at Benjamini-Hochberg adjusted critical values, any of the relationships between the social predictor variables and participants' perceptions of fatigue (all $p > .05$); see Appendix C, Table C 12 – Table C 14 (pp. 346 – 348).

### 5.3.9 Mediators of social predictor variables

I ran a series of multilevel mediation models to test whether participants' feelings of energy mediated relationships between the social predictor variables and participants' 5 km run times. Bauer et al. (2006) demonstrate that data sets with small numbers ($n < 5$) of observations per level two unit (here, survey responses per participant) do not support models with complex random effects structures and lead to high rates of non-convergence. Given that in the present data set nearly half (48%) of participants responded to the survey fewer than five times, I used a simpler random effects structure for the models in the mediation analyses. This method of mediation involved running one multilevel model with the mediator as the outcome and another with the mediator and a social predictor variable on the outcome of participants' 5 km run times (Tingley et al., 2014). Random effects were included for the social predictor variables only in these models (more complex random effects structures failed to converge). Whether or not participants slowed down to run with their running partner(s) was included as a covariate for models on participants' 5 km run times. Models employed bias-corrected and accelerated (BCa) bootstrap-based confidence intervals (1000 simulations). Run times were logged to improve model fit and interpretation.

#### 5.3.9.1 Hypothesis 5.1

The first mediation analysis tested whether participants' felt energy mediated the relationship between who participants came or met up with and their (logged) run times. Results showed a significant average indirect effect of −0.002 (95% CI: [−0.004, −0.001], $p = .008$), a non−significant average direct effect of −0.005 (95% CI: [−0.020, 0.012], $p = .562$), and a non−significant total effect of −0.006 (95% CI: [−0.022, 0.010], $p = .432$): the relationship

between who participants came or met up with and logged run times was mediated by how energised they felt. The average indirect effect was significant at its Benjamini-Hochberg adjusted critical value.

As shown in Figure 5.3 and Figure 5.4 (H 5.1), those who came or met up with their friends/family at parkrun felt more energized, $a = 0.254$, $SE = 0.080$, $t(678.3) = 3.17$, $p = .002$, and these higher felt energy levels predicted faster logged running times, $b = -0.007$, $SE = 0.003$, $t(609.1) = -2.31$, $p = .022$ (see Appendix C, Table C 15 and Table C 16, pp. 349 – 350, for full model results). In other words, participants who came or met up with their friends/family at parkrun felt more energised, and this lead to a 0.17% decrease in run times, or runs that were 3.43 s faster for parkrunners with run times equal to the overall average (27 min 52 s). The lack of a significant direct effect means that the effect of whether or not participants came or met up with friends/family does not affect run times when controlling for how energised participants felt (Hayes, 2013). Regarding the non-significant total effect, although somewhat rare, it is possible to observe significant indirect effects and non-significant total effects, especially when the effect size of the direct effect is small (as is the case here) or in the opposite direction, since the total effect is the indirect effect plus direct effect (Hayes, 2013; Rucker, Preacher, Tormala, & Petty, 2011).

#### 5.3.9.2 Hypothesis 5.2

The second mediation analysis tested whether participants' felt energy mediated the relationship between their scores on the parkrun community factor and their (logged) 5 km run times. Analysis revealed a significant average indirect effect of −0.007 (95% CI: [−0.011, −0.003], $p < .001$), a significant average direct effect of 0. 012 (95% CI: [0.004, 0.020], $p = .002$), and a non-significant total effect of 0.004 (95% CI: [−0.003 0.011], $p = .220$): how energised participants felt mediated the relationship between the parkrun community component and participants' 5 km run times. The average indirect effect was significant at its Benjamini-Hochberg adjusted critical value.

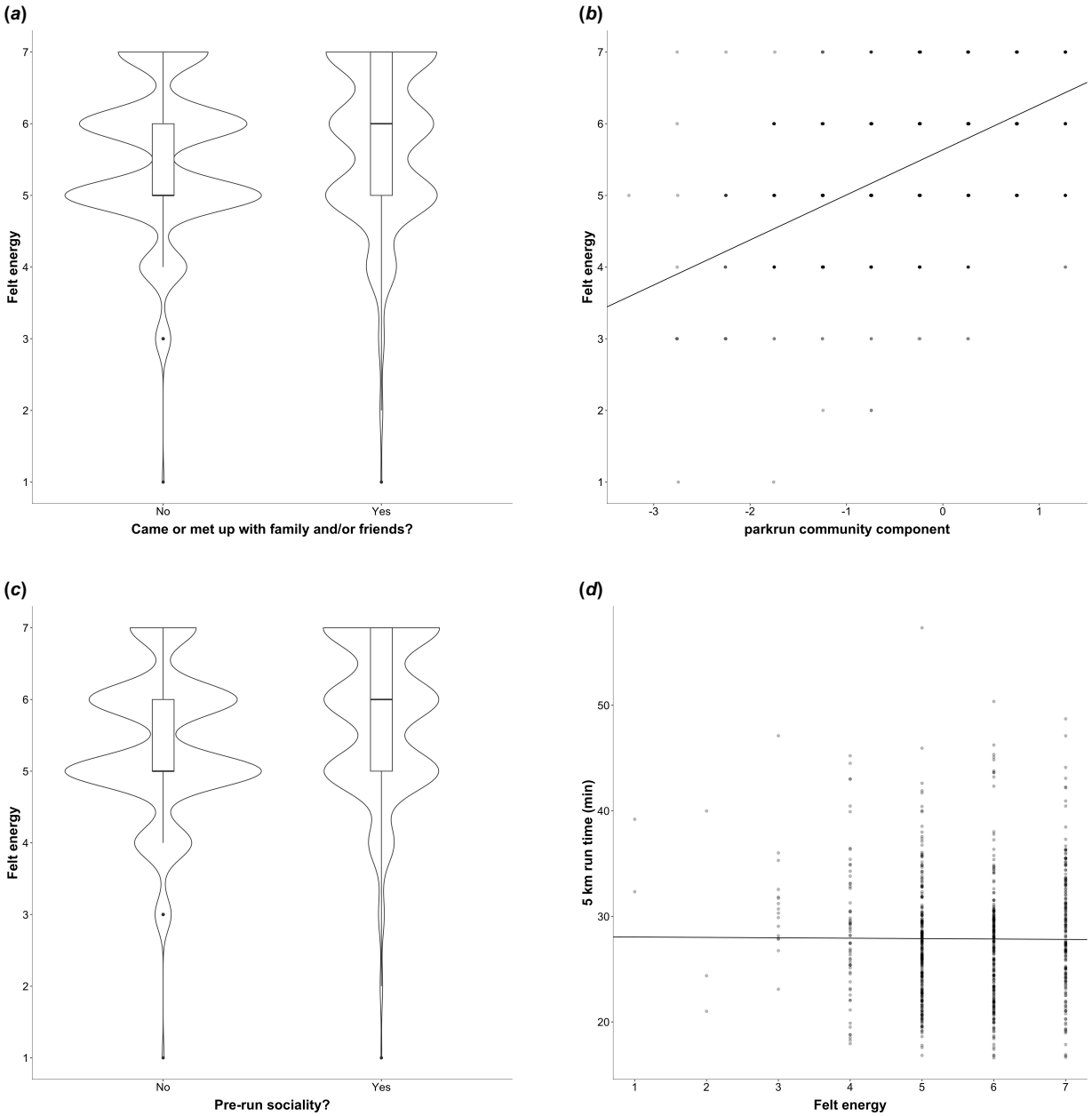



**Figure 5.3** (*a*) Violin plot (with box plot underlay) of the relationship between whether or not participants came or met up with family and/or friends at parkrun and their levels of felt energy, (*b*) scatter plot of the relationship between participants' parkrun community component score and their levels of felt energy, (*c*) violin plot (with box plot underlay) of the relationship between participants' pre-run sociality and their levels of felt energy, and (*d*) scatter plot of the relationship between participants' levels of felt energy and their 5 km run times.

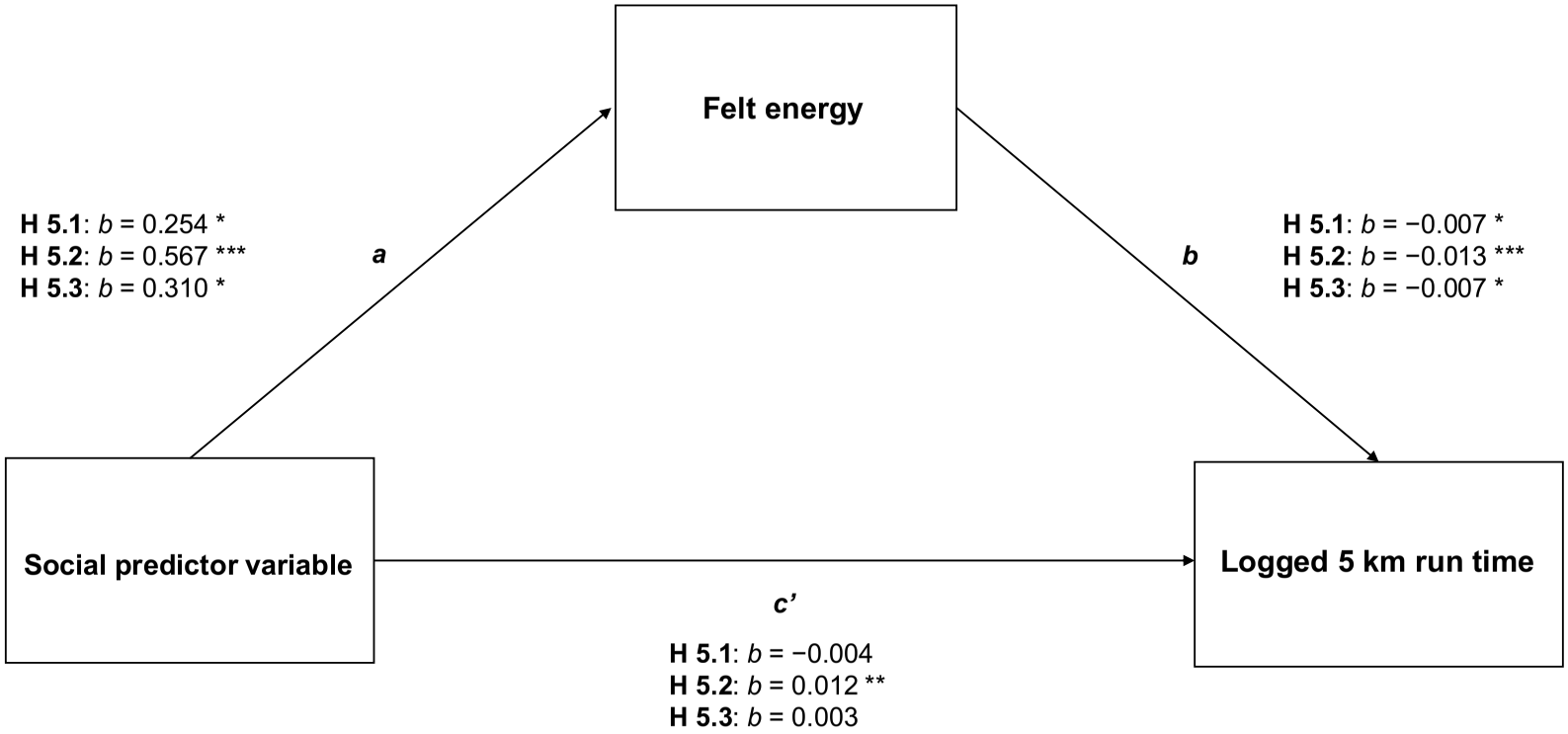
As shown in Figure 5.3 and Figure 5.4 (H 5.2), scoring high on the community component predicted increases in felt energy, $a = 0.567$, $SE = 0.042$, $t(101.6) = 13.38$, $p < .001$, and these higher felt energy levels predicted faster logged running times, $b = -0.013$, $SE = 0.003$, $t(582.7) = -3.76$, $p < .001$ (for full model summaries see Appendix C, Table C 17 and Table C

18, pp. 351 – 352). In other words, a one point increase in the parkrun community component led to increased feelings of felt energy, and this lead to a 0.74% decrease in run times, or runs that were 11.70 s faster for parkrunners with run times equal to the overall average. The negative effect of the parkrun community component on run times existed only through its effect on how energised participants felt. The direct pathway is a positive relationship. When controlling for felt energy, there is a significant, positive relationship between the parkrun community component and 5 km run times; increases in the parkrun community component predict *slower* 5 km run times. Since the positive direct effect is of a similar size to the negative effect of the indirect pathway, there is a non-significant total effect of the parkrun community component on 5 km run times (MacKinnon, Fairchild, & Fritz, 2007).

#### 5.3.9.3 Hypothesis 5.3

The third mediation analysis tested whether participants' felt energy mediated the relationship between their pre-run sociality and their (logged) run times. Results showed a significant average indirect effect of −0.002 (95% CI: [−0.005, < 0.001], $p$ = .002), a non-significant average direct effect of 0.003 (95% CI: [−0.011, 0.017], $p$ = .670), and a non-significant total effect of 0.001 (95% CI: [−0.013, 0.015], $p$ = .922). The average indirect effect was significant at its Benjamini-Hochberg adjusted critical value.

As shown in Figure 5.3 and Figure 5.4 (H 5.3), how energized participants felt mediated the relationship between their pre-run sociality and 5 km run times, so that participants who were socialising with others felt more energized, $a$ = 0.339, $SE$ = 0.08, $t$(60.6) = 3.84, $p$ < .001, and these higher felt energy levels predicted faster running times, $b$ = −0.007, $SE$ = 0.003, $t$(612.6) = −2.44, $p$ = .015 (for full model summaries, see Appendix C, Table C 19 and Table C 20, pp. 353 – 354). In other words, pre-run sociality led participants to feel more energised, and this led to a 0.25% decrease in run times, or runs that were 3.43 s faster for parkrunners with 5 km run times equal to the overall average. A lack of significant direct and total effects means that pre-run sociality did not affect run times when controlling for how energised participants felt, or when ignoring (not including in the model) how energised participants felt, respectively




| Model | Indirect effect (*ab*) | Direct effect (*c'*) | Total effect (*c'* + *ab*) |
|---|---|---|---|
| **H 5.1** | −0.002, $p$ = .008 | −0.005, $p$ = .562 | −0.006, $p$ = .432 |
| **H 5.2** | −0.007, $p$ < .001 | 0.012, $p$ = .002 | 0.004, $p$ = .220 |
| **H 5.3** | −0.002, $p$ = .002 | 0.003, $p$ = .670 | 0.001, $p$ = .922 |

**Figure 5.4** Mediation diagram depicting the direct, indirect, and total effects of the social predictor variables – whether or not participants came or met up with family and/or friends (H 5.1), their score on the score on the parkrun community component (H 5.2), and their pre-run sociality (H 5.3) – on 5 km run times, with participants' felt energy as a potential mediator.

*** Statistically significant at $p$ < .001
** Statistically significant at $p$ < .01
* Statistically significant at $p$ < .05

(Hayes, 2013). Again, although somewhat rare, it is possible to observe significant indirect effects and non-significant total effects, especially when the effect size of the direct effect is small or in the opposite direction (both are the case here), since the total effect is the indirect effect plus direct effect (Hayes, 2013; Rucker et al., 2011).

### 5.3.10 Survey response lag time

As discussed in Section 5.3.1, and shown in Figure 5.2a (p. 161), there was a significant amount of lag in participants' response times. Only 27% of surveys were returned within one day of receipt (9:45 a.m. on Saturdays during the study period). While this lag is unlikely to have affected descriptive responses (e.g., who participants reported coming to parkrun with), it may have affected affective responses, such as self-reports of fatigue, felt energy, and enjoyment. To test whether this was the case, I ran four additional multilevel models with logged (to facilitate model fit) response times as the predictor variable (with random effects) and participants' reports of fatigue, felt energy, and enjoyment, and the parkrun community component as the outcomes. None of these variables were significantly related to response times (see Appendix D, Table C 21 – Table C 24, pp. 355 – 358).

## 5.4 Discussion

Using a repeated measures survey design, this study examined social support effects on exercise experiences and performances in a naturalistic, group exercise setting. Participants provided multiple responses over time on a variety of measures related to their motivations for attending parkrun, the availability of social support (represented by the social predictor variables), and their running experiences. These variables allowed for the examination of direct, moderated, and mediated effects of social variables on run times and experiences at parkrun. Results give partial support to my hypotheses, and suggest a more qualified, nuanced theory on how social environments affect experiences and outputs during physical exercise.

Survey results confirmed previous findings of high levels of sociality at parkrun (Hindley, 2018; Stevinson et al., 2014; Wiltshire et al., 2018): in over half of the surveys, participants reported coming or meeting up with friends and family, or a mixture of friends, family, and acquaintances (*n* = 394, 54%). This sociality was shown to have an effect on 5 km run times and experiences. The observed effects of the social predictor variables (who participants came or met up with, their pre-run sociality, and the parkrun community component), which measured different aspects of social support and integration at parkrun, suggest that the presence of supportive, inclusive relationships at parkrun leads to increases in enjoyment and felt energy, which is in line with my hypotheses (Hypotheses 3.1 – 3.3). However, the social predictor variables did not directly predict participants' run times or perceptions of fatigue, with the exception of coming or meeting up with friends/family predicting lower levels of fatigue (Hypothesis 2.1), although this was also not significant at its Benjamini-Hochberg adjusted critical value. It was only through indirect effects that these predictors affected run times (Hypotheses 5.1 – 5.3). Specifically, the social predictor variables were positively related to felt energy levels, and felt energy levels were negatively related to 5 km run times (i.e., relatively higher energy levels were associated with faster 5 km run times).

### 5.4.1 Lack of hypothesised direct effects of social predictor variables on run times

The social predictor variables did not predict run times directly (Hypotheses 1.1 – 1.3); they only predicted run times through increases in felt energy. When there is a significant indirect (mediation) effect but a lack of direct and total effects between three variables, it means that the predictor variable does not significantly affect the outcome variable when controlling for the mediator, and that the predictor only affects the outcome *through* its influence on the mediator variable (Hayes, 2013). For this study, this means that the social predictor variables *only* affected 5 km run times through their influence on parkrunners' felt energy levels. This suggests that the presence of socially supportive others is not sufficient in itself to improve performance in exercise; it matters how support is perceived and received.

For example, research has shown that social support can be deleterious if it communicates to recipients that they are inefficacious (Bolger & Amarel, 2007). This is important considering felt physical energy as a mood state related to an individual's perceived capacity to complete a physically demanding task (O'Connor & Puetz, 2005). If some participants appraised others as supportive generally, but this prompted negative appraisals of their physical competence, they may not have performed better, owing to a lack of felt energy, and, more generally, confidence that they could run the 5 km at a (relatively) high level. Additionally, the presence of others, even family and friends, might not always be experienced as supportive; social comparison and feelings of inadequacy or incompetence could interfere with the hypothesised links between social support and the psychophysiological, self-regulatory mechanisms underpinning fatigue, pain, and physical performance. Other personality (and cultural) factors can affect the receipt of social support. Research has shown that highly neurotic individuals focus on the interpersonal costs of receiving social support while highly independent individuals can react to social support with feelings of compromised independence (Park et al., 2013). These responses have been hypothesised to reduce (or even abolish) the positive effects of social support on coping with stressors (Park et al., 2013; Uchida, Kitayama, Mesquita, Reyes, & Morling, 2008).

Overall, then, it may be that the felt energy variable is an indicator of how social support at parkrun was received by participants; if it was received in a positive manner that gave participants confidence and motivation, then this boosted their felt energy, which led to faster 5 km run times. This seems plausible in a context like parkrun, where motivation to perform is highly variable – parkrun goes to great lengths to reduce any external performance standards, which results in parkrunners setting their own pace on a given day. In contrast, direct effects of social support on physical outputs may more likely exist in ‘high stakes’ contexts, where individuals push themselves to a point where fatigue sets in as a protective ‘brake’ on outputs (see Section 2.2.5, p. 69). In this case, supportive environments might relax this brake, enabling athletes to go faster for longer. However, even in these instances, felt energy might

be an important mediator, due its supposed connections with activity in the endogenous opioid and endocannabinoid systems (Boecker et al., 2008; Dietrich & McDaniel, 2004).

### 5.4.2 Indirect effects of social predictor variables on run times: energy as a mediator

The mediation analyses revealed that all of the social predictor variables of interest had significant indirect negative effects on 5 km run times (Hypotheses 5.1 – 5.3). Via positive effects on energy levels, which predicted faster running times, one unit increases in the social predictor variables led to between 0.17% and 0.74% decreases (depending on the predictor variable) in 5 km run times, so that 5 km runs are between 3.34 s and 11.70 s faster for a participant with a run time equal to that of the overall average of 27 min 52 s (Hayes, 2013). Taken together, these results suggest that, even among those who generally run slower times, it is not social support *per se* that leads to reductions in run times, but rather social support leads to greater feelings of energy, and these feelings of energy predict faster 5 km run times.

All of the social predictor variables predicted how energised participants felt. Felt energy has been described as a mood state associated with greater perceived capacities to complete physically challenging tasks (O'Connor & Puetz, 2005). This is broadly in line with evolutionary theories linking increased physical activity levels with social integration and support, which have historically been associated with safety and resource abundance (Cacioppo, Cacioppo, et al., 2014). These associations make supportive, cohesive social environments optimal for activities that are costly in terms potential harm and bodily resource use, such as strenuous physical exercise. Increased feelings of energy may be the emotional mechanism through which these cues to optimal environments for strenuous physical exertion affect outputs. Future studies could investigate relationships among social support, self-efficacy, and felt energy at parkrun, and in social exercise settings more generally.

Felt energy as a mediator between the social predictor variables and run times is relevant from a mechanistic perspective. Although not tested directly, my hypotheses are based on the claim that perceptions of social support and cohesion lead to increases in endogenous opioid

and endocannabinoid activity, as both of these systems are involved in the formation and maintenance of mammalian social bonds, and, more specifically, feelings of social connection (Dunbar, 2012; Inagaki et al., 2016; Trezza et al., 2010). Importantly, these systems are also involved in the regulation of strenuous physical activity – activation of these systems is thought to facilitate continued strenuous physical activity through counteracting the attenuating effects of fatigue-signalling muscle afferents on central motor drive (Amann et al., 2009; Noakes, 2012). Activity in these systems could thus affect participants' perceptions of energy, as well as their 5 km running outputs. The endorphin and endocannabinoid 'highs' that are underpinned by these systems are said to be felt as 'euphoria' and 'boundless energy'. Participants' responses to the question about felt energy may therefore reflect activity in these systems (Boecker et al., 2008; Dietrich & McDaniel, 2004).

### 5.4.3 Effects of social predictor variables on fatigue

Contrary to Hypotheses 2.2 and 2.3, neither participants' scores on the parkrun community component nor their pre-run sociality predicted fatigue levels. However, coming or meeting up with friends/family at parkrun predicted decreases in perceptions of fatigue during participants' runs (Hypothesis 2.1). Even though this effect was not significant at its Benjamini-Hochberg adjusted critical value, I will discuss what are interesting trend-level effects of this variable on 5 km run times.

An important factor in the effects of social support is the closeness and quality of the relationship between the supporter and the supported (e.g., Coan et al., 2006). Compared to the parkrun community component, which measures support from and inclusion in the broader parkrun community, and participants' pre-run sociality, coming or meeting up with friends and/or family at parkrun is likely the most direct indicator of the presence of close, supportive relationships.

Given that this effect held while controlling for run times, it may be that the presence of friends/family leads to heightened activity in endogenous pain and fatigue modulation

systems. The presence of close others, and even cues to their presence, have been shown to reduce perceptions of pain, a neurological correlate of fatigue (Eisenberger et al., 2011; Master et al., 2009). Further, endogenous opioids have been shown to mediate both feelings of social closeness (Inagaki et al., 2016) and perceptions of fatigue during exercise (Amann et al., 2009). Thus, it may be that the presence of close supportive others at parkrun – in this case, participants' friends and family – led to heightened activity in systems involved in the regulation of fatigue during participants' runs.

Another possible explanation of the null results for the effects of the parkrun community component and pre-run sociality on fatigue levels is that heightened activity in the endorphin and endocannabinoid systems was not best represented by the fatigue measure used. The 'highs' from activity in these systems are often associated with feelings of energy, which often do not correlate highly with fatigue levels (Dietrich & McDaniel, 2004; O'Connor & Puetz, 2005). Indeed, it seems like the measure of fatigue used in this study captured a construct that is distinct from felt energy, as the two variables were only weakly correlated ($r$ = 0.111). Considering the findings on felt energy from this study, it is possible that felt energy is a better construct than fatigue in measuring the psychological states that correlate with activity in endogenous systems involved in the self-regulation of physical outputs. It is also possible that not all forms social support have strong effects on perceptions of fatigue. The emotional and instrumental support provided by present friends/family may have been particularly salient to participants, as compared to the support gleaned from acquaintances or the parkrun community as a whole. Ultimately, however, more research is needed to better understand how different types and sources of social support interact with self-regulatory mechanisms during strenuous physical exertion to affect individuals' motivation and perceptions of pain, fatigue, and energy.

### 5.4.4 Effects of social predictor variables on enjoyment levels

As hypothesised (Hypotheses 3.1 – 3.3), the survey results suggest that pre-run sociality, the presence of family/friends, and feeling supported and included in the parkrun community led

participants to enjoy their runs more. This could be interpreted in multiple (complementary) ways. For example, the enjoyment associated with the social predictor variables could be explained by the neurological reward of positive social interactions (Acevedo et al., 2012; Inagaki & Eisenberger, 2013), which likely correlate positively with the social predictor variables. This is not incongruent with the claim that perceptions of social support at parkrun increase activity in the endogenous opioid and endocannabinoid systems, leading to positive affect and reductions in the unpleasantness of strenuous physical exercise, as these systems are also involved in social reward (Boecker et al., 2008; Inagaki & Eisenberger, 2013; Inagaki et al., 2016; Raichlen et al., 2012; Trezza et al., 2010). This finding is also in line with observational research showing that perceptions of social support and cohesion at parkrun can lead runners to have more positive experiences (Stevinson et al., 2014).

### 5.4.5 Limitations

The results of this study should be considered in light of its limitations. These limitations stem from the difficulties of making causal inferences from observational data and a lack of validated measures in the survey. Further, there are issues with generalising from a survey sample that is likely influenced by the relatively few individuals who answered the survey many times, and with the suitability of the sample (mostly casual runners) for investigating the hypotheses of this thesis. Finally, competition is a potential confound that could explain some of the main findings of this study.

#### 5.4.5.1 Causal inference

The study was observational in nature and causality can only be inferred. There were also logistical constraints on the collection of data. Surveys were sent out 45 min after the beginning of each parkrun (i.e., on every Saturday morning at 9:45 a.m. for the duration of the study). Although parkrun posts run times on its websites up to one day after a run's completion, it is likely that some participants knew their 5 km run times before completing the survey, as some parkrunners track their times on personal watches, and some completed the survey after run times were posted. The median time taken to return the survey was around 4.5 hr,

and 20% of surveys were returned over 24 hr after they were received (again, see Figure 5.2a). All returned surveys were included in the analysis. Knowing that they performed better or worse than usual could have influenced participants' responses to the survey. However, as shown in Section 5.3.10, response time did not significantly predict variables related to participants' affective experiences (i.e., their self-reports of fatigue, energy, or enjoyment) or their scores on the parkrun community component, and there is no theoretical reason to assume that this prior knowledge would affect reports of pre-run sociality or who participants reported coming to or meeting up with at parkrun.

Nevertheless, researchers have suggested that athletes often assess their own performance in real time (Beedie et al., 2012). This presents a problem that is therefore difficult to circumvent given the current design. Slight changes to the survey procedure – such as having parkrunners answer questions on felt energy immediately before their runs, or using technology that allowed for real time updates of parkrunners experiences – could reduce potential biases in survey results.

#### 5.4.5.2 Validation of survey measures

Given the novelty of this survey, many of the measures used have not been systematically validated. Questions may thus measure something other than the constructs of interest. However, the survey questions were based on previously validated measures, qualitative research on integration and social support at parkrun, and past operationalisations of social support. Further, they were adapted only to the extent that they would make sense to participants in the study. For example, the question measuring fatigue was adapted from "Circle the number that best describes how [fatigued] you feel right now." (0 – *not at all*, 4 – *extremely*) (Grove & Prapavessis, 1992), to "How physically fatigued did you feel during your run today?" (0 – *not at all*, 7 – *extremely*). Nevertheless, future research could work to validate measures for social support and its effects in naturalistic exercise settings.

#### 5.4.5.3 Generalisability of the participant sample

Another issue is that the results of this study were influenced most by the relatively few participants that responded to the survey a relatively high number of times. Just 34 participants (24%) – those that responded more than seven times – made up 52% (*n* = 385) of the total responses. Further, there was a relatively high proportion of singletons; 29 participants (20%) responded to the survey only one time, and the majority (64%) of participants filled out the survey less than five times. These patterns are likely partially due to the fact that some parkrunners attend parkrun only on a sporadic basis (Stevinson et al., 2014). This study did not try to influence attendance levels, stressing to participants that they should attend parkrun as usual during the study period and that they were not required to respond to surveys when they did so (again, this was done at the request of the parkrun Research Board; see Section 5.2.1, p. 156). However, future studies could work with parkrun to create greater incentives for participation from a wider sample of parkrunners and to ensure lower attrition rates from these participants (i.e., encourage participants to always respond to surveys when they attend a parkrun event).

#### 5.4.5.4 Suitability of the participant sample

As argued in Section 2.2.5 (p. 69), social support effects are likely to be strongest when individual are pushing themselves toward their psychophysiological maxima, and are feeling stress, fatigue, and even pain. Survey data from Stevinson et al. (2014) shows that parkrun attracts a diverse set of participants with varying reasons for attendance. These reasons range from ‘enjoying social interaction’ and ‘getting in shape,’ to training for competitive runs and improving 5 km run times. Thus, while parkrun attracts participants with ambitious fitness goals and motivations to improve run times on a weekly basis, many participants have other equally or more important priorities, such as socialising and getting out in nature (Stevinson et al., 2014). Given that the majority (*n* = 448, 61%) of participants in the current study reported attending parkrun “to run together with other people” – as opposed to attending to improve run times or rank (finish place) – it is possible that a large portion of the study sample was not

motivated to perform at or near their psychophysiological limits. Future studies could work to identify a subset of the parkrun population that is motivated to do this on a consistent basis. Future work could also study other forms of group exercise. Although 5 km runs offer a good context in which to test the hypotheses of this thesis – they allow for the possibility of individuals pushing themselves toward their psychophysiological maxima – more research is needed into how social support effects translate to differing forms of strenuous physical exertion.

#### 5.4.5.5 Competition as a confound

Competition as a confounder of putative ergogenic social support effects at parkrun has already been discussed in Section 4.7.4.2 (p. 141), however, its relation to felt energy should be considered here. It could be that the presence of known social others increased levels of competition and motivation among parkrunners, and that these effects were captured by the felt energy variable. Indeed, motivation and felt energy are likely overlapping constructs, both leading to increased physical outputs (Hettinga et al., 2017). It is certainly possible that the presence of friends and/or family members increases competition levels at parkrun. However, it is unclear why socialising before the event or feeling more included and supported by the parkrun community would predict higher competition levels. Competition and its relation to the findings of this thesis as a whole are discussed further in Section 7.3.2.1 (p. 242).

### 5.4.6 Conclusions

A large and diverse scientific literature suggests that social support changes the way humans deal with stressors, generally leading to more liberal interpretations of threats and uses of bodily resources. As previously discussed in Chapter 1 and Chapter 2, social support and cohesive group environments have been shown to reduce perceptions of pain, enhance immunity and healing, and even to improve adherence to exercise (Cohen et al., 2015; Kulik & Mahler, 1989; Master et al., 2009; Spink & Carron, 1994). However, little work has been done on the effects of social support on exercise performance and motivations, especially in naturalistic settings. The study reported here attempted to fill this gap – and inform the findings

of Chapter 4 – with a survey-based study on parkrun over a four-month period (how Chapter 4 and Chapter 5 should be interpreted in light of each other will be discussed in Section 7.2.3, p. 239). The survey included measures of a variety of aspects of parkrun participation that aimed to capture the effects of the presence of close, supportive relationships available to parkrunners on a given day. I tested whether and how these social predictors affected parkrunners' 5 km run performances and experiences.

Results indicate that social factors related to parkrunners' perceptions of social support affect 5 km run times through influencing their perceptions of felt energy. How energised participants felt as a result of being with other parkrunners mediated performance-enhancing indirect effects of the social predictor variables on participants' 5 km run times. It thus seems that felt energy is crucial to observing the hypothesised ergogenic social support effects at parkrun; if participants did not feel increases in felt energy, the effects of social support on run times were non-significant or in the opposite direction of my predictions.

In line with my hypotheses, coming to or meeting up with friends and/or family at parkrun (v. coming alone or coming or meeting up with acquaintances) predicted reductions in perceptions of fatigue, while controlling for run outputs (i.e., 5 km times). This is the only hypothesised, significant direct effect of the social predictor variables, and is perhaps due to this variable being the 'strongest' measure of social support, in that it measures the presence of close, supportive relationships. However, it should be noted that this effect was not significant at its Benjamini-Hochberg adjusted critical value (Benjamini & Hochberg, 1995). Nevertheless, future research could look to further investigate the type of social relationships that lead to ergogenic social support effects; the results presented here suggest that it is the quality of social relationships that matters, and this accords with previous research (e.g., Coan et al., 2006).

This study sheds light on the mechanisms by which socially supportive, cohesive environments affect self-regulation during exercise. Owing to evolutionarily ancient

associations of close, supportive relationships with safety and resource abundance, it may be that cues to social support before or during exercise lead to increases in felt energy, which allow or motivate increases in bodily resource use, with the ultimate effect of enhancing physical outputs. This finding has far-ranging implications for understandings of the interactions between social variables and physical outputs in both ancient and modern environments. For example, felt energy and lowered perceptions of fatigue could be a means through which social environments influenced physical outputs and the evolution of human long-distance hunting (see Section 7.4.2.3.1, p. 253). The same principles can be employed in explaining the importance of social support and cohesion in group exercise in modern contexts – the phenomena of CrossFit*,* Tough Mudder, and parkrun are all heavily based on supportive relationships among participants, and the energy and motivation derived from these social environments (Hindley, 2018; Stevinson et al., 2014).

These findings offer the first naturalistic, empirical evidence for social support effects on performance during exercise, while offering new methods and causal mechanisms that can be used in future research. This future research could also look into new ways of gathering information on relevant variables, such as methods to obtain real-time feedback on perceptions of energy and fatigue (e.g., via wearable devices and voice recognition software). Finally, future investigations of ergogenic social support effects could employ experimental methods that reduce the noise found in naturalistic data sets – such as the parkrun data analysed in this thesis – and offer a more straightforward means of testing hypothesised causal mechanisms. The study presented in Chapter 6 aims to do this; it employs a (fMRI-compatible) factorial experimental design that allows for the testing of ergogenic social support effects, and the comparison of these effects to ergogenic placebo effects, thus giving its findings the capacity to shed light on the causal mechanisms underpinning endogenous performance-enhancement during exercise.

## Chapter 6 – Comparing ergogenic placebo and social support effects

All R and MATLAB scripts referenced in this chapter can be found here:
https://github.com/arranjdavis/DPhil_Thesis_Chapter_6_Data_Analyses

Where appropriate, these scripts acknowledge the contributions of Dr Ben Crittenden, who was the primary author of the MATLAB script used in this study. This script produced the experimental stimuli and recorded participants' hand grip outputs. Further, Dr Crittenden contributed to the assembly and testing of the fMRI-compatible handgrip used in the exercise trials. He also made a theoretical contribution to the study through helping to conceive the experimental design.

**Abstract**

This study tested social support and placebo effects on hand grip outputs and perceptions of difficulty in an fMRI-compatible experiment. Participants' hand grips and perceptions of difficulty were measured over two exercise blocks (one with placebo and one without, counterbalanced across participants), each containing 42, 8 s hand grip exercise trials. During trials, participants saw photos of either a support figure or stranger, and were asked to produce grip strength outputs that were either 40%, 50%, or 60% of their maxima (photo and target grip strength orders were 'random' to participants). It was hypothesised that both social support and placebo would enhance hand grip performance as evidenced by increases in outputs and/or reductions in perceptions of difficulty, and that these effects would be stronger in trials where participants were asked to perform closer to their maximum hand grip strength. Results revealed significant main effects of social support and non-significant main effects of placebo on hand grips. Further, social support effects were moderated by trial difficulty; these effects increased in size along with target grip strengths. Despite producing greater outputs overall during the social support conditions, participants did not perceive these trials to be more difficult. There was also a significant exercise block $\times$ placebo interaction on perceptions of difficulty, with participants who received the placebo before the second exercise block reporting lower perceptions of difficulty (as compared to their counterparts who did not receive the placebo before this block). Results are discussed within the context of self-regulation and previous findings on ergogenic placebo and social support effects.

## 6.1 Introduction

Perceptions of pain and fatigue are a core component of adaptive self-regulation during exercise (Lambert, Gibson, & Noakes, 2005; Noakes et al., 2005). Occupying ranges on a single spectrum of physical discomfort, pain and fatigue are two neurologically similar, self-regulatory emotions that inhibit central motor drive and physical outputs (Amann et al., 2009; Noakes, 2012; Pollak et al., 2014; Robson-Ansley et al., 2004; Stein et al., 2007). Although they are major limiting factors on physical performance, functioning to protecting the body from harmful overexertion, pain and fatigue thresholds are also known to be susceptible to a wide range of internal and external environmental influences. Included in these influences are the analgesic effects of social support and placebo treatments (Coan et al., 2006; Petrovic, Kalso, Petersson, & Ingvar, 2002). Here, I explore the hypothesis that, through their effects on pain and fatigue, social support and placebo treatments influence physical performance. The research presented in Chapter 3 suggests that social environments can influence maximal physical outputs in laboratory settings (Davis & Cohen, 2018). Chapter 4 and Chapter 5 show the effects of social environments in naturalistic physical exercise settings; these findings are generally in line with observational and ethnographic work on the relationship between supportive social environments and physical outputs (e.g., Gotaas, 2012; Kraus et al., 2010), while a more developed body of experimental work has shown a variety of ergogenic placebo effects on physical outputs (Beedie & Foad, 2009; Pollo et al., 2008). The study presented in this chapter aimed to explore the relative effects of social support and ergogenic placebo treatments on physical performance and fatigue, and to develop and test a methodological paradigm suited to future neuroimaging investigations of underpinning mechanisms.

As reviewed in Section 2.2.3 (p. 53), pain and fatigue signalling have similar neurobiological underpinnings, and both work to limit outputs during physical exertion. As levels of pain and fatigue increase, central motor drive, positive affect, and motivation to continue physical exertion decrease (Amann et al., 2009; Noakes, 2012). Pain and fatigue can thus be understood as self-regulatory emotions that, in the context of physical exercise, function to

protect against the negative consequences of exhaustion and injury. Given their protective function, it is not surprising that pain and fatigue work to conserve bodily resources; recreational athletes will stop exercise due to 'exhaustion' at around 30% of skeletal muscle recruitment, and professional athletes improve upon this by approximately 10 – 20% (Noakes et al., 2005). Considering these findings, it is clear that physical outputs are not dependent solely on the capacity of peripheral muscles, but rather on a feedback loop between the periphery and CNS, which ultimately regulates the recruitment of skeletal muscles (Noakes, 2012; Stein et al., 2007). While skeletal muscle capacity remains relatively constant across contexts, CNS regulation of muscle recruitment can vary, with pain and fatigue inversely related to how much continued physical exertion "can be safely sustained at that particular exercise intensity *under those specific conditions* [italics added]" (Noakes et al., 2005, p. 122). Research suggests that tacit assessments of safety can be influenced by both internal and external environments, such as individuals' perceived physiological capabilities, or the availability of care, support, and access to resources (Cole, Balcetis, & Zhang, 2013; Eisenberger et al., 2011; Schnall et al., 2008). Cues that change both conscious and subconscious perceptions of internal and external environmental conditions are thus likely to alter CNS regulation of physical outputs through their effects on perceptions of pain and fatigue.

Ergogenic placebos are perhaps the best studied of these environmental cues. Numerous studies have shown substantial improvement in physical outputs – accompanied by reductions in fatigue – when exercisers believe they have the aid of a performance-enhancing substance (Beedie & Foad, 2009), and research has shown that these effects are likely underpinned by endogenous opioid and endocannabinoid activity (Benedetti, Pollo, et al., 2007; Pollo et al., 2008, 2011). Activity in these systems during physical exertion attenuates ascending signals from nociceptive and metaboreceptive nerve fibres, thereby dampening perceptions of pain and fatigue as well as their inhibitory effects on CNS motor drive (Amann et al., 2009; Sgherza et al., 2002). Although no brain-imaging studies have been conducted that investigate

ergogenic placebo effects, it is likely that endogenous opioid and endocannabinoid activity function to block signals of fatigue during physical exertion through neurobiological mechanisms similar to those that have been shown to underpin placebo analgesia (Bingel & Tracey, 2008; Wager et al., 2007). For example, Benedetti, Pollo, et al. (2007) showed that both verbal suggestion and (morphine) conditioning lead to substantial ergogenic placebo effects on pain endurance and physical performance, and that these effects could be *partially* blocked by naloxone (an opioid receptor antagonist). The partial blockade produced by naloxone suggests that endogenous opioid activity underpins some, but not all, of the observed ergogenic placebo effects; the authors propose the endocannabinoid system as a potential additional mechanism for ergogenic placebo effects (Benedetti, Pollo, et al., 2007).

Other environmental cues are also likely to affect perceptions of pain and fatigue. In humans, where evolutionary fitness is linked to close, supportive relationships with conspecifics, social environments can influence a variety of psychophysiological outcomes (see Section 1.4, p. 15, for a full review), ranging from healing and immunity to stress levels and well-being (Holt-Lunstad, Birmingham, & Light, 2011; Holt-Lunstad et al., 2010; Holt-Lunstad & Uchino, 2008). Regarding pain and fatigue, multiple studies have shown that cues to social support – such as holding the hand of a loved one, or simply viewing the photo of a loved one – can have analgesic effects on experimentally induced pain (Coan et al., 2006; Eisenberger et al., 2011; Master et al., 2009). Two of these studies used fMRI, and focused regions of interest (ROIs) on brain areas associated with threat, safety, and pain. Compared to control conditions, social support led to increases in activity in safety-signalling neural regions, and decreases in activity in regions associated with threat and pain unpleasantness (Coan et al., 2006; Eisenberger et al., 2011). These studies have not investigated potential overlap between top-down pain modulation networks involved in placebo analgesia, though Eisenberger et al. (2011) speculate that socially-induced increases in endogenous opioid activity might explain observed pain reductions in social support conditions. Both the endogenous opioid and endocannabinoid systems have been linked to the formation, signalling, and maintenance of

strong social bonds in humans, offering a means through which social cues could affect perceptions of pain and fatigue during exercise (Inagaki et al., 2016; Machin & Dunbar, 2011; Tarr et al., 2017; Trezza et al., 2010).

Given these findings on the analgesic effects of social support, and the neurobiological links between pain and fatigue, it is surprising that, to date, no studies have experimentally investigated the potential ergogenic effects of social support, barring the study presented in Chapter 3, now published as Davis and Cohen (2018). As reviewed in Chapter 2, observational, ethnographic, and experimental work suggests a positive influence of social support and team cohesion on athletic performance, but performance measures have been entirely related to competitive outcomes and have focused on skill and coordination-based sports (Carron et al., 2002; Gotaas, 2012; Kraus et al., 2010; Rees et al., 2007).

In summary, a relatively large number of studies have shown positive effects of ergogenic placebos on physical performance, whereas experimental research on ergogenic social support effects is only beginning. Moreover, previous work suggests possible shared neurobiological pathways – underpinned by the endogenous opioid and endocannabinoid systems – between ergogenic placebo and social support effects. Nevertheless, this theory needs additional experimental evidence. The neurobiological and ergogenic effects of social support during physical exertion have not yet been studied, and ergogenic placebo research has only used opioid antagonists to implicate the endogenous opioid system in observed effects (Benedetti, Pollo, et al., 2007). Thus, the potential neural overlap of mechanisms responsible for ergogenic placebo and social support effects has not yet been demonstrated, although previous neuroimaging research on the analgesic effects of placebo and social support suggest that this is a potentially fruitful avenue of research.

This behavioural study aims to add to nascent research on social support effects during physical exercise, and to compare these effects to those of an ergogenic placebo. An important consideration in the development of this study's methods was to create a design

that will be used in follow-up neuroimaging research[32], which will examine potential overlap in the neurobiological mechanisms underpinning placebo and social support effects during exercise. The study employs a repeated-measures, factorial design, so that participants perform a standardised hand-gripping exercise after taking a (placebo) performance-enhancing drug (placebo condition), or nothing at all (placebo control condition), and while looking at the face of someone with whom they have a close, supportive relationship (social support condition), or the face of a stranger (social support control condition). Further, the trials were grouped into two blocks (one with placebo and one without) for each participant (and counterbalanced across participants). Within each block, exercise trials varied in objective difficulty, requiring participants to maintain a hand-grip at either 40%, 50%, or 60% of their maxima. The factorial design is thus 2 (placebo/control) × 2 (social support/control) × 2 (exercise block) × 3 (trial difficulty: 40%, 50%, 60% of the participant's maximum hand grip strength).

There are several reasons why I chose to use a within-subject factorial design to simultaneously investigate ergogenic placebo and social support effects. Primarily, this study's fMRI-compatibility means that future researchers could investigate the neurobiological mechanisms that underpin placebo and social support effects, and how these effects interact. As discussed in Section 2.2.3 (p. 53), I hypothesise that both effects are underpinned by similar underlying mechanisms – activity in the endogenous opioid and endocannabinoid systems. While this is yet to be investigated with regard to ergogenic social support effects, several studies implicate the endogenous opioid and endocannabinoid systems in ergogenic placebo effects (Benedetti, Pollo, et al., 2007; Pollo et al., 2008). However, no studies have used neuroimaging to elucidate the mechanisms underpinning ergogenic effects (placebo or otherwise) in physical exercise. This study not only provides the design to do this, but it also allows for research that would marry a relatively unestablished body of research on ergogenic

[32] This follow-up study, in which I will collaborate with Dr Ulrike Bingel at the University of Duisburg-Essen, Germany, is scheduled to begin in autumn of 2018.

social support effects to the larger, more diverse field of placebo analgesia and performance-enhancement. There are also practical reasons for choosing this within-subjects design; it facilitated participant recruitment and made financially possible a comparison of both placebo and social support effects.

The main outcome measure of interest was participants' physical outputs during 8 s trials of the hand-gripping exercise, and their perceptions of how difficult these exercise trials were. After each 8 s trial, participants were asked how hard it was to perform the exercise task in the previous trial. This question was designed to measure participants' perceptions of pain or fatigue during the exercise trials. Piloting suggested that participants were reluctant to call sensations evoked by difficult trials 'painful.' Further, they often interpreted fatigue as lethargy. I thus used a more colloquial description of the pain and fatigue sensations felt during exercise: how 'hard' the trials were. This wording is likely more appropriate in this context, given that it becomes more difficult – or harder – to continue muscle drive as signals of pain and fatigue increase (Noakes, 2012; Noakes et al., 2005). Henceforth, I will refer to this question as the question on trial difficulty. Following the question on trial difficulty, participants were asked how much effort they put into the previous trial. This variable will be used as a control in the statistical models; although not of direct interest for the purposes of hypothesis testing, effort levels could account for differences between conditions.

### 6.1.1 Hypotheses

The main hypothesis of interest is that, compared to their respective control conditions, the placebo and social support conditions will predict (while controlling for effort levels) either (a) greater physical outputs and lower perceived difficulty, (b) greater physical outputs at equivalent levels of perceived difficulty, or (c) equivalent outputs at lower levels of perceived difficulty (see Table 6.1 for a full list of hypotheses). Although relative effect sizes between placebo and social support conditions will be compared for exploratory reasons, there is no *a priori* hypothesis of differences between the two. If social support has comparable effects to

**Table 6.1** Hypotheses

| | |
|---|---|
| **Hand grip outputs and ratings of perceived difficulty** | |
| **Hypotheses 1 – 2** | Compared to control conditions, the social support (Hypothesis 1) and placebo (Hypothesis 2) conditions will enhance performance in the hand grip exercise as evidenced by:<br>(a) greater hand grip outputs with lower ratings of perceived difficulty, or<br>(b) greater hand grip outputs with equivalent ratings of perceived difficulty, or<br>(c) equivalent hand grip outputs with lower ratings of perceived difficulty. |
| **Hand grip outputs and objective trial difficulty** | |
| **Hypotheses 3 – 4** | Social support (Hypothesis 3) and placebo (Hypothesis 4) effects on hand grip outputs will interact with objective trial difficulty, such that these effects will increase as target grip strength increases. |
| **Predictors of social support effects** | |
| **Hypothesis 5** | Participants' need for social assurance will positively predict observed social support effects on hand grip outputs. |
| **Hypothesis 6** | Participants' neuroticism will negatively predict observed social support effects on hand grip outputs. |
| **Hypothesis 7** | The quality of participants' relationship with their support figure will positively predict observed social support effects on hand grip outputs. |
| **Hypothesis 8** | The extent to which participants believe they can depend on others to be available when needed will positively predict observed social support effects on hand grip outputs. |

placebo, however, this will benchmark and confirm the importance of social support alongside placebo interventions as a potentially powerful performance enhancer in physical challenges.

The factorial design offers the possibility of testing for interactions between ergogenic placebo and social support effects, and between these effects and exercise difficulty. Regarding the placebo × social support interaction, I do not know of any research to suggest that social support and placebo effects will interact in any significant way, or have additive effects, and posit no hypotheses in this regard. The factorial design also offers the possibility to test the hypothesis that social support (and placebo) effects will be strongest when individuals are nearest to their physiological maxima. Research suggests that social support and placebo manipulations affect physical outputs via endogenous pain and fatigue regulation, and

protective, self-regulatory perceptions of pain and fatigue influence outputs most when individuals are relatively close to their physiological maxima, thus suggesting enhanced social support and placebo effects at the higher target grip strengths in this study (see Section 2.2.5, p. 69, for a full review of the literature underpinning this hypothesis).

Several personality factors have also been identified in previous research as potential predictors of social support responses (see Section 3.1, p. 78, for a full discussion of these effects). Individuals' need for social assurance, neuroticism, the quality of their relationships with those supporting them, and the extent to which they believe they can depend on others to be available when needed have all been shown to affect responses to social support (Coan et al., 2006; Cohen et al., 2015; Davis & Cohen, 2018; Lee & Robbins, 1995; Park et al., 2013). These variables were measured and used to predict social support effects observed in participants' hand grip outputs (see Table 6.1).

## 6.2 Methods

### 6.2.1 Participant recruitment

Participants were recruited via flyers around the city of Oxford, UK, Oxford University College mailing lists, and the Oxford Psychology Research Participant Recruitment Scheme for a study putatively investigating "personality, social relationships, and performance-enhancement during exercise" (see Appendix D, Figure D1, p. 381). Participants were required to be aged 18 – 49 and able to sustain moderate intensity exercise (e.g., brisk walking or easy jogging) for a minimum of 30 min. Participants also needed to have refrained from doing strenuous exercise or using illegal drugs and alcohol in the 12 hr preceding their participation in the study (participants were told they could use caffeine and tobacco as they would normally). In addition, participants were required to be free of any prior or current conditions/injuries that would have prevented them from safely completing the hand-gripping exercise tasks in the study. Finally, participants were required to submit a photo of "someone you feel you have a close connection with and that you can depend on in times of need – such

as a friend, family member, or partner." These photos were to be as close to 'passport style' as possible – that is, front-on headshots against a white or beige background (smiles were allowed). Individuals meeting the above requirements were asked to come to the John Radcliffe Hospital, Oxford, UK, to complete a two-hour experiment for which they would be remunerated between £25 and £30 (in reality, all participants were paid the maximum amount £30). This study was approved by the Medical Sciences Inter-Divisional Research Ethics Committee, University of Oxford (reference number: R47623/RE001). Data collection did not continue after data analysis.

### 6.2.2 Procedures

Upon arrival, participants were given an information form (see Appendix D, Figure D 2, p. 382), which explained the experimental procedure and introduced them to the "performance-enhancing drug," beta-alanine (β-alanine):

> Large clinical trials have shown that beta-alanine supplementation leads to enhanced performance by delaying the onset of muscle fatigue and pain during exercise. Beta-alanine reduces concentrations of molecules that lead to feelings of pain and fatigue during exercise, thereby altering perceptions and enhancing performance (specifically, beta-alanine in muscle cells is necessary for the synthesis of carnosine, a molecule that reduces intramuscular acidosis, an important cause of pain and fatigue during exercise). The beta-alanine pill you are taking is relatively fast-acting – it will start to affect you about 20 minutes after you take it and these effects will last for about 45 minutes.
>
> Beta-alanine is a naturally occurring amino acid and, generally, it is very well tolerated (most individuals experience no side effects), particularly at the dose used in this study. However, we will monitor you carefully after you have taken your dose and we will ask you to report any potential side-effects at the end of the study. Beta-alanine is legal and not restricted in the UK.

After reading the information form, participants were brought into the experimental room and introduced to the hand-gripping exercise by the experimenter (myself; see Appendix D, Section 1, p. 362). They were given 20 s to use the handgrip and see feedback from their squeezing activity on a computer screen. After this, they were asked if they had any current or previous illnesses or injuries that could prevent them from completing the exercises in the experiment. If participants answered 'no' to this question (all did), they were asked to complete the consent form (see Appendix D, Figure D 3, p. 385). The experimenter then asked them to give their 'maximum strength squeeze,' which was used to calibrate the hand-gripping exercise to their strength levels (see below). Participants were then weighed – putatively so that the pharmacist could calculate their body-weight-dependent β-alanine dose – and asked if they were on any medication or had ever taken β-alanine before. These questions were asked solely to increase the efficacy of the placebo manipulation (i.e., to make participants believe they were taking a real drug instead of a placebo).

Following this, participants were given a full description of the experimental procedure and exercise task (see below and Appendix D, Section 1, p. 362). This included a practice session of the hand-grip exercise task where participants completed a block of three of the 8 s hand-grip exercise trials. Participants were informed that they would be asked questions on their personality and how they relate to other people because the study's aim was to 'understand why some people experience stronger reductions in pain and fatigue from β-alanine than do others.' The experimenter explained that he hypothesised that differences in β-alanine effects could be predicted with information on individuals' personality and how they relate to other people. This was given as the reason why participants would see the photo of their friend, family member, or partner as well as a photo of a stranger during the hand-grip exercise trials; after the experiment, participants would report on how they felt about these people while exercising.

With cover stories established for both the placebo and social support manipulations, and the experimental procedure fully explained, participants were told to begin the pre-exercise questionnaire (which took 10 – 15 min), while the experimenter went to 'retrieve their body-weight-dependent dose of β-alanine from the hospital pharmacy.'

#### 6.2.2.1 Pre-exercise questions

Pre-exercise questions were presented and answered on a desktop computer using a Qualtrics online survey. Participants first provided their age and sex. They were then asked if they had exercised (excluding transporting themselves to the experiment) or used illegal drugs and/or alcohol within the past 12 hr. Participants also indicated if they had heard of β-alanine in relation to performance enhancement during exercise before reading the information sheet in this study. Following this, participants answered the 44-item Big Five Inventory (John & Srivastava, 1999), the close relationship version of the Revised Adult Attachment Scale (RAAS; Collins, 1996; Collins & Read, 1990), and a modified version of the short form of the Fear of Pain Questionnaire, as a means of priming thoughts about exercise-induced pain (FPQ; McNeil et al., 2018; McNeil & Rainwater, 1998); see Appendix D, Figure D 4 (p. 387). Finally, as a means of invoking strong sentiments about their support figure, participants were asked to fill an open text box with a memory describing an instance of feeling either close to or supported by this person.

#### 6.2.2.2 Placebo manipulation

The placebo manipulation was carried out using two main blocks of exercise. In a counterbalanced fashion, and as a means of inducing positive performance expectations, participants took what they were told was β-alanine (actually a placebo – 430 mg of sucrose – presented in a black pouch with a pharmacist's label containing the participant's name and the alleged dosage of β-alanine; see Appendix D, Figure D 5, p. 388) along with 200 ml of water before either the first or second main exercise block. If participants took the placebo and 200 ml of water before the first main block, they took only 200 ml of water before the

second main block, and vice versa. As a means of both allowing participants to recover between exercise blocks, and convincing them that they had actually taken β-alanine (the putative effects of which were said to last 45 min), each main exercise block was preceded by a 30 min break during which participants completed an unrelated memory task. Therefore, for participants who took β-alanine before the first block, the first 30 min break was to "allow for the β-alanine to be absorbed and take effect," while the second 30 min break was to "allow for β-alanine levels to drop back down to baseline and for adequate recovery from the first block of exercise." Participants who took the β-alanine before the second block were told that the 30 min break before the first block was to "ensure that they had the same experience as those who took β-alanine before the first block" and that the purpose of the second block was to "allow for both the β-alanine to be absorbed and take effect and for adequate recovery from the first block of exercise."

#### 6.2.2.3 Hand grip exercise

The hand grip exercises were carried out in two main exercise blocks using an fMRI-compatible handgrip, which was designed according to the specifications of Bützer et al. (2016). Within each main block of exercise, which lasted for about 22 min, there were 14 sub-blocks consisting of three, 8 s hand-gripping trials. Each block of three trials involved squeezing the handgrip at a target difficulty of either 40%, 50%, or 60% of the participant's maximum grip strength (one trial at each difficulty level per block, in randomised order). The trials involved participants squeezing the handgrip, which caused a line on the screen to move along a vertical axis according to their grip strength – the harder they squeezed, the higher the line raised (see Figure 6.1). Their goal was to raise the line above the target bar – causing it to turn from red to green – and to keep the line above the target bar for the duration of the 8 s trial. Regardless of trial difficulty, the target bar remained stationary and was always in the same place on the screen. In other words, raising the movable bar to the stationary target bar required a stronger grip strength as the objective difficulty of the trials increased. Participants were not told that trials would be at either 40%, 50%, or 60% of their maximum; they were

(*a*) (*b*)



**Figure 6.1** Hand grip exercise interface when participant is squeezing at (a) 0% of their maximum and (b) above their target grip strength (either 40%, 50%, or 60% of their maximum), which was represented by a white line superimposed on top of a 300 × 300 pixel photo of participants' support figure (social support condition) or a photo of a stranger (control condition; matched to social support condition face on gender, age, and ethnicity).

simply told that the difficulty of the trials would vary. This was done to investigate hypotheses on the moderating effects of difficulty on ergogenic placebo and social support effects (see Section 6.1.1). This manipulation also discouraged habituation effects in participants' responses to the question on trial difficulty.

Each trial was preceded by a screen reading "Get ready…" for 1 s, after which the trial began and participants saw the screen displayed in Figure 6.1. Participants were instructed pre-experiment (see below and Appendix D, Section 1, p. 362) to immediately begin squeezing to move the line above the target bar upon seeing the screen displayed in Figure 6.1, and to continue keeping the line above the bar until the line turned yellow at the end of the 8 s. The line remained yellow for between 1 – 2 s (exact time randomly selected), after which the post-trial questions began (see below).

As a means of increasing motivation, participants were told – during the pre-experiment instructions described above and in Appendix D, Section 1 (p. 362) – that if they were maintaining the grip-strength-dependent line above the target bar at a randomly selected time point in a randomly selected trial, they would receive an additional £5 for their efforts.

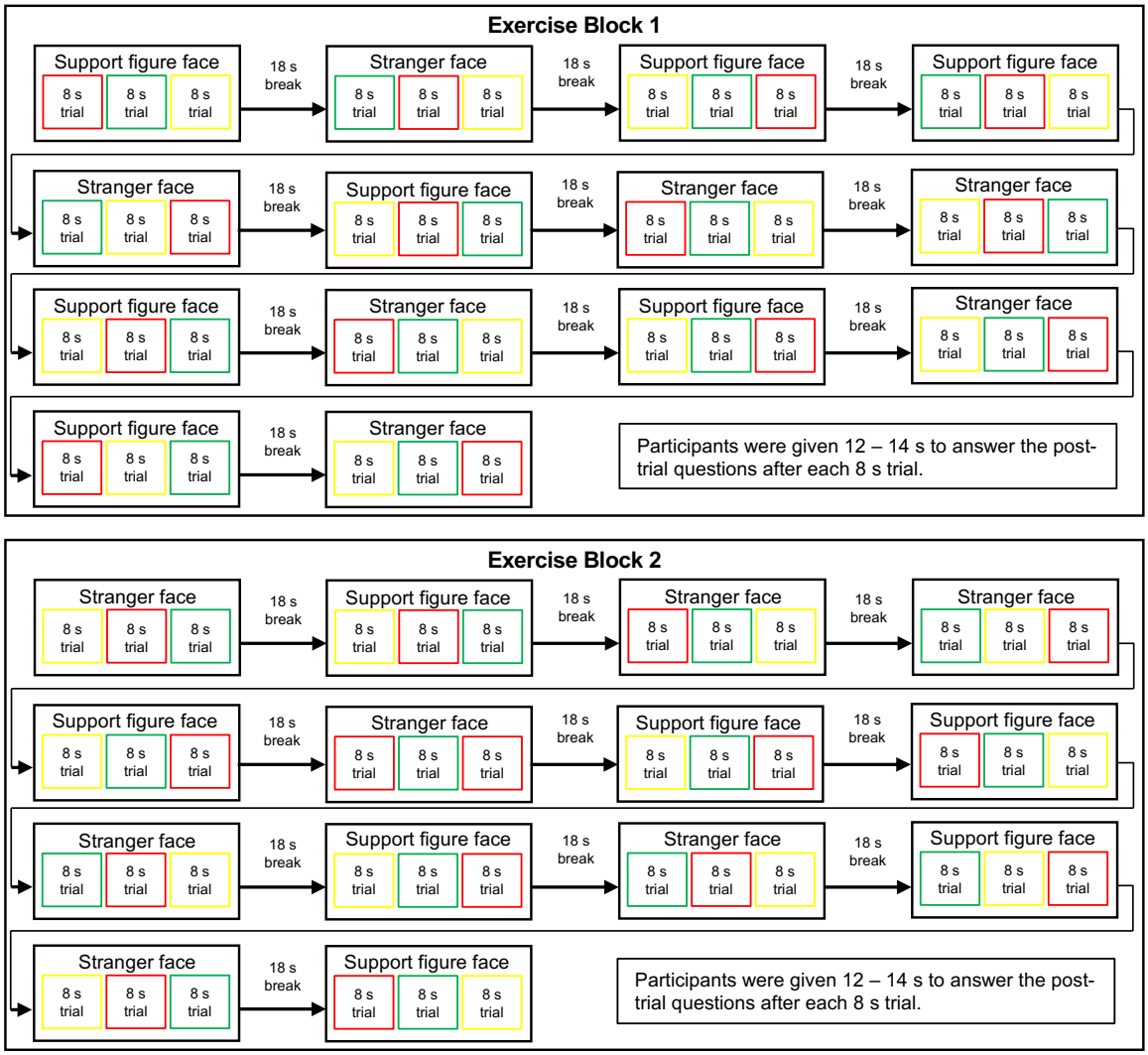



**Figure 6.2** A schematic depiction of the experimental design; green, yellow, and red squares represent trials with target grip strengths of 40%, 50%, and 60% of participants' maxima, respectively. Participants took the placebo in either Exercise Block 1 or Exercise Block 2, in a counterbalanced fashion. For each exercise block, the order of trial difficulty and of the faces seen during the exercise trials (support figure face or stranger face) was pseudo-counterbalanced, as shown here.

The order of the difficulty of the 8 s trials was 'random' to participants (i.e., in an unpredictable pattern), although there were actually two separate patterns – one for each exercise block – that participants encountered in a counterbalanced fashion. This was done to avoid complications in counterbalancing pseudo-randomised trial difficulty orders (see Figure 6.2).

As a means of manipulating social support, participants viewed pre-selected images on the screen during the trials. Participants either viewed the image of the face of the support figure

that they had submitted before coming to the experiment or an image of the face of a stranger (matched to the support figure on gender, age, and ethnicity), that was taken from the online photo bank (www.3d.sk) managed by Smartnet IBC LTD. Thus, participants saw the same face for three trials in a row. Faces were seen in the 'background' – behind the movable line and target bar – and were displayed in 300 × 300 pixels square in the centre of the screen for the duration of the trial (see Figure 6.1). The order of the 14 sub-blocks of three trials was also 'random' to participants, although two random-appearing orders of faces for the 14 sub-blocks were counterbalanced across participants (i.e., some participants saw 'Face Order A' Exercise Block 1 and 'Face Order B' during Exercise Block 2, and vice versa; see Figure 6.1).

During the 8 s trials, participants' grip strengths were measured between 160 and 240 times. This variance was not a necessary element of the experimental design, but rather a function of the fibre optic sensing system used in the handgrip technology. Although the number of measurements varied per trial, the timing of these measurements was not biased (measurement number correlated perfectly with time over the 8 s trials, regardless of the total number of measurements). A simple solution to the problem of unequal observations per trial, which can lead to trials having undue influence in statistical models (Snijders & Bosker, 2012), was to randomly sample (without replacement) 160 observations from each trial. Doing this yielded an unbiased average of 20 grip strength measurements per second over the 8 s trials. This produced a total of 13,440 grip strength observations for each participant: 160 measurements during each of the 42 trials in each of the two exercise blocks. A MATLAB script was used to present the hand grip exercise interface; this script was also used to collect data from the hand grip sensor (Bützer et al., 2016).

#### 6.2.2.4 Post-trial questions

After each 8 s trial, participants answered two questions in the following order: "How hard was it to keep the bar above the line?" (sliding scale ranging from "*not hard at all*" to "*extremely hard*") and "How much effort did you put in to keep the bar above the line?" (sliding scale, with random starting points, ranging from "*no effort at all*" to "*maximum effort*"). Participants were

given 5 s to answer each question, after which their answer was confirmed to them for 0.5 s (the sliding dot on the scale turned red). Piloting had determined this to be a sufficient amount of time to answer these questions given that their order and content remained constant over the trials. Before each question there was a break lasting between 1 – 2 s (exact time randomly selected). After each sub-block of three hand-grip trials and post-trial questions, participants saw a blank, black screen for 18 s. In addition to making the experimental design fMRI-compatible, these 18 s pauses allowed for participants' attention to reset between sub-blocks and gave them short a recovery period. The graphics cycle for the next sub-block of trials began immediately after this.

#### 6.2.2.5 Post-exercise questions

Immediately following the completion of the second and final main exercise block, participants answered a further series of questions. These questions were presented and answered on the same computer using a Qualtrics online survey. Participants were first asked to rate their agreement with the following statements on a 5-point Likert scale (1 = *Strongly disagree*, 2 = *Disagree a little*, 3 = *Neither agree nor disagree*, 4 = *Agree a little*, 5 = *Strongly agree*): "I felt close to my friend, family member, or partner when I saw their photo during the exercise trials." and "I felt close to the other person whose photo I saw during the exercise trials."

Next, using sliding scales, participants were asked two questions on their experience with β-alanine: "What effect did the beta-alanine have on your performance during the exercise trials?" (0 = *Strong negative effect*, 50 = *No effect*, 100 = *Strong positive effect*) and "What effect did the beta-alanine have on how hard the exercise trials were?" (0 = *It made them easier*, 50 = *No effect*, 100 = *It made them harder*). Participants were also given the opportunity to list any side-effects they felt from the beta-alanine.

Following this, participants answered a series of questions regarding their relationship with their support figure. This included the Social Assurance Scale (SAS; Lee & Robbins, 1995), and two questions on the quality and duration of their relationship with this person. Regarding

the quality of the relationship, participants answered on a 7-point Likert scale (1 = *Not at all*, 7 = *Very much*) the extent to which their support figure was “someone you feel you have a close connection with and that you can depend on in times of need.” Regarding the duration of the relationship, participants were asked to provide the number of years and months they had known their support figure in this way.

Finally, as a means of checking whether participants had guessed the experimental hypotheses, participants were asked to describe in an open text box what they thought this experiment was about. If answers indicated that a participant may have guessed a hypothesis, the experimenter asked them further questions in order to ascertain the degree to which they understood the experiment and its conditions (questions included which condition participants thought they were in, why they saw the photo they submitted during the exercise trials, when they began to suspect deception regarding β-alanine, etc.).

### 6.2.3 Analyses

#### 6.2.3.1 Participants and exclusions

A power analysis for multilevel linear models generated a recruitment goal of 80 participants (Brysbaert & Stevens, 2018; Green & MacLeod, 2016). The power analysis assumed small effects sizes ($d$ = .1) in the placebo and social support conditions over the 84 hang-grip trials, a power of .8, an α of .05, and random variance proportions of .8, .19 and .01 for the residual, intercept, and slope, respectively, for both the placebo and social support fixed effects. In total, 85 individuals participated in the study. Of these 85 participants, four were excluded from analyses due to having incomplete data resulting from malfunctions with experimental equipment. Of the remaining 81 participants, an additional six were excluded upon analyses of their grip strength data. Specifically, these six participants’ mean grip strength did not increase by trial difficulty. If participants were trying to meet the target grip strengths of 40%, 50%, and 60% of their maxima for the differing trial difficulty levels, then their mean grip strength should at least increase as the target grip strength increases, even if they did not

meet their target grip strengths. This was not the case for these six participants, who, in addition to not showing increasing means with trial difficulty, also had mean grip strengths well below the targets for each difficulty level. These outlying participants were thus excluded from analyses because they did not adhere to the experimental task. The exclusion of these six participants left a total of 75 participants for analysis (42 females, age range = 18 – 40 years, *M* = 23.81 years, *SD* = 4.42 years). None of the remaining participants reported exercising or using illegal drugs and/or alcohol in the 12 hr preceding their participation in the study. Only five participants (7%) had heard of β-alanine in relation to performance enhancement during exercise, and none reported having used β-alanine before.

#### 6.2.3.2 Model selection

Repeated measures designs, such as the one employed in this study, are typically analysed using repeated measures ANOVA. However, multilevel modelling offers an alternative means of analysing repeated measures designs that has the added benefits of higher power in hypothesis testing and fewer assumptions about the data being analysed (Quené & Van den Bergh, 2004). From a multilevel perspective, the repeated measures data are obtained from a multilevel sample; first participants are ('randomly') selected from the sample population and then trials are sampled within participants. Participants thus make up a level-two random factor in the multilevel models employed here, while the experimental conditions (and covariates) represent fixed factors (Quené & Van den Bergh, 2004).

The multilevel linear regression model described above is a type of linear model that is appropriate for modelling continuous outcome variables, such as participants' grip strength data (Bates et al., 2014). However, all types of linear models produce biased estimates when 'ceiling effects' exist in the outcome variable (McBee, 2010). A ceiling effect occurs when "information regarding true differences between individuals scoring at the highest possible value is lost" (McBee, 2010; p. 314) due to a measurement being at the maximum of a scale, or at a scale's 'censoring point'. This is the case for the post-trial question on difficulty (scores for this question were created as a percentage of progress on the sliding scale used for

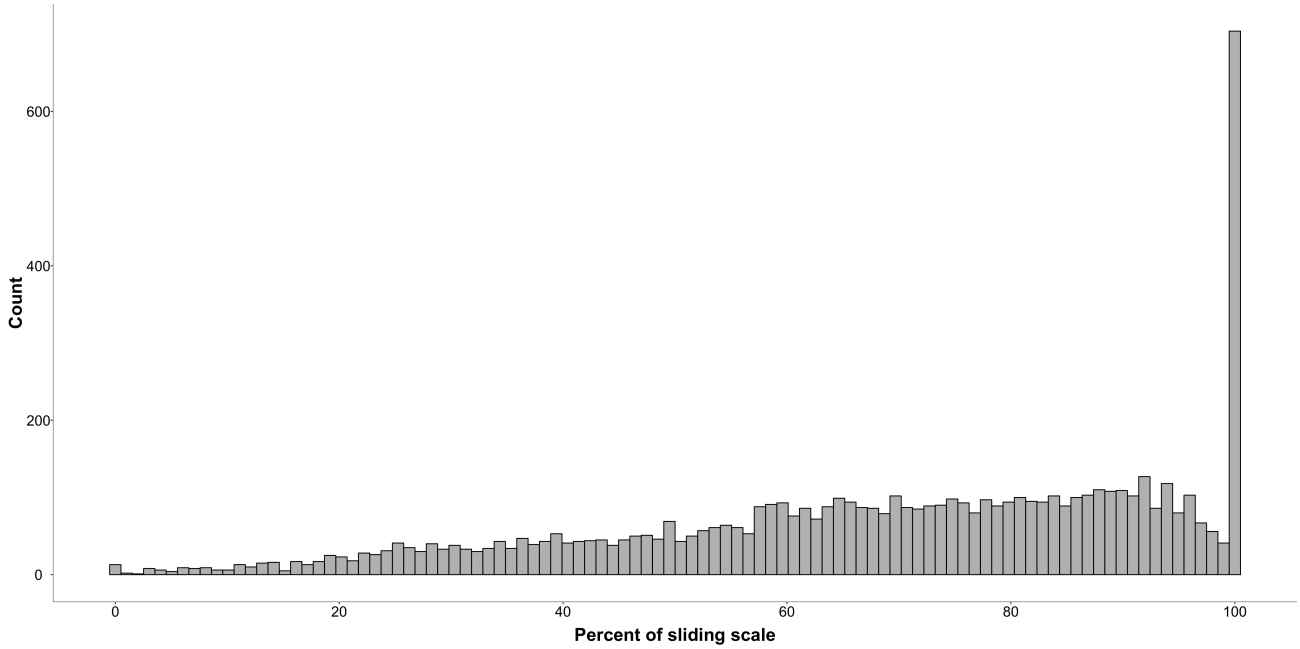



**Figure 6.3** Histogram of participants' answers (as a percentage of the sliding scale used) to the post-trial questions on how hard the previous trial was (0 = *not hard at all*, 100 = *extremely hard*).

responses; 0% = *not hard at all*, 100% = *extremely hard*; see Figure 6.3). Given the subjectivity and potential range of levels of exertion that participants might consider to be 'extremely hard' vary within and across individuals, it cannot be assumed that answers at the maxima of the scale represent the same magnitude. Further, the mode answer was 100, suggesting that the data set would have had more variation had the question not censored responses at the upper end of the scale. Given the question, and, more importantly, the structure of the data, a linear model was inappropriate. For this reason, a multilevel, censored regression (or Tobit model; Tobin, 1958) was applied to the post-trial question on difficulty following the methods of Henningsen (2010). These models have been shown to produce unbiased estimates (i.e., estimates approximately equal to regression estimates had the outcome variable not been censored) on data where ceiling effects are present (Long, 1997; McBee, 2010).

The R packages *lme4* (Bates et al., 2014) and *lmer* (Kuznetsova et al., 2015) were used to carry out multilevel linear models. Marginal $R^2$ ($R^2_m$) and conditional $R^2$ ($R^2_c$) for the multilevel models were calculated using functions from the *piecewiseSEM* package in R (Nakagawa & Schielzeth, 2013). The R packages *censReg* and *plm* were used to estimate the multilevel,

censored regressions (Croissant & Millo, 2008; Henningsen, 2010). The R package *emmeans* was used for post hoc tests on significant interactions estimated using multilevel models (Lenth, Love, & Hervé, 2018); *t*-tests were used for post hoc tests on significant interactions estimated using multilevel censored regression, as there is currently no method for carrying out post hoc tests on *censReg* model objects (Henningsen, 2010). Model diagnostics – assumption checks and outlier influence tests – for all models with significant findings are reported in Appendix D, Section 3 (p. 368).

#### 6.2.3.3 Model construction for analyses of grip strength data

The experiment had a $2 \times 2 \times 2 \times 3$ design, with two levels of the placebo and social support variables (manipulation and control), two levels of exercise block (first or second), and three levels of difficulty (40%, 50%, and 60% of participants' maximum grip strength). Snijders and Bosker (2012) recommend that multilevel models be specified as parsimoniously as possible, and a $2 \times 2 \times 2 \times 3$ design leads to an extremely complex model. The exercise block variable can be seen as an artefact of the experimental design: the placebo had to be manipulated over two separate blocks. I was not interested in the effects of this variable on exercise performance *per se*. Thus, I only include the exercise block interaction with the main variables of interest if this interaction is significant, otherwise this variable was included only as a covariate.

Regarding the exercise block variable, only its interaction with placebo condition was tested, since the other experimentally manipulated variables of interest were counterbalanced across exercise blocks within participants. This model included placebo condition, exercise block, and their interaction as fixed effects, and trial number (1 – 42) and a variable representing participants' effort in the trial (participants' answers to the post-trial question on effort, henceforth, participant reported effort) as covariates. Only the placebo variable was given a random effect, as this was the most complex random effects structure that allowed for model convergence. The placebo $\times$ exercise block interaction was non-significant, $b = 5.951$, $SE =$

3.105, $t(74) = 1.92$, $p = .059$. This variable was thus dropped from future analyses, making the model a $2 \times 2 \times 3$ design. Although it was not included in factorial interactions, the main effect of exercise block remained in the model as a covariate, as a means of improving model fit.

The final model thus included the three-way interaction between placebo condition, social support, and trial difficulty, as well as all of its constituent interactions (i.e., placebo × social support, placebo × trial difficulty, and social support × trial difficulty). Covariates included trial number, exercise block, and participant effort. The maximal random effects structure that allowed for model convergence was used (Barr et al., 2013); in this case, random effects for the placebo and social support variables only[33]. The trial difficulty variable was coded using 'main effects parameterization' (−1 = 40% of maximum, 0 = 50% of maximum, 1 = 60% of maximum), so that the effects of placebo and social support would be estimated at trials with target outputs of 50% of participants' maxima (Hayes, 2013).

#### 6.2.3.4 Model construction for analysis of perceptions of difficulty

In order to test participants' perceptions of how difficult the exercise trials were, the same process of model identification was used as for participants' grip strength data. The first step was to test the interaction between placebo and exercise block. This model included as covariates trial number and participants' reported effort, and the placebo and exercise block variables, and their interaction, as predictors. The placebo × exercise block interaction was significant, $b = 10.907$, $SE = 0.425$, $t(6,300) = 25.65$, $p < .001$. For this analysis, I thus retained the $2 \times 2 \times 2 \times 3$ factorial interaction that resulted from the experimental design. As such, the multilevel censored regression model contained as predictors exercise block, placebo and social support condition, and trial difficulty, as well as their four-way interaction and all constituent interactions. Trial number and participants' reported effort were also included as covariates.

[33] See Section 4.4.1.1 (p. 114) for a justification and explanation of the procedures followed when a model failed to converge.

#### 6.2.3.5 Creation of social support response variables

Following the methods used by Lyby, Aslaksen, and Flaten (2010), I created social support response variables by subtracting participants' mean grip strength in the stranger condition from their mean grip strength in the social support condition. Linear models were used to test whether these variables were significantly related to factors hypothesised to predict the magnitude of social support effects: participants' need for social assurance, neuroticism, ability to depend on others, and the quality of their relationships with support figures.

## 6.3 Results

### 6.3.1 Manipulation checks

Regarding the effectiveness of the placebo manipulation, on average, participants reported that β-alanine had a significant positive effect (as compared to no effect) on their performance during the exercise trials, $M = 58.12$, $SD = 12.13$, range = 19 – 87, $t(74) = 5.78$, $p < .001$, and on how difficult the trials were (data reverse scored such that 100 indicates 'It made them easier'); $M = 56.08$, $SD = 16.60$, range = 10 – 95, $t(74) = 3.17$, $p = .002$. No major psychophysiological side effects were reported.

Regarding the effectiveness of the social support manipulation, on average, participants felt significantly closer to their support figure when seeing their photo during the exercise trials ($M = 3.75$, $SD = 1.09$, range = 1 – 5) than they felt towards the stranger when seeing their photo ($M = 1.77$, $SD = 1.02$, range = 1 – 5); $W = 2{,}098$, $p < .001$. Further, 89% ($n = 67$) of participants answered with either a 6 or 7 (*Very much*) on the 7-point Likert scale ($M = 6.41$, $SD = 0.72$, range = 4 – 7) to the question about how well their support figures met the description of "someone you feel you have a close connection with and that you can depend on in times of need." Participants reported having known their support figures for an average of 11.03 years ($SD = 9.97$, range = 0.25 – 40.83). All participants were able to provide an instance of feeling supported by this person (for example responses from participants, see Appendix D, Section

**Table 6.2** Mean percentage of maximum grip strength for target grip strength

| Target grip strength | Observed mean grip strength |
|---|---|
| 40% of maximum | 42.18% of maximum |
| 50% of maximum | 49.51% of maximum |
| 60% of maximum | 55.89% of maximum |
| **Exercise block** | |
| 1 | 50.00% of maximum |
| 2 | 48.38% of maximum |

2, p. 367). For full descriptive statistics on manipulation checks and other variables relevant to analyses (e.g., moderators of social support effects), see Appendix D, Table D 1 (p. 374).

### 6.3.2 Grip strength data

Figure 6.4 shows that participants were able to meet and sustain the target grip strengths of 40%, 50%, and 60% of their maxima for the various objective trial difficulty levels. Table 6.2 shows mean grip strength data for the full trial duration across the three target levels. Because this figure includes grip strength data from the trial onset – when participants began squeezing to obtain the target grip strength – observed means are slightly lower than target grip strengths. Table 6.2 also shows the difference between exercise blocks; and Figure 6.5 shows that the mean percentage of maximum grip strength was lower in the second exercise block, as compared to the first, at all target difficulty levels.

Finally, 32 grip strength readings (0.003% of all readings) from three participants were greater than 100% of their individual maxima, which means that these participants were squeezing harder than when their maximum grip strengths were recorded before the experiment. Given the natural variability in maximum performance during exercise – 'maximum' physical outputs, especially in novices, are highly variable and dependent on factors such as motivation and familiarity with a task (Noakes, 2012) – these data points were not excluded from analyses.

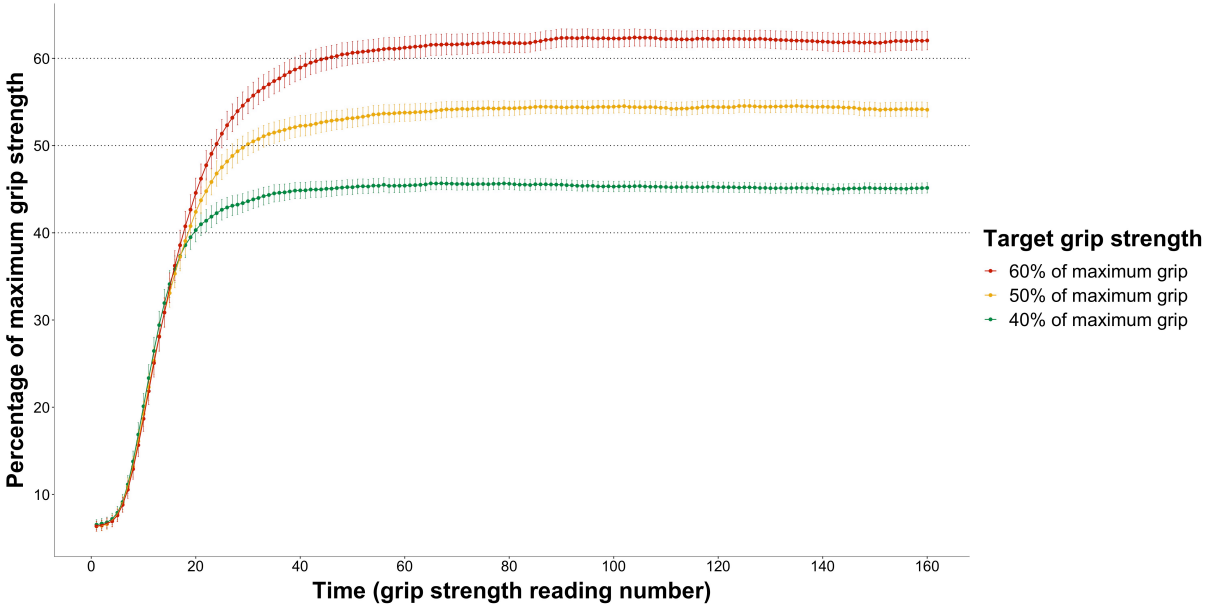



**Figure 6.4** Mean (± 4 *SE*) grip strength (as a percentage of maximum) over time (grip strength readings 0 – 160) by target grip strength.

### 6.3.3 Post-trial questions

Participants had highly correlated responses ($r$ = .803) to questions about how hard the previous trial was ('difficulty') and how much effort they had put into it. Responses to both questions get closer to the scales' maxima (i.e., 'extremely hard' and 'maximum effort') as trial difficulty increases and in the second experimental session, relative to the first (see Appendix D, Table D 2, p. 375). Further, for both the difficulty and effort questions, 11% of responses were at the maxima of the sliding scales (see Figure 6.3, and Appendix D, Figure D 6, p. 389).

### 6.3.4 Main analysis of experimental effects on grip strength data

As described in Section 6.2.3.2 and Section 6.2.3.3, I ran a multilevel linear model to test the effects of the placebo and social support conditions, trial difficulty, and their interactions, on participants' grip strength data. The covariates included in this model were exercise block, trial number, and participants' reported effort levels (scores for this variable represent the percentage of progress on the sliding scale used for responses; 0% = *no effort at all*, 100% = *maximum effort*) for each trial. Random slopes were included for the social support and placebo variables.

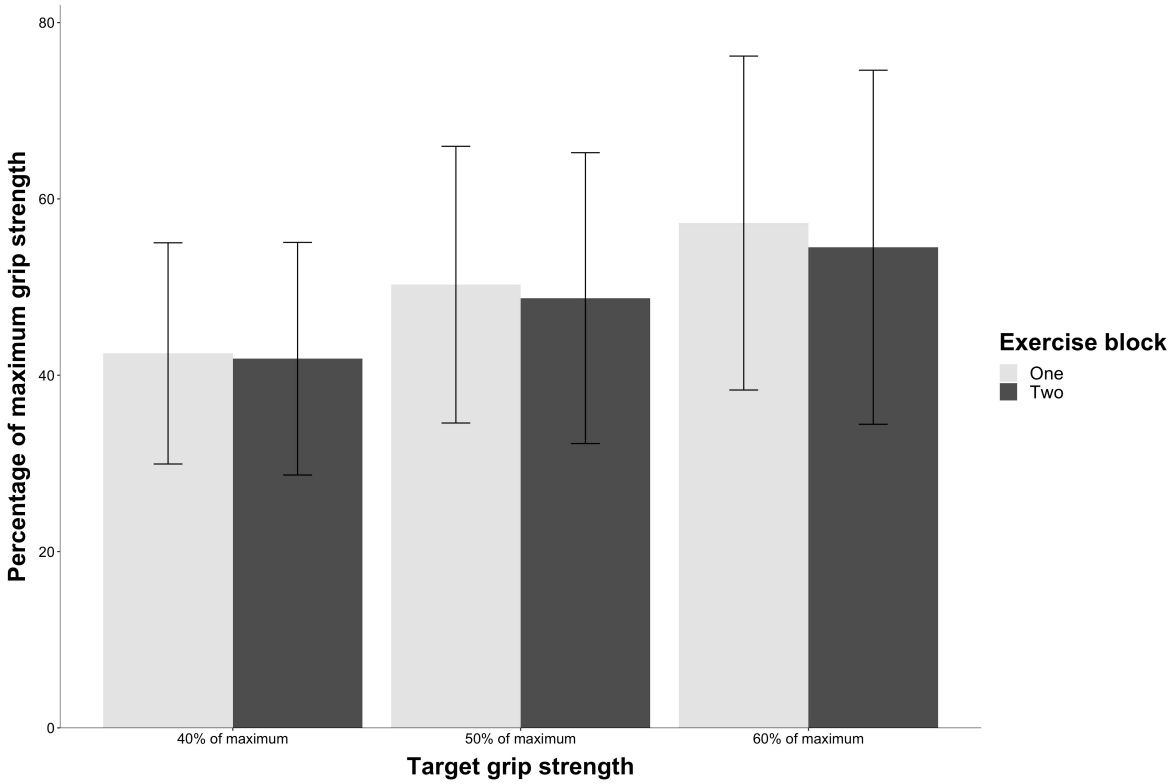



**Figure 6.5** Mean (± 1 *SD*) grip strength (as a percentage of maximum) by and target grip strength and exercise block.

The model, summarised in Table 6.3, revealed a significant main effect of social support on hand grip outputs (Hypothesis 1), $b = 0.42$, $SE = 0.15$, $t = 2.84$, $p = .005$, 95% CI: [0.13, 0.72], $d = 0.03$. Across conditions of trial difficulty, exercise block, and placebo, when participants saw the photo of their support figure, they performed 0.42% closer to their maximum[34] than when they saw the photo of a stranger. There were non-significant effects of placebo (Hypothesis 2), $b = 0.44$, $SE = 0.45$, $t = 0.97$, $p = .335$, 95% CI: [−0.45, 1.33], $d = 0.03$, and its interaction with trial difficulty (Hypothesis 4), $b = -0.05$, $SE = 0.05$, $t = -0.96$, $p = .336$, 95% CI: [−0.15, 0.05], on hand grip outputs.

There was also a significant social support × trial difficulty interaction (Hypothesis 3), $b = 0.22$, $SE = 0.05$, $t = 4.26$, $p < .001$, 95% CI: [0.12, 0.32] (see Figure 6.6) on hand grip outputs. Post

[34] This is for illustration only. Participants were not attempting to perform at their maximum grip strength capabilities, but instead were constrained by pre-determined target thresholds that were a percentage of their maximum grip strength (see Section 6.2.2.3, p. 199).

**Table 6.3.** Estimates for multilevel model on participants' hand grip outputs

| **Fixed effect** | **Coefficient** | ***SE*** | ***df*** | ***t*** | ***p*** | **95% CI** |
|---|---|---|---|---|---|---|
| Intercept | 50.550 | 1.022 | 137 | 49.48 | < .001 | [48.558, 52.553] |
| Social support | 0.424 | 0.149 | 80 | 2.84 | .005 | [0.131, 0.717] |
| Placebo | 0.440 | 0.454 | 75 | 0.97 | .335 | [−0.449, 1.330] |
| Trial difficulty | 6.283 | 0.038 | $1.008 \times 10^6$ | 164.03 | < .001 | [6.207, 6.358] |
| Exercise block | −1.660 | 0.451 | 74 | −3.68 | < .001 | [−2.543, −0.776] |
| Trial number | −0.112 | 0.001 | $1.003 \times 10^6$ | −86.57 | < .001 | [−0.114, −0.110] |
| Effort | 0.044 | 0 .001 | $9.925 \times 10^5$ | 43.97 | < .001 | [0.042, 0.046] |
| Social support × placebo | −0.033 | 0.060 | $1.008 \times 10^6$ | −0.55 | .582 | [−0.151, 0.085] |
| Social support × trial difficulty | 0.221 | 0.052 | $1.008 \times 10^6$ | 4.26 | < .001 | [0.119, 0.323] |
| Placebo × trial difficulty | −0.050 | 0.052 | $1.008 \times 10^6$ | −0.96 | .336 | [−0.151, 0.052] |
| Social support × placebo × trial difficulty | 0.013 | 0.073 | $1.008 \times 10^6$ | 0.18 | .854 | [−0.130, 0.157] |
| **Random part** | **Variance Component** | ***SD*** | | | | |
| Intercept | 44.450 | 6.667 | | | | |
| Social support | 1.539 | 1.241 | | | | |
| Placebo | 15.284 | 3.909 | | | | |
| $R^2_m = 0.113$, $R^2_c = 0.251$ | | | | | | |

hoc analyses of the social support × trial difficulty interaction (with Bonferroni-corrected α values) revealed that the performance-enhancing effects of social support on hand grip outputs increased with trial difficulty (Hypothesis 3). Significant differences in hand grip outputs between the social support condition and its control condition were revealed for trials with grip strength targets at 50% ($b$ = −0.41, $SE$ = 0.15, $Z$ = −2.79, $p$ = .005, 95% CI: [−0.69,

**Table 6.4** Post hoc contrasts (mean difference: support figure face – stranger face) for the interaction between trial difficulty and social support

| Trial difficulty | Estimate | *SE* | *Z* | *p* |
|---|---|---|---|---|
| 40% of maximum | 0.188 | 0.152 | 1.24 | .217 |
| 50% of maximum | 0.393 | 0.152 | 2.58 | .010 |
| 60% of maximum | 0.644 | 0.152 | 4.23 | < .001 |

−0.12], *d* = 0.03) and 60% (*b* = −0.64*, SE* = 0.15, *Z* = −4.21, *p* < .001, 95% CI: [−0.93, −0.34], *d* = 0.03) of participants' maxima (see Table 6.4 for full post hoc contrast results).

### 6.3.5 Main analysis of experimental effects on perceptions of difficulty

I used a multilevel censored regression model to analyse the post-trial question on how hard participants felt the previous trial was. This model contained exercise block, placebo and social support condition, and trial difficulty, as well as their four-way interaction (and all constituent interactions) as predictors. Trial number and participants' reported effort were included as covariates. The model revealed a significant placebo × exercise block interaction, or order effect (*b* = 9.79, *SE* = 0.82, *t* = 12.01, *p* < .001, 95% CI: [8.19, 11.39]; see Figure 6.7. Post-hoc analyses confirm this, showing a significant difference in perceptions of difficulty between the control and placebo conditions in the second exercise block (*t* = 4.68, *p* < .001, 95% CI: [2.38, 5.83], *d* = 0.17), but not in the first (*t* = −0.36, *p* = .720, 95% CI: [−1.93, 1.33]). Higher perceptions of difficulty among these participants were accompanied by (non-significantly) lower hand grip outputs. Returning to the censored regression results, there were non-significant effects for social support, *b* = −1.922, *SE* = 1.737, *t*(6,300) = −1.11, *p* = .268, and the interaction between placebo and social support, *b* = 0.033, *SE* = 2.929, *t*(6,290) = 0.01, *p* = .991 (see Appendix D, Table D 3, p. 376, for a full summary of this model).

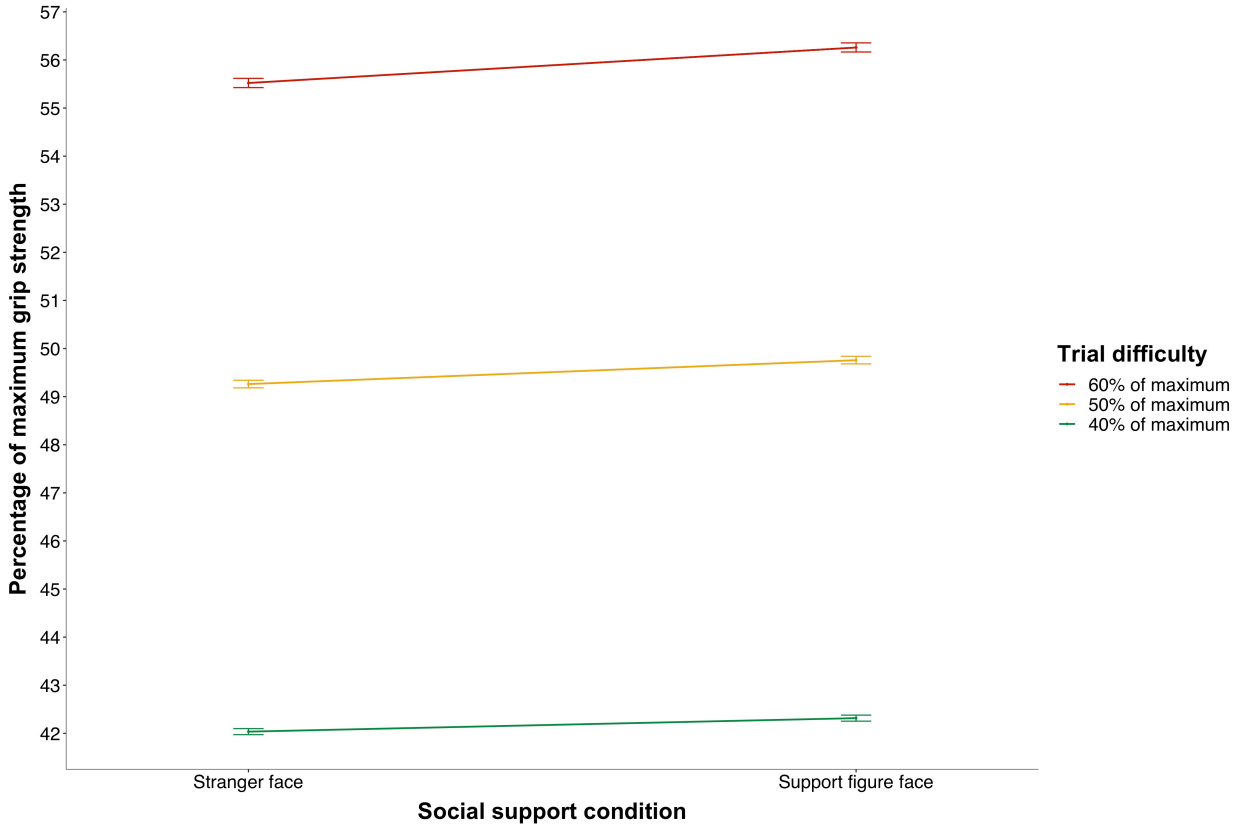



**Figure 6.6** Mean (± 2 *SE*) hand grip outputs by social support condition and objective trial difficulty.

### 6.3.6 Predictors of social support effects on grip strength

Participant neuroticism, need for social assurance, ability to depend on others, and the quality of their relationship with their support figure were all tested as potential predictors of observed social support effects on hand grip outputs. The quality of participants' relationships with their support figures was measured by their responses to the question about how well the person whose photo they submitted met the description of 'someone you feel you have a close connection with and that you can depend on in times of need' (see Section 6.2.2.5). However, this variable was not analysed as a potential predictor of social support effects due to a lack of variation in participants' responses (see Section 6.3.1). As a proxy for the quality of participants' relationships with their support figures, I instead used a ratio of how close participants reported feeling to the support figure they saw during the exercise trials to how close they reported feeling to the stranger they saw. This variable had a much wider variance ($M$ = 2.63, $SD$ = 1.32, range = 0.25 – 5).

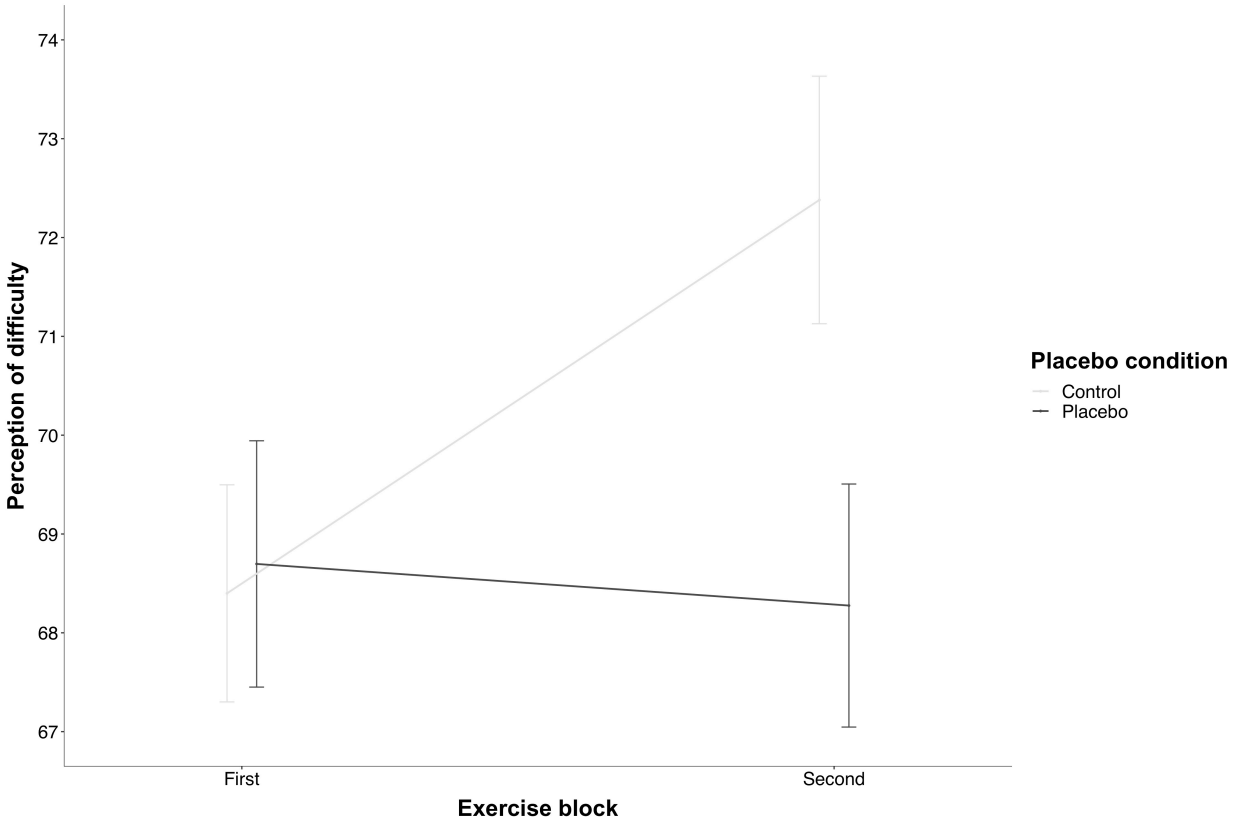



**Figure 6.7.** Mean (± 2 *SE*) perceptions of difficulty (as a percentage of the sliding scale used for responses; 0 = *not hard at all*, 100 = *extremely hard*) by placebo condition and exercise block.

The models with observed social support effects on hand grip outputs as the outcome variable included the main predictor variables of interest listed above, as well as participant sex. These models revealed non-significant effects on the outcome variable for participants' need for social assurance (Hypothesis 5), $b = 0.007$, $SE = 0.197$, $t(73) = 0.04$, $p = .971$ (see Appendix D, Table D 4, p. 377), their neuroticism (Hypothesis 6), $b = -0.557$, $SE = 0.672$, $t(73) = -0.83$, $p = .410$ (see Appendix D, Table D 5, p. 378), the ratio of how close they felt to their support figure to how close they felt to the stranger (Hypothesis 7), $b = 0.134$, $SE = 0.118$, $t(71) = 1.14$, $p = .260$ (see Appendix D, Table D 6, p. 379), and the extent to which they believe they can depend upon others when needed (Hypothesis 8), $b = -0.118$, $SE = 0.217$, $t(72) = -0.55$, $p = .588$ (see Appendix D, Table D 7, p. 380).

## 6.4 Discussion

This experiment investigated the effects of a placebo manipulation and cues to social support on performance and experiences during a difficult hand-grip exercise. In line with Hypothesis 1, results revealed a significant, performance-enhancing main effect of social support on hand grip outputs. These effects were shown to be moderated by trial difficulty; in accordance with Hypothesis 3, the performance-enhancing effects of social support increased along with the difficulty of the exercise (see Figure 6.6). The placebo condition did exhibit differences across trial difficulty, but the differences between the control and placebo condition were not significant at any level of trial difficulty (Hypothesis 2 and Hypothesis 4). Increased hand-grip outputs in the social support condition did not correspond to higher perceived difficulty ratings. In some participants – those who received the placebo before the second exercise block – perceived difficulty was significantly lower than that of their counterparts who did not receive a placebo. This is despite these participants displaying marginally (non-significant) higher outputs than their counterparts who did not receive a placebo before the second exercise block (see Figure 6.7).

Enhanced performance as a result of receiving a cue to social support during exercise offers a novel finding that is in accordance with previous experimental and observational research linking socially supportive environments with improved performance (Carron et al., 2002; Davis et al., 2015; Kraus et al., 2010). This is the first study to cue social support during an exercise task that is heavily dependent on fatigue and self-regulation. Previous studies have all cued social support before exercise, and have generally focused on skill-based tasks (Freeman & Rees, 2008, 2009; Rees & Freeman, 2010), with the exception of two recent experiments involving aerobic (Davis et al., 2015) and anaerobic (Davis & Cohen, 2018) performance, the latter of which makes up Chapter 3 of thesis.

The lack of significant ergogenic placebo effects observed here runs counter to results from similar designs (e.g., Pollo et al., 2008), and a wider body of literature on placebo effects in sport and exercise (Beedie & Foad, 2009). There are several possible reasons for this. First,

it should be noted that (non-significant) model estimates for placebo effects were actually larger (in the direction of performance enhancement) than (significant) model estimates for social support. The model presented in Section 6.3.4 estimated increases of 0.42% (as a percentage of maximum grip strength) for participants taking a placebo versus 0.41% for participants viewing the photo of a support figure (compared to controls). However, the standard error of the estimate for the placebo effect was more than three times the standard error of the estimate for the social support effect (0.453 versus 0.146). This led to statistically non-significant estimates for the difference between the placebo conditions, and likely resulted from the high random effects variance of the placebo effect (see Table 6.3). In other words, there was a lot of variability in participants' responses to the placebo treatment; some participants displayed strong placebo responses whereas other performed *worse* after receiving the placebo. This caused high random effects variance and subsequent high standard errors for the fixed effect of the placebo treatment (Snijders & Bosker, 2012). More generally, this is in line with research showing a large amount of intra-individual variability in placebo responses (McQuay, Carroll, & Moore, 1996), which will be discussed further below.

Second, participants may not have believed they were actually taking β-alanine. Although it would add an additional design complication, future studies could employ procedures to ensure that participants believed in the efficacy of the purported drug being taken. Placebo studies have found that conditioning procedures (as compared to suggestion alone) tend to lead to stronger analgesic and performance-enhancing effects (e.g., Benedetti, 2009; Pollo et al., 2008, 2011). The current design could thus be improved by conditioning participants to expect performance-enhancement from β-alanine. For example, following the methods of Pollo et al. (2008), surreptitious reductions in difficulty after placebo treatments could be used in a series of pre-experiment exercise trials. This procedure was shown to lead to larger ergogenic placebo effects, as compared to suggestion alone (which was used in the present study).

Third, there may be ways in which the presentation of the purported performance-enhancing drug could be improved. This study was intentionally carried out at a hospital, and the drug was presented as if it had come directly from a pharmacist. These performative aspects were included as a means of increasing participants' beliefs about the efficacy of β-alanine. One possible improvement, however, could come with the information form (see Appendix D, Figure D 2, p. 382), as the ethical requirements of the University were such that this form needed to state my department (the Institute of Cognitive and Evolutionary Anthropology) and position (doctoral student). Savvy participants might have thus suspected that these credentials were dubious at best for conducting a study with a biomedically active ingredient.

Aside from the main effects, I also hypothesised two interactions: that the performance-enhancing effects of both social support and placebo would increase with trial difficulty. This was confirmed for social support, but not for placebo. Regarding the moderation of social support effects by trial difficulty, environmental cues – such as social support – are likely to be the strongest when individuals are experiencing high degrees of pain and fatigue (for a full discussion of this idea, see Section 2.2.5, p, 69). At high levels of physical exertion that drive individuals toward exhaustion, outputs are determined largely through top-down processes whereby the CNS attenuates muscle use as a result of feedback from peripheral muscles (Noakes, 2012). In other words, the 'protective brakes' of pain and fatigue become more influential when individuals are nearer to their physiological maximum. However, the protective, self-regulatory employment of pain and fatigue will not be constant across all situations. When environmental cues signal safety or increased access to resources tacit calculations of the costs of sustained physical exertion will be diminished. Interpreting social support as a cue to safety and access to resources could perhaps explain why top-down self-regulatory processes led to greater outputs when participants were looking at the photo of someone they could depend upon in times of need (Eisenberger et al., 2011).

A lack of interaction between the placebo and social support conditions suggests that their effects on exercise performance are independent; the effect of placebo was similar regardless

of the social support condition and vice versa. Further, social support effects were more consistent across participants in this study, as evidenced by lower random effects variances (1.539 v. 15.284; see Table 6.3), although the estimated performance-enhancing effects of social support were similar to those of receiving a placebo (see above). This suggests that social support – at least as construed here – might be a more reliable source of performance enhancement. As discussed in Section 1.4 (p. 15), humans likely have adaptations that cause them to respond to cues to social support with general reductions in stress and perceptions of pain and fatigue. Although these effects vary within and between individuals, the nature of this particular social support manipulation – a photo of a person who is, in theory, participants' support figure of choice – might have reduced the potential complications of receiving social support (such as feeling indebted to the supporter or incapable as a result of receiving support), thereby stabilising social support effects across individuals. As discussed above, there are reasonable explanations for why participants showed such variation in placebo response, and placebo effects are generally known vary between individuals, with around one third of individuals (in varying contexts) showing meaningful placebo responses (Benedetti, 2009; McQuay et al., 1996).

Regarding participants' answers to the question about how difficult the trials were, there was a non-significant effect of social support and a significant interaction between exercise block and placebo condition. As explained in Section 6.2.2.4 (p. 202), the trial difficulty variable was intended as an indirect measure of pain and fatigue, as it becomes more difficult – or harder – to continue muscle drive as signals of pain and fatigue increase (Noakes, 2012; Noakes et al., 2005). Non-significant social support effects existed in the presence of greater outputs in the social support condition; even though participants were producing greater outputs in this condition, they reported the trials to be less difficult – around 2% less on the scale (see Section 6.3.5) – although not significantly so. Regarding the interaction of the placebo condition with exercise block, significant placebo effects existed only in the second exercise block, with

participants who did not receive the placebo before this block rating the exercise trials as significantly more difficult than their counterparts who received placebo.

The effect of placebo on perceptions of trial difficulty in the second exercise block was thus driven by participants who did *not* receive the placebo. It is possible that these participants rated trials as more difficult due to a *nocebo* effect, which can result from negative expectations and beliefs about a treatment, or lack of treatment, in this case (Benedetti, 2009; Benedetti, Lanotte, et al., 2007). Participants who had β-alanine effectively 'withdrawn' may have expected trials to be more difficult without the aid of the performance-enhancer; these expectations may have affected their experiences of the trials (Benedetti, Lanotte, et al., 2007). Given that those receiving placebo in the second exercise block did not report trials to be significantly less difficult than those in the first exercise block (before which they did not receive the placebo), it is possible that levels of peripheral muscle fatigue in the hand and forearm played a role in the observed exercise block × placebo interaction. If participants who did not receive the placebo before the second exercise block felt muscle fatigue at the beginning of this block, which they likely did, given their lower hand grip outputs in this block across experimental conditions (see Table 6.2), it is possible that they attributed their enhanced perceptions of fatigue to a lack of aid from β-alanine (which they were told would reduce their pain and fatigue levels). This may have led to negative expectations about impending trials, ultimately leading to the nocebo effect observed among these participants. Conversely, increased muscle fatigue at the beginning of the second exercise block may have eroded beliefs of the effectiveness of β-alanine among those participants who received the placebo before this block, resulting in the null placebo effects on perceptions of difficulty observed in these participants.

However, the fact that the same pattern is not also present for the hand-grip performance data (there was no significant main effect of placebo, and a significant effect of social support) suggests that this result may be an artefact of self-reports, with participants reporting trials to

be more difficult because they thought they should be more difficult. However, as explained in Section 6.1.1 (p. 193), self-reports of trial difficulty were not necessarily hypothesised to mirror hand-grip outputs. Nevertheless, to further investigate the validity of these self-reports, future neuroimaging work could focus on patterns of activity that suggest greater levels of physical discomfort or on patterns associated with endogenous analgesia (Bingel & Tracey, 2008; Eisenberger et al., 2011). I discuss this further in Section 7.3.3 (p. 245). These future studies could also work to avoid the order effects observed here (i.e., placebo effects on perceived difficulty being contingent on exercise block). This could be achieved through a between subject design (not ideal for fMRI compatibility, which this study was designed for) or by carrying out the study over the course of two or more days, for example, with participants taking the placebo on different days, in a counterbalanced fashion (e.g., Pollo et al., 2008).

Regarding moderators of social support identified in previous research (e.g., Coan et al., 2006; Cohen et al., 2015; Park et al., 2013; Zimet et al., 1988), observed social support effects on hand grip outputs were not predicted by need for social assurance, neuroticism, ability to depend on others, or relative felt closeness with support figures. Aside from the non-significant effect of neuroticism, these results replicate the findings presented in Chapter 3 of this thesis (Davis & Cohen, 2018). Relative felt closeness to support figures may not be the best measure of relationship quality, which in previous work has been shown to moderate the effects of social support (from a spouse) on experimentally induced pain (Coan et al., 2006). The variable that was initially intended to be used to test the effects of relationship quality on social support effects showed little variation in responses; a ratio of felt closeness to support figures (as compared to strangers in the control condition photo) was thus used instead (see Section 6.3.6). However, this variable likely does not provide the fine-grained assessment of relationship quality provided by the measure used by Coan et al. (2006); the Dyadic Adjustment Scale (Spanier, 1976). This may explain the null results observed here. Regarding need for social assurance and ability to depend upon others, it may be that the nature of the social support manipulation meant that its effects did not depend on these variables, since

support figures were not actually present to provide instrumental or emotional social support. Finally, the null effects of neuroticism may again be best explained by the social support manipulation. It has been argued that neurotic individuals may not experience the benefits of social support because they focus on the potential costs of its receipt, such as inconveniencing those who are supporting them (Park et al., 2013). However, these concerns may have been less pertinent to the neurotic individuals in this study, since their support figures were not physically present, and therefor unlikely to have been inconvenienced by the social support manipulation employed. How ergogenic social support effects are affected by personality factors will be further discussed in Section 7.2.2 (p. 235).

The fact that, in the presence of cues to social support, participants produced greater outputs while reporting trials to be equally or less difficult suggests involvement of top-down systems involved in self-regulation during physical exercise. Both the endogenous opioid and endocannabinoid systems are known to be involved in endogenous analgesia, and in reducing perceptions of fatigue during exercise (Benedetti, Amanzio, et al., 2011; Benedetti, Pollo, et al., 2007; Boecker et al., 2008; Wager et al., 2007). Importantly, activation of the endogenous opioid system (the endocannabinoid system has not yet been studied in this context) is thought to 'block' incoming signals of pain and fatigue from peripheral muscles during exercise (Amann et al., 2009). In the context of this study, participants in the social support condition may have had elevated activity in these systems. Since pain and fatigue make motor drive more difficult, their attenuation may have caused participants to produce greater outputs while experiencing the exercise to be equally or less difficult. Ultimately, the involvement of these systems can only be elucidated through future research using brain imaging techniques (e.g., Gorka, Fitzgerald, de Wit, & Phan, 2015; Wager et al., 2007); indeed, the design of this study makes it replicable using methods such as fMRI (again, see Section 7.3.3, p. 245).

Finally, the observed social support and placebo effects are of a similar (although slightly smaller) magnitude to those observed in other research on ergogenic placebos and social environments in sport – these variables have generally been shown to alter physical outputs

by around 1 – 2% (Beedie & Foad, 2009; Beedie et al., 2006; Davis et al., 2015). These studies have, for the most part, focused on tests of maximal physical outputs. Here, effects may have been constrained by the target outputs of each trial, which would have discouraged maximal physical outputs. This may have resulted in a curbing of social support and placebo effects that would have otherwise allowed participants to produce outputs closer to their physiological maxima.

### 6.4.1 Conclusions

This study allowed for the comparison of ergogenic social support and placebo effects on a fMRI-compatible hand-grip task. Results indicated that social support led to greater physical outputs at equivalent levels of perceived difficulty, while, in the second exercise block, placebo led to significantly lower perceptions of difficulty at (non-significantly) higher hand grip output levels. These results give general support to a fundamental claim of this thesis: that environmental cues of safety and resource abundance can lead to enhanced physical performance, especially when individuals are performing nearer their psychophysiological maxima. The observed placebo and social support effects were in the same direction and of a similar magnitude to each other and to effects observed in previous research on ergogenic placebos and social support manipulations (Beedie & Foad, 2009; Beedie et al., 2006; Davis et al., 2015), although only social support effects were statistically significant, owing to large inter-individual variation in placebo effects. Findings are generally in line with the hypothesis that both effects are underpinned by activity in the endogenous opioid and endocannabinoid systems, which studies suggest are involved in ergogenic and analgesic placebo effects (Benedetti, Amanzio, et al., 2011; Benedetti, Pollo, et al., 2007). This study's methods offer an fMRI-compatible design that will allow for more direct investigation of these mechanisms and of the neurological activity underpinning the effects observed here. Overall, then, the study presented here offers novel findings on ergogenic social support effects, and opens new avenues of research that will be of interest to multiple academic disciplines, such as

neuroscience, placebo research, sport psychology, and cognitive and evolutionary anthropology.

# Chapter 7 – General discussion

**Abstract**

This chapter provides an overview of the empirical findings of this thesis, situating them within broader bodies of relevant literature while discussing their limitations and implications for current understandings and future research. After an overview of the main findings of the studies presented here, I examine what these empirical findings imply for current understandings of ergogenic social support effects, focusing on how social support may affect self-regulatory strategies during strenuous physical exercise and how these effects may vary according to personality differences. Next, the main limitations of this thesis are discussed, which include a lack of diversity in experimental participant samples, plausible alternative explanations to empirical findings (chiefly, competition effects), and a lack of direct investigations into the proposed causal mechanisms of ergogenic social support effects. Finally, the methodological, empirical, and theoretical contributions of these thesis are reviewed, with a focus on their relation to research in cognitive and evolutionary anthropology and scientific and public discourse more broadly.

## 7.1 Overview

This thesis explored the hypothesis that cues to social support can change the self-regulation of strenuous physical exercise, leading to reductions in perceptions of pain and fatigue, and, ultimately, enhanced outputs. The hypothesised ergogenic effects of social support are situated within a broader argument, presented in Chapter 1, about why social environments should affect activity in a variety of self-regulatory mechanisms, such as those involved in immune response, pain perception, and recovery from illness and injury. Given the intense dependence on social relationships for safety and access to physical and cultural resources displayed throughout the human lifespan (Henrich, 2015; Tomasello, 2014; Tomasello et al., 2012), indicators of social support and cohesion are likely to lead to more liberal self-regulatory responses to potential threats and losses. In the context of strenuous physical exertion, this suggests that estimates of the costs of potential injury and exhaustion will be reduced in the presence of supportive social relationships, and that activity in self-regulatory pain- and fatigue-reducing mechanisms will be increased to allow for greater physical outputs. In four studies (Chapter 3 – Chapter 6), I tested this hypothesis using diverse methods and measures. I aimed to demonstrate ergogenic social support effects in both experimental and naturalistic settings, taking measures of aerobic and anaerobic performance, and indicators of self-regulatory processes related to pain, fatigue, and physical outputs.

### 7.1.1 Summary of findings

The experiment reported in Chapter 3 implemented a direct manipulation of social support before a standard measure of anaerobic performance (Bar-Or, 1987). Results indicated that participants in the social support condition produced greater initial outputs and steeper declines over time (compared to participants in the control condition), and that this effect was moderated by a personality factor related to how social support is received. Greater initial outputs and steeper declines over time are in line with previous research using the opioid agonist fentanyl. Amann et al. (2009) showed that an opioid-mediated blockade of pain and fatigue signals led cyclists to ‘overshoot’ optimal output levels in the first half of a 5 km trial,

leading to greater first half outputs, but also to higher levels of peripheral muscle fatigue, and, ultimately, diminished outputs in the second half of the trial. A similar process might have occurred with socially supported individuals in the Chapter 3 study. These individuals may have experienced attenuated perceptions of pain and fatigue – owing to activity in the endogenous opioid and endocannabinoid systems resulting from the presence of a close social other (Benedetti, Amanzio, et al., 2011; Benedetti, Pollo, et al., 2007; Inagaki et al., 2016; Machin & Dunbar, 2011; Trezza et al., 2010) – leading to greater initial outputs, but also greater peripheral muscle fatigue and steeper declines in outputs over time. Further, the effects of social support were moderated by participant neuroticism; in line with previous findings (Park et al., 2013), participants scoring low in neuroticism performed better when in the social support condition (compared to the control condition) whereas those scoring high in neuroticism showed the opposite pattern. This may be due to differences in behavioural strategies – which neuroticism indicators might capture (Figueredo et al., 2005) – that are tuned to the likelihood of receiving the benefits of social support (this will be discussed further in Section 7.2.2). In sum, this study offered the most direct test of ergogenic social support effects to date. Results are consistent with hypotheses, suggesting that, depending on personality type, social support can alter physical exercise outputs, possibly through affecting systems involved in the self-regulation of pain and fatigue.

Chapter 4 studied social support and cohesion effects in a naturalistic setting; a community-based, group exercise event known as parkrun. Through the analysis of a large data set, I showed that the presence of strong social relationships and community integration (both measured via social network metrics) predicted faster 5 km run times. These findings were in line with the hypothesis that the presence of close, supportive others can enhance exercise outputs. However, given that the study was observational in nature, I cannot say to what degree these findings were confounded by competition among rival parkrunners. In order to address the shortcomings of this strictly observational study, and to further investigate hypothesised causal mechanism in ergogenic social support effects, I designed a longitudinal

survey of British parkrunners, with the aim of obtaining more information on parkrunners' sociality, motivations, and experiences.

The longitudinal survey study of parkrun was presented in Chapter 5. The survey was administered to participating parkrunners after their completion of a parkrun 5 km run each week for a four-month period. The survey asked about parkrunners' pre-run sociality, their motivations for attending parkrun, and their run experience. Results revealed that coming to or meeting up with friends and/or family at parkrun, socialising before runs, and feeling included and supported in the parkrun community all predicted faster running times via increases in participants' self-reported energy levels (i.e., felt energy mediated significant indirect, performance-enhancing effects of the social predictor variables on 5 km run times). Importantly, these social predictor variables had no significant direct or total effects on 5 km run times. The importance of felt energy as a mediator of ergogenic social support effects will be discussed further Section 7.2.2. The survey also revealed significant, positive direct effects of all social predictor variables on how much participants enjoyed their runs. Overall, this study largely corroborates and informs the findings of the parkrun big data study presented in Chapter 4; when parkrunners are in the presence of close social others, they feel more energised, and this leads them run faster over 5 km. In related work, it has been theorised that felt energy and positive affect (enjoyment) can result from the endogenous opioid and endocannabinoid activity that underlies the runner's high (Boecker et al., 2008; Raichlen et al., 2012; Sparling, Giuffrida, Piomelli, Rosskopf, & Dietrich, 2003). Thus, this study potentially provides further indirect evidence for the hypothesis that social support leads to activity in the self-regulatory endogenous opioid and endocannabinoid systems, thereby reducing perceptions of pain and fatigue, and leading to enhanced physical outputs.

Chapter 6 attempted to provide a framework for further testing the involvement of the endogenous opioid and endocannabinoid systems in ergogenic social support effects. It did this through employing an fMRI-compatible, $2 \times 2 \times 3$ factorial design which included placebo and social support conditions that varied by trial difficulty. The two main dependent measures

of interest were hand grip exercise performance and measures of perceived exercise difficulty. It is well established that endogenous opioid and endocannabinoid activity underpin analgesic and ergogenic placebo effects (Benedetti, Amanzio, et al., 2011; Benedetti, Pollo, et al., 2007; Pollo et al., 2008, 2011); this study thus allowed for a comparison, at the behavioural level, of ergogenic placebo effects with ergogenic social support effects. Results indicated that participants had higher outputs (i.e., applied more force to the handgrip) when in the social support condition, and that these effects increased with trial difficulty (see Figure 6.6, p. 215). These enhanced hand grip outputs held when controlling for self-reported effort levels, and were *not* accompanied by increases in perceptions of difficulty. Further, despite displaying relatively higher outputs after receiving the placebo (this was not statistically significant, owing to large standard errors), participants who received the placebo in the second exercise block reported the exercise trials in this block to be *less* difficult than those who received no placebo in this block and those who received the placebo in the second block (see Figure 6.7, p. 216). In sum, this study shows ergogenic placebo and social support effects of a similar magnitude (about 1 – 2% increases in performance), corroborating previous research on ergogenic placebos (Beedie & Foad, 2009; Benedetti, Pollo, et al., 2007; Pollo et al., 2008), and extending findings and methods on social support based analgesia to the field of physical exercise (Eisenberger et al., 2011). Considering the similarity of the social support and placebo effects observed here, and that endogenous opioid and endocannabinoid activity are known to be involved in ergogenic and analgesic placebo effects, these findings offer further evidence for the hypothesis that endogenous opioid and endocannabinoid activity underpin ergogenic social support effects (although see Section 7.3.3 for a full discussion of the limitations of these findings).

## 7.2 How does social support affect strenuous physical exercise?

As summarised above, the empirical results of this thesis suggest that social support generally has a positive effect on exercise performance; compared to controls, socially supported individuals produced greater outputs despite similar reported effort levels and either similar or

reduced perceptions of physical discomfort. However, this account requires some caveats and qualifications. These include (a) the fact that social support may cause an overshoot of optimal outputs due to reduced functioning in pain and fatigue feedback systems (see Section 3.4, p. 92), (b) the degree to which individuals are putting forth maximum physical effort Section 2.2.5, p. 69, and Section 6.4, p. 217), and (c) that ergogenic social support effects may depend on how support from others is received (see Section 1.4.1, p. 19, Section 3.4, p. 92, and Section 5.4.2, p. 177). These caveats will be discussed below. Further, although the results presented are in line with the proposal that endogenous opioids and endocannabinoids mediate the effects of social support on strenuous physical outputs, activity in these systems was not examined directly; I will discuss why this was the case and present ideas for future research in Section 7.3.

### 7.2.1 Ergogenic social support effects over time

Results from Chapter 3 suggest that social support effects may cause an overshoot of optimal exertion levels, initially enhancing performance but eventually leading to higher levels of peripheral muscle fatigue and lower physical outputs. As discussed in Section 3.4 (p. 92), this effect may result from enhanced endogenous opioid and endocannabinoid activity in socially supported individuals, which blocks incoming signals of pain and fatigue that would otherwise reduce central motor drive and physical outputs (see Amann et al., 2009). If social support leads to reductions in perceptions of pain and fatigue, then this overshoot effect may be a potential outcome of social support during strenuous physical exercise. As a result, socially supported individuals may end up producing initial outputs that are too great, given their physiological capabilities and the duration for which these outputs need to be sustained.

This finding highlights the possibility that social support effects during strenuous physical exertion may have costs in terms of future outputs. Instead of allowing for enhanced outputs over the entirety of an event, social support may instead alter the profile of physical outputs, such that individuals produce greater initial outputs at the expense of subsequent outputs. As in the study of Amann et al. (2009) – reviewed in Section 2.2.3.2, (p. 57) – these greater initial

outputs may lead to excessive muscle fatigue, leaving individuals in a relatively immobile, vulnerable state. Vulnerability induced by greater-than-optimal physical outputs is discussed by Amann et al. (2009); participants were reported to have needed help walking after opioid-induced overshoots in initial optimal cycling outputs. Considering the potential adaptive function of such overshoots (given their potential high costs), it may be that producing greater initial outputs (at the expense of subsequent outputs) is advantageous in particular settings. For example, greater initial outputs could function as a signal of physical fitness that dissuades competitors, rivals, or predators from further challenges. Individuals in relatively safe, resource rich social environments may be better suited to deal with the costs incurred by overshoots in initial outputs that leave them relatively vulnerable and resource-depleted.

However, this overshoot effect was not observed in the results of the other chapters of this thesis. In particular, the ergogenic social support effects observed in Chapter 6 did not change significantly over time (the data from Chapter 4 and Chapter 5 were not well suited to examine overshoot effects). This suggests that the overshoot effect observed in Chapter 3 may be a result of the participant sample and experimental design.

The ‘recreationally fit’ exercisers recruited for the experiment were likely unfamiliar with anaerobic fitness testing and relevant pacing strategies. Compared to those in the control condition, socially supported participants may have thus been particularly susceptible to overshooting optimal initial outputs, either because they estimated the task to be easier (Schnall et al., 2008), or because they experienced reduced pain and fatigue signalling from peripheral muscles. The study from Chapter 6 may have produced different results because of the more moderate and controlled nature of the hand grip exercise; participants were given performance targets that were at 40%, 50%, and 60% of their maximum grip strength. Thus, they were not putting forth maximal effort, and this may have permitted self-regulatory strategies that allowed for sustained enhanced outputs, despite also having impaired feedback from pain and fatigue signalling peripheral muscles.

Another difference between the experiments presented in Chapter 3 and Chapter 6 is the social support manipulation. In the experiment reported in Chapter 3, participants were only cued to the presence of social support before the exercise trials, whereas participants saw the support figure photo at intervals throughout the Chapter 6 experiment. The declining ergogenic effects of social support observed over the four bouts of maximum-effort cycling in the Chapter 3 experiment could perhaps be explained by the decreasing salience of social support over time. This effect did not occur over the hand grip exercise trials in the Chapter 6 experiment, likely because participants received consistent cues to social support (i.e., they saw the photo of their support figure) throughout the exercise portion of the experiment.

In sum, then, the empirical findings I present in this thesis offer mixed evidence as to how ergogenic social support effects vary with time. It is possible that the results presented in Chapter 3 are an artefact of the experimental design (i.e., the decreasing salience of social support over time) or the participants used in the study, who were (likely) inexperienced with maximum-effort anaerobic trials, making it difficult for them to produce optimally-paced outputs that reflected the potential advantage afforded by the presence of social support. Self-regulatory strategies among socially supported participants may have also been affected by reduced pain and fatigue perceptions resulting from heightened endogenous opioid and endocannabinoid activity (see Section 3.4, p. 92, for a full discussion of this process). These effects would have been more pronounced in the study presented in Chapter 3, as compared to that presented in Chapter 6, because its anaerobic exercise trials required maximal anaerobic efforts. As discussed in Section 2.2.5 (p. 69), pain and fatigue signalling likely affect performance most when individuals are performing at or near their physiological maxima (Noakes, 2012).

Ultimately, more research is needed to understand the factors that cause declines in ergogenic social support effects over time (see Section 7.3 for a discussion of potential future research). This research should include improved and varied social support measures, and different populations of participants; additional findings would be relevant to better

understanding how different exercises and exercisers lead to varying outputs profiles during bouts of strenuous physical exertion (see Section 7.5).

### 7.2.2 Individual differences in social support effects

The empirical findings of this thesis also suggest that social support effects depend on the way social support is received. Chapter 3 described results showing positive effects of social support on anaerobic exercise performance among individuals scoring low in neuroticism and negative effects of social support on anaerobic exercise performance among individuals scoring high in neuroticism (though this finding was not replicated in the Chapter 6 experiment). The survey study of parkrunners presented in Chapter 4 suggested that the positive effects of social support on 5 km run times at parkrun depend on perceptions of social support enhancing feelings of energy (which ultimately lead to faster 5 km run times). Although it appears tautological that social support must be received as support (instead of as a burden, for example) to have ergogenic effects, it is important to bear in mind that social presence and cues to support availability are open to interpretation. The studies reported here aimed to manipulate or measure the effects of the presence of or cues to socially supportive friends, partners, or loved ones on physical outputs during exercise, but it is possible that (some) participants would have responded more to other forms of social support (e.g., instrumental social support; Cohen & Wills, 1985), or did not feel socially supported at all in the context of the physical tests observed. That being said, the social support manipulations used in this thesis were closely aligned with those used in previous research which showed reductions in stress responses (Chapter 3; Heinrichs et al., 2003) and perceptions of pain (Chapter 6; Eisenberger et al., 2011) in socially supported individuals. Overall, then, these results shed light on how the receipt of different types of social support varies across individuals and contexts and how these differences might affect physical exercise outputs.

The findings on neuroticism from Chapter 3 suggest that personality type may be an important factor in determining whether or not individuals benefit from social support. Other research on health outcomes (Cohen et al., 2015; Park et al., 2013) mirrors the findings of Chapter 3;

individuals scoring low in neuroticism tend to benefit from social support (i.e., they respond to it with reduced levels of stress and enhanced immune functioning, for example), whereas those scoring high in neuroticism do not experience such benefits. In the case of the data presented in Chapter 3, highly neurotic participants actually performed *worse* on the anaerobic exercise bouts when in the presence of their support figures. Park et al. (2013) explain that highly neurotic individuals are likely to worry about the potential social costs of receiving support from others (e.g., feeling like they are inconveniencing those that support them), and that this shift in focus diminishes the potential benefits of social support. This explanation would fit more generally with the empirical findings of this thesis. Neuroticism levels did not moderate the social support effects reported in Chapter 6. This may be because I used a *cue* to social support in this study (i.e., a photo of a support figure), instead of actually having the support figure present. Of course, neurotic individuals' perceptions of the social costs of having a support figure attend an experimental session are likely to be much higher than the perceived social costs elicited by simply being reminded that they have a support figure (through seeing their photo).

Research suggests that personality is (at least in part) ontogenetically tuned to particular developmental environments (Figueredo et al., 2005); it may be that environments of support and safety lead to personality types that are low in neuroticism, whereas high neuroticism results from less predictable access to safe, supportive environments. Regardless, personality types affect how social support is received. This thesis focused on those personality factors that had been repeatedly identified in the literature as moderators of social support effects, but additional factors undoubtedly exist (Coan et al., 2006; Cohen et al., 2015; Kinzler, Shutts, DeJesus, & Spelke, 2009; Park et al., 2013; Zimet et al., 1988). Even acute mood states – which vary within individuals over time and across contexts, and when summed, comprise personality traits (Judge, Simon, Hurst, & Kelley, 2014) – are likely to affect how social support is received, although research is yet to investigate this prospect in detail. Further, the

availability of social support itself can change acute mood states and even personality factors, such as need for assurance from others (Holt-Lunstad & Uchino, 2008).

Nevertheless, several variables that represent personality factors related to how social support is received failed to moderate the ergogenic social support effects observed in this thesis. In the studies presented in Chapter 3 and Chapter 6, none of the following variables significantly interacted with social support in affecting physical outputs: participants' need for social assurance, their perceived available social support in daily life (as measured by the Multidimensional Scale of Perceived Social Support in Chapter 3 and the Revised Adult Attachment Scale in Chapter 6), and the quality of their relationship with their support figures. It is possible that the moderating effects of these variables on cues to emotional social support during strenuous physical exercise are weaker, and that a different kind of social support, such as one that focuses on increasing exercisers' self-efficacy, might have been more strongly influenced by these moderators. For example, Rees and Freeman (2010) manipulated both emotional support and esteem support (in the same condition) in their golf-putting experiment, and this led to a significant interaction between received social support and participants' perceived daily social support, such that social support effects were stronger among those scoring relatively low in perceived daily social support, as compared to those scoring relatively high on this construct. This again suggests that, as a means of enhancing the efficacy of social support manipulations, future studies could expand the types of social support provided. Specifically, these studies could focus on forms of social support that increase recipients' self-efficacy, which could cause them to evaluate exercise tasks as less difficult while enhancing their felt energy levels (Christensen et al., 2006; O'Connor & Puetz, 2005; Schnall et al., 2008).

The effects of social support on acute mood states was demonstrated by the results of the parkrun survey presented in Chapter 5. Results showed that parkrunners' felt energy levels mediated the relationship between social predictor variables and 5 km run times. Researchers have described the mood of energy as "positive feelings about the capacity to complete mental or physical activities" (p. 229; O'Connor & Puetz, 2005). It may be that, as with some forms of

ergogenic placebo effects (e.g., Kalasountas, Reed, & Fitzpatrick, 2007), enhanced self-efficacy is an important mediator of social support effects on physical performance. Noakes et al. (2005) argued that perceptions of pain and fatigue increase in a manner inversely related to the amount of exercise an individual can safely complete under a given set of circumstances. Felt energy may thus be an indicator of individuals' (tacit) calculations of the costs and benefits of physical exertion. As I have argued throughout this thesis, social support likely reduces the perceived costs of physical exertion, thereby leading to mechanistic activity – such as activity in the endogenous opioid and endocannabinoid systems – that facilitates physical movement. Indeed, felt energy is a symptom of the so-called runner's high, which has been theorised to be underpinned by activity in both of these systems (Boecker et al., 2008; Raichlen et al., 2012; Sparling et al., 2003).

The empirical results from this thesis thus suggest two important individual-level factors in determining how social support affects strenuous physical outputs: neuroticism levels and how energised individuals feel as a result of receiving social support. These two factors are likely related. For example, it is possible that highly neurotic individuals feel less energised after the receipt of social support, due to them having a personality type that generally has more negative or blunted responses to the provision of social support, possibly because of concerns about reciprocation (Park et al., 2013). Focusing on the potential costs of receiving social support, or simply having a negative affective response to social support, may lead highly neurotic individuals to be impervious to the provision of social support. Felt energy might also be related to individuals' perceptions of social support. Since felt energy is related to beliefs about self-efficacy, and individuals are likely to feel more capable of performing strenuous physical exercise when they feel socially supported (e.g., Schnall et al., 2008), felt energy may indicate that individuals perceive social support (either implicitly or explicitly). The findings on neuroticism and felt energy may then suggest that *perceived* social support, instead of received social support, is the important predictor of ergogenic effects. This is in line with a large body of findings highlighting the relative importance of perceived social support (as

compared to received social support) in predicting positive health outcomes (see Holt-Lunstad & Uchino, 2008 for a review).

### 7.2.3 Discrepancies between the parkrun big data and survey analyses

The analyses of parkrun's database from Chapter 4 should be considered in light of the parkrun survey results from Chapter 5. The survey results suggest that the social predictor variables only affect run times through their effects on parkrunners' felt energy (see Section 5.4.1, p. 175). These results contradict the findings from Chapter 4, which suggest that perceptions of cohesion and the presence of close social relationships at parkrun have significant ergogenic (total) effects on 5 km run times.

It is possible that the social predictor variables captured in the survey were different than those derived from the parkrun data set. Analysis A and Analysis B of Chapter 4 were meant to measure the effect of the presence of a highly bonded partner on 5 km run times; the relationships among the individuals included in this data set might thus be of higher quality than those captured by the binary social predictor variables derived from the parkrun survey analysis, which were based on whether or not survey participants reported being social before their runs (or not), and whether they came to parkrun with friends or family (or not). What parkrunners define as friends *might* include considerably weaker social relationships than, say, parkrunners who have travelled to eight or more separate parkrun locations together (as was the case in Analysis B). It is thus possible that stronger social relationships identified in Analysis A and Analysis B had direct and total effects on 5 km run times, whereas the weaker social relationships represented by the binary social predictor variables derived from the survey analysis only affected 5 km run times indirectly, through their effects on parkrunners' felt energy levels.

However, this interpretation does not explain why the parkrun community component derived from survey responses had no direct or total effect on 5 km run times, whereas the FPRS variable (Analysis C of Chapter 4) suggests that social integration at parkrun has ergogenic

effects that are not contingent on felt energy levels. It may be that FPRS effects were driven by something other than social support, such as competition, which is discussed in Section 4.7.4.2 (p. 141) and again (considering all empirical results from this thesis) in Section 7.3.2.1, and that perceptions of support and inclusion at parkrun only affect run performance through their effects on felt energy.

Ultimately, the discrepancies between the results from Chapter 4 and Chapter 5 will only be elucidated through further research on parkrun. If survey-based, such future research projects should first attempt to obtain a more representative sample of parkrunners, since some discrepancies between the big data and survey results could be due to the fact that the survey was conducted on a narrow sample of parkrunners from in and around Oxford, UK, who volunteered to participate in the study. This could have biased the survey sample (relative to the larger sample used in Chapter 4) toward particular demographics, or toward individuals who were particularly involved with the parkrun community. These studies could also strive to ask questions that more explicitly quantify the presence of close social relationships (for example, using a measure of felt closeness similar to that employed in Chapter 6; see Section 6.2.2.5, p. 203), and the amounts of material, emotional, and instrumental support that parkrunners' feel they have on a given day (for a summary of potential measures, see Holt-Lunstad & Uchino, 2008). Analyses of the parkrun database could also be informed by parkrun survey data, and vice versa. For example, survey data could be used to check whether the presence of a finishing or travel partner predicts increases in perceptions of social support. These changes may help to better elucidate the apparent discrepancies between the results of Chapter 4 and Chapter 5. Further, these methods could be used in tandem with the pre-registered design procedures discussed in Section 4.7.5 (p. 144) to test the hypotheses of this thesis using data from a different data set on group exercise, such as the social fitness network provided by Strava.

## 7.3 Limitations and future directions

Although the empirical research presented in this thesis offers the first systematic test of the hypothesis that social support enhances the performance of strenuous physical exercise, it is limited in several key aspects. Here, I will discuss these limitations, and then propose several avenues of potential investigation that can serve to guide future research.

### 7.3.1 Participant samples

All four studies presented in this thesis were conducted with participants who are, generally, casual or everyday exercisers. The exception to this might be some extremely talented parkrunners, although these people make up a small proportion of the survey sample and also a small proportion of parkrunners overall. Compared to casual exercisers, highly trained amateur and professional athletes can be assumed to be more familiar with pacing and self-regulatory strategies (pain management, pushing through fatigue, etc.) more generally. Specifically, highly trained athletes may be able to maintain constant outputs despite changes in perceptions of pain and fatigue, which are likely to have stronger effects on individuals who are unfamiliar with the task or these affective states. Further, highly trained athletes are likely more capable of putting forth physical efforts that are closer to their 'true' (psycho)physiological maxima, as learning how to overcome neurobiological restraint mechanisms (i.e., pain and fatigue) can take years of training (Noakes et al., 2005). This has implications for the generalisability of the findings from this thesis.

For example, producing (individually) optimal outputs over a series of four maximal-effort anaerobic trials – which participants were asked to do in the experiment presented in Chapter 3 – is made easier when individuals have pacing strategies based on their own physiological abilities. This requires familiarity with the task, which the majority of participants likely did not have. Running the same experiment on highly trained athletes, who are both familiar with the task and putting forth maximal effort, may have yielded different results. Indeed, even familiarising participants with the task beforehand may have altered results. These concerns are also potentially relevant to the hand grip exercise employed in the study presented in

Chapter 6, although the controlled nature of this exercise – participants were asked to squeeze the handgrip at either 40%, 50%, or 60% of their respective maximum grip strengths – likely reduced the effects of pacing strategies and task familiarity on performance outcomes, since it gave participants specific output goals regardless of potential differences in self-regulatory pain and fatigue systems.

Future studies should consider using different samples and methods to test the ergogenic effects of social support. As discussed, trained athletes who are familiarised with the particular exercise task – and putting forth maximum effort – may provide results that are less affected by sub-optimal pacing strategies. Another means of reducing the impact of sub-optimal (here, total output-reducing) pacing strategies would be to give participants training sessions before the experimental session. This would allow participants to familiarise themselves with optimal pacing strategies before performing the exercise during the experiment.

### 7.3.2 Alternative explanations

Several aspects of the research presented in this thesis lend themselves to alternative explanations. Firstly, since social support effects are underpinned by individuals' perceptions of particular social situations, it is possible that what I have called social support effects are actually better explained by alternative theories. Chief among these are theories related to competition effects. Second, the observational nature of the studies presented in Chapter 4 and Chapter 5 make it difficult to draw causal inferences from the findings; the time order of the occurrence of predictor and outcome variables was sometimes ambiguous in these studies (Agresti & Finlay, 1997). When possible, I tried to eliminate alternative explanations in the study design and analysis, but, ultimately, more research will be needed to further clarify my findings.

#### 7.3.2.1 Competition

Research has shown that competition can enhance physical performance in sport and exercise settings through increasing motivation levels (Corbett et al., 2012; Konings et al.,

2016; McCormick et al., 2015; Tomazini et al., 2015), and competition in sport and exercise has itself been described as a costly signal of physical fitness to potential rivals and mates (De Block & Dewitte, 2009; Miller, 1999). Of course, these effects exist, and often times they will be impossible to disentangle from social support effects. In naturalistic settings, such as the running competitions lined with cheering spectators which Gotaas (2012) describes in *Running: A Global History*, it is possible that individuals will show enhanced performance because of social support *and* competition effects. Indeed, it is feasible that the same person could elicit both types of effects in an individual. This is perhaps the biggest challenge to studying ergogenic social support effects (especially in naturalistic settings), although I attempted to employ experimental designs which helped to circumvent the problem.

Because of their observational nature, the findings from my studies on parkrun – the big data research presented in Chapter 4 and the survey presented Chapter 5 – lend themselves to interpretations involving competition and costly signalling. For example, instead of representing the availability of social support, the FPRS variable employed in Chapter 4 could represent the presence of competition; parkrunners who consistently finish near one another could develop rivalries, thereby increasing perceptions of competition and subsequent motivation levels. Further, increased sociality at parkrun might also increase competition levels. At parkrun, it is likely that competition and costly signalling do explain *some* of the effects that I currently attribute to social support.

Given this, I created two additional variables using the parkrun data set; one looking at the effect of running with a faster running partner and another looking at the effect of attending parkrun with a frequent travel partner with *dissimilar* running times. Both of these variables were created, at least partly, in an attempt to reduce the confound of competition. The faster running partners in my data set necessarily slowed down to run with their slower partners, seemingly in a supportive, non-competitive fashion. The travel partners I examined never ran together (I explicitly removed any travel partners that ever finished within 1 min of each other); travel partners thus likely perceived the presence of their partners to be supportive, rather

than competitive. Results showed that parkrunners ran faster 5 km times when attending a parkrun event with a travel partner. Although competition is still a possible explanation for these findings, it seems unlikely in these subsets of parkrunners. In sum, I took several steps to use variables that minimised the possibility of incorrectly attributing competition effects to social support effects in my studies on parkrun.

I also took measures to control for competition and signalling effects in the experimental studies presented in this thesis. The Chapter 3 study used a modified version of a previously used social support manipulation – bringing a friend to an experiment for emotional social support (Heinrichs et al., 2003) – that attempted to reduce observation effects (and, by extension, competition and costly signalling effects). Since companions waited in another room while participants completed the exercise task, remaining oblivious to participants' performance, it is unlikely that participants were competing or signalling to companions. Regarding the cue to social support used in the Chapter 6 study (a photo of someone participants felt they were close with and could depend upon in times of need), this manipulation of social support should be entirely free from any observation or competition effects that would bias the experimental results.

Future research investigating ergogenic social support effects could endeavour to test for competition effects as well. In their simplest form, these tests could involve asking participants how competitive they felt during the exercise task. For example, in the parkrun survey study, participants could have been asked about how competitive they felt during their runs. This could offer a slight improvement to the question about competition that I used in this study: "Besides other motivations you might have had for attending parkrun today, which of the following options best applies to you? I was motivated to… (a) improve my ranking; (b) improve my time; (c) run together with other people." Only 2% ($n$ = 18) of responses indicated competition ("improve my ranking"). However, if asked explicitly about feelings of competitiveness, responses may have indicated a different scenario. More subtle measures of competition effects could be captured by measuring participants' motivation levels across

experimental conditions, although these measures would need to be developed in a way that allows researchers to separate motivation derived from social support and motivation derived from competition (a difficult task). Ultimately, researchers interested in ergogenic social support effects should strive to design studies that control for competition effects when possible, while also using measures of competition as a means of identifying it as a potential confound.

### 7.3.3 Evidence on endogenous opioid and endocannabinoid activity

Much of the theoretical basis of this thesis rests on mechanistic explanations of why social support is likely to affect the performance of strenuous physical exercise. Specifically, I propose that social support is likely to activate the endogenous opioid and endocannabinoid systems, as these systems are involved in the formation, maintenance, and signalling of social bonds (Dunbar, 2012; Inagaki et al., 2016; Trezza et al., 2010). Endogenous opioid and endocannabinoid activity have been shown to reduce perceptions of both pain and fatigue during strenuous physical exercise (Amann et al., 2009; Pollo et al., 2011). Given their involvement in signalling the presence of close social others, and in the self-regulation of physical outputs, I hypothesised that social support enhances outputs and experiences during strenuous physical exercise, and that these relationships would be mediated by activity in the endogenous opioid and endocannabinoid systems. These systems are thus crucial to the theoretical basis of my thesis, as they offer a mechanistic link between social support and the self-regulation of strenuous physical exercise outputs.

Despite my theoretical focus on these systems, I did not directly test their activity levels in any of the studies presented in this thesis. Previous research has measured endocannabinoid levels using blood samples (Raichlen et al., 2013) and endogenous opioid levels through measuring opioidergic ligand activation with PET (Boecker et al., 2008). Needless to say, both of these methods are expensive and require a considerable amount of technical expertise. Given this, and the largely novel nature of my research questions – ergogenic social support effects on aerobic and anaerobic outputs had not yet been tested, much less the mechanisms

that underpin them – I measured self-reports of physical discomfort and perceptions of exertion and fatigue as a proxy for activity in the endogenous opioid and endocannabinoid systems.

Previous research has shown positive relationships between placebo analgesia – confirmed with self-reports – and activity in neural regions that make up the endogenous opioid system and are involved in perceptions of pain (Petrovic et al., 2002; Richardson, 2000; Wager et al., 2013; Wager et al., 2007). For example, Wager et al. (2007) showed placebo-induced opioid system activation in a number of brain areas, including the PAG and rostral anterior cingulate cortex (rACC). However, to my knowledge, no brain imaging studies have been carried out on endocannabinoid-based analgesia; these links have been shown only through cannabinoid receptor antagonists (Benedetti, Amanzio, et al., 2011). Further, those studies that have linked endogenous opioid activity to reductions in self-reports of pain have not always found positive relationships between opioid activity and analgesia (see Wager et al., 2007 for a discussion of these findings). Nevertheless, the links between self-reports of pain and brain activity in areas related to pain perception are robust, and endogenous opioid and endocannabinoid activity are understood to be the two principal neurochemical systems underpinning endogenous analgesia and self-regulation during physical exercise (e.g., Benedetti, 2009; Bingel & Tracey, 2008; Eisenberger et al., 2011; Pollo et al., 2011). Thus, it is reasonable, although not ideal, to take self-reports of pain and fatigue (a neurological correlate of pain; see Section 2.2.3.2, p. 57) as indicative of endogenous opioid and endocannabinoid activity.

Now that a behavioural basis for my mechanistic claims has been preliminarily established by the research reported here, future research could clarify these findings by measuring activity in the endogenous opioid and endocannabinoid systems. Indeed, the study presented in Chapter 6 provides an fMRI-compatible design that can be used to compare the neural pathways involved in the top-down modulation of fatigue and exercise outputs that result from placebo treatments and cues to social support. Demonstrating shared neural pathways in ergogenic placebo and social support effects would give credence to my hypotheses.

Benedetti, Pollo, et al. (2007) showed that endogenous opioid activity underpins ergogenic placebo effects and speculated that endocannabinoid activity plays a similar role. A more direct test of the involvement of these two systems in ergogenic social support effects could be achieved through the use of PET methods (Boecker et al., 2008; Lindsey, Glaser, & Gatley, 2005) and modifications to the experimental design presented in Chapter 6, or through pharmacological blocking methods, such as those used by Benedetti, Pollo, et al. (2007). Ultimately, the findings from this thesis should encourage new programmes of research investigating the interaction between social environments, prior appraisals of difficulty, motivations, perceptions of fatigue and energy, and the mechanisms underpinning self-regulation during strenuous physical exercise more generally (Amann et al., 2009; Noakes, 2012; Pollo et al., 2008; Schiphof-Godart, Roelands, & Hettinga, 2018; Tanaka & Watanabe, 2012).

## 7.4 Contributions to the literature

This thesis makes empirical, methodological, and theoretical contributions to a range of academic disciplines. I will first discuss the methodological and empirical contributions of each study, before moving on to the broader theoretical implications for related fields of research, and cognitive and evolutionary anthropology more specifically.

### 7.4.1 Empirical and methodological contributions

The empirical chapters of this thesis are novel in that they test, for the first time, the effects of social support on strenuous physical exercise outputs in both experimental (Chapter 3 and Chapter 6) and naturalistic (Chapter 4 and Chapter 5) settings. Numerous studies and meta-analyses have shown positive effects of cohesion – a correlate of perceived social support – in sport and exercise (Burke et al., 2008; Carron et al., 2002; Filho et al., 2014), although none of these studies have, to my knowledge, measured physical outputs directly. Rather, they focus on either competitive outcomes in sport or exercise adherence. Regarding social support effects in sport, studies have only looked at skill-based tasks (e.g., Rees et al., 2007) or used indirect cues to social support, such as behavioural synchrony (Davis et al., 2015).

More generally, social support research has focused on stress, pain, immune function, and physical and mental health more broadly (Cohen et al., 2015; Eisenberger et al., 2011; Heinrichs et al., 2003; Holt-Lunstad & Uchino, 2008). The experiments presented in Chapter 3 and Chapter 6 used modified social support manipulations from previous studies (Eisenberger et al., 2011; Heinrichs et al., 2003; Rees & Freeman, 2010), thereby extending this research to consider strenuous physical exercise outputs and informing empirical findings that used different constructs of social support. Similarly, the observational studies presented in Chapter 4 and Chapter 5 also extend previous research on social support effects in exercise groups and programmes, testing how social support affects physical outputs and experiences during voluntary, strenuous physical exercise.

Specifically, Chapter 3 was the first direct test of social support – as previously operationalised (Heinrichs et al., 2003; Rees & Freeman, 2010) – on strenuous exercise outputs. This was an important step in understanding the effects of social support on physical outputs. A series of studies on synchrony, which researchers have taken as a cue to social support (see Section 1.4.6, p. 35, and Section 2.2.4, p. 57), had previously shown analgesic effects of synchronous exercise (Sullivan & Rickers, 2013; Sullivan et al., 2014), and one has shown that synchronous warm-ups among teammates leads to enhanced aerobic performance (Davis et al., 2015). The study presented in Chapter 3 thus informs this body of work, using a more direct manipulation of social support before a strenuous physical exercise task.

The study presented in Chapter 6 also modified a manipulation of social support that was previously used in a study on pain perception (Eisenberger et al., 2011), coupling it with a standard ergogenic placebo treatment (Beedie et al., 2006), and exercise difficulty manipulation, to create a $2 \times 2 \times 3$ experimental design. Crucially, this design is fMRI-compatible, offering future researchers a procedure that allows for a comparison of the cognitive mechanisms involved in ergogenic social support and placebo effects. Although previous research suggests the involvement of the endogenous opioid and endocannabinoid systems in ergogenic placebo effects (e.g., Benedetti, Pollo, et al., 2007; Pollo et al., 2011),

underlying cognitive mechanisms have not yet been elucidated. Further, by using a social support manipulation that was previously shown to have analgesic effects, this study helps to relate research on endogenous pain modulation to research on ergogenic placebo effects (see Section 7.4.2 for a further discussion of this). As I have argued in Chapter 1 and Chapter 2, these effects may result from activity in similar neurobiological mechanisms (i.e., activity in the endogenous opioid and endocannabinoid systems).

Chapter 4 and Chapter 5 offer a big data and survey study of parkrun. Researchers have long been interested in the social influences of exercise experiences and adherence in group exercise classes (e.g., Spink & Carron, 1994), and even at parkrun itself (Hindley, 2018; Stevinson et al., 2014). Yet, to date, no work has been done to understand how these social variables affect the performance of voluntary, strenuous physical exercise. Further, the statistical methods used in Chapter 4 might also be of use to social scientists more generally. With the increasing availability of large data sets that describe human behaviour, procedures for quantifying and characterising social relationships, such as the analyses of social networks used in the analyses presented in Chapter 4, will become increasingly useful. While these procedures may inform future work on social data sets more generally, they are especially suited for use in the analysis of social exercise networks derived from online digital apps, such as Strava, RaceRunner, and SoulCycle: Indoor Cycling. Finally, the results from my big data and survey studies of parkrun should be of interest not only to parkrun researchers, but, more generally, to those interested in how and why social variables influence exercise outputs and experiences.

### 7.4.2 Theoretical contributions

In addition to the empirical and methodological contributions of the individual studies in this thesis, I have also attempted to make two broader theoretical contributions. One contribution relates specifically to sport, exercise, and strenuous physical activity; throughout this thesis, I draw on diverse bodies of literature to give a theory that explains ergogenic social support effects at both the proximate and ultimate level. The other contribution is my theory of cultural

buffering, which focuses on the function and impact of cultural items that signal social support and concurrent increases in safety and access to resources (see Chapter 1). Below, I will briefly outline the relevance of these contributions to fields of research ranging from sport and exercise psychology and physiology to cognitive and evolutionary anthropology.

#### 7.4.2.1 Cross-species understandings of social buffering and physical movement

In Chapter 1, I argue that natural selection has occurred for mechanisms that lead to the attenuation of protective or conservative psychophysiological states (e.g., the pain or stress response) when the costs outweigh the benefits, such as when social environments signal relative safety or resource abundance. Although the social buffering literature tends to focus on proximate causes (but see Hennessy et al., 2009 for an adaptationist perspective), I suggest that these mechanistic adaptations are the ultimate cause of social buffering effects (Kikusui et al., 2006). In Chapter 2, I extend this argument to physical exertion in humans, arguing that when social cues indicate that an environment is safe and resources are abundant, the potential costs of physical exertion (e.g., exhaustion and injury) are reduced, and consequent psychophysiological changes occur that facilitate physically exertive states. With some caveats, the empirical findings of this thesis give general support to this theory.

Generally, the theory and findings of this thesis are relevant to the large body of literature on social buffering in animals (reviewed in Section 1.3, p. 11), and help to provide a cross-species account of how and why social buffering effects are likely to occur during physical exertion in highly social species. To my knowledge, the social buffering literature is yet to consider how social environments might affect levels of physical exertion, although, there is some evidence to suggest that such effects exist in highly social non-human animals. For example, self-regulatory systems (e.g., the endocannabinoid system) that affect motivation for foraging and hunting behaviours in social animals seem to be susceptible to social cues (Galdino et al., 2014; Raichlen et al., 2012; Wei, Allsop, Tye, & Piomelli, 2017; Wei et al., 2015). Further, stress responses during physically strenuous and dangerous territorial boundary patrols in chimpanzees have been shown to be buffered by socially supportive conspecifics (Wittig et

al., 2016). The theory of social buffering during physical exertion put forth in this thesis might provide a useful perspective on which to base hypotheses about foraging, hunting, and inter-group conflict behaviours in animals. These studies could examine how social variables predict movement patterns and energy expenditures during such situations. The theories put forth in this thesis allow for an extension of (largely proximate) social buffering accounts, putting forth an ultimate explanation of how and why social environments might affect animal behaviours ranging from foraging to intergroup conflict.

#### 7.4.2.2 Mechanisms underpinning ergogenic social support

In explaining my hypothesised proximate and ultimate mechanism behind ergogenic social support effects, I draw on diverse findings from research on social bonding, placebo effects, pain perception, and exercise science. Although this research does not focus specifically on how and why social environments affect the performance of strenuous physical exercise, my synthesis of the findings from these fields may facilitate novel, theory-driven hypotheses and future cross-disciplinary research.

At the ultimate level, my theory explains variation in physical outputs as a result of changes in tacit cost-benefit analysis; if social support is perceived to be available, the potential costs of physical exertion are reduced, as social support signals relative safety and access to resources (e.g., for recovery). Viewing physical outputs as being determined by tacit cost-benefit analyses may help researchers to better understand why ergogenic placebo effects occur; if placebo treatments suggest enhanced capabilities, then the potential costs of a given exercise output (such as maladaptive overexertion) may be reduced. My work also further extends research on the self-regulation of physical outputs, offering social support as another variable which could change the theorised correlation between pain and fatigue levels and the amount of continued exercise that can be safely sustained under a particular set of environmental conditions (e.g., Noakes et al., 2005). This has theoretical implications for researchers interested in the potential motivators and deterrents of physical exercise (Barkley et al., 2012; Hawkley et al., 2009)

At the proximate level, I offer a theoretically plausible means through which social environments could affect strenuous physical exercise outputs. I draw from research on the neurobiological underpinnings of the creation, maintenance, and signalling of social bonds in linking social environments to the neurobiological mechanisms involved in the self-regulation of strenuous physical exercise. In particular, I have focused on the endogenous opioid and endocannabinoid systems, which have been identified as modulators of perceptions of pain and fatigue in ergogenic and analgesic placebo studies (Benedetti, Amanzio, et al., 2011; Benedetti, Pollo, et al., 2007; Pollo et al., 2008, 2011), and are important in mediating responses to inter-personal relationships (Dunbar, 2012; Inagaki et al., 2016; Trezza et al., 2010). Through identifying this neurobiological overlap, I help to join disparate bodies of literature, offering potential neurobiological pathways through which social environments could affect perceptions of pain and fatigue, and, ultimately, physical exercise outputs. This has the potential to be relevant not only to researchers interested in the mechanisms of social support-based analgesia (e.g., Chiang, Eisenberger, et al., 2012; Eisenberger et al., 2011; Inagaki et al., 2016; Master et al., 2009), but also to those interested in the neurobiological mechanisms underpinning the self-regulation of strenuous physical exercise (e.g., Amann et al., 2009; Noakes, 2012; Pollak et al., 2014). In sum, marrying literature on ergogenic placebos, which is relatively developed, to literature on social support in strenuous physical exertion and stressful environments more generally, which is relatively scant, may be useful to those researchers interested in how perceptions of social support and cohesion affect responses to stressors ranging from experimentally induced pain to sport and exercise performance and motivation

More broadly, the theoretical contributions outlined in this section are relevant to understanding a variety of cultural practices in sport and exercise. From cheering fans and synchronised pre-game rituals to words of encouragement at parkrun, humans have come to use cues to social support and cohesion as a means of dealing with the stressor that is strenuous physical exertion. This is an example of what I call cultural buffering, and it has

implications for understanding not just sport and exercise, but human cultural life and evolution.

#### 7.4.2.3 Contributions to cognitive and evolutionary anthropology

In Chapter 1, I reviewed evidence for how perceptions of social support and cohesion can alter psychophysiological responses to illness, injury, pain and environmental stressors more generally; a phenomena known as social buffering (Kikusui et al., 2006). I argued that these results can be explained by the positive correlation between the availability of social support, and relative safety and access to resources that existed during human evolution. When social support signals safety and resource abundance, less cautious responses to stressors become more optimal; individuals become more liberal with immune resource use when fighting off illnesses, are less sensitive to pain, and show attenuated stress responses (Cohen et al., 2015; Eisenberger et al., 2011; Heinrichs et al., 2003; Master et al., 2009). When social support indicates true safety and resource access, these attenuated responses become adaptive. When considering this, it becomes apparent that human cultures have come to use cultural symbols, practices, and rituals to signal the presence of social support and induce less cautious responses to stressors. When social buffering effects occur because of cultural symbols, practices, and rituals, I argue that cultural buffering takes place. The theory of cultural buffering has wide-ranging relevance for the field of cognitive and evolutionary anthropology, as cultural buffering effects have implications for the evolution of human endurance running and collective, cohesion-signalling rituals.

##### 7.4.2.3.1 Implications for research on the evolution of human distance running

Section 2.2.1 (p. 46) argues for the importance of social environments in determining the evolutionary trajectory of long-distance running abilities in humans. Research in this field has primarily focused on the plausibility of long-distance running during hunting and scavenging as a means of acquiring nutrient-rich meat resources in early *Homo*, and on the adaptations theorised to have arisen due to selection for these practices (Bramble & Lieberman, 2004; Bramble, Lieberman, & Daley, 2000; Lieberman, Bramble, Raichlen, & Shea, 2009; Raichlen

et al., 2008). To date, this body of research has not yet fully considered how social environments might have interacted with these evolutionary processes.

I propose that the neurobiological systems involved in the self-regulation of long-distance running are likely influenced by social cues, and I review ethnographic evidence for the highly social nature of long-distance hunting and scavenging in modern humans. By surrounding these activities – which would have been an important means of dietary supplementation (Bramble & Lieberman, 2004; Carrier et al., 1984) – with rituals that build and signal cohesion to in-group members (e.g., song and dance), human ancestors may have reduced the forecasted costs associated with physical overexertion and exhaustion. For example, the perceived costs of potential injury and exhaustion after a long-distance pursuit may have been diminished when individuals received reliable cues to the assurance of care and access to resources. This suggests potential selection for the ability to respond to cues of social support in an adaptive manner. Those individuals with accurate tacit calculations of the diminished potential costs of extreme exertion – owing to the availability of care and resource provision from others – may have been able to acquire more nutrient-rich resources from animal carcases, and subsequent increases in social status and evolutionary fitness. The possible social influences on the emergence of long-distance hunting and scavenging thus offer a new avenue of inquiry for those researchers traditionally interested in the biological and psychological adaptations that make humans exceptionally good distance runners.

#### 7.4.2.3.2 Implications for research on collective rituals

Since its beginning, anthropology has been interested in the function of collective rituals (Durkheim, 1912/1965). Many explanations have been proposed since Durkheim, most prominent are those related to coalition signalling and social bonding and prosociality (Fischer, Callander, Reddish, & Bulbulia, 2013; Hagen & Bryant, 2003b). Section 1.4.6 (p. 35) offers a mostly complementary – although sometimes competing – explanation of collective rituals: that they function to buffer in-group members from environmental stressors through signalling to them that they belong to a cohesive, supportive social group. As argued in this section, this

explanation of cultural practices that involve song, dance, synchronous movement, and 'collective-effervescence' more generally is perhaps most relevant when these practices occur in stressful events, such as before inter-group conflict or during famine or epidemics. The theory of cultural buffering may thus prove useful in helping anthropologists to understand a variety of long-studied ritual forms and cultural practices.

### 7.5 Broader implications and generalisability of findings

The results and theories presented in this thesis could be generalised to multiple topics and areas of research. In particular, they may be relevant to researchers interested in public health, as well as those interested in the factors that lead to healthy exercise patterns and peak physical performance.

Novel claims about cultural buffering presented here posit that cultural rituals, symbols, and practices that signal social support and cohesion can be used to change individuals' responses to a wide variety of stressors. These cultural items could be employed to reduce stress levels and pain perceptions, and even to alter immune functioning. For example, hospitals could experiment with using more overt cues to social support and resource abundance, such as extra check-ins with patients, support groups, and access to green areas that cue the relative material abundance of summertime (Fuller, Irvine, Devine-Wright, Warren, & Gaston, 2007; Kulik & Mahler, 1989). At the societal level, cohesion-building and signalling festivals, feasts, and celebrations may have the power to reduce stress levels within populations, ultimately benefiting public health (Dunbar et al., 2017). In sum, then, societies may benefit from considering how to use cues to relative safety and resource abundance to change how individuals respond to stressors and deal with ailments ranging from chronic pain to the common flu.

Further, the findings of this thesis generally suggest that exercise is made more enjoyable and less difficult when individuals feel socially supported. This is in line with previous findings on the positive correlation between perceptions of social support and exercise adherence (e.g.,

Spink & Carron, 1994). Combining the results of this thesis with this research suggests that adherence to exercise regimes can be increased via social support effects on pain, fatigue, and physical outputs. The implication of this for those interested in increasing exercise adherence is that organisers of exercise classes and regimes should consider ways in which to enhance exercisers' perceptions of social support, especially during daily exercise sessions.

Finally, my findings will be relevant to those interested in maximising performance in sport. To date, this research has focused largely on the experiences of athletes as individuals, and on how psychological interventions can help them to deal with the stress and challenges they face (e.g., Lane, Soos, Leibinger, Karsai, & Hamar, 2005; Lane et al., 2010; Stanley, Beedie, Lane, Friesen, & Devonport, 2012). My research suggests that interpersonal relationships are also crucial in determining physical outputs. Specifically, perceptions of social support and cohesion may lead to changes in self-regulatory mechanisms that ultimately have the effects of allowing athletes to push harder for longer. Sports psychologists, coaches, and athletes should thus strive to build supportive, cohesive social environments among their teams and fans. Research suggests that support and cohesion can be signalled through pre-game rituals, such as the synchronised movements of the New Zealand All Blacks haka, and cooperative in-game touch, such as high-five, daps, and pound hugs, and that these signals of support and cohesion can enhance performance (Davis et al., 2015; Kraus et al., 2010). Further practices that indicate support and resource abundance, such as team meals and send-offs, cheering and singing fans, and attentive, competent, well-equipped training staff may also have similar performance-enhancing effects.

The ideas put forth in this section have potentially wide-ranging implications. However, more research is needed to validate my claims related to the public health benefits of social support and cohesion-signalling cultural items. The same can be said about research on sport and exercise performance, as work on the interpersonal determinants of physical performance is

still in its infancy. Investigating these lines of research could lead to fruitful findings that have the potential to influence not just exercisers and athletes, but also society more generally.

## 7.6 Conclusions

The strong correlation during human evolution between the presence of close social relationships and access to the physical and cultural resources needed to both survive and thrive mean that social environments play a major role in determining optimal psychophysiological states and behavioural strategies. Cues to the presence of supportive, cohesive social relationships, where safety and access to resources are relatively likely, can lead to social buffering effects, whereby adverse responses to a range of stressors are attenuated, and bodily resources are used in a less cautious manner. I argue that humans have come to use cultural items that cue social support and cohesion as a means of inducing additional social buffering effects. While cultural buffering exists in a variety of contexts, it seems particularly prevalent in sport and exercise, where social support and group cohesion are signalled by cheering fans, encouraging co-exercisers, club colours, and team rituals.

In this thesis, I used several unique methods to test the hypothesis that social support leads to enhanced performance during strenuous physical exertion through changing activity in self-regulatory pain and fatigue mechanisms. Overall, my results suggest that social support (and even cues to the presence of social support figures) leads to performance enhancement during physical exercise. An important mediator of this effect may be individuals' felt energy levels, and an important moderator may be how individuals receive social support. My results are largely consistent with the hypothesis that social support affects physical outputs via enhancing activity in the endogenous opioid and endocannabinoid systems, which has the effect of reducing perceptions of pain and fatigue. However, this hypothesis was never directly tested, leaving this an open question, and a potentially fertile avenue of future research. In conclusion, this thesis provided several novel results that demonstrate how perceptions of social support enhance the performance of strenuous physical exercise in both experimental

and naturalistic settings. These findings add to disparate bodies of literature and deepen our understandings of why human movement is so often a social endeavour.

## Appendix A

## 1 Anaerobic fitness estimate

To estimate exercisers' anaerobic fitness we used a slightly extended version of the sport index in the Habitual Physical Activity Questionnaire (Baecke et al., 1982). Our alteration was to allow exercisers to list four sports instead of two in order to better estimate time spent doing anaerobic activities. Thus, we used the following formula:

$$\text{Anaerobic fitness} = \sum_{i=1}^{4} (\text{intensity} \times \text{time} \times \text{proportion})$$

Where, according to Baecke et al. (1982), intensity is 0.76 for low intensity sports, 1.26 for medium intensity sports, and 1.76 for high intensity sports, time is 0.5 for less than 1 hour per week spent playing the sport, 1.5 for 1 – 2 hours per week, 2.5 for 2 – 3 hours per week, 3.5 for 3 – 4 hours per week, and 4.5 for greater than 4 hours per week spent playing the sport, and proportion is 0.04 for less than 1 month per year playing the sport, 0.17 for 1 – 3 months per year, 0.42 for 4 – 6 months per year, 0.67 for 7 – 9 months per year, and 0.92 for greater than 9 months per year playing the sport.

A score of 0 was given when no sport was listed.

## 2 Social support manipulation

The following table summarises the social support manipulation, given verbally by a hypothesis blind experimenter:

| Solo condition | Companion condition |
|---|---|
| "Okay, good. So, you've finished the questionnaire part of the study. Your companion also finished their questionnaire and has left. You will do the strenuous exercise part of the study on your own. I'll now give you the instructions for the strenuous exercise you will be doing. After I give you these instructions, I will give you a brief recap. After this you will begin the strenuous exercise portion of the study." | "Okay, good. So, you've finished the questionnaire part of the study. Your companion also finished their questionnaire. I'll now give you the instructions for the strenuous exercise you will be doing. While I do this your companion will be reading a version of the instructions you will be receiving - even though they will not be doing the strenuous exercise part of the study, they will understand what it entails. After I give you these instructions, I will give you a brief recap. Your companion will come into the exercise room to observe this recap of your instructions so that they can better understand what you will be doing. After this you will begin the strenuous exercise portion of the study." |
| Pre-exercise instructions are given to the exerciser (see 3.2). | |
| Exerciser is given a recap (see 3.2) of the instructions. | The companion is brought into the room with the exerciser and they are both given a recap (see 3.2) of the instructions. |
| "Okay, you will now begin the strenuous exercise portion of the study." | "Okay, your companion is going to go back to their seat in the next room. They will be there for you if you need anything at all and will wait for you there until you are finished. You will now begin the strenuous exercise portion of the study." |
| While participating in the exercise portion of the study, the exerciser is given instructions on how to complete the warm-up and maximum-effort cycling bouts (see 3.3 and 3.4). | |

## 3 Exercise trial procedure and measures

### 3.1 Procedure

The cycling bouts involved pedalling for a set amount of time at a fixed amount of resistance, 6.5% of the exerciser's body weight (McArdle et al., 2010), on a Monark 874E ergometer (hereafter 'stationary cycle').

Exercisers began the exercise portion of the study with a 4 min warm-up on the stationary cycle. During the warm-up, exercisers cycled at their chosen pace. At 2 and 3 min into the warm-up, they practiced the 10-s flying start (see below) followed by 10 s of maximum effort cycling at their respective resistance.

Following the warm-up, exercisers were given a 3-min break before beginning their first of four 30-s cycling bouts. Before beginning each bout, exercisers were reminded that it was "crucial" they give maximum effort during the 30-s bouts.

The test began with a 'flying start' in which exercisers cycled as fast as possible at no resistance for 10 s before their body-weight adjusted resistance was applied. The experimenter counted down aloud the final 5 s of the flying start ("5-4-3-2-1-GO") and applied the resistance while saying "GO". The trial began at "GO" and ended with a 5 s countdown ("5-4-3-2-1-STOP").

After each bout, exercisers were given a 3-min break during which they completed the Borg Scale of Perceived Exertion (Borg, 1982) and indicated the amount of physical discomfort they felt during the exercise bout they had just completed using a 20-point scale adopted from previous research on experimentally induced pain (Eisenberger et al., 2011). Exercisers answered these questions at a standing desk next to the stationary cycle.

The experimenter notified exercisers when their 3-min break was almost finished and asked them to return to the stationary cycle to begin their next maximum-effort bout.

Exercisers repeated this procedure until they had completed four maximum-effort, 30-s cycling bouts in total.

### 3.2 Pre-exercise instructions

These instructions were read to exercisers before the social support manipulation took place:

> "This is the cycle on which you will complete the maximum effort exercise bouts. This basket holds the weights that work to apply resistance. When I drop the basket, resistance is applied. The amount of weight to be applied depends on how much you weigh.
>
> Each maximum effort cycling bout will last 30 seconds. Before the 30-second period begins, you will have a 10 second period during which you will pedal to move this wheel as fast as possible. I will count you into the beginning of the 30-second period with '5-4-3-2-1-GO'. When I say 'go' I will drop this basket, and this will apply resistance to the wheel. This is the beginning of the 30-second bout. You will pedal at maximum effort for the next 30 seconds. You will feel fatigue and discomfort in your legs, but should try your hardest to keep pedalling as fast as you can. I will count down the final five seconds of the 30-second period with '5-4-3-2-1-STOP'. When I say 'stop', you are to stop pedalling.
>
> You will then be given a three-minute break during which you will answer some questions on the computer. After you finish this you will start the next cycling bout as described above.
>
> Before you begin, you will do a four-minute warm-up at no resistance. Two times during this warm-up [at the two and three-minute mark] I will drop the basket and you will do 10 seconds of maximum effort cycling to get used to exercising at the level we want. After the warm-up, you will answer questions on the computer as well. Then you will do the maximum-effort cycling bouts."

### 3.3 Pre-exercise recap

This recap was read to exercisers either in the presence (companion condition) or absence (solo condition) of their companion:

> "I'll now give you a quick recap of what you will be doing. The exercise portion of the study consists of 30-second maximum effort cycling bouts on this stationary cycle. As I said, this is the basket that will give you a resistance that depends on your weight. When I pull the basket up there is no resistance. Dropping the basket adds resistance. Before each 30-second cycling bout you will have a 10-second warm-up in which you are to start pedalling as fast as possible. Five seconds into this warm-up – so 5 seconds before you begin the 30-seconds of maximum effort – I will count down from 5 and when I say 'go' I will drop the weight basket and your 30-second cycling bout will begin. I will count down the final five seconds of the 30-second period with '5-4-3-2-1-STOP'. When I say 'stop', you are to stop pedalling. Remember, you have to give maximum effort despite feelings of fatigue and discomfort in your legs. After the 30 seconds of cycling you will have a three-minute recovery period in which you will remain standing while you answer some questions at your computer. I'll let you know

> when your three minutes is up and you will do another 30-second maximum-effort bout with a 10-second warm-up, the same as last time. Then, you'll again have three minutes to rest and answer questions. We'll repeat this procedure until you are done with the exercise portion of the study."

### 3.4 Instruction for exercise warm-up and trials

These instructions were read to exercisers immediately before and during the exercise trials:

"Okay, you can now get on the cycle and begin warming up at a pace that is comfortable to you. At two minutes and three minutes I will drop the weight basket and you will practice giving maximum effort.

"Okay, you may begin."

At 2 min: "Okay, I am going to drop the weight basket now, when I say go pedal as hard as you can. 5-4-3-2-1-GO!"

After 10 s: "Good job, but I think you could pedal a bit harder. Continue pedalling until the three-minute mark and I will drop the weight basket again."

At 3 min: "Okay, I am going to drop the weight basket again, when I say go pedal as hard as you can. 5-4-3-2-1-GO!"

After 10 s: "Okay, that is better but during the 30-second trials I need you to try even harder – as hard as you possibly can."

At 4 min: "Okay that is the end of the warm-up, please go to the computer and answer the questions on the screen. You will begin the 30-second maximum effort cycling bouts after a three-minute rest period."

After 3 min:

> "Okay, you will now begin your first 30-second bout of maximum effort cycling. Remember there is a 10 second 'warm-up' period of cycling before the 30-second maximum effort bout, and I'll count you down from five seconds. When I say 'go' I will drop the weight basket and your 30 seconds will begin. Remember, it is crucial that

> you give maximum effort during these 30 seconds. This is the first of four 30-second bouts you will be doing today. Are you ready to begin? Okay, begin."

After 5 s: "5-4-3-2-1-GO!"

After 25 s: "5-4-3-2-1-STOP!"

After the first trial: "Okay good, you've completed one of the four 30-second exercise bouts. Please go to the computer and follow the directions on the screen. Remember to catch your breath and rest; you have three minutes until the next trial."

After 3 min: "Okay, your three-minute rest period is up. Please get back on the bike. You will now begin your second 30-second bout of maximum effort cycling. The procedure is the same as last time. Are you ready to begin? Okay, being."

This continues for the next two trials (same instructions).

After the fourth trial: "Okay, you have finished your last 30-second bout of exercise. Please go to the computer and follow the directions on the screen. Remember to catch your breath and rest."

## 4 Social support and assurance measures

| **Multidimensional Scale of Perceived Social Support (MSPSS)** |
|---|
| There is a special person who is around when I am in need. |
| There is a special person with whom I can share my joys and sorrows. |
| My family really tries to help me. |
| I get the emotional help and support I need from my family. |
| I have a special person who is a real source of comfort to me. |
| My friends really try to help me. |
| I can count on my friends when things go wrong. |
| I can talk about my problems with my family. |
| I have friends with whom I can share my joys and sorrows. |
| There is a special person in my life who cares about my feelings. |
| My family is willing to help me make decisions. |
| I can talk about my problems with my friends. |
| Answered on a seven-point Likert scale (1 = *Disagree*, 7 = *Agree*) |

| **Social Assurance Scale (SAS)** |
|---|
| I feel more comfortable when someone is constantly with me. |
| I'm more at ease doing things together with other people. |
| Working side by side with others is more comfortable than working alone. |
| My life is incomplete without a buddy beside me. |
| It's hard for me to use my skills and talents without someone beside me. |
| I stick to my friends like glue. |
| I join groups more for the friendship than the activity itself. |
| I wish to find someone who can be with me all the time. |
| Answered on a seven-point Likert scale (1 = *Disagree*, 7 = *Agree*) |

## 5 Peak power calculation

Peak power outputs were calculated using the equation (McArdle et al., 2010):

$$PP\ (W) = 6g(kp)r / 5$$

where PP (W) is peak power output in watts, 6 is the distance travelled per pedal revolution in metres, g is gravitational acceleration in metres per second squared, kp is the resistance applied to the wheel in kilograms (6.5% of the exerciser's body mass), r is the total number of complete pedal revolutions during the 5 s of the 30-s exercise bout where the exerciser produced the greatest number of pedal revolutions (this is usually, but not necessarily, the first 5 s of the bout), and 5 is the time in seconds when r was measured.

## 6 Exerciser-companion relationship component

Examination of scree plots, communalities after extraction, and internal consistency tests from a principal components analysis suggested that one component (comprised of the questions related to closeness, connectedness, and how much exercisers felt their companion was there for them in times of need) should be extracted from the four questions measuring exercisers' opinions about their relationship with their companion (see Section 3.2.2, p. 83). The question on exercisers' similarity to their companion had low correlations with the questions in the component, and was thus dropped from further use. A subsequent analysis revealed that the component explained 82% of the variance in the three questions. Cronbach's α, based on standardised question scores, indicated good internal consistency for the exerciser-companion relationship component (α = .883).

# 7 Model assumptions

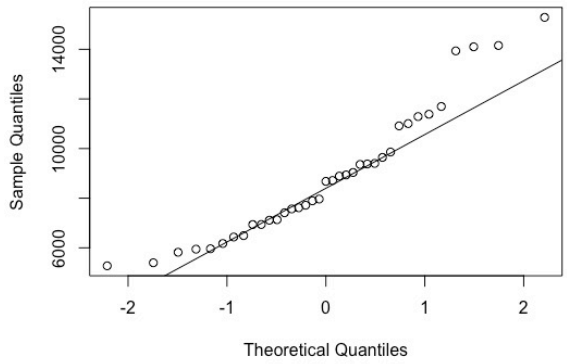
Here, I report analyses meant to check the assumptions of the models reported in Section 3.3. For the mixed ANOVAs, I tested the assumptions of normality (that the distribution of anaerobic outputs was normally distributed in each cell), homogeneity of variance, sphericity, and homogeneity of inter-correlations (Field et al., 2012). I only report those models where claims of statistical significance are made.

## 7.1 Main analysis of anaerobic outputs

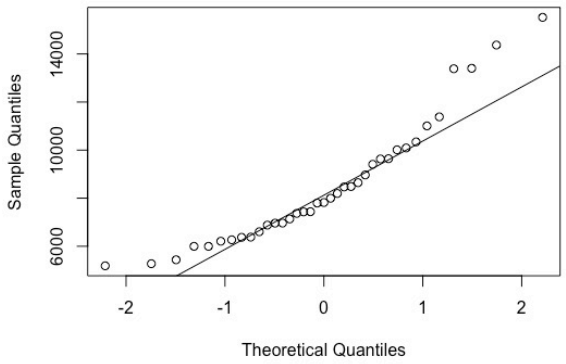
Regarding the normality of anaerobic outputs within cells, all cells had approximately normal distributions, Shapiro-Wilk normality tests (all *W*'s > 0.956 and *p*'s > .05), except for bouts 2 (*W* = 0.925 and *p* = .015), 3 (*W* = 0.905 and *p* = .004), and 4 (*W* = 0.929 and *p* = .021) of the solo condition, although examination of normal Q-Q plots (see Appendix A Figure 1) revealed that these deviations from normality are rather small. Further, research has shown that the *F*-statistic is robust to non-normality when group sizes are roughly equal, as is the case with this analysis; there were 37 participants in the solo condition and 38 in the companion condition (Field et al., 2012; Glass, Peckham, & Sanders, 1972)

The homogeneity of variance assumption was met; Levene's tests revealed that variances in anaerobic outputs between bouts over conditions were approximately equal; all $F(1, 73) < 0.400$, $p > .05$. A Box's *M* test revealed that the homogeneity of interclass correlations assumption was broken, *M*, $F(10, 25{,}434.13) = 33.508$, $p < .001$. However, this may have more do with the non-normality of anaerobic outputs within cells (Morrison, 1998). Using a log transformation of anaerobic outputs yields a model with more normally distributed data in each cell, and similar results to the main mixed ANOVA reported in Section 3.3 (i.e., a significant exercise bout × condition interaction), and a Box's *M,* $F(10, 25{,}434.13) = 29.026$, $p = .002$, that previous research suggests to ignore: Morrison (1998) writes that, due to its sensitivity to deviations from normality, all Box's *M* tests with significance levels greater than $p = .0001$ should be ignored. Give this, the results of the main mixed ANOVA used to measure anaerobic outputs should be robust to these assumption violations.

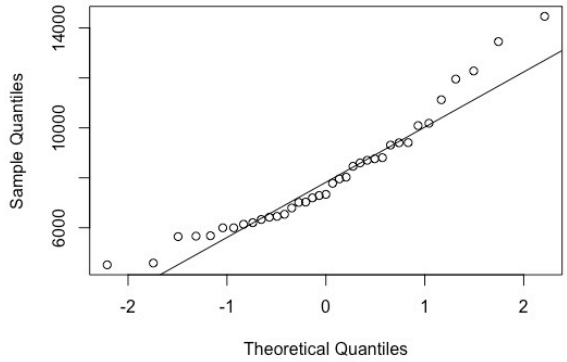
(*a*)




(*b*)




(*c*)



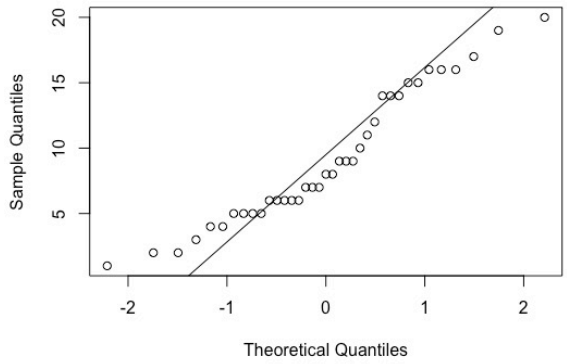

**Appendix A Figure 1** Normal Q-Q plot of anaerobic outputs for exercise bout (*a*) 2, (*b*) 3, (*c*) 4 in the solo condition.

The sphericity assumption was violated for the repeated measures effect of exercise bout ($M$ = .536, $\chi^2$ (5) = 43.421, $p$ < .001). Considering the Greenhouse-Geisser estimate of sphericity (.698), all $F$-ratios reported in Section 3.3 use the Greenhouse-Geisser correction (Field et al., 2012).

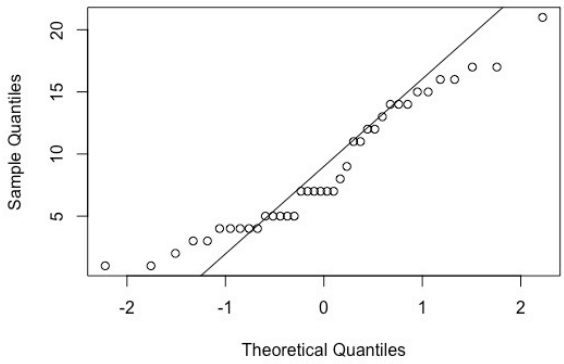
### 7.2 Analysis of physical discomfort

Regarding the normality of physical discomfort self-reports within cells, all cells had approximately normal distributions, Shapiro-Wilk normality tests (all $W$'s > 0.965 and $p$'s > .05), except bout 4 in the solo condition ($W$ = 0.939 and $p$ = .043) and bouts 3 ($W$ = 0.932 and $p$ = .024) and 4 ($W$ = 0.934 and $p$ = .026) in the companion condition, although examination of normal Q-Q plots (see Appendix A Figure 2) revealed that these deviations from normality

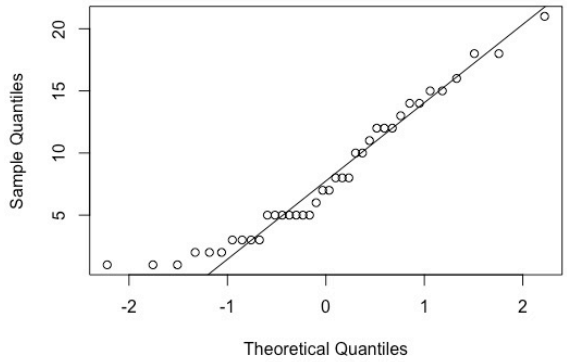
(*a*)




(*b*)




(*c*)

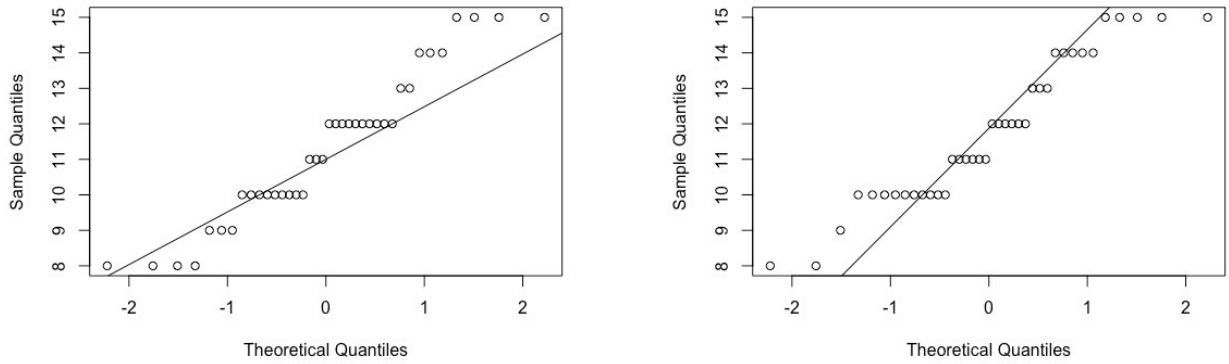



**Appendix A Figure 2** Normal Q-Q plot of physical discomfort for exercise bout (*a*) 4 in the solo condition and (*b*) 3 and (*c*) 4 in the companion condition.

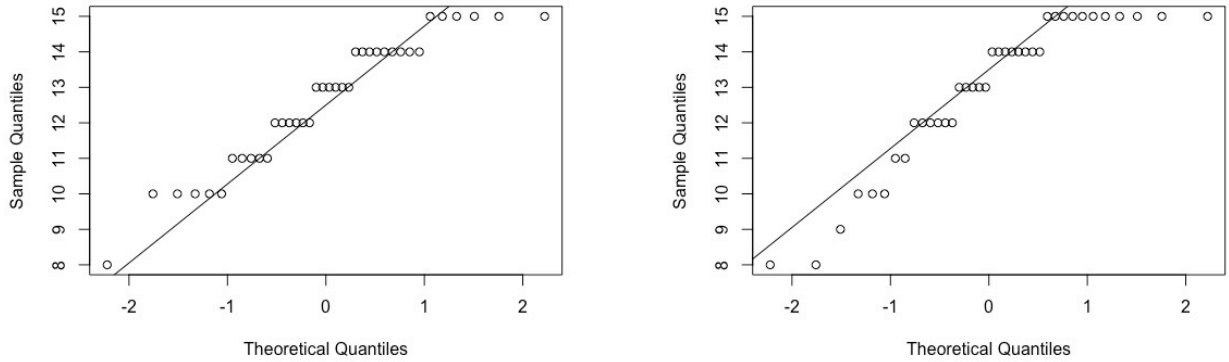
are rather small. Again, research has shown that the *F*-statistic is robust to non-normality when group sizes are roughly equal, as is the case with this analysis (Field et al., 2012; Glass et al., 1972).

The homogeneity of variance assumption was met; Levene's tests revealed that variances in anaerobic outputs between bouts over conditions were approximately equal; all $F(1, 75) < 1.200$, $p > .05$. A Box's *M* test revealed that the homogeneity of interclass correlations assumption was broken, *M*, $F(10, 26{,}849.262) = 24.134$, $p = .012$, although this test is extremely sensitive to departures from multivariate normality, and researchers have suggested that tests with significance levels greater than $p = .0001$ be ignored (Box, 1949; Morrison, 1998).

(*a*) (*b*)




(*c*) (*d*)



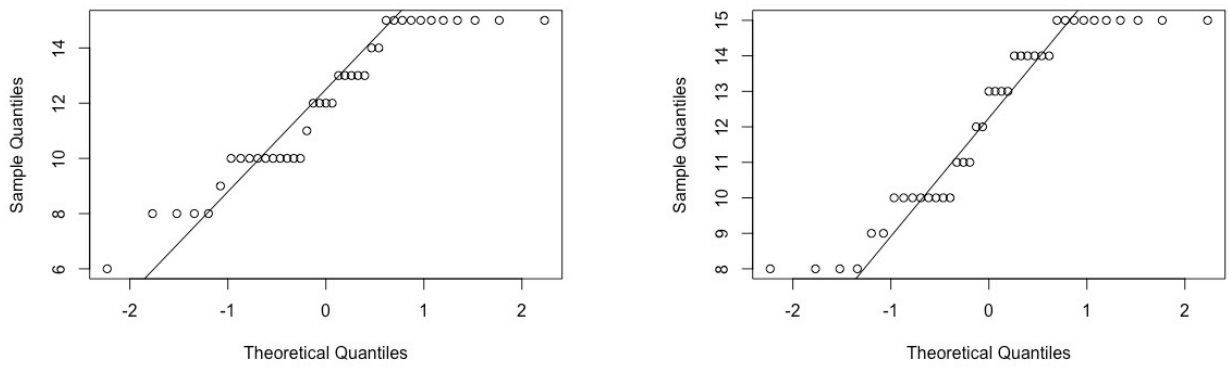

**Appendix A Figure 3** Normal Q-Q plot of RPE for exercise bout (*a*) 1, (*b*) 2, (*c*) 3, and (*d*) 4 in the solo condition.

The sphericity assumption was violated for the repeated measures effect of exercise bout; $M = .399$, $\chi^2 (5) = 67.676$, $p < .001$. Considering the Greenhouse-Geisser estimate of sphericity (.645), all *F*-ratios reported in Section 3.3 (p. 88) use the Greenhouse-Geisser correction (Field et al., 2012).

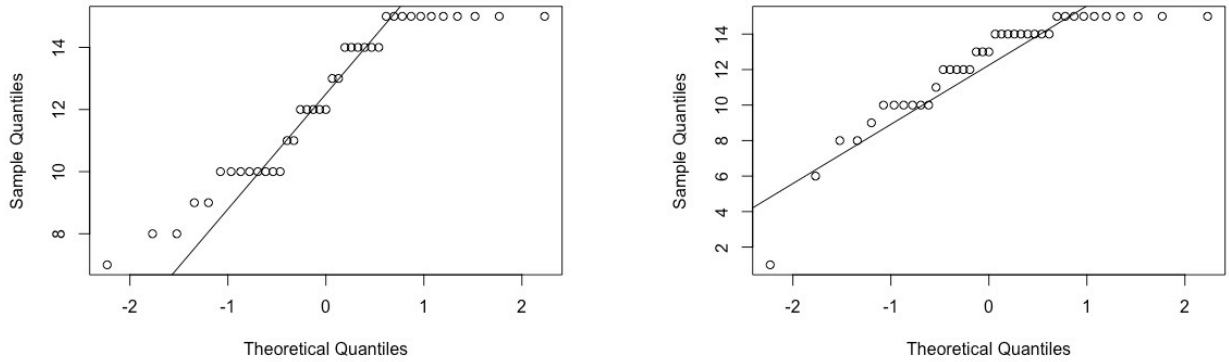
### 7.3 Analysis of rate of perceived exertion (RPE)

Shaprio-Wilks tests revealed that the normality assumption had been violated (all *W*'s < 0.940 and *p*'s < .05); RPE was not normally distributed within cells (see Appendix A Figure 3 and Appendix A Figure 4). However, given that group sizes in this study were roughly equal across the social support conditions, the *F*-statistic used here should be robust to violations of the normality assumption (Field et al., 2012; Glass et al., 1972).

(*a*) (*b*)




(*c*) (*d*)

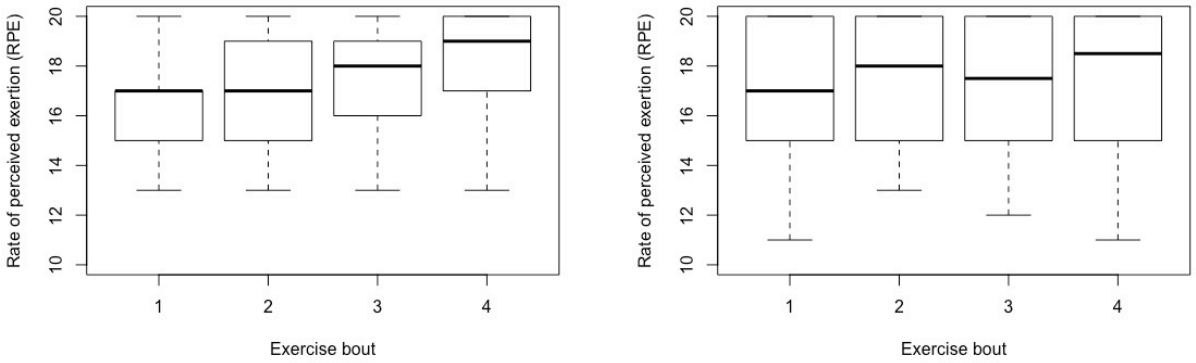



**Appendix A Figure 4** Normal Q-Q plot of RPE for exercise bout (*a*) 1, (*b*) 2, (*c*) 3, and (*d*) 4 in the companion condition.

The homogeneity of variance assumption was also violated, although, again, research has shown that ANOVA tests are robust to departures from this violation, especially when these departures are small and group sizes are roughly equal (Field et al., 2012; Glass et al., 1972). This is the case with this data (see above for group sizes), as evidenced by Levene's tests, which were only significant for exercise bouts 2, $F(1, 75) = 4.674$, $p = .034$, and 3, $F(1, 75) = 6.727$, $p = .011$, and plots of RPE variance between the solo and companion conditions across the four exercise bouts (see Appendix A Figure 5).

A Box's *M* test revealed that the homogeneity of interclass correlations assumption was also broken, *M*, $F(10, 26{,}849.262) = 22.252$, $p = .021$, although this test is extremely sensitive to

(*a*) (*b*)




**Appendix A Figure 5** RPE variance across the four exercise bouts by the (*a*) solo and (*b*) companion conditions.

departures from multivariate normality, and researchers have suggested that tests with significance levels greater than $p = .0001$ be ignored (Box, 1949; Morrison, 1998).

Finally, the assumption of sphericity was also broken for the repeated measures effect of exercise bout ($M = .425$, $\chi^2$ (5) = 63.126, $p < .001$). Considering the Greenhouse-Geisser estimate of sphericity (.666), all *F*-ratios reported in Section 3.3 use the Greenhouse-Geisser correction (Field et al., 2012).

Given that this model was particularly problematic – the assumptions about normality, homogeneity of variance, interclass correlations, and sphericity were all not met – I ran a robust mixed ANOVA using trimmed means on the same data (Wilcox, 2012). This provided similar findings to the mixed ANOVA reported in Section 3.3; a non-significant effect of social support condition ($Q = 0.112$, $p = .740$), a main effect of exercise bout ($Q = 13.149$, $p < .001$), and a condition × exercise bout interaction ($Q = 3.894$, $p = .016$) on participants' RPE (see Appendix A Table 1).

**Appendix A Table 1** Robust two-way mixed ANOVA on rates of perceived exertion

| Variable | *Q* | *p* |
|---|---|---|
| Condition | 0.112 | .740 |
| Exercise bout | 13.149 | < .001 |
| Exercise bout × condition | 3.894 | .016 |

### 7.4 Moderation of anaerobic outputs

Regarding the normality of anaerobic outputs within cells, all cells 16 cells had approximately normal distributions of anaerobic outputs, as evidenced by Shapiro-Wilk normality tests (all *W*'s > 0.855 and *p*'s > .05).

The homogeneity of variance assumption was met; Levene's tests revealed that variances in anaerobic outputs between bouts over conditions were approximately equal, all $F(3, 44) < 0.550$, $p > .05$. A Box's *M* test revealed that the homogeneity of interclass correlations assumption was met, $M$, $F(30, 3{,}972.04) = 30.313$, $p = .729$.

The sphericity assumption was violated for the repeated measures effect of exercise bout ($M = .371$, $\chi^2 (5) = 40.405$, $p < .001$). Considering the Greenhouse-Geisser estimate of sphericity (.661), all *F*-ratios reported in Section 3.3 use the Greenhouse-Geisser correction (Field et al., 2012).

## Tables

**Table A 1** Manipulation checks

| Variable | Scale | Solo condition *M* (*SD*) | Companion condition *M* (*SD*) | Mann-Whitney *U* | *p* |
|---|---|---|---|---|---|
| Age | Years | 23.55 (5.99) | 23.64 (4.94) | 637.5 | .288 |
| Anaerobic fitness estimate | HPAQ | 3.79 (3.23) | 5.06 (3.80) | 613.5 | .193 |
| Enjoyment | Seven-point Likert | 4.32 (1.31) | 3.72 (1.88) | 584.0 | .101 |
| Liking of experimenters | Seven-point Likert | 5.11 (1.34) | 5.13 (1.74) | 697.0 | .647 |
| Self-consciousness | Seven-point Likert | 4.13 (2.16) | 3.72 (2.03) | 644.0 | .317 |
| Comfort and support | Seven-point Likert | 5.21 (1.28) | 4.74 (1.82) | 661.0 | .405 |
| Anxiety | Seven-point Likert | 3.18 (1.56) | 3.41 (1.59) | 691.0 | .604 |
| Tried harder during exercise bouts? | Seven-point Likert | 3.11 (1.93) | 3.08 (1.72) | 731.5 | .921 |
| Perceived daily social support | MSPSS[1] | 66.34 (10.62) | 70.41 (11.44) | 569.0 | .079 |
| Need for social assurance | SAS[2] | 29.45 (9.80) | 31.59 (9.93) | 646.5 | .335 |
| Extraversion | Big 5[3] | 6.19 (2.14) | 7.13 (1.94) | 302.5 | .875 |
| Agreeableness | Big 5 | 7.32 (1.47) | 6.36 (1.71) | 223.0 | .083 |
| Conscientiousness | Big 5 | 6.97 (1.60) | 7.49 (1.60) | 232.0 | .120 |
| Neuroticism | Big 5 | 5.66 (1.91) | 6.08 (1.89) | 280.5 | .551 |
| Openness | Big 5 | 7.66 (1.70) | 7.64 (2.17) | 296.5 | .781 |
| Length of relationship | Months | 33.61 (48.86) | 32.10 (38.34) | 715.5 | .795 |
| Frequency of contact | Six-option multiple choice | 5.05 (0.96) | 5.15 (1.11) | 664.0 | .401 |
| Relationship with companion | Component | −0.08 (1.13) | 0.08 (0.87) | 699.5 | .672 |
| Sex | The solo condition consisted of 12 males and 26 females. The companion condition consisted of 12 males and 27 females ($\chi^2$ = .006, $p$ = .939). | | | | |

1. Zimet et al. (1988)
2. Lee and Robbins (1995)
3. Rammstedt and John (2007)

**Table A 2** Effects of companion sex and age on anaerobic outputs

| Variable | Condition | | | | | |
|---|---|---|---|---|---|---|
| | Solo | | Companion | | Overall | |
| | ***F*** **(*df*)** | ***p*** | ***F*** **(*df*)** | ***p*** | ***F*** **(*df*)** | ***p*** |
| Companion sex | 0.03 (1, 36.00) | .870 | 0.23 (1, 37.03) | .634 | 0.29 (1, 75.02) | .592 |
| Companion age | 0.86 (2, 35.01) | .431 | 0.54 (2, 36.01) | .587 | 1.25 (2, 74.02) | .292 |

**Table A 3** Results of main mixed ANOVA on total anaerobic outputs (see also Table A 4)

| Variable | *df* (error *df*) | *F* | *p* | $\eta_p^2$ |
|---|---|---|---|---|
| Intercept | 1 (71) | 45.97 | < .001 | .393 |
| Exerciser sex | 1 (71) | 55.22 | < .001 | .438 |
| Anaerobic fitness | 1 (71) | 3.92 | .052 | .052 |
| Condition | 1 (71) | 0.06 | .810 | .001 |
| Exercise bout | 2.09 (148.67) | 0.23 | .805* | .003 |
| Exercise bout × condition | 2.09 (148.67) | 5.34 | .005* | .070 |

*Greenhouse-Geisser interpretation of *F* due to violation of assumption of sphericity

**Table A 4** Descriptive statistics and post-hoc contrast summaries for main mixed ANOVA on total anaerobic outputs (related to Table A 3)

| | **Bout 1** | | **Bout 2** | | **Bout 3** | | **Bout 4** | |
|---|---|---|---|---|---|---|---|---|
| | **Estimated Marginal Mean** | ***SD*** | **Estimated Marginal Mean** | ***SD*** | **Estimated Marginal Mean** | ***SD*** | **Estimated Marginal Mean** | ***SD*** |
| Solo Condition | 9,754.06 | 2,794.94 | 8,850.40 | 2,612.32 | 8,499.41 | 2,573.17 | 8,043.00 | 2,368.51 |
| Companion Condition | 10,420.75 | 3,113.74 | 9,196.38 | 2,295.19 | 8,265.79 | 2,127.69 | 8,124.23 | 1,957.74 |

**Post-hoc Contrasts**

| **Contrast** | ***df* (error *df*)** | ***F*** | ***p*** | $\eta_p^2$ |
|---|---|---|---|---|
| Bout 1 – Bout 2 | 1 (71) | 2.27 | .136 | .176 |
| Bout 1 – Bout 3 | 1 (71) | 8.73 | .004 | .331 |
| Bout 1 – Bout 4 | 1 (71) | 4.71 | .033 | .250 |

**Table A 5** Results of mixed ANOVA on peak power outputs (see also Table 6 A)

| Variable | *df* (error *df*) | *F* | *p* | $\eta_p^2$ |
|---|---|---|---|---|
| Intercept | 1 (71) | 48.44 | < .001 | .406 |
| Exerciser sex | 1 (71) | 37.06 | < .001 | .343 |
| Anaerobic fitness | 1 (71) | 2.24 | .139 | .031 |
| Condition | 1 (71) | 0.06 | .812 | .001 |
| Exercise bout | 2.47 (175.02) | 0.46 | .672* | .006 |
| Exercise bout × condition | 2.47 (175.02) | 4.36 | .009* | .058 |

*Greenhouse-Geisser interpretation of *F* due to violation of assumption of sphericity

**Table A 6** Descriptive statistics and post-hoc contrast summaries for mixed ANOVA on peak power outputs (related to Table A 5)

| | **Bout 1** | | **Bout 2** | | **Bout 3** | | **Bout 4** | |
|---|---|---|---|---|---|---|---|---|
| | **Estimated Marginal Mean** | ***SD*** | **Estimated Marginal Mean** | ***SD*** | **Estimated Marginal Mean** | ***SD*** | **Estimated Marginal Mean** | ***SD*** |
| Solo Condition | 432.31 | 131.98 | 405.75 | 126.80 | 395.47 | 118.39 | 393.84 | 88.08 |
| Companion Condition | 458.25 | 131.91 | 429.17 | 106.40 | 394.19 | 94.59 | 383.10 | 105.29 |

**Post-hoc Contrasts**

| **Contrast** | ***df* (error *df*)** | ***F*** | ***p*** | $\eta_p^2$ |
|---|---|---|---|---|
| Bout 1 – Bout 2 | 1 (71) | 0.19 | .661 | .003 |
| Bout 1 – Bout 3 | 1 (71) | 4.67 | .034 | .062 |
| Bout 1 – Bout 4 | 1 (71) | 6.62 | .012 | .085 |

**Table A 7** Results of mixed ANOVA on average heart rate

| Variable | *df* (error *df*) | *F* | *p* | $\eta_p^2$ |
|---|---|---|---|---|
| Intercept | 1 (60) | 504.47 | < .001 | .894 |
| Exerciser sex | 1 (60) | 1.46 | .232 | .024 |
| Anaerobic fitness | 1 (60) | 1.04 | .312 | .017 |
| Condition | 1 (60) | 0.14 | .712 | .002 |
| Time[+] | 1.37 (82.23) | 1.78 | .184[*] | .029 |
| Time[+] × condition | 1.38 (82.23) | 1.84 | .175[*] | .030 |

This analysis included 31 exercisers from the solo condition and 33 exercisers from the companion condition (the heart rate sensor failed to yield complete data for the remaining 11 exercisers, so their data was not included in this analysis).

[+]Average heart rates were calculated for exercise bouts 1, 2, 3, and 4

[*]Greenhouse-Geisser interpretation of *F* due to violation of assumption of sphericity

**Table A 8** Results of mixed ANOVA on rates of perceived exertion (see also Table A 9)

| Variable | *df* (error *df*) | *F* | *p* | $\eta_p^2$ |
|---|---|---|---|---|
| Intercept | 1 (73) | 2556.27 | < .001 | .972 |
| Condition | 1 (73) | < 0.01 | .977 | < .001 |
| Exercise bout | 1.91 (139.58) | 19.61 | < .001* | .212 |
| Exercise bout × condition | 1.91 (139.58) | 5.34 | .007* | .068 |

*Greenhouse-Geisser interpretation of *F* due to violation of assumption of sphericity

**Table A 9** Descriptive statistics and post-hoc contrast summaries for mixed ANOVA on rates of perceived exertion (related to Table A 8)

| | **Bout 1** | | **Bout 2** | | **Bout 3** | | **Bout 4** | |
|---|---|---|---|---|---|---|---|---|
| | **Estimated Marginal Mean** | ***SD*** | **Estimated Marginal Mean** | ***SD*** | **Estimated Marginal Mean** | ***SD*** | **Estimated Marginal Mean** | ***SD*** |
| Solo Condition | 11.35 | 2.11 | 11.78 | 2.06 | 12.68 | 1.80 | 13.05 | 1.93 |
| Companion Condition | 11.95 | 2.64 | 12.13 | 2.52 | 12.29 | 2.49 | 12.55 | 2.44 |

**Post-hoc Contrasts**

| **Contrast** | ***df* (error *df*)** | ***F*** | ***p*** | $\eta_p^2$ |
|---|---|---|---|---|
| Bout 1 – Bout 2 | 1 (73) | 4.97 | .029 | .064 |
| Bout 1 – Bout 3 | 1 (73) | 21.27 | < .001 | .226 |
| Bout 1 – Bout 4 | 1 (73) | 26.72 | < .001 | .268 |

**Table A 10** Results of mixed ANOVA on reports of physical discomfort

| Variable | *df* (error *df*) | *F* | *p* | $\eta_p^2$ |
|---|---|---|---|---|
| Intercept | 1 (73) | 342.43 | < .001 | .824 |
| Condition | 1 (73) | 1.61 | .208 | .022 |
| Exercise bout | 1.78 (130.24) | 31.85 | < .001 | .304 |
| Exercise bout × condition | 1.94 (130.24) | 0.54 | .566 | .007 |

**Table A 11** Mixed ANOVA on total anaerobic outputs with the exerciser-companion relationship component as moderator of exercise bout × condition interaction

| Variable | *df* (error *df*) | *F* | *p* | $\eta_p^2$ |
|---|---|---|---|---|
| Intercept | 1 (45) | 24.37 | < .001 | .351 |
| Exerciser sex | 1 (45) | 28.62 | < .001 | .389 |
| Anaerobic fitness | 1 (45) | 3.67 | .062 | .075 |
| Condition | 1 (45) | 0.03 | .876 | .001 |
| Exercise bout | 2.31 (103.87) | 0.10 | .904* | .003 |
| Exercise bout × condition × exerciser-companion relationship component | 2.31 (103.87) | 2.29 | .098* | .049 |

*Greenhouse-Geisser interpretation of *F* due to violation of assumption of sphericity

**Table A 12** Mixed ANOVA on total anaerobic outputs with perceived daily social support as moderator of exercise bout × condition interaction

| Variable | *df* (error *df*) | *F* | *p* | $\eta_p^2$ |
|---|---|---|---|---|
| Intercept | 1 (40) | 23.80 | < .001 | .373 |
| Exerciser sex | 1 (40) | 25.42 | < .001 | .389 |
| Anaerobic fitness | 1 (40) | 2.40 | .129 | .057 |
| Condition | 1 (40) | 0.97 | .330 | .024 |
| Exercise bout | 2.28 (91.09) | 0.61 | .565* | .015 |
| Exercise bout × condition × support in daily life | 2.28 (91.09) | 0.52 | .619* | .013 |

*Greenhouse-Geisser interpretation of *F* due to violation of assumption of sphericity

**Table A 13** Mixed ANOVA on total anaerobic outputs with need for social assurance as moderator of exercise bout × condition interaction

| Variable | *df* (error *df*) | *F* | *p* | $\eta_p^2$ |
|---|---|---|---|---|
| Intercept | 1 (46) | 21.86 | < .001 | .322 |
| Exerciser sex | 1 (46) | 31.89 | < .001 | .409 |
| Anaerobic fitness | 1 (46) | 2.69 | .108 | .055 |
| Condition | 1 (46) | <0.01 | .996 | .000 |
| Exercise bout | 2.03 (93.36) | 0.33 | .805* | .007 |
| Exercise bout × condition × need for social assurance | 2.03 (93.36) | 0.16 | .853* | .004 |

*Greenhouse-Geisser interpretation of *F* due to violation of assumption of sphericity

**Table A 14** Mixed ANOVA on total anaerobic outputs with neuroticism as a moderator of the exercise bout × condition interaction (see also Table A 15)

| Variable | *df* (error *df*) | *F* | *p* | $\eta_p^2$ |
|---|---|---|---|---|
| Intercept | 1 (46) | 44.50 | < .001 | .514 |
| Exerciser sex | 1 (46) | 26.24 | < .001 | .385 |
| Anaerobic fitness | 1 (46) | 0.03 | .860 | .001 |
| Condition | 1 (46) | 0.20 | .656 | .005 |
| Exercise bout | 1.98 (83.27) | 0.08 | .920* | .002 |
| Exercise bout × condition × neuroticism | 1.98 (83.27) | 5.69 | .005* | .119 |

*Greenhouse-Geisser interpretation of *F* due to violation of assumption of sphericity

**Table A 15** Descriptive statistics and post-hoc contrast summaries for mixed ANOVA on total anaerobic outputs with neuroticism as a moderator of the exercise bout × condition interaction (related to Table A 14)

| | | **Exercise bout 1** | | **Exercise bout 2** | | **Exercise bout 3** | | **Exercise bout 4** | |
|---|---|---|---|---|---|---|---|---|---|
| | | **Estimated Marginal Mean** | ***SE*** | **Estimated Marginal Mean** | ***SE*** | **Estimated Marginal Mean** | ***SE*** | **Estimated Marginal Mean** | ***SE*** |
| Low neuroticism | Solo condition | 9,372.73 | 637.32 | 8,168.46 | 576.17 | 8,220.84 | 534.58 | 8.011.03 | 514.34 |
| | Companion condition | 11,992.16 | 648.80 | 9,903.40 | 586.55 | 8,844.47 | 544.21 | 8,669.18 | 523.60 |
| High neuroticism | Solo condition | 10,376.46 | 529.01 | 9,320.39 | 478.25 | 8,915.51 | 443.73 | 8,337.81 | 426.93 |
| | Companion condition | 9,319.53 | 503.55 | 8,426.38 | 455.24 | 7,752.37 | 422.38 | 7,553.42 | 406.38 |

**Post-hoc contrasts**

| **Contrast** | ***df* (error *df*)** | ***F*** | ***p*** | $\eta_p^2$ |
|---|---|---|---|---|
| Bout 1 – Bout 2 | 1 (46) | 2.69 | .108 | .060 |
| Bout 1 – Bout 3 | 1 (46) | 8.31 | .006 | .165 |
| Bout 1 – Bout 4 | 1 (46) | 8.04 | .007 | .161 |

**Figures**

# Do you exercise?

UNIVERSITY OF OXFORD

## Get **paid £15** to do it!



## Participate in our experiment:

We are currently recruiting participants* for an experiment on the links between personality, friendship, and exercise. The experiment will involve completing several short bouts of maximum-effort stationary cycling and computer-based questionnaires. The experiment will last between 45 minutes and an hour.

*Participants must be aged 18-49 and at least recreationally fit. You **must** bring a companion with you to the experiment – this person must be someone you feel you have a close connection with and that you can depend on in times of need (such as a friend, romantic partner, or family member). Companions will not take part in the exercise portion of the experiment but will be compensated for their time (£10). Participants do **not** need to be students at the University.

**Please contact arran.davis@anthro.ox.ac.uk with any questions and/or sign up here:**

http://doodle.com/tcc9g2xub8hsfs8x

**Figure A 1** Participant recruitment flyer.

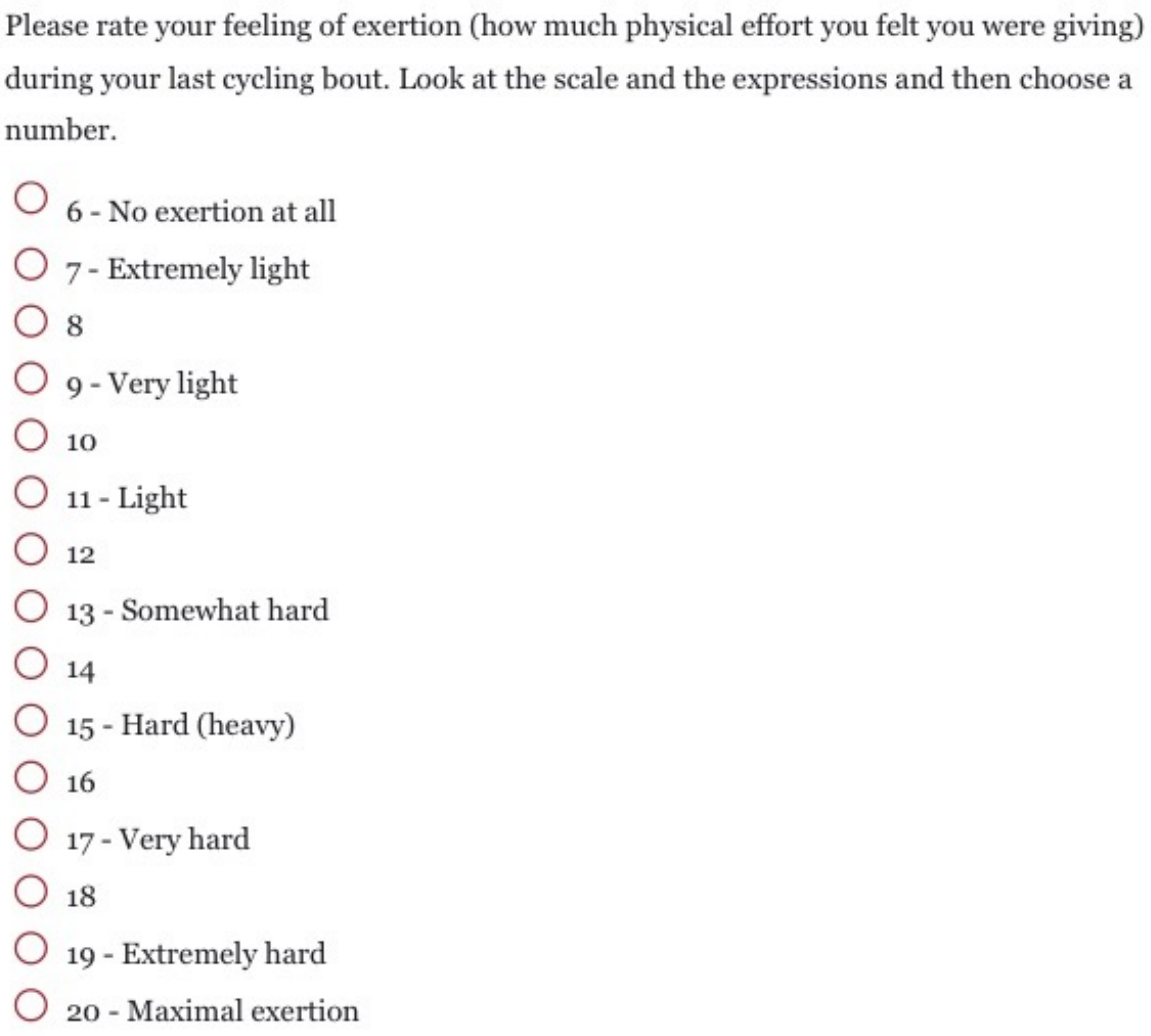



**Figure A 2** Borg Scale of Perceived Exertion.

Please rate the physical discomfort you felt during your last cycling bout. Look at the scale and the expressions and then choose a number.

- ○ 20
- ○ 19
- ○ 18
- ○ 17 - Very intolerable
- ○ 16 - Intolerable
- ○ 15
- ○ 14 - Very distressing
- ○ 13 - Slightly intolerable
- ○ 12 - Very annoying
- ○ 11 - Distressing
- ○ 10 - Very unpleasant
- ○ 9 - Slightly distressing
- ○ 8 - Annoying
- ○ 7 - Unpleasant
- ○ 6 - Slightly annoying
- ○ 5 - Slightly unpleasant
- ○ 4
- ○ 3
- ○ 2
- ○ 1
- ○ 0 - Neutral

**Figure A 3** 20-point scale on physical discomfort.

## Appendix B

## 1 Multilevel model assumption checks

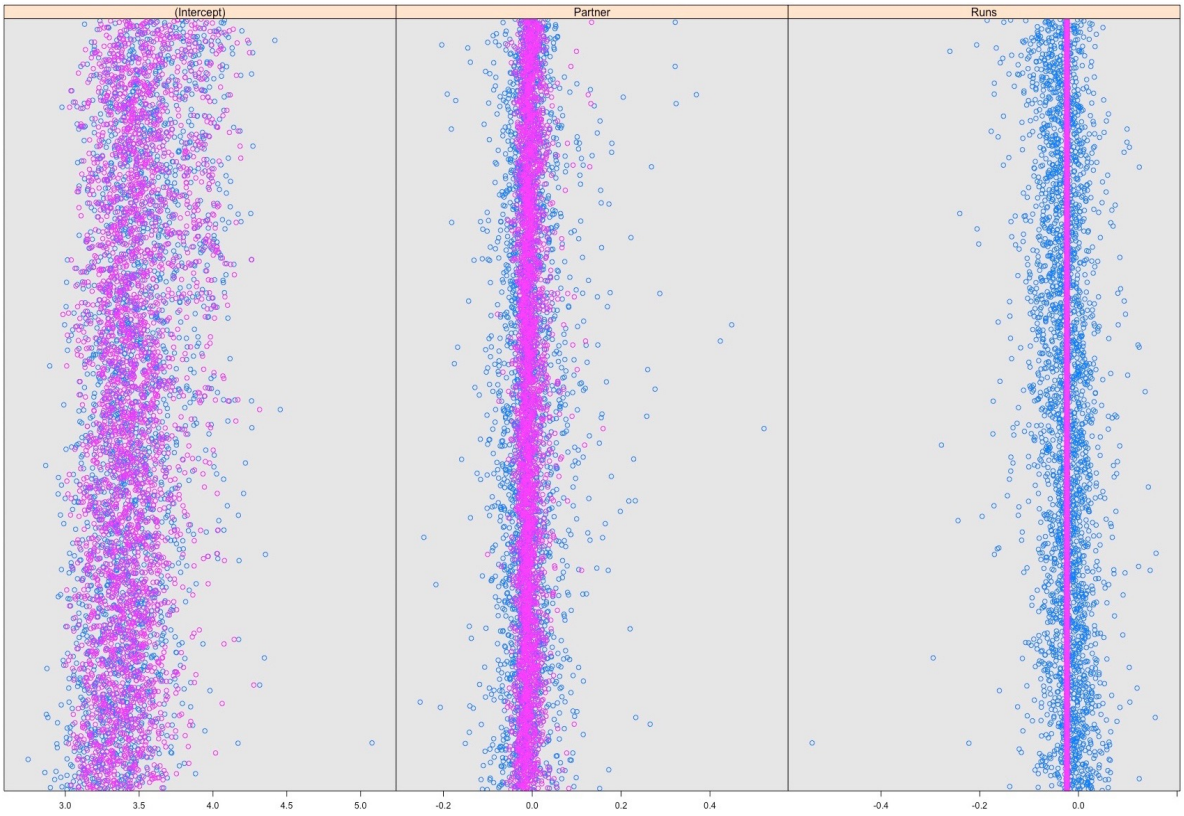
Model assumptions were checked according to the methods published by Snijders and Bosker (2012).

Level-one heteroscedasticity was tested by looking at between-group (i.e., parkrunner) differences in level-one residual variance, acquired through running separate OLS regressions on the data from the parkrunners included in the main model. The variability of posterior means estimated by the multilevel model should be similar to variability of coefficients estimated by the separate OLS regressions.

Well-specified models should also have constant (i.e., homoscedastic) level-one residual variance with residual dispersion measures that are normally distributed. This can be tested using the method of Raudenbush and Bryk (2002), which tests a (squared) standardised residual dispersion measure (*d*) against a null hypothesis of homoscedastic level-one residual variance; *d* will have a Gaussian distribution when there is level-one homoscedasticity. When testing constant level-one residual variance, Snijders and Bosker (2012) suggest, to avoid bias, only including data from relatively large level-two groups. For all models reported in this appendix, only parkrunners with more than 20 runs were used.

Regarding level one residuals, Snijders and Bosker (2012) recommend plotting unstandardised ordinary least squares (OLS) residuals against level-one explanatory variables to check the linearity of fixed effects, and normal probability plots of standardised OLS residuals to test the assumption of normally distributed level-one residuals.

Regarding residuals at level two, Snijders and Bosker (2012) recommend plotting unstandardised level-two residuals as a function of ‘relevant level-two variables’ to check for linearity (there are none for this model), plotting squared standardised level-two residuals against relevant level-two variables (in this case, the finish partner variable) to check for homoscedasticity, and normal probability plots of standardised level-two residuals to check for level-two residual normality.



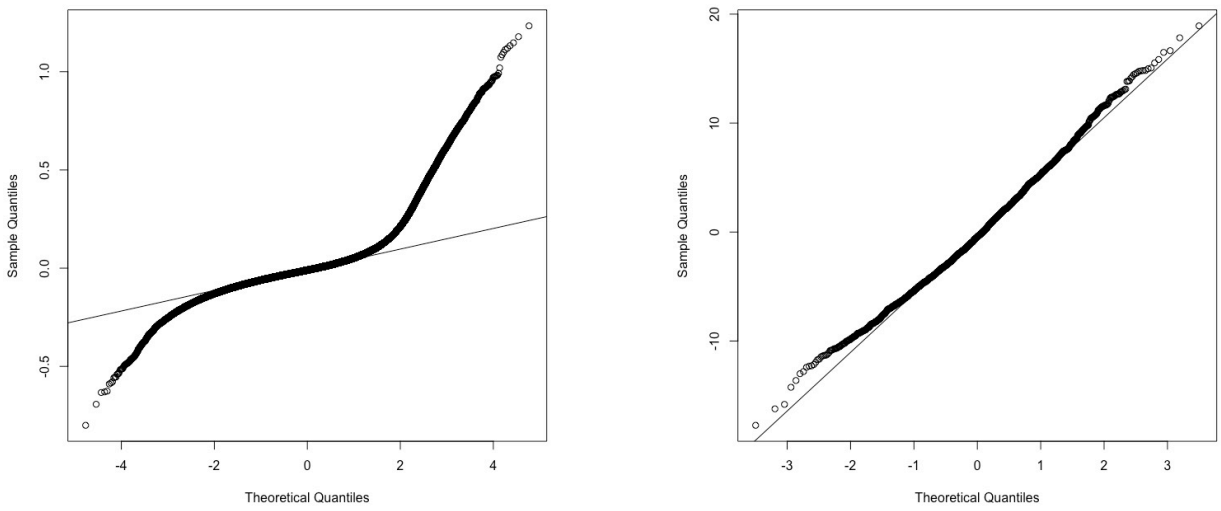

**Appendix B Figure 1** OLS coefficient estimates for each of the sampled parkrunners (blue) versus the posterior means for each parkrunner in the multilevel model (pink). The OLS regressions and the multilevel model use the same sample of parkrunners (*n* = 3,196). 'Partner' represents the finish partner presence variable and 'Runs' represents the previous runs variable.

Influential data points were checked using the *influence.ME* package in R, which is designed to detect groups of data points (level-two units; parkrunners, in this case) that exert an undue influence on the model (Nieuwenhuis, te Grotenhuis, & Pelzer, 2012). This package works by iteratively omitting single level-two units from the model and checking whether the exclusion of a level-two unit leads to significantly different estimates.

### 1.1 Analysis A

Regarding level one homoscedasticity, Appendix B Figure 1 shows that the variability of posterior means estimated by the multilevel model are similar to the variability of coefficients estimated by the separate OLS regressions (thus suggesting level-one homoscedasticity), with the exception of extreme coefficient estimates resulting from small sample sizes (i.e.,

(*a*) (*b*)

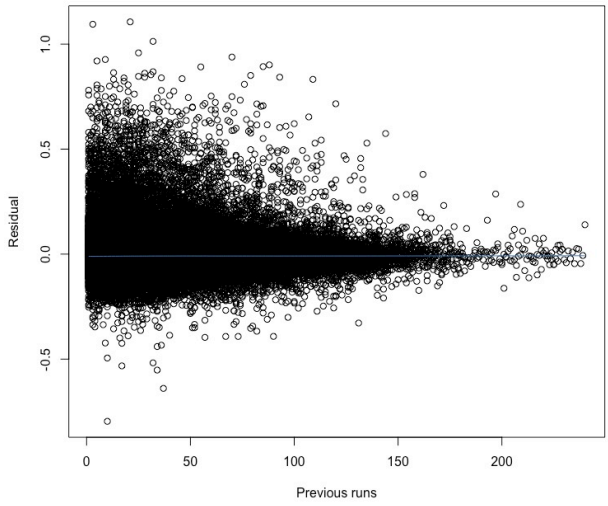



**Appendix B Figure 2** Q-Q plot of (*a*) level one residuals for multilevel model on parkrunners' 5 km run times and (*b*) of the standardised residual dispersion measure, *d*.

from parkrunners with relatively few runs). For example, 76% of parkrunners with outlying coefficient estimates (± 0.2) for the $\log_2$ of the finishing partner variable had fewer total runs than the overall average (46.34). Snijders and Bosker (2012) argue that relatively small group sizes are likely to cause deviant coefficient estimates, and suggest that in this case these outliers are not problematic.

Nevertheless, the null hypothesis of level-one homoscedasticity was rejected for this data, $H$ = 60,856.39, $df$ = 2,133 , $p$ < .001, indicating level-one heteroscedasticity. However, $H$ depends on the normality of the level-one residuals. Snijders and Bosker (2012) write that heavier-tailed distributions of level-one residuals will cause inflated values of $H$, even if the residuals have constant variance. The level-one residuals for the current model are indeed heavily tailed (see Appendix B Figure 2a). Given this, and that a Q-Q plot of *d* (see Appendix B Figure 2b) reveals that it is close to being normally distributed, it can be assumed that the model has an unproblematic amount of heteroskedasticity (Snijders & Bosker, 2012).

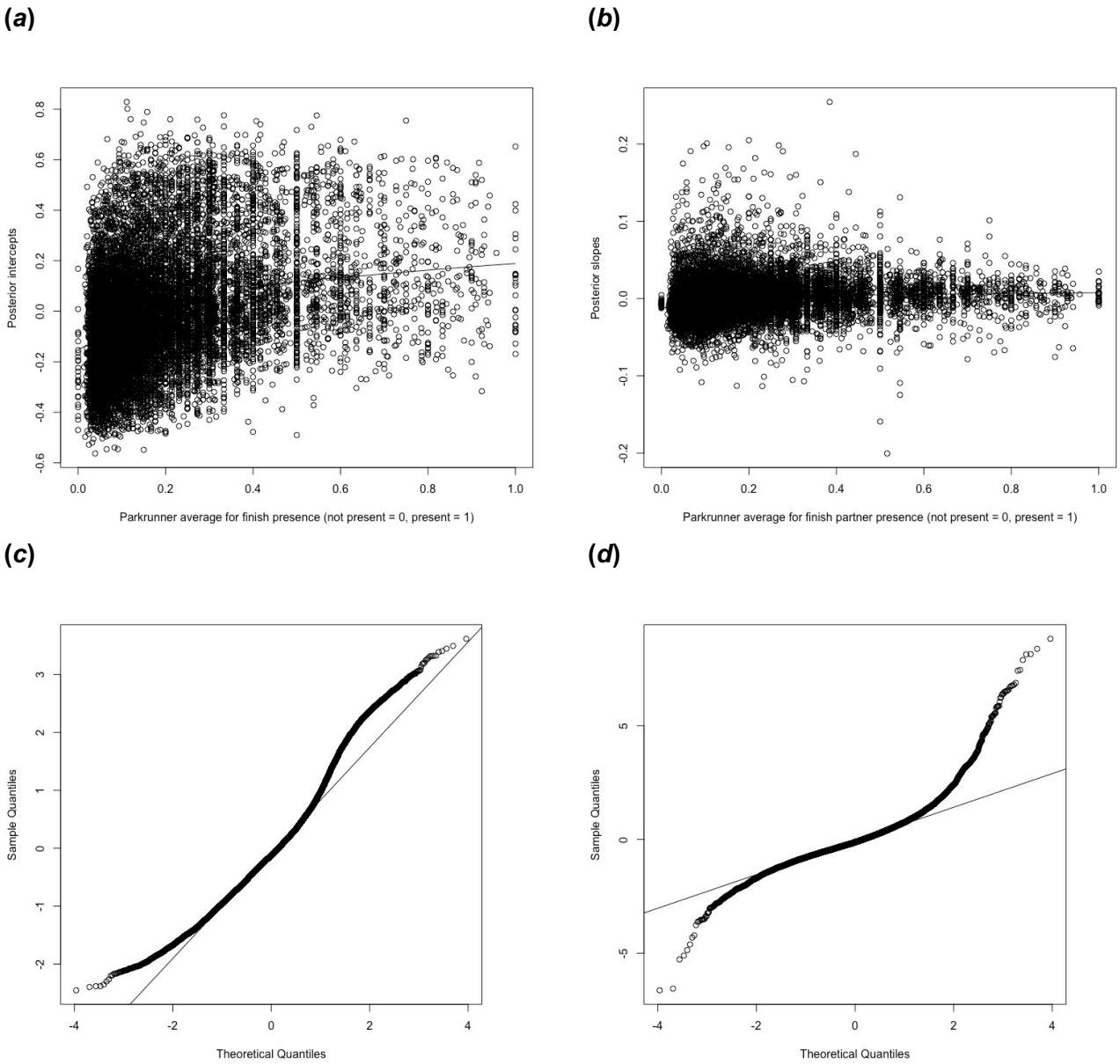
Regarding level one residuals, level-one linearity was confirmed by plots of the unstandardised OLS residuals against the only relevant level-one predictor (the previous runs variable); residuals were centred around 0 at all levels of this predictor (see Appendix B Figure




**Appendix B Figure 3** Unstandardised OLS residuals by previous runs with LOWESS (locally weighted scatterplot smoothing) line.

3). The normality of level-one residuals was checked by making a normal probability plot of the standardised OLS residuals. Appendix B Figure 2a shows that the normality assumption has been violated, due to longer tails than what would be expected with the normal distribution; specifically, the residuals display positive skew. Regardless, Seco, García, García, and Rojas (2013) have demonstrated that fixed effects estimates are robust to violations of the normality assumption; multilevel models with non-normally distributed residuals do not produced biased fixed effect parameter estimates.

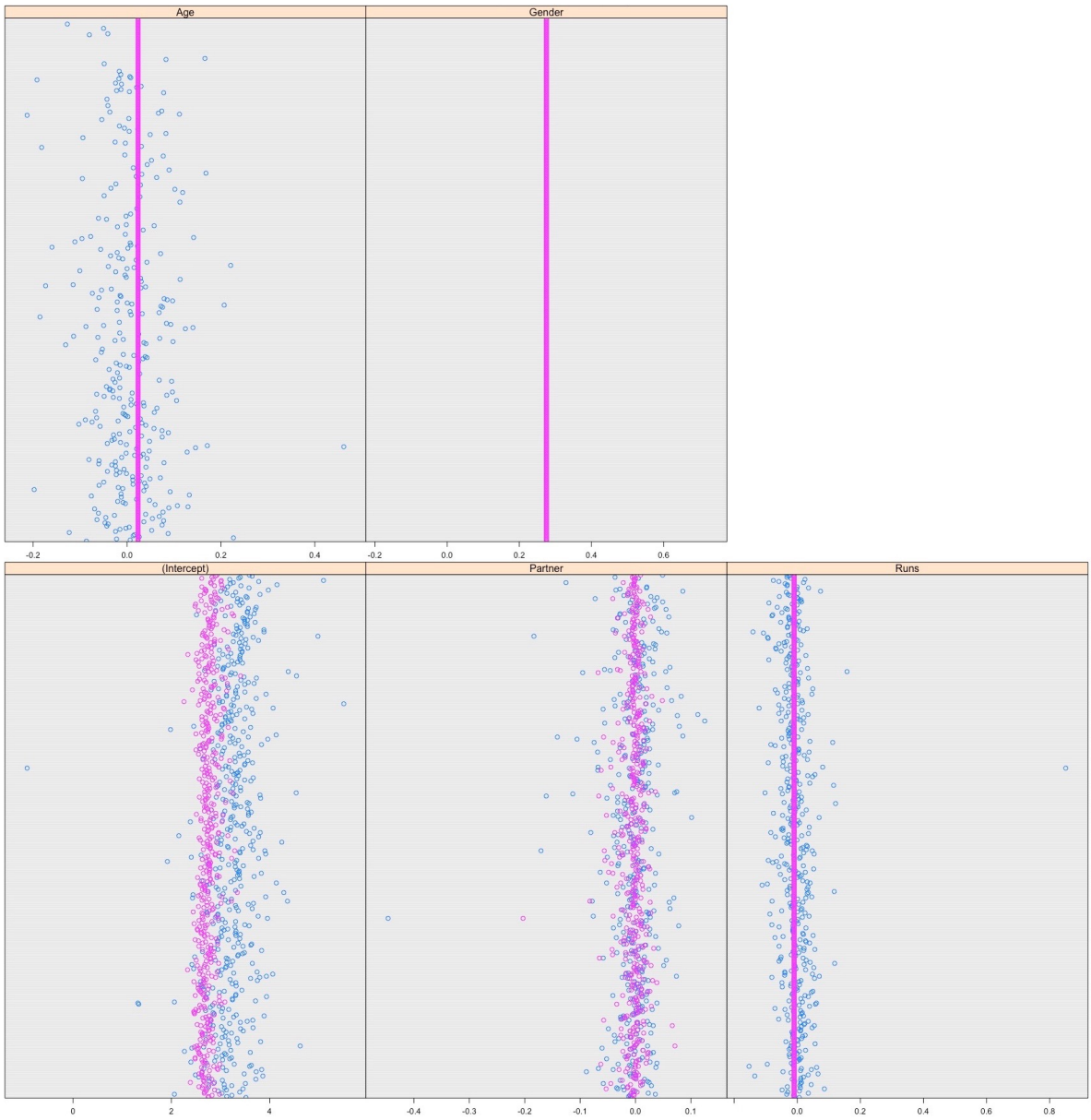
Regarding residuals at level two, plots of posterior intercepts and slopes for the finish partner effect as a function of average finish partner presence for each parkrunner revealed that level-two residuals were homoscedastic (see Appendix B Figure 4a and Appendix B Figure 4b). Normal Q-Q plots of standardised level-two residuals for random intercepts and slopes suggest deviations from normality for the random intercepts and slopes (see Appendix B Figure 4c and Appendix B Figure 4d). However, Maas and Hox (2004) have shown that estimates of fixed effects and their standard errors are robust to non-normal level-two residual errors when there are at least 50 level-two units (this study had between 195 to 24,780,




**Appendix B Figure 4** Checks of level-two residuals for multilevel model on parkrunners' 5 km run times: (*a*) random intercepts and (*b*) random slopes as a function of each parkrunners average finish partner presence (0 = never present, 1 = always present), with LOWESS lines, and standardised level-two (*c*) intercept residuals and (*d*) finish partner random slope residuals versus the expected order statistics of a normal distribution (Q-Q plot).

depending on the cut-off used for minimum number or partner finishes). Given this, it can be assumed that fixed effect estimates (and their standard errors) are unbiased.

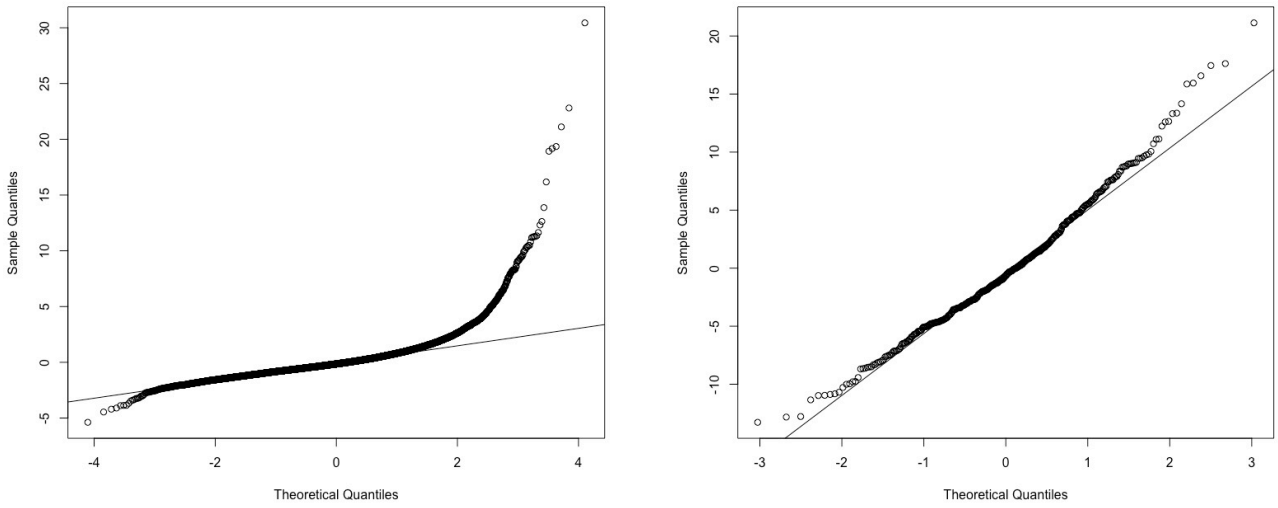
Given the inordinate amount of time needed to carry out the *influence.ME* procedure in R (described in Section 1 of this appendix) on the full model, which was run on the data of 24,780 parkrunners, I instead carried out the procedure for the same subset (25% of total) of




**Appendix B Figure 5** OLS coefficient estimates for each of the sampled parkrunners (blue) versus the posterior means for each parkrunner in the multilevel model (pink).

parkrunners used to check level-one heteroscedasticity. Results revealed that there were no significantly influential data points; no parkrunners had Cook's Distances greater than 1 ($M$ = 0.001, $SD$ = 0.003, range = <0.001 – 0.11), suggesting that no parkrunners had an undue influence on the model (Field et al., 2012). Indeed, the significance of the predictor variables was not changed as a result of excluding the data of any of the sampled parkrunners. Given this, it is unlikely that a single parkrunner had an undue influence on the model.

(*a*) (*b*)

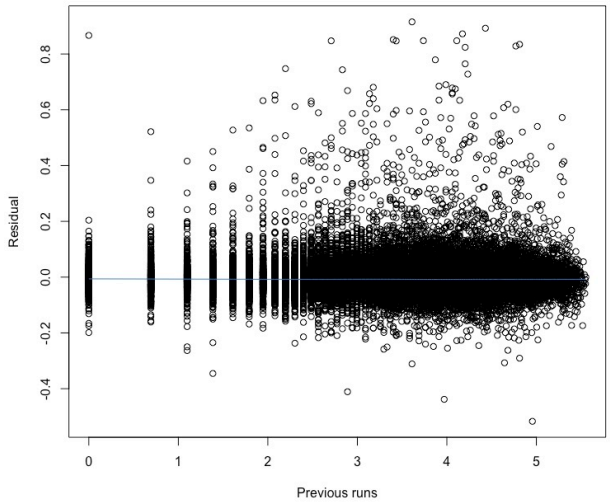



**Appendix B Figure 6** Q-Q plot of (*a*) level-one residuals for multilevel model on parkrunners' 5 km run times and (*b*) of the standardised residual dispersion measure, *d*.

### 1.2 Analysis B

Appendix B Figure 5 shows that posterior means estimated by the multilevel model are similar to the variability of coefficients estimated by the separate OLS regressions (thus suggesting level-one homoscedasticity), with the exception of extreme coefficient estimates resulting from small sample sizes (i.e., from parkrunners with relatively few runs); for example, 91% of parkrunners with outlying coefficient estimates (± 0.1) for the travel partner presence variable had fewer total runs than the overall average (61.18). Snijders and Bosker (2012) argue that relatively small group sizes are likely to cause deviant coefficient estimates, and suggest that in this case these outliers are not problematic.

Nevertheless, the null hypothesis of level-one homoscedasticity was rejected for this data, $H$ = 12,795.03, $df$ = 404, $p$ < .001. However, $H$ depends on the normality of the level-one residuals. Snijders and Bosker (2012) write that heavier-tailed distributions of level-one residuals will cause inflated values of $H$, even if the residuals have constant variance. The level-one residuals for the current model are indeed heavily tailed (see Appendix B Figure 6a). Given this, and that a Q-Q plot of $d$ (see Appendix B Figure 6b) reveals that it is close to being

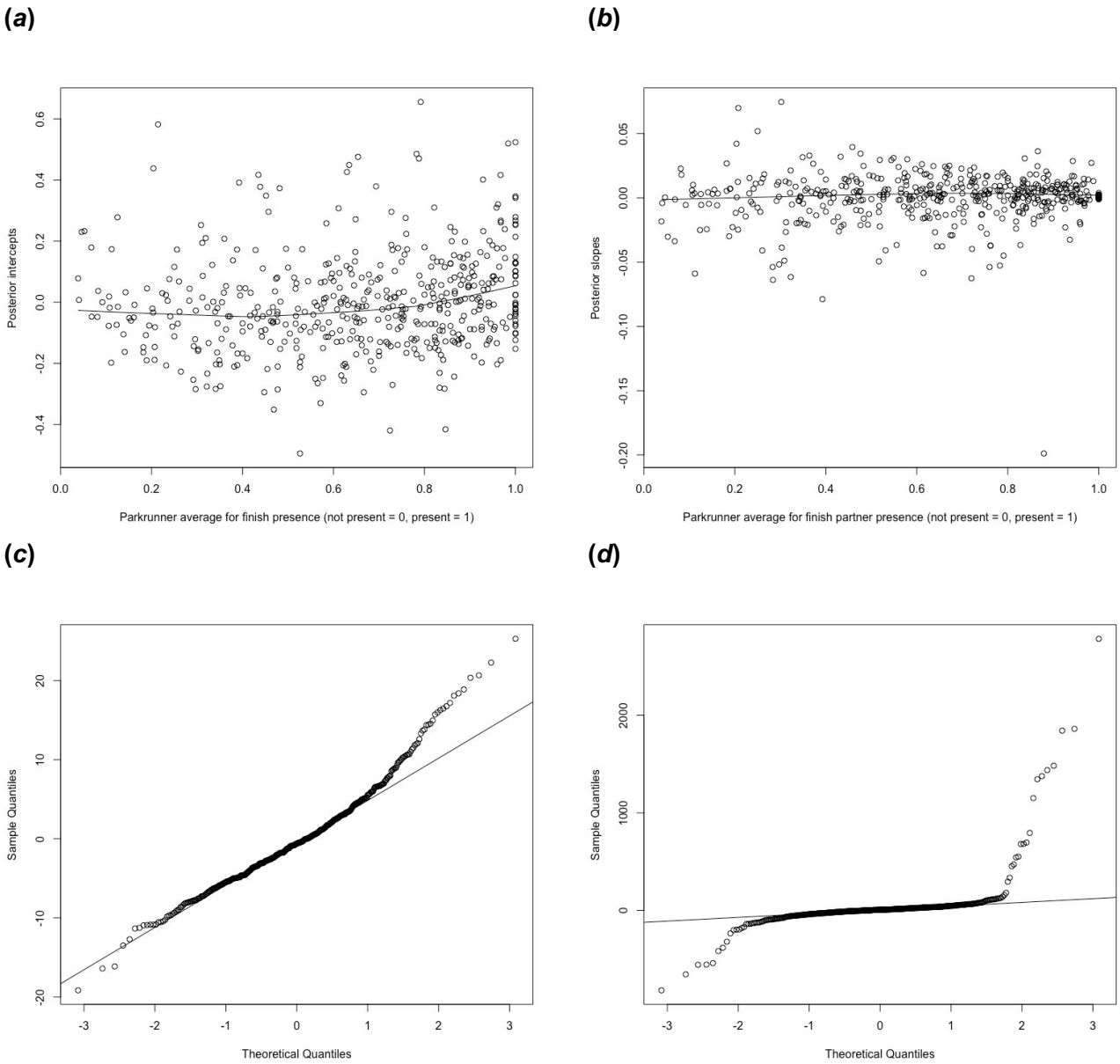



**Appendix B Figure 7** Unstandardised OLS residuals by previous runs with LOWESS line.

normally distributed it can be assumed that the model has an unproblematic amount of heteroskedasticity (Snijders & Bosker, 2012).

Regarding level-one residuals, plots of the unstandardised OLS residuals against the only relevant level-one predictor – the previous runs variable – showed that residuals were centred around 0 at all levels of this predictor, indicating that the linearity assumptions had been met for this model (see Appendix B Figure 7). The normality of level-one residuals was checked by making a normal probability plot of the standardised OLS residuals. Appendix B Figure 6a shows that the normality assumption has been violated, due to longer tails than what would be expected with the normal distribution; specifically, the residuals display positive skew. Regardless, Seco et al. (2013) have demonstrated that fixed effects estimates are robust to violations of the normality assumption.

Regarding residuals at level two, plots of posterior intercepts and slopes for the travel partner effect as a function of average travel partner presence for each parkrunner revealed that level-two residuals were homoscedastic (see Appendix B Figure 8a and Appendix B Figure 8b). Normal Q-Q plots of standardised level-two residuals for random intercepts and slopes suggest deviations from normality for the random intercepts and slopes (see Appendix B




**Appendix B Figure 8** Checks of level-two residuals for multilevel model on parkrunners' 5 km run times: (*a*) random intercepts and (*b*) random slopes as a function of each parkrunner's average travel partner presence (0 = never present, 1 = always present), with LOWESS lines, and standardised level-two (*c*) intercept residuals and (*d*) travel partner random slope residuals versus the expected order statistics of a normal distribution (Q-Q plot).

Figure 8c and Appendix B Figure 8d). However, Maas and Hox (2004) have shown that estimates of fixed effects and their standard errors are robust to non-normal level-two residual errors when there are at least 50 level-two units (this study had between 81 to 8,211, depending on the cut-off used for minimum number or partner finishes). Given this, it can be assumed that fixed effect estimates (and their standard errors) are unbiased.

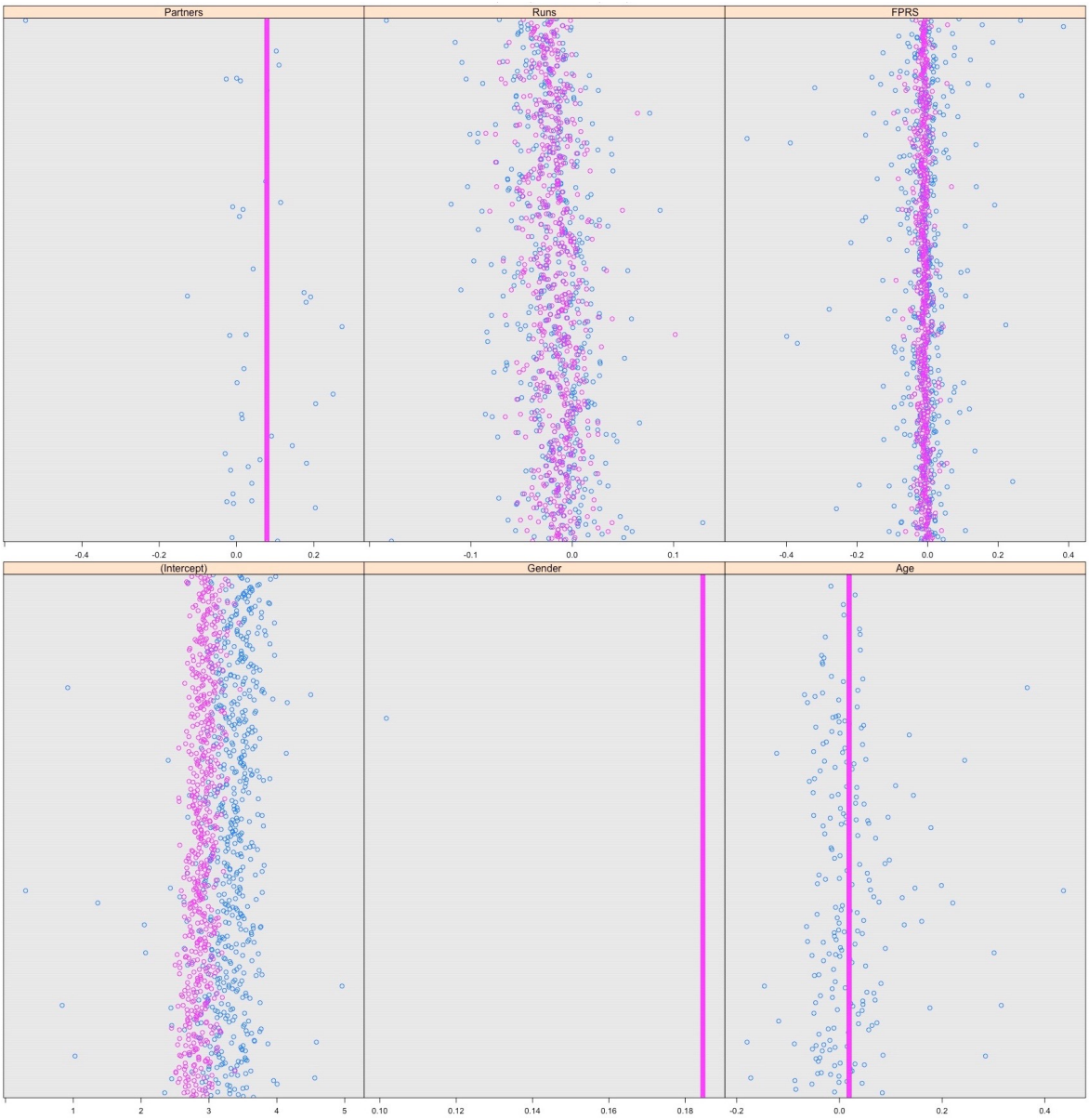
Influential data points were checked using the *influence.ME* package in R (described in Section 1 of this appendix). Results revealed that there were no significantly influential data points; no parkrunners had Cook's Distances greater than 1 ($M$ = 0.01, $SD$ = 0.05, range = < 0.001 – 0.91), suggesting that no observations had an undue influence on the model (Field et al., 2012). Indeed, the significance of the predictor variables was not changed as a result of excluding the data of any of the sampled parkrunners.

### 1.3 Analysis C

The assumptions for this model were checked with a model run on a subset of the data used in the analysis. This was done to facilitate interpretation of model assumption checks, as diagnostic plots and some test statistics lose meaning with extremely large data sets. The subset was made up of runs from the Burnley parkrun only, and was reduced in accordance with the procedures described in Section 4.2.1 (p. 109). After reduction, it contained information on 16,296 runs from 598 parkrunners; an average of 27.25 runs per parkrunner, which is in line with that of the average of the full data set (22.84). This subset of the main data set was chosen because the model described in Section 4.6.2 (p. 128) yielded a similar fixed effect estimate for the FPRS variable when run on this subset ($b$ = −0.011) and on the full data set used in Analysis C.

Appendix B Figure 9 confirms level-one homoscedasticity, with the exception of extreme coefficient estimates resulting from small sample sizes (i.e., from parkrunners with relatively few runs); for example, 94% of parkrunners with outlying coefficient estimates (± 0.1) for the FPRS variable had fewer total runs than the overall average, and these outliers averaged 13.30 total runs, as compared to the overall average of 27.25 runs. Snijders and Bosker (2012) argue that small group sizes are likely to cause deviant coefficient estimates, and suggest that these outliers are not problematic.

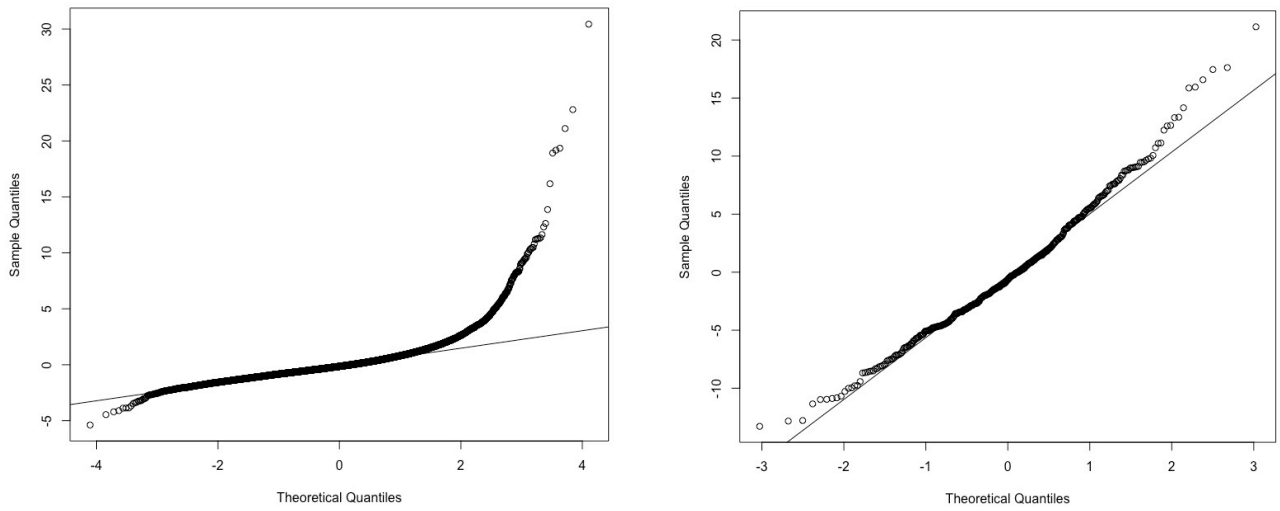
For this model, the null hypothesis of homoscedastic level-one residual variance was rejected, $H$ = 5,929.66, $df$ = 234, $p$ < .001, indicating level-one heteroscedasticity. However, $H$ depends




**Appendix B Figure 9** OLS coefficient estimates for each of the sampled parkrunners (blue) versus the posterior means for each parkrunner in the multilevel model (pink). 'FPRS' represents the $\log_2$ FPRS variable.

on the normality of the level-one residuals. Snijders and Bosker (2012) write that heavier-tailed distributions of level-one residuals will cause inflated values of *H*, even if the residuals have constant variance. The level-one residuals for the current model are indeed heavily tailed (see Appendix B Figure 10a). Given this, and that a Q-Q plot of *d* (see Appendix B Figure 10b) reveals that it is close to being normally distributed – *d* will have a Gaussian distribution when there is level-one homoscedasticity – it can be assumed that the model has level-one homoscedasticity (Snijders & Bosker, 2012).

(*a*) (*b*)

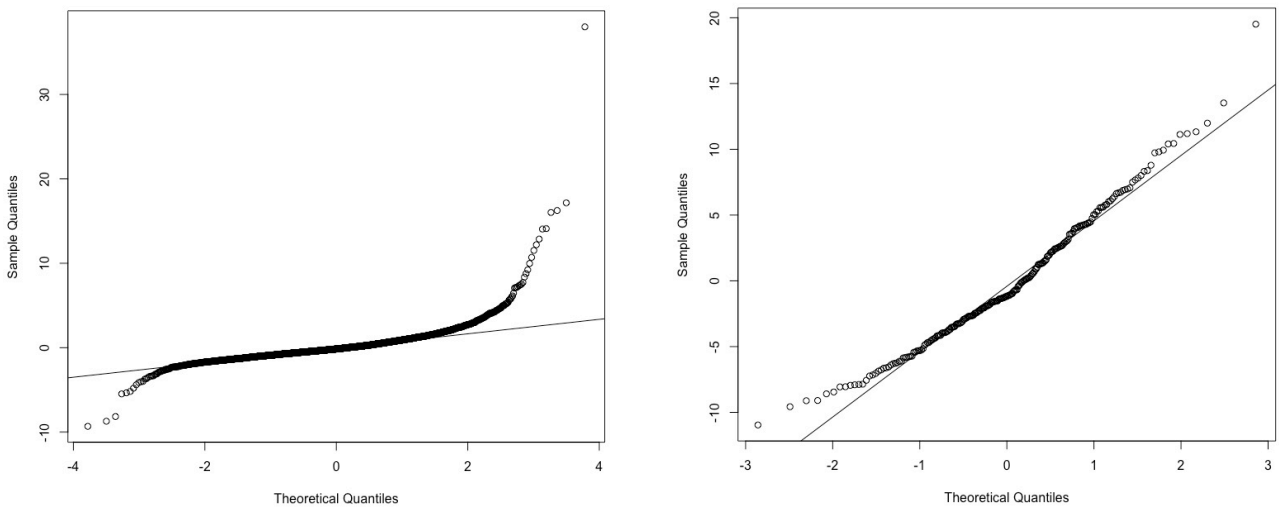



**Appendix B Figure 10** Q-Q plot of (*a*) level one residuals for multilevel model on parkrunners' 5 km run times and (*b*) of the standardised residual dispersion measure, *d*.

The normality of level-one residuals was checked by making a normal probability plot of the standardised OLS residuals. Appendix B Figure 11a shows that the normality assumption has been violated, due to longer tails than what would be expected with the normal distribution; specifically, the residuals display positive skew. Regardless, Seco et al. (2013) have demonstrated that fixed effects estimates are robust to violations of the normality assumption; multilevel models with non-normally distributed residuals do not produced biased fixed effect parameter estimates. Regarding level-one linearity, plots of the unstandardised OLS residuals against relevant level-one predictors showed that residuals were centred around 0 at all levels of these predictors, indicating that linearity assumptions had been met for this model (see Appendix B Figure 12).

Plots of unstandardised level-two residuals – which here are the posterior intercepts and posterior slopes for the $\log_2$ of the previous runs and FPRS variables – by parkrunner age (averaged over the time during which data was available) revealed that the linearity assumption was met (see Appendix B Figure 12a and Appendix B Figure 12b). Normal Q-Q plots of standardised level-two residuals for random intercepts and slopes suggest slight deviations from normality for the random slopes (see Appendix B Figure 12c and Appendix B

(*a*) (*b*)

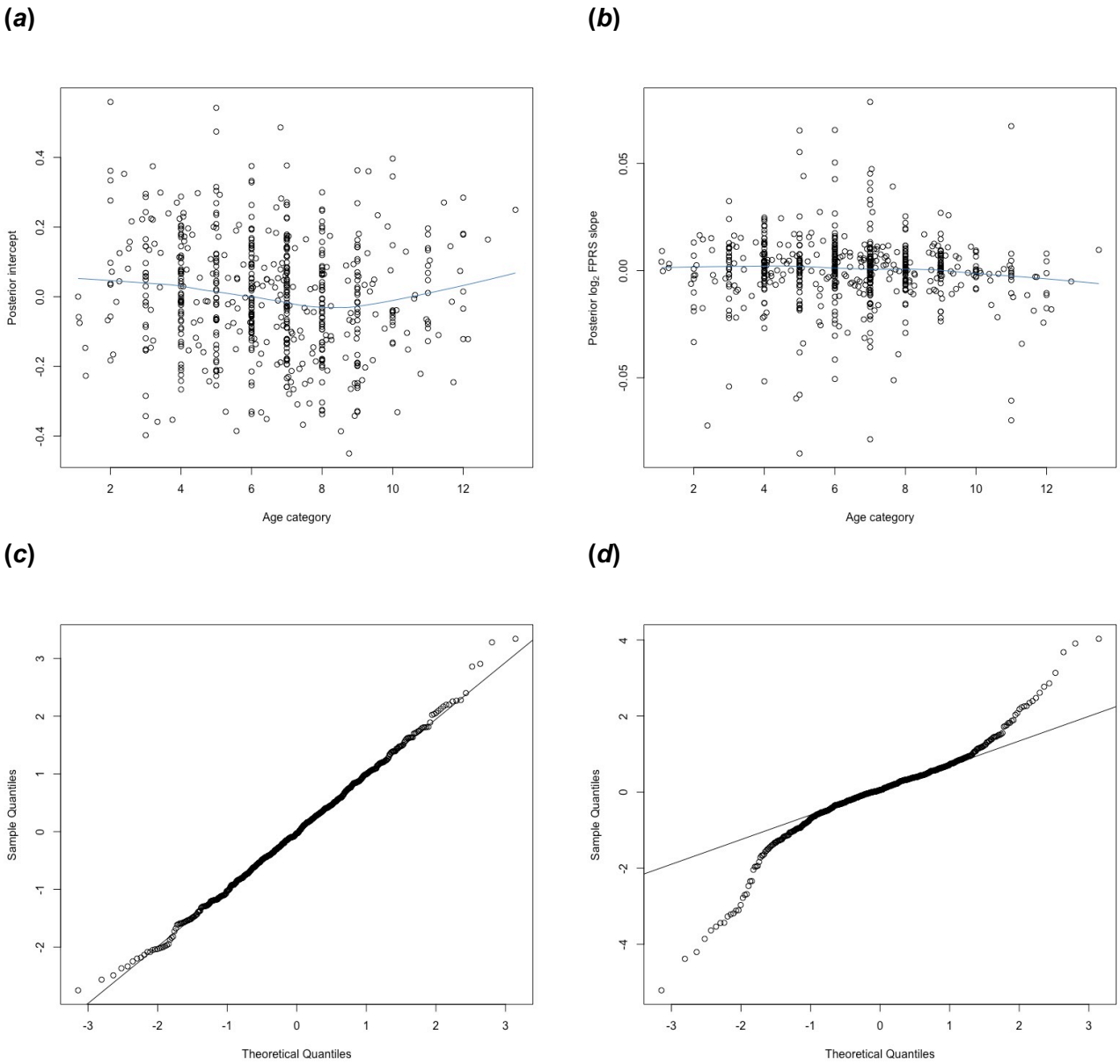



**Appendix B Figure 11** Q-Q plot of (*a*) level one residuals for multilevel model on parkrunners' 5 km run times and (*b*) of the standardised residual dispersion measure, *d*.

Figure 12d). However, Maas and Hox (2004) have shown that estimates of fixed effects and their standard errors are robust to non-normal level-two residual errors when there are at least 50 level-two units (the full data set had 150,725). Given this, it can be assumed that fixed effect estimates (and their standard errors) are unbiased.

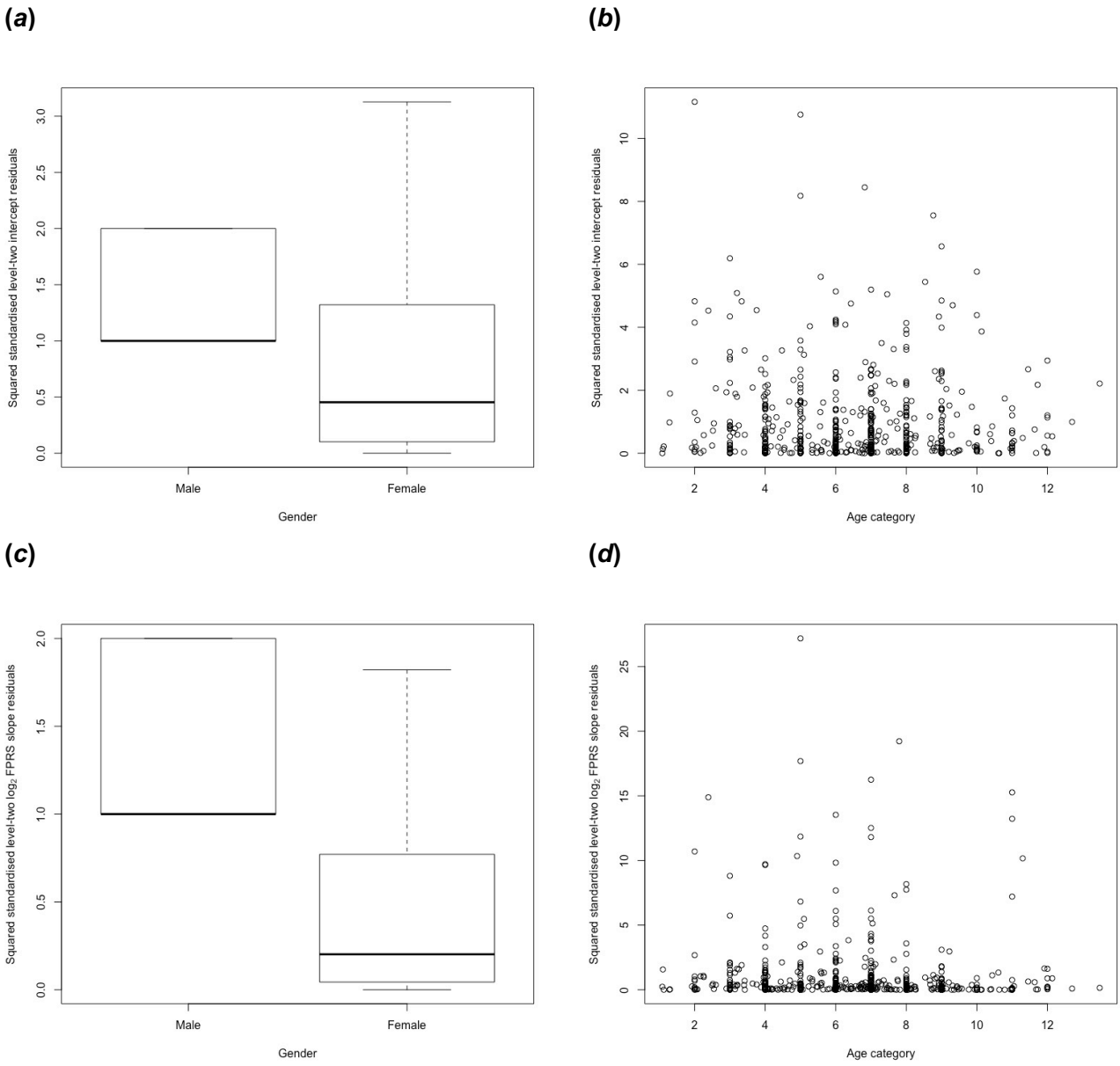
Plots of squared standardised level-two residuals for the random intercepts and slopes of the $\log_2$ of the FPRS variable by parkrunner age (averaged over the time during which data was available) and gender revealed that the homoscedasticity assumption was met for the age variable (see Appendix B Figure 14b and Appendix B Figure 14d). The gender variable displayed more heteroscedasticity, with squared standardised random intercept and slopes having greater variance for females than males (see Appendix B Figure 14a and Appendix B Figure 14c, p. 309). This variable was not a main variable of interest, however, and its exclusion from the model does not change the significance of any of the findings reported in the Chapter 4.

Influential data points were checked using the *influence.ME* package in R, (described in Section 1 of this appendix). Results revealed that there were no significantly influential data points; no parkrunners had Cook's Distances greater than 1 ($M$ = 0.003, $SD$ = 0.02, range =



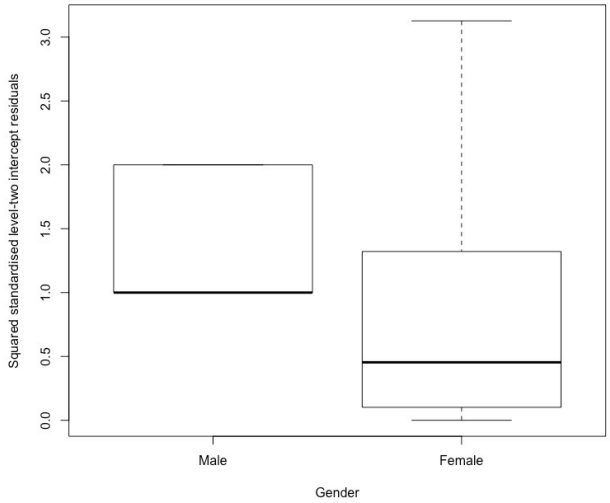

**Appendix B Figure 12** Checks of level-two residuals for multilevel model on parkrunners' 5 km run times: unstandardised (*a*) random intercepts and (*b*) random slopes as a function of parkrunner age averaged over all appearances in the data set (with LOWESS lines), and standardised level-two (*c*) intercept residuals and (*d*) travel partner random slope residuals versus the expected order statistics of a normal distribution (Q-Q plot).

<0.001 – 0.24), suggesting that no observations had an undue influence on the model (Field et al., 2012). Indeed, the significance of the predictor variables was not changed as a result of excluding the data of any of the sampled parkrunners.

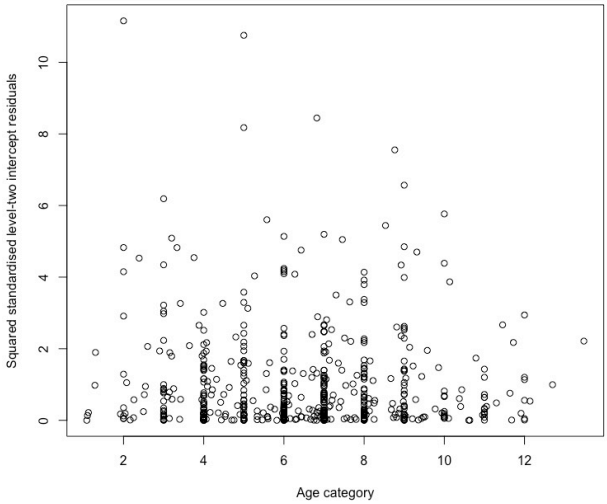



**Appendix B Figure 13** Checks of level-two residual homogeneity: standardised random intercepts by (*a*) gender and (*b*) age averaged over all appearances in the data set and standardised random slopes for the $\log_2$ FPRS variable by (*c*) gender and (*d*) age averaged over all appearances in the data set.

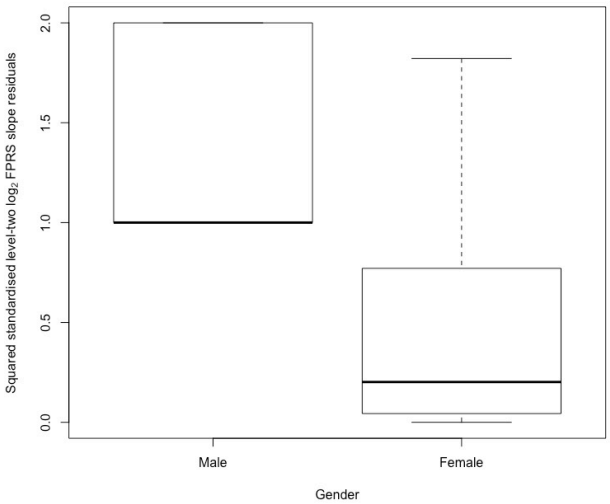
(*a*)



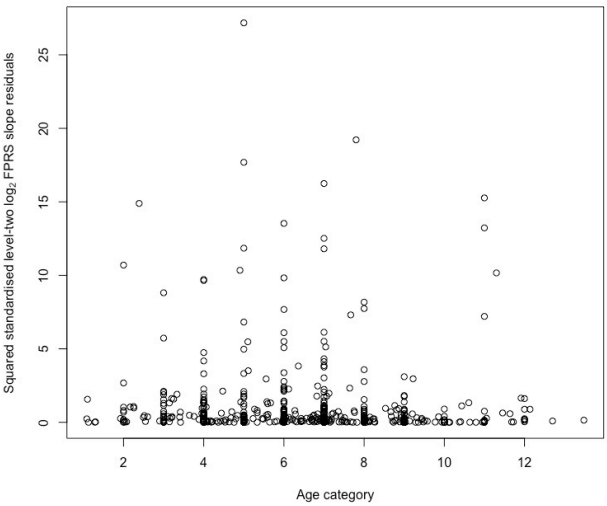

(*b*)




(*c*)




(*d*)




**Appendix B Figure 14** Checks of level-two residual homogeneity: standardised random intercepts by (*a*) gender and (*b*) age averaged over all appearances in the data set and standardised random slopes for the $\log_2$ FPRS variable by (*c*) gender and (*d*) age averaged over all appearances in the data set.

## Tables

**Table B 1** Main multilevel model testing effects of the $log_2$ FPRS variable on logged 5 km run times (using a 1 min cut-off for the FPRS variable)

| **Fixed effect** | **Coefficient** | ***SE*** | ***df*** | ***t*** | ***p*** |
|---|---|---|---|---|---|
| Intercept | 3.143 | < 0.001 | 390,000 | 3,485.43 | < .001 |
| $Log_2$ FPRS | −0.013 | < 0.001 | 76,850 | −62.45 | < .001 |
| $Log_2$ previous runs | −0.011 | < 0.001 | 146,700 | −150.24 | < .001 |
| Partner presence | 0.088 | < 0.001 | 4,249,000 | 350.79 | < .001 |
| Gender (female) | 0.197 | < 0.001 | 152,300 | 259.69 | < .001 |
| Age | 0.019 | < 0.001 | 673,400 | 168.03 | < .001 |
| **Random part** | **Variance** | ***SD*** | | | |
| Intercept | 0.032 | 0.178 | | | |
| $Log_2$ FPRS | 0.003 | 0.051 | | | |
| $Log_2$ previous runs | < 0.001 | 0.023 | | | |
| $R^2_m$ = 0.264, $R^2_c$ = 0.816 | | | | | |

**Table B 2** Main multilevel model testing effects of the $log_2$ FPRS variable on logged 5 km run times (using a 2 min cut-off for the FPRS variable)

| **Fixed effect** | **Coefficient** | ***SE*** | ***df*** | ***t*** | ***p*** |
|---|---|---|---|---|---|
| Intercept | 3.134 | < 0.001 | 388,100 | 3,469.07 | < .001 |
| $Log_2$ FPRS | −0.007 | < 0.001 | 76,910 | −33.56 | < .001 |
| $Log_2$ previous runs | −0.011 | < 0.001 | 146,900 | −154.20 | < .001 |
| Partner presence | 0.084 | < 0.001 | 4,219,000 | 332.95 | < .001 |
| Gender (female) | 0.198 | < 0.001 | 152,400 | 260.40 | < .001 |
| Age | 0.020 | < 0.001 | 688,700 | 168.56 | < .001 |
| **Random part** | **Variance** | ***SD*** | | | |
| Intercept | 0.030 | 0.174 | | | |
| $Log_2$ FPRS | 0.003 | 0.051 | | | |
| $Log_2$ previous runs | < 0.001 | 0.023 | | | |

$R^2_m$ = 0.252, $R^2_c$ = 0.809
*This model produced warnings for convergence failure

**Table B 3** Main multilevel model testing effects of the $\log_2$ FPRS variable on logged 5 km run times (using a 3 min cut-off for the FPRS variable)

| **Fixed effect** | **Coefficient** | ***SE*** | ***df*** | ***t*** | ***p*** |
|---|---|---|---|---|---|
| Intercept | 3.128 | < 0.001 | 387,000 | 3,472.31 | < .001 |
| $\text{Log}_2$ FPRS | −0.004 | < 0.001 | 78,180 | −18.57 | < .001 |
| $\text{Log}_2$ previous runs | −0.011 | < 0.001 | 146,900 | −156.21 | < .001 |
| Partner presence | 0.082 | < 0.001 | 4,181,000 | 324.1 | < .001 |
| Gender (female) | 0.198 | < 0.001 | 152,400 | 260.75 | < .001 |
| Age | 0.020 | < 0.001 | 686,000 | 168.97 | < .001 |
| **Random part** | **Variance** | ***SD*** | | | |
| Intercept | 0.029 | 0.171 | | | |
| $\text{Log}_2$ FPRS ($U_{1j}$) | 0.003 | 0.050 | | | |
| $\text{Log}_2$ previous runs ($U_{2j}$) | < 0.001 | 0.023 | | | |
| $R^2_m$ = 0.241, $R^2_c$ = 0.800 | | | | | |

## Appendix C

# 1 Model assumption checks

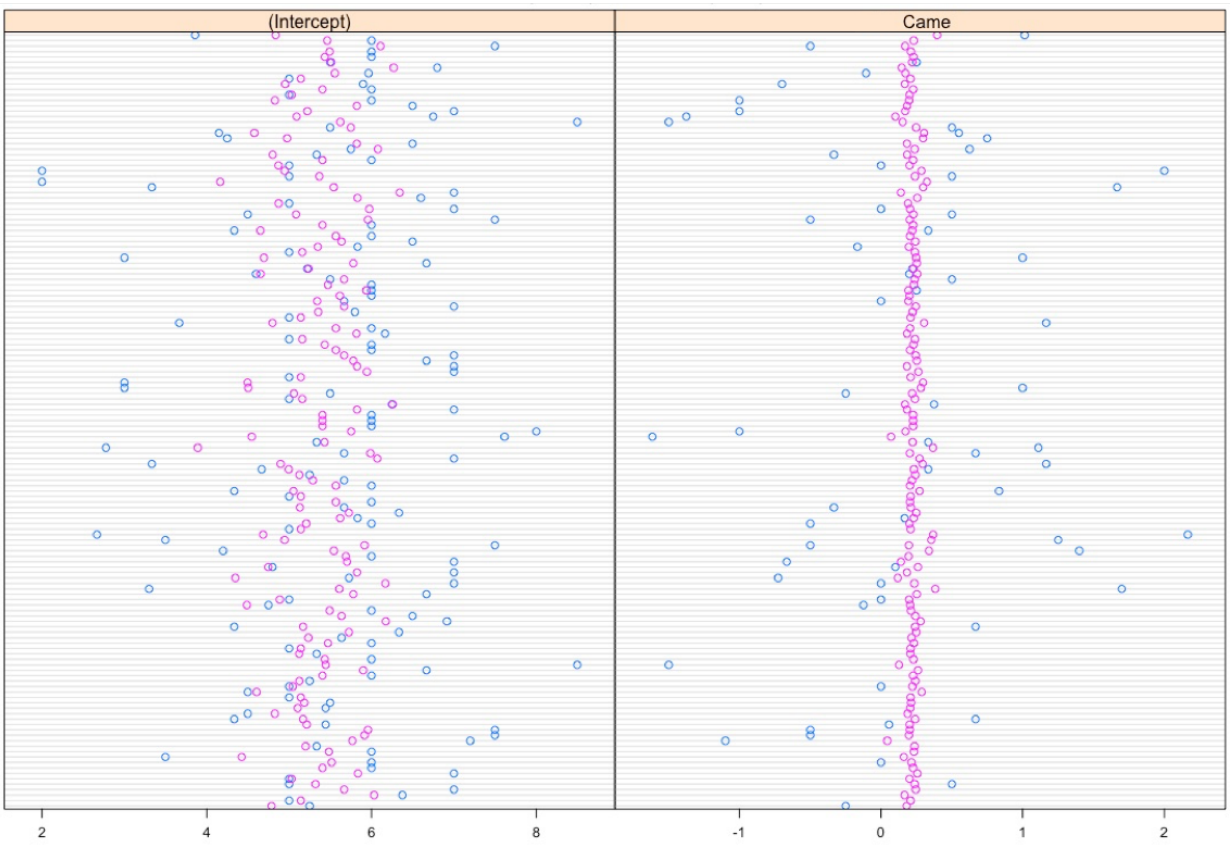
Given the large number of models in this chapter, and their relative equivalence in random and fixed effects structure, the assumptions of only a subset of the models presented in the main text were tested. Firstly, only significant models were checked. Second, of these significant models, the binary variables representing who participants came or met up with, and pre-run sociality were taken as equivalent, as these variables were estimated to have highly similar effects on the outcomes of interest. Thus, the assumptions of the models for pre-run sociality effects on perceptions of enjoyment and run times (within the multilevel mediation process) were checked but not reported here; results were taken to be similar to those from the models with who participants came or met up with as the main predictor. These assumption checks indicated no major issues with these models.

For the multilevel models, the assumptions were checked in accordance with the procedures put forth my Snijders and Bosker (2012). These procedures are described in Section 1 of Appendix B (p. 295). As with the assumption checks presented in Appendix B, I only included data from relatively large level-two groups. In this case, participants with more than 9 survey responses (20 participants).

The procedure described by Imai, Keele, and Yamamoto (2010) was used to check the additional assumption of multilevel mediation models; the sequential ignorability assumption, which assumes that there are no unobserved confounding variables.

## 1.1 Effects of who participants came or met up with on levels of enjoyment (Hypothesis 3.1)

Regarding homoscedasticity of level-one residual variance, Appendix C Figure 1 shows that the variability of posterior means estimated by the multilevel model are similar to the variability of coefficients estimated by the separate OLS regressions (an assumption of multilevel modelling; see Appendix B, Section 1, p. 295), with the exception of extreme coefficient estimates resulting from small sample sizes (i.e., from participants with relatively few survey

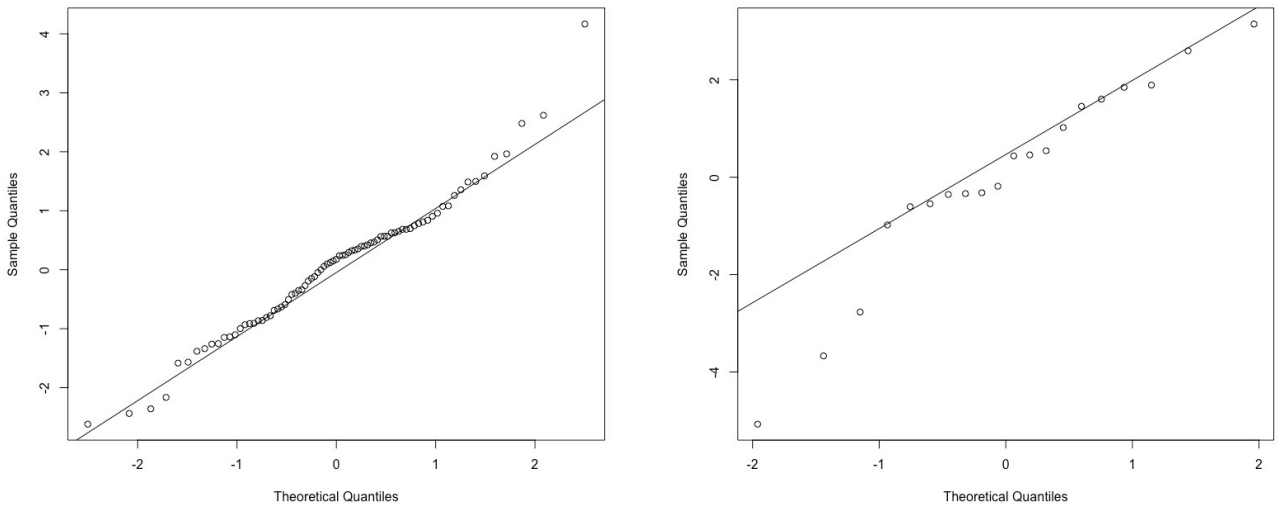



**Appendix C Figure 1** OLS coefficient estimates for each participant (blue) versus the posterior means for each participant in the multilevel model (pink). 'Came' represents the variable describing who parkrunners came or met up with.

responses); for example, 100% of participants with outlying coefficient estimates (± 1) for the variable representing whether or not participants reported coming or meeting up with friends and/or family had fewer total survey responses than the average of 5.13.

For this data, the null hypothesis of homoscedasticity for level-one residual variance was rejected, H = 78.89, df = 20, p = < .001, indicating level-one heteroscedasticity (Snijders & Bosker, 2012). However, H depends on the normality of the level-one residuals. Snijders and Bosker (2012) write that heavier-tailed distributions of level-one residuals will cause inflated values of H, even if the residuals have constant variance. However, the level-one residuals for the current model are only somewhat heavily tailed of *d* (see Appendix C Figure 2b) reveals that it is not close to being normally distributed; this model thus has a potentially problematic amount of heteroscedasticity (Snijders & Bosker, 2012).

(*a*) (*b*)



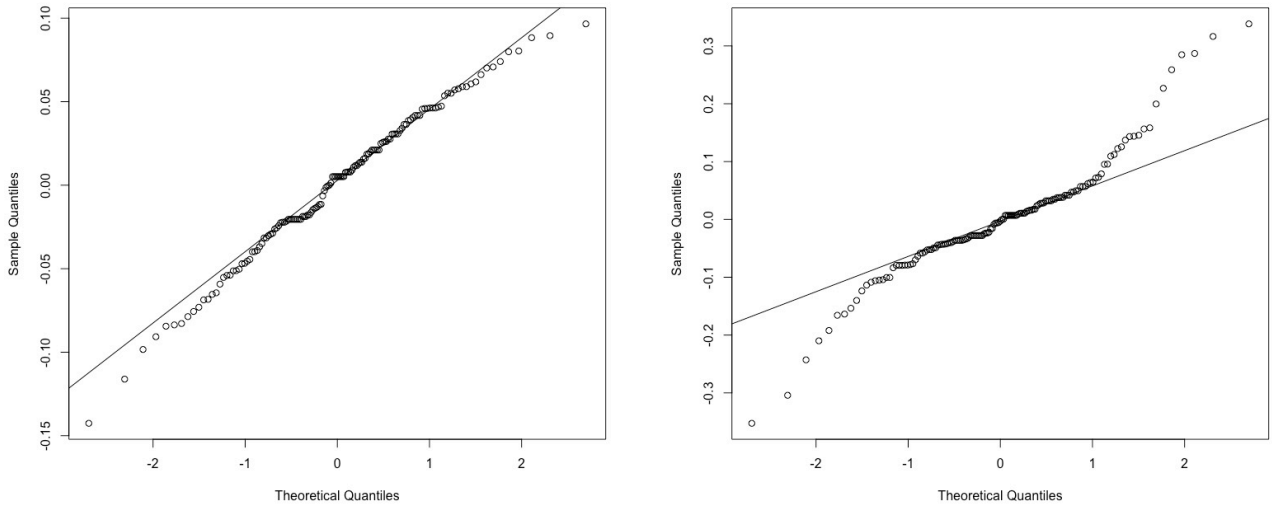

**Appendix C Figure 2** Q-Q plot of (*a*) standardised level-one residuals for multilevel model on enjoyment levels and (*b*) of the standardised residual dispersion measure, *d*.

The normality of level-one residuals was checked by making a normal probability plot of the standardised OLS residuals. Appendix C Figure 2a shows that the normality assumption has been met, with the exception of one outlying value, which did not have an undue influence on the model (see below for checks of influential data points).

Normal Q-Q plots of standardised level-two residuals for random intercepts and slopes suggest deviations from normality for the model's random slopes, but not its random intercepts (see Appendix C Figure 3). However, Maas and Hox (2004) have shown that estimates of fixed effects and their standard errors are robust to non-normal level-two residual errors when there are at least 50 level-two units (this study had 143). Given this, it can be assumed that fixed effect estimates (and their standard errors) are unbiased.

Influential data points were checked using the *influence.ME* package in R (described in Appendix B, Section 1, p. 295). Cook's distances revealed that no participants had an undue influence on the model ($M$ = 0.01, $SD$ = 0.01, range = < .001 – 0.08).

(*a*) (*b*)



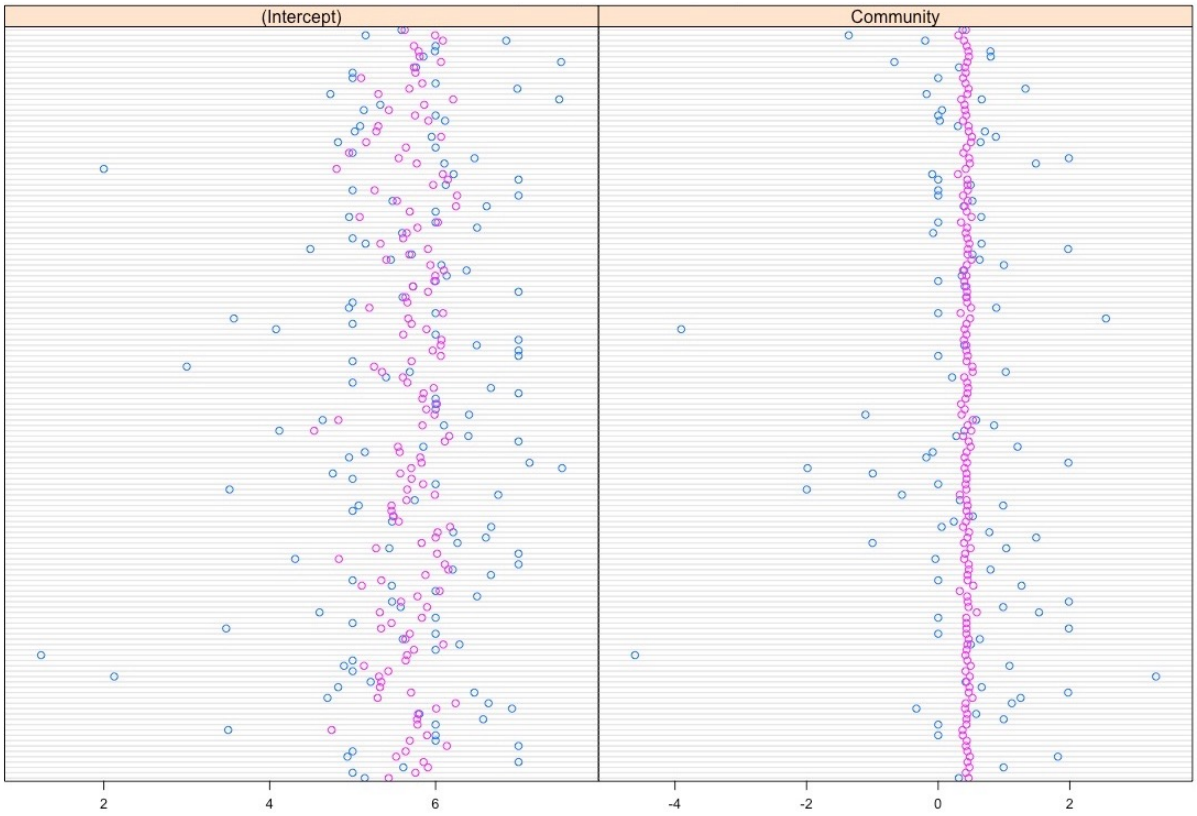

**Appendix C Figure 3** Standardised level-two (*a*) intercept and (*b*) random slope residuals (for the variable representing whether or not participants reported coming or meeting up with friends and/or family) versus the expected order statistics of a normal distribution (Q-Q plot).

### 1.2 Effects of parkrun community component on levels of enjoyment (Hypothesis 3.2)

Appendix C Figure 4 shows that the variability of posterior means estimated by the multilevel model are similar to the variability of coefficients estimated by the separate OLS regressions (suggesting level-one homoscedasticity), with the exception of extreme coefficient estimates resulting from small sample sizes (i.e., from participants with relatively few survey responses); for example, 81% of participants with outlying coefficient estimates (± 1) for the parkrun community component had fewer total survey responses than the average of 5.13.

Regarding constant level-one residual variance, the null hypothesis was not rejected, $H$ = 31.22, $df$ = 14, $p$ = .65, indicating homoscedasticity in level-one residual variance (Snijders & Bosker, 2012).

The normality of level-one residuals was checked by making a normal probability plot of the standardised OLS residuals. Appendix C Figure 5 shows that the normality assumption has been violated, due to longer tails than what would be expected with the normal distribution.

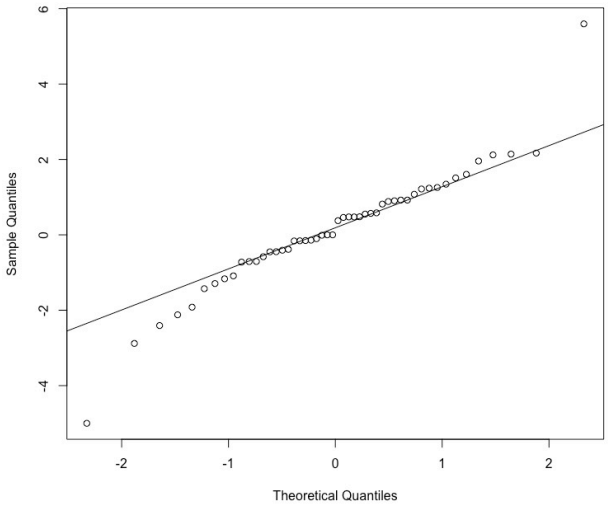



**Appendix C Figure 4** OLS coefficient estimates for each participant (blue) versus the posterior means for each participant in the multilevel model (pink). 'Community' represents the parkrun community component.

Regardless, Seco et al. (2013) have demonstrated that fixed effects estimates are robust to violations of the normality assumption; multilevel models with non-normally distributed residuals do not produced biased fixed effect parameter estimates.

Normal Q-Q plots of standardised level-two residuals for random intercepts and slopes suggest deviations from normality for the random intercept and slope of the model (see Appendix C Figure 6). However, Maas and Hox (2004) have shown that estimates of fixed effects and their standard errors are robust to non-normal level-two residual errors when there are at least 50 level-two units (this study had 143). Given this, it can be assumed that fixed effect estimates (and their standard errors) are unbiased.

Influential data points were checked using the *influence.ME* package in R (described in Appendix B, Section 1, p. 295). Cook's distances revealed that no participants had an undue influence on the model ($M$ = 0.01, $SD$ = 0.01, range = < .001 – 0.09).




**Appendix C Figure 5** Q-Q plot of standardised level-one residuals for multilevel model with parkrun community component predicting enjoyment levels.

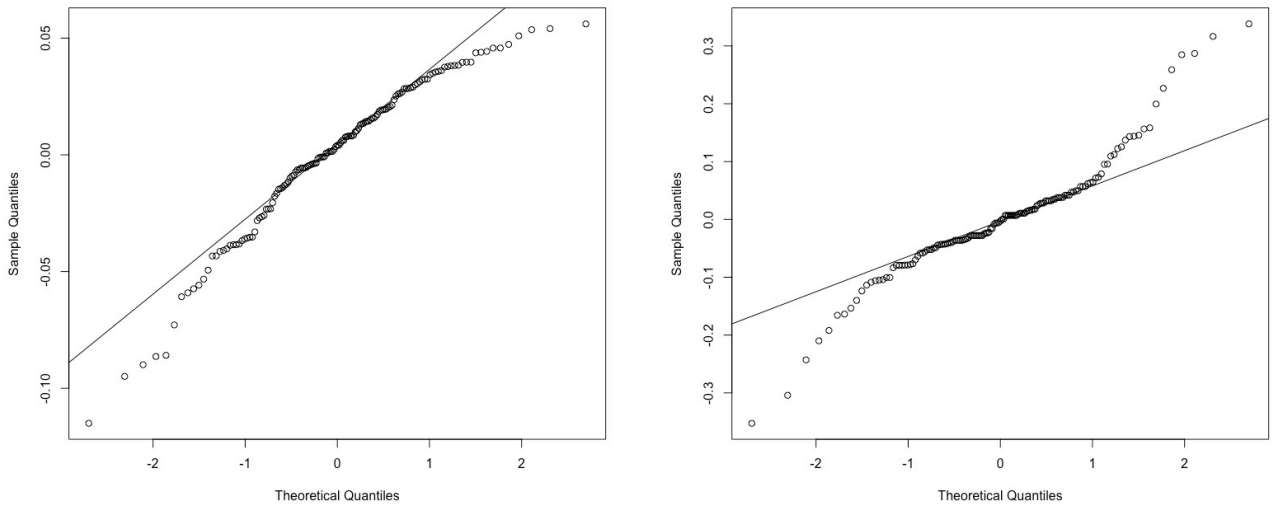
## 1.3 Felt energy as a mediator of the effects of who participants came or met up with on 5 km run times

Below, I report assumption checks for the regression models involved in the significant indirect effect found in the mediation analysis reported in Section 5.3.9.1 (p. 169) and in Figure 5.4 (p. 173): the model using who participants came or met up with to predict their feelings of energy (model '*a*'), and the model using felt energy levels to predict 5 km run times, while controlling for who participants came or met up with to predict run times (model '*b*'). I also report the assumption checks for the multilevel mediation model itself.

### 1.3.1 Constituent model '*a*': who participants came or met up with on felt energy

I could not compare the variability of posterior means estimated by the multilevel model to the variability of coefficients estimated by the separate OLS regressions, because the multilevel model could not be estimated using the *nlme* package in R due to a convergence failure (the model in the main text was estimated in *lmer* without issue). The methods for comparing OLS and multilevel estimate variability provided by Snijders and Bosker (2012) require *nlme* objects. Thus, level-one homoscedasticity could not be checked for this model.

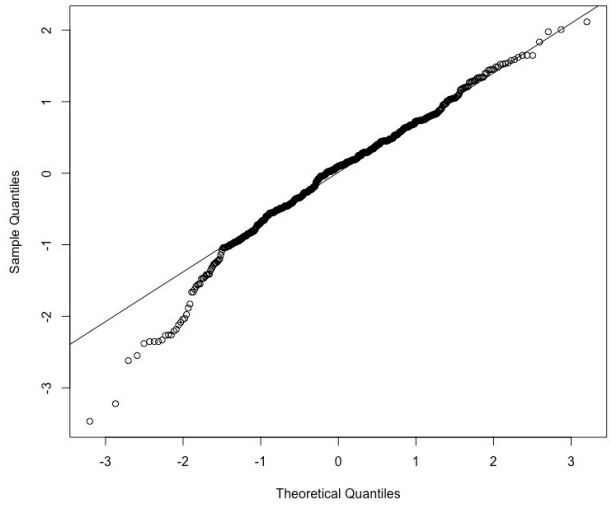
(*a*) (*b*)




**Appendix C Figure 6** Standardised level-two (*a*) intercept and (*b*) random slope residuals (for the parkrun community component) versus the expected order statistics of a normal distribution (Q-Q plot).

The normality of level-one residuals was checked by making a normal probability plot of the unstandardised residuals. Appendix C Figure 7 shows that the normality assumption has been violated, due to longer tails than what would be expected with the normal distribution. Regardless, Seco et al. (2013) have demonstrated that fixed effects estimates are robust to violations of the normality assumption; multilevel models with non-normally distributed residuals do not produced biased fixed effect parameter estimates.

Normal Q-Q plots of standardised level-two residuals for random intercepts and slopes suggest deviations from normality (and, strangely, highly similar distributions) for the random intercept and slope of the model (see Appendix C Figure 8). However, Maas and Hox (2004) have shown that estimates of fixed effects and their standard errors are robust to non-normal level-two residual errors when there are at least 50 level-two units (this study had 143). Given this, it can be assumed that fixed effect estimates (as well as their standard errors) are unbiased.




**Appendix C Figure 7** Q-Q plot of unstandardised level-one residuals for multilevel model with who participants came or met up with predicting felt energy.

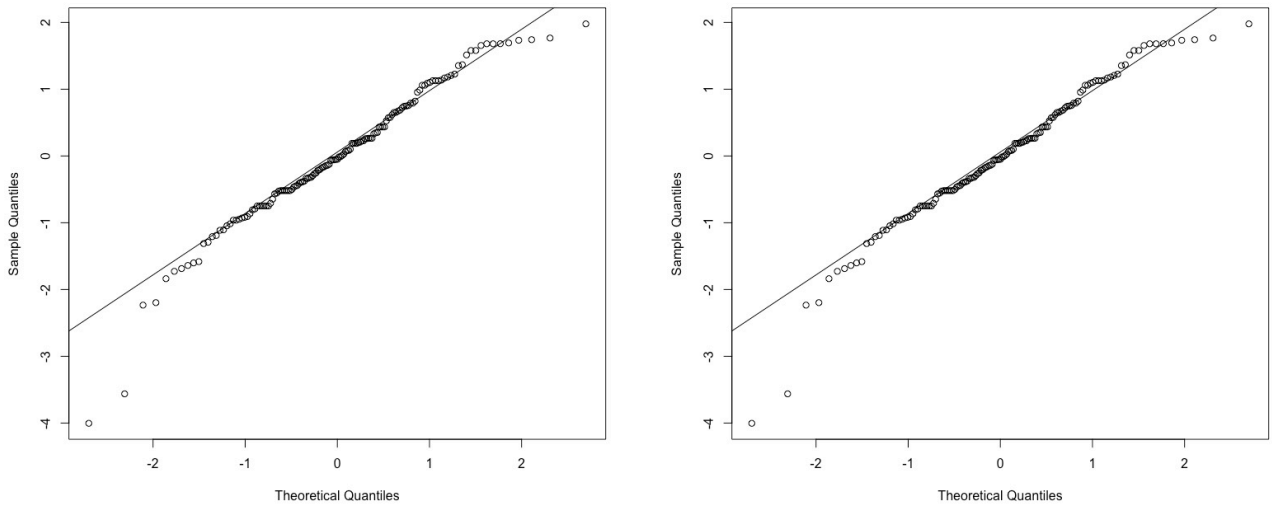
Influential data points were checked using the *influence.ME* package in R (described in Appendix B, Section 1.1, p. 296). Cook's distances revealed that no participants had an undue influence on the model ($M$ = 0.01, $SD$ = 0.01, range = < .001 – 0.10).

### 1.3.2 Constituent model '*b*': felt energy on logged 5 km run times, while controlling for who participants came or met up with

Regarding level-one homoscedasticity, Appendix C Figure 9 shows that the variability of posterior means estimated by the multilevel model are similar to the variability of coefficients estimated by the separate OLS regressions, with the exception of extreme coefficient estimates resulting from small sample sizes (i.e., from participants with relatively few survey responses); for example, 100% of participants with outlying coefficient estimates (± .1) for the felt energy variable had fewer total survey responses than the average of 5.13. Given this, it can be assumed that the observed level-one heteroscedasticity is unproblematic and the result of participants with relatively few survey responses.

For this model, the null hypothesis of homoscedastic level-one residual variance was rejected, $H$ = 165.369, $df$ = 23, $p$ = < .001, indicating level-one residual heteroscedasticity (Snijders & Bosker, 2012). However, $H$ depends on the normality of the level-one residuals. Snijders and

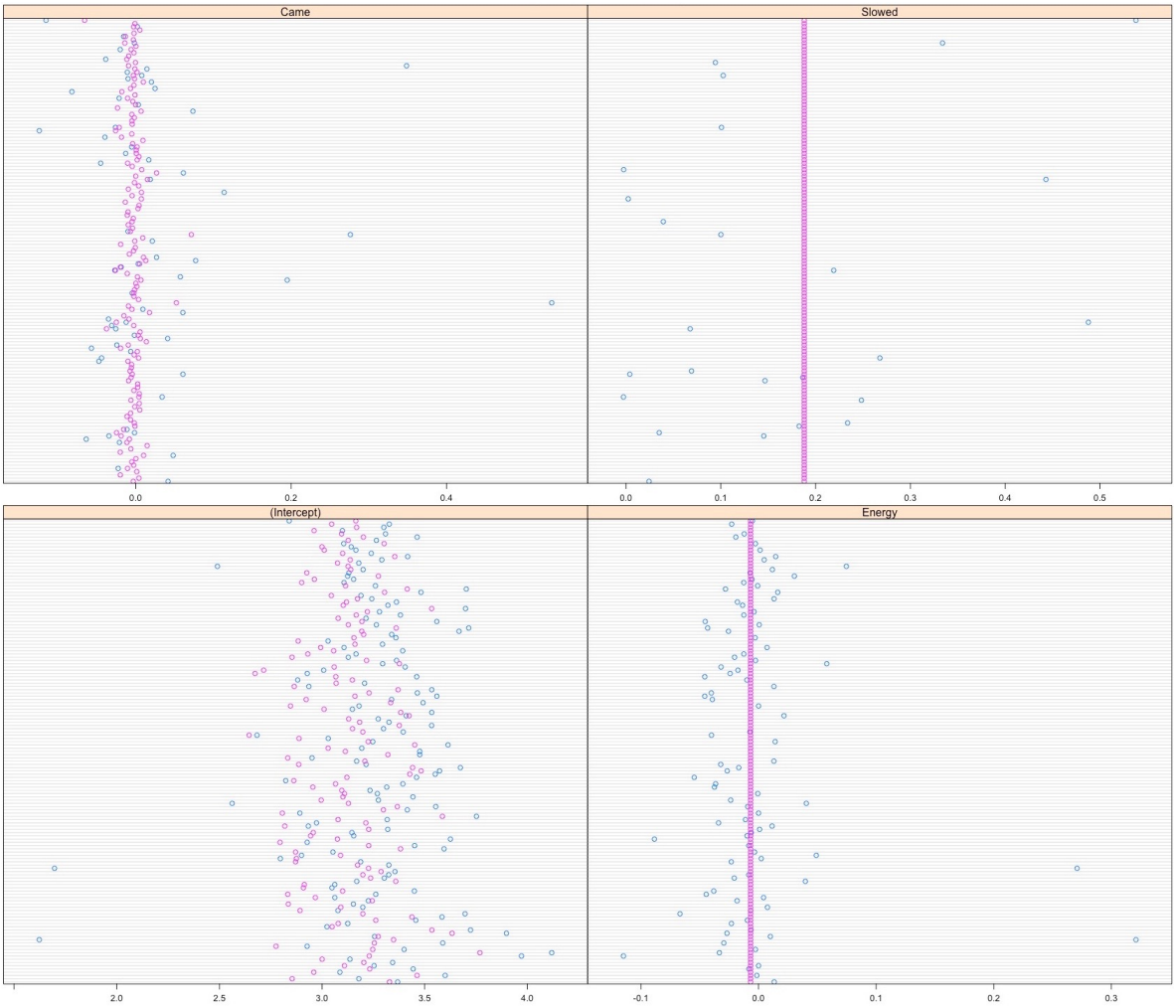
(*a*) (*b*)




**Appendix C Figure 8** Standardised level-two (*a*) intercept and (*b*) random slope residuals (for the variable representing whether or not participants reported coming or meeting up with friends and/or family) versus the expected order statistics of a normal distribution (Q-Q plot).

Bosker (2012) write that heavier-tailed distributions of level-one residuals will cause inflated values of *H*, even if the residuals have constant variance. The level-one residuals for the current model are indeed heavily tailed (see Appendix C Figure 10a). Given this, and that a Q-Q plot of *d* (see Appendix C Figure 10b) reveals that it is close to being normally distributed – *d* will have a Gaussian distribution when there is level-one homoscedasticity – it can be assumed that the model has an unproblematic amount of heteroskedasticity (Snijders & Bosker, 2012).

The normality of level-one residuals was checked by making a normal probability plot of the standardised OLS residuals. Appendix C Figure 10a shows that the normality assumption has been violated, due to longer tails than what would be expected with the normal distribution; specifically, the residuals display positive skew. Regardless, Seco et al. (2013) have demonstrated that fixed effects estimates are robust to violations of the normality assumption; multilevel models with non-normally distributed residuals do not produced biased fixed effect parameter estimates.

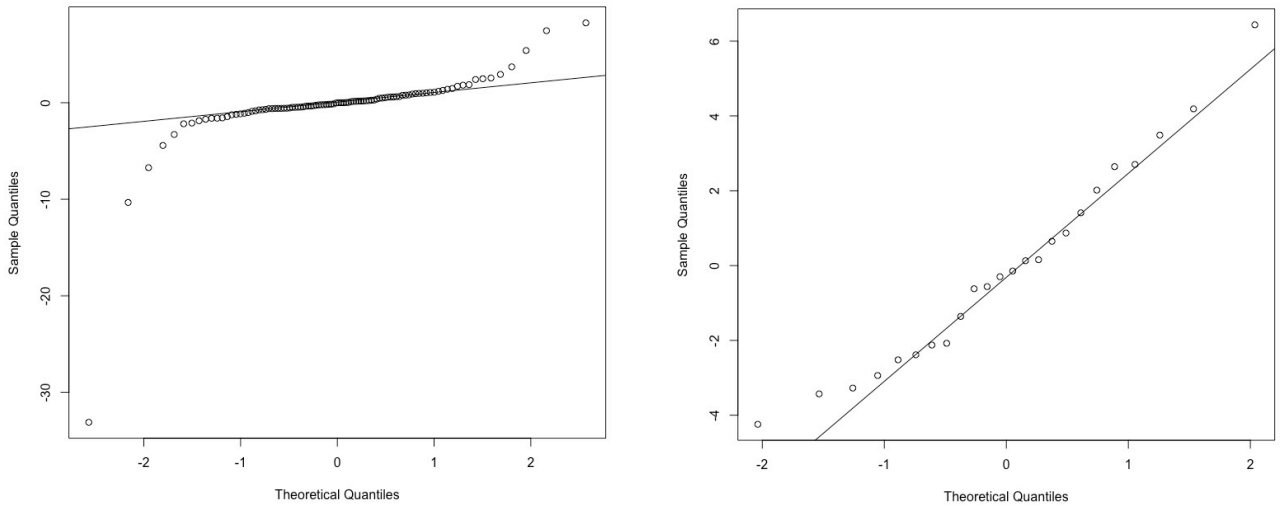



**Appendix C Figure 9** OLS coefficient estimates for each participant (blue) versus the posterior means for each participant in the multilevel model (pink). 'Came' represents the variable describing who parkrunners came or met up with, 'Slowed' is the variable representing whether or not they slowed down to run with their slower running partners, and 'Energy' is the felt energy variable.

Normal Q-Q plots of standardised level-two residuals for random intercepts and slopes suggest deviations from normality for the random slopes of the model[35] (see Appendix C Figure 11). However, Maas and Hox (2004) have shown that estimates of fixed effects and their standard errors are robust to non-normal level-two residual errors when there are at least 50 level-two units (this study had 143). Given this, it can be assumed that fixed effect estimates (and their standard errors) are unbiased.

[35] This model only contained random slopes for the control variable of who participants came or met up with; including random slopes for the felt energy variable caused the model to fail to converge.

(***a***) (***b***)



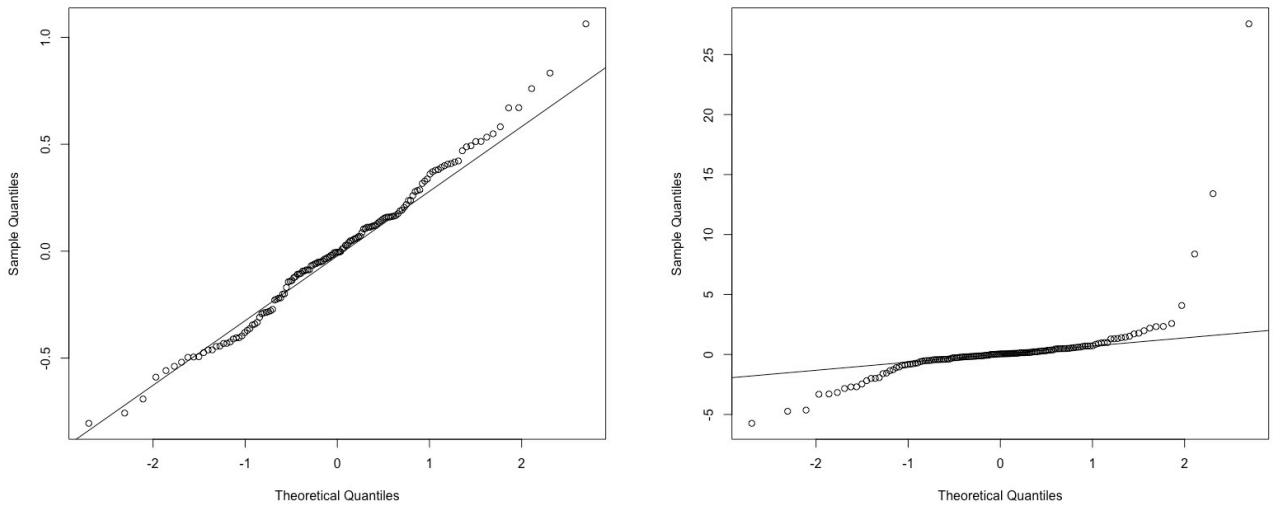

**Appendix C Figure 10** Q-Q plot of (*a*) standardised level-one residuals for multilevel model on 5 km run times and (*b*) of the standardised residual dispersion measure, *d*.

Influential data points were checked using the *influence.ME* package in R (described in Appendix B, Section 1, p. 295). Cook's distances revealed that no participants had an undue influence on the model ($M$ = 0.03, $SD$ = 0.13, range = < .001 – 1.15).

### 1.3.3 Mediation analysis

Regarding the additional assumption for mediation analyses (here, unobserved confounders), tests revealed that the model met the sequential ignorability assumption (see Appendix C Figure 12) *if* the product for the coefficients for (potential) unobserved confounders and the mediator and outcome are positive, as indirect effects are estimated to be negative in this scenario, which is in accordance with the findings of the mediation analysis being checked here (see Section 5.3.9.1, p. 169) (Imai et al., 2010; Tingley et al., 2014). The model is less robust to potential confounders with a negative relationship to both the mediator and outcome, as all indirect effect estimates are positive in this scenario (contrary to the effect observed in the mediation analysis being checked here). However, it is not obvious what such a confounder would be, as this variable would need to correlate negatively with felt energy and 5 km run times.

(*a*) (*b*)



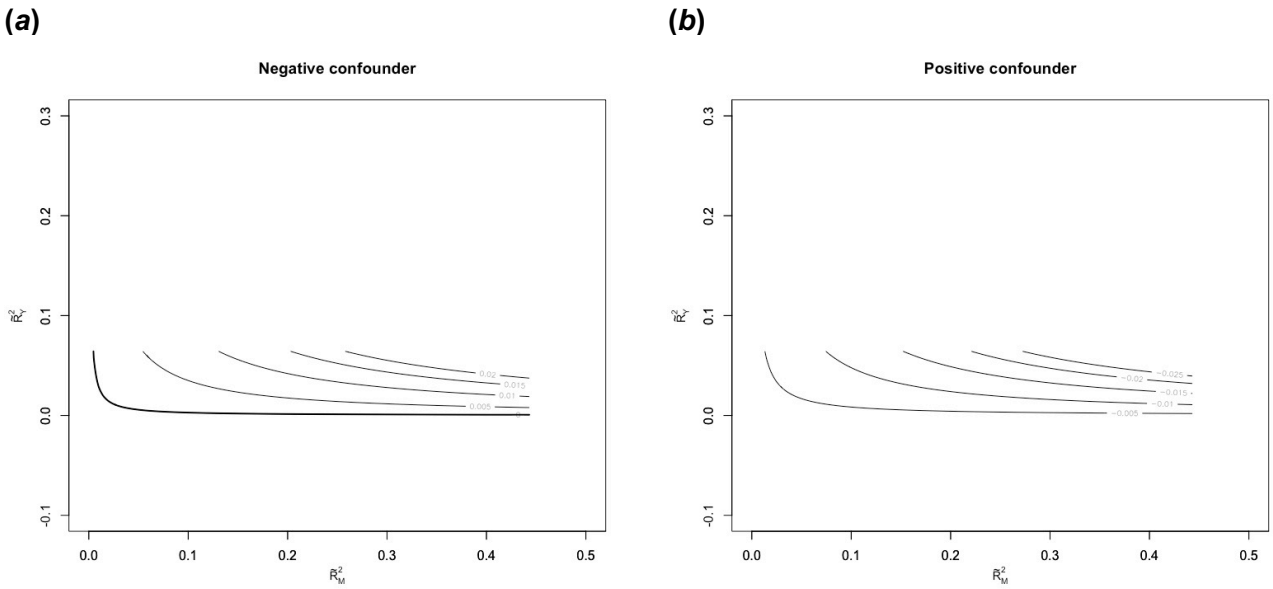

**Appendix C Figure 11** Standardised level-two (*a*) intercept and (*b*) random slope residuals (for the variable representing whether or not participants reported coming or meeting up with friends and/or family) versus the expected order statistics of a normal distribution (Q-Q plot).

## 1.4 Felt energy as a mediator of the effects of the parkrun community component on 5 km run times

### 1.4.1 Constituent model '*a*': parkrun community component on felt energy

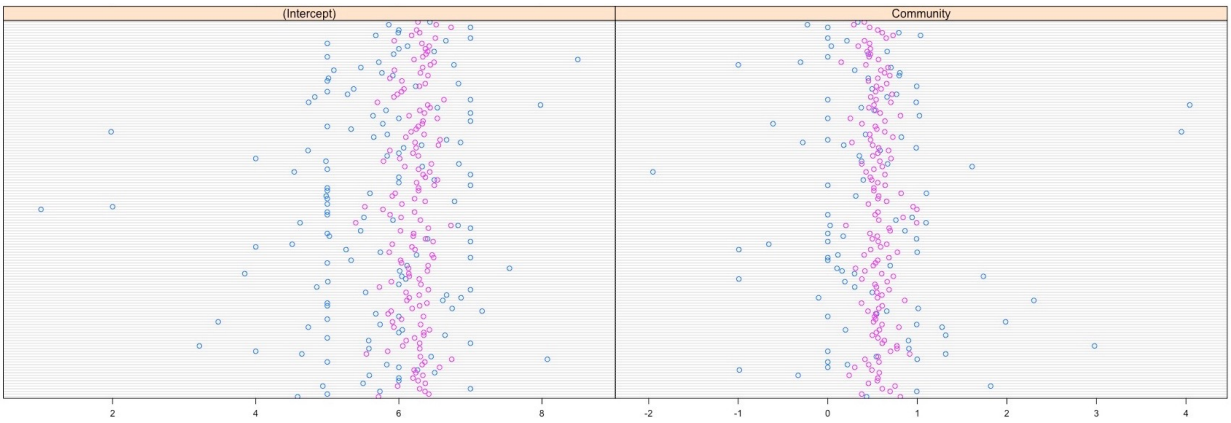
Regarding level-one homoscedasticity, Appendix C Figure 13 shows that the variability of posterior means estimated by the multilevel model are similar to the variability of coefficients estimated by the separate OLS regressions, with the exception of extreme coefficient estimates resulting from small sample sizes (i.e., from participants with relatively few survey responses); for example, 88% of participants with outlying coefficient estimates (± .1) for the parkrun community component had fewer total survey responses than the average of 5.13.

For this model, the null hypothesis of homoscedastic level-one residual variance was rejected, $H$ = 46.706, $df$ = 22, $p$ = .002, indicating level-one residual heteroscedasticity (Snijders & Bosker, 2012). However, $H$ depends on the normality of the level-one residuals. Snijders & Bosker (2012) state that heavier-tailed distributions of level-one residuals will lead to inflated



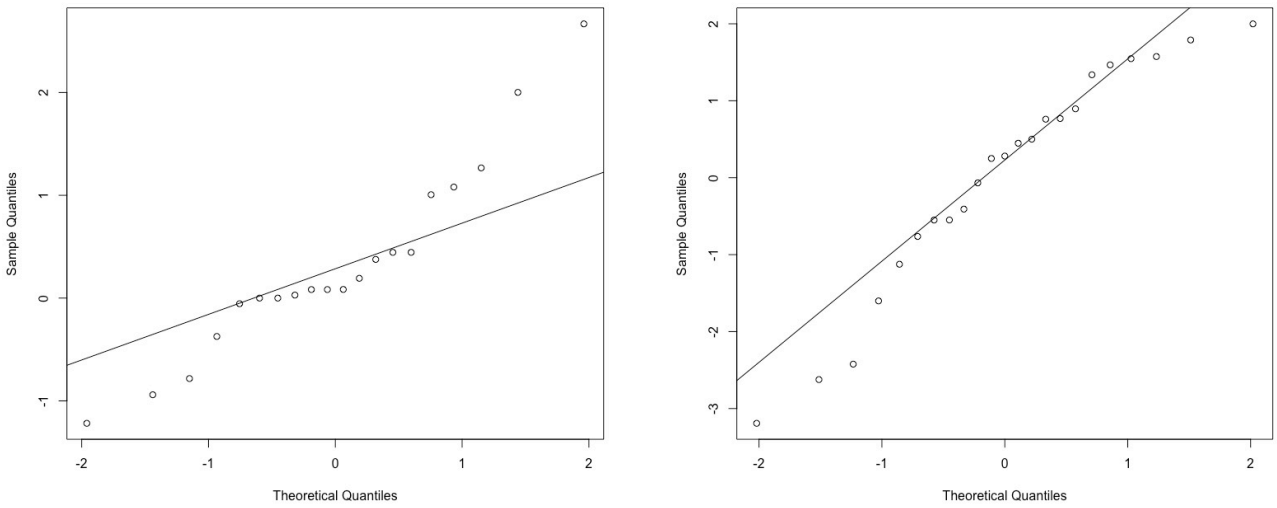

**Appendix C Figure 12** Sequential ignorability assumption check for (a) negative and (b) positive confounders.

values of *H*, even if the residuals have near-constant variance. The level-one residuals for the current model are indeed heavily tailed (see Appendix C Figure 14a). Given this, and that a Q-Q plot of *d* (see Appendix C Figure 14b) reveals that it is relatively normally distributed, it is assumed that the model has an unproblematic amount of heteroskedasticity (Snijders & Bosker, 2012).




**Appendix C Figure 13** OLS coefficient estimates for each participant (blue) versus the posterior means for each participant in the multilevel model (pink). 'Community' represents the parkrun community component.

(*a*) (*b*)

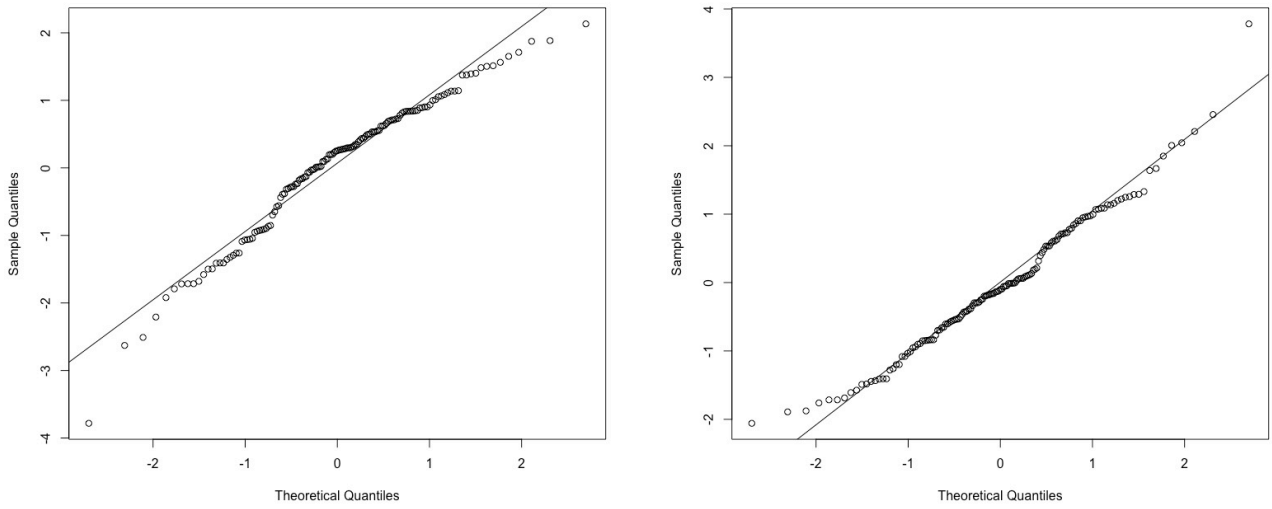



**Appendix C Figure 14** Q-Q plot of (*a*) standardised level-one residuals for multilevel model on enjoyment levels and (*b*) of the standardised residual dispersion measure, *d*.

The normality of level-one residuals was checked by making a normal probability plot of the standardised OLS residuals. Appendix C Figure 14a shows that the normality assumption has been violated, due to longer tails than what would be expected with the normal distribution; specifically, the residuals display positive skew. Regardless, Seco et al. (2013) have demonstrated that fixed effects estimates are robust to violations of the normality assumption; multilevel models with non-normally distributed residuals do not produced biased fixed effect parameter estimates.

Normal Q-Q plots of standardised level-two residuals for random intercepts and slopes suggest slight deviations from normality for the random slopes of the model (see Appendix C Figure 15). However, Maas and Hox (2004) have shown that estimates of fixed effects and their standard errors are robust to non-normal level-two residual errors when there are at least
50 level-two units (this study had 143). Given this, it can be assumed that fixed effect estimates (and their standard errors) are unbiased.

(*a*) (*b*)



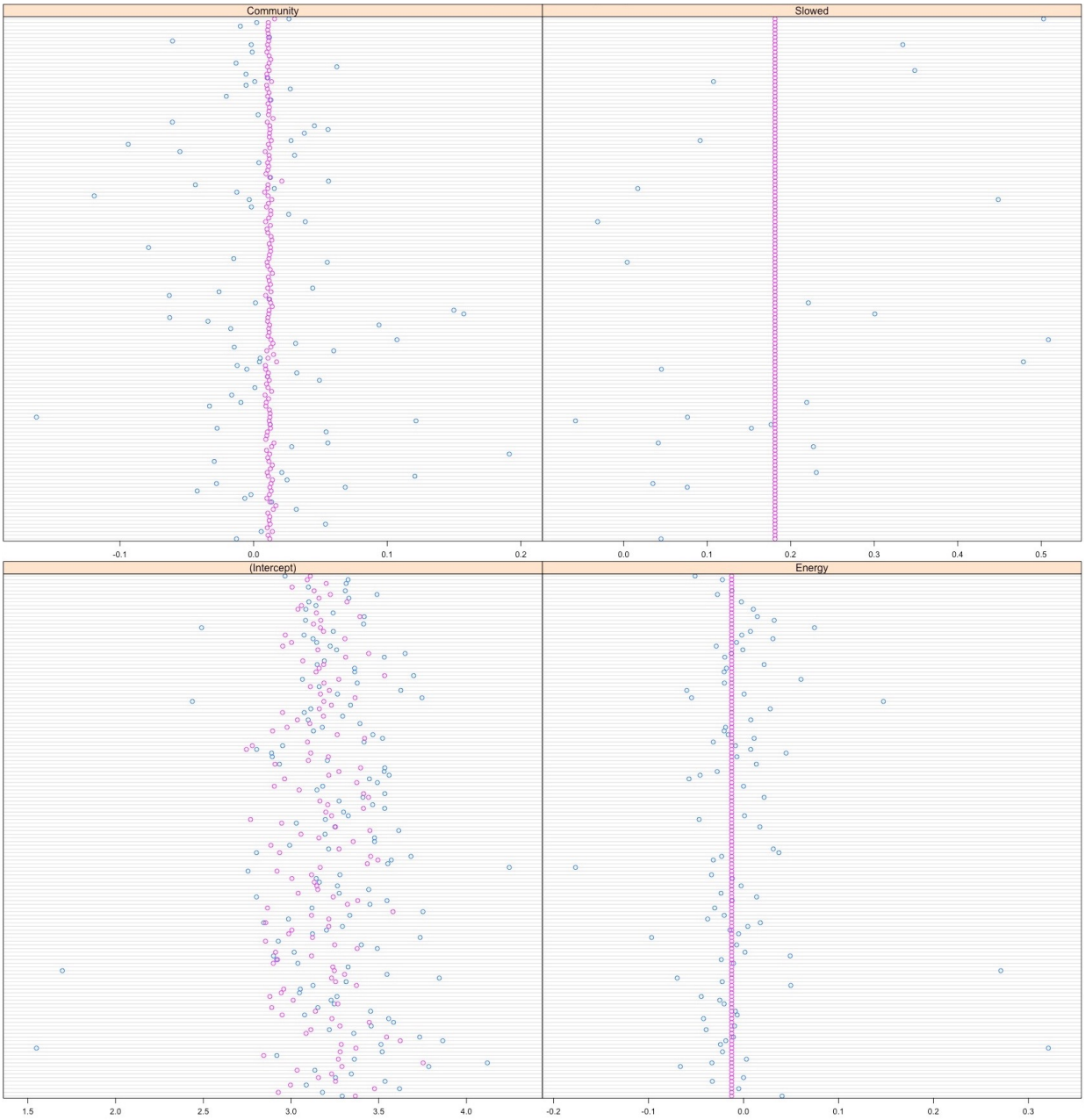

**Appendix C Figure 15** Standardised level-two (*a*) intercept and (*b*) random slope residuals (for parkrun community component) versus the expected order statistics of a normal distribution (Q-Q plot).

Influential data points were checked using the *influence.ME* package in R (described in Appendix B, Section 1, p. 295). Cook's distances revealed that no participants had an undue influence on the model ($M$ = 0.01, $SD$ = 0.013, range = < .001 – 0.11).

### 1.4.2 Constituent model '*b*': felt energy on logged 5 km run times, while controlling for the parkrun community component

Regarding level-one homoscedasticity, Appendix C Figure 16 shows that the variability of posterior means estimated by the multilevel model are dissimilar to the variability of coefficients estimated by the separate OLS regressions, although this seems to be driven largely by participants with relatively few survey responses. For example, 100% of participants with outlying coefficient estimates (± .1) for the felt energy variable had fewer total survey responses than the average of 5.13.

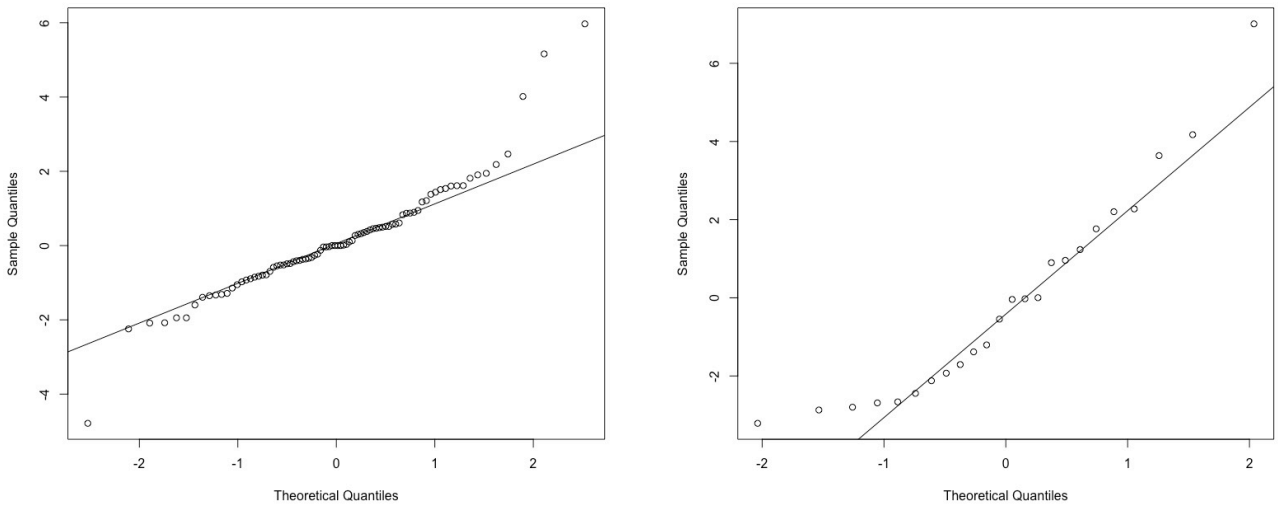
For this model, the null hypothesis of homoscedastic level-one residual variance was rejected, $H$ = 157.70, $df$ = 23, $p$ < .001, indicating level-one residual heteroscedasticity (Snijders & Bosker, 2012). However, $H$ depends on the normality of the level-one residuals. Heavier-tailed




**Appendix C Figure 16** OLS coefficient estimates for each participant (blue) versus the posterior means for each participant in the multilevel model (pink). 'Community' is the parkrun community component, 'Slowed' is the variable representing whether or not participants slowed down to run with their slower running partners, and 'Energy' is the felt energy variable.

distributions of level-one residuals will cause inflated values of *H*, even if the residuals have constant variance. The level-one residuals for the current model are heavily tailed (see Appendix C Figure 17a). Considering this, and the Q-Q plot of *d* (see Appendix C Figure 17b),

(*a*) (*b*)



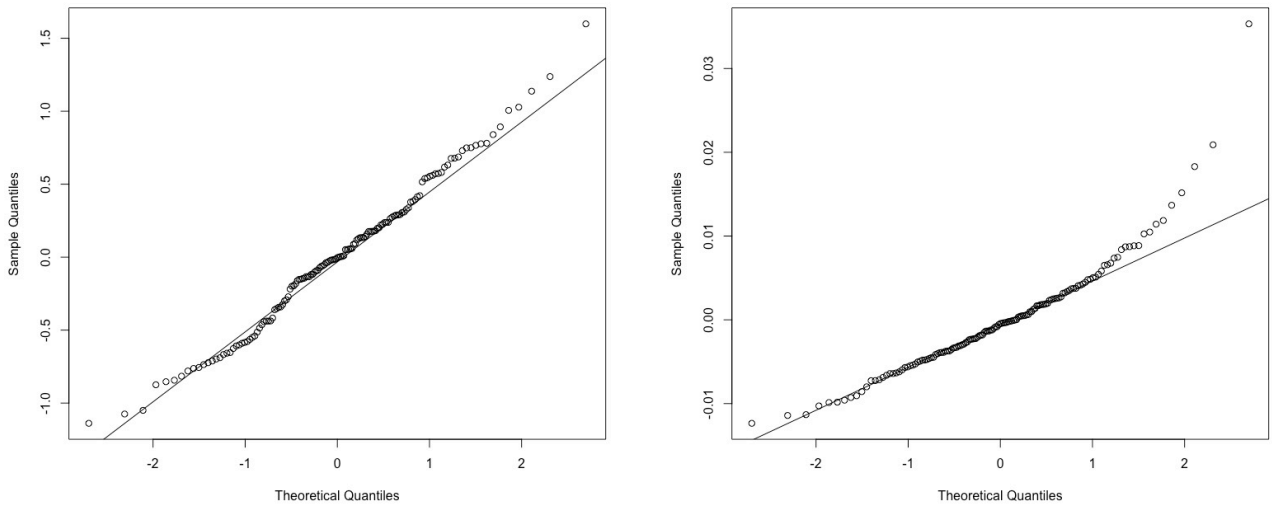

**Appendix C Figure 17** Q-Q plot of (*a*) standardised level-one residuals for multilevel model on enjoyment levels and (*b*) of the standardised residual dispersion measure, *d*.

which reveals that it is relatively normally distributed, it can be assumed that the model has an unproblematic amount of heteroskedasticity (Snijders & Bosker, 2012).

The normality of level-one residuals was checked by making a normal probability plot of the standardised OLS residuals. Appendix C Figure 17a shows that the normality assumption has been violated, due to longer tails than what would be expected with the normal distribution; specifically, the residuals display positive skew. Regardless, Seco et al. (2013) have demonstrated that fixed effects estimates are robust to violations of the normality assumption; multilevel models with non-normally distributed residuals do not produced biased fixed effect parameter estimates.

Normal Q-Q plots of standardised level-two residuals for random intercepts and slopes suggest slight deviations from normality for both random intercepts and random slopes (see Appendix C Figure 18). However, Maas and Hox (2004) have shown that estimates of fixed effects and their standard errors are robust to non-normal level-two residual errors when there are at least 50 level-two units (this study had 143). Given this, it can be assumed that fixed effect estimates (and their standard errors) are unbiased.

(*a*) (*b*)



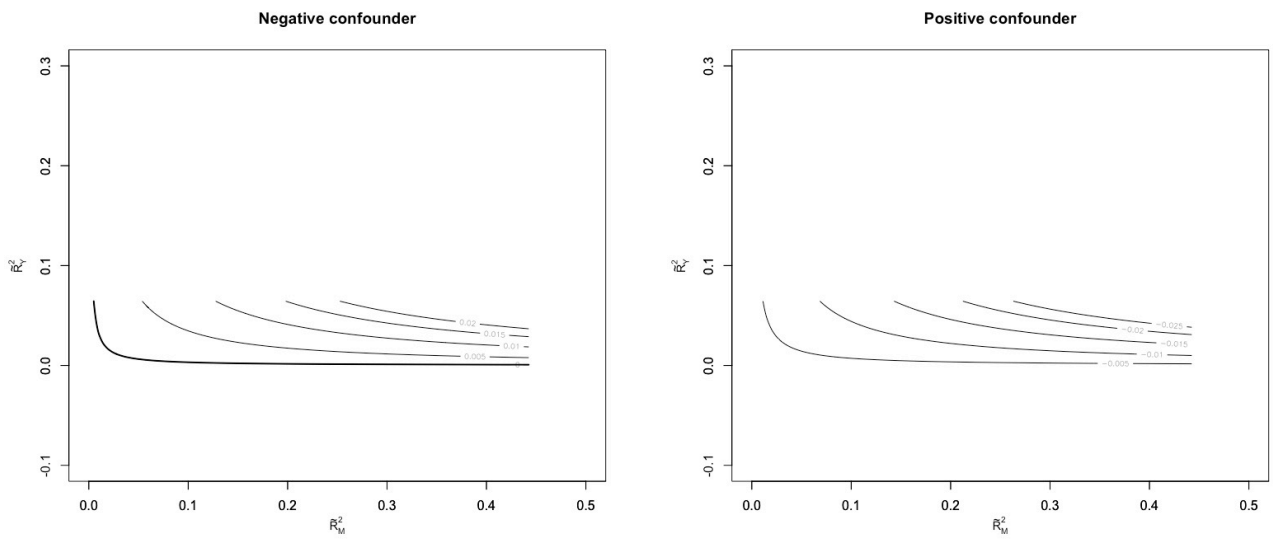

**Appendix C Figure 18** Standardised level-two (*a*) intercept and (*b*) random slope residuals (for parkrun community component) versus the expected order statistics of a normal distribution (Q-Q plot).

Influential data points were checked using the *influence.ME* package in R (described in Appendix B, Section 1, p. 295). Cook's distances revealed that no participants had an undue influence on the model (mean = 0.026, *SD* = 0.118, range = < .001 – 1.089).

### 1.4.3 Mediation analysis

Regarding the additional assumption for mediation analyses (here, unobserved confounders), tests revealed that the model was robust to the sequential ignorability assumption (see Appendix C Figure 19) *if* the product for the coefficients for (potential) unobserved confounders and the mediator and outcome are positive, as indirect effects are estimated to be negative in this scenario, which is in accordance with the findings of the mediation analysis being checked here (see Section 5.3.9.2, p. 170) (Imai et al., 2010; Tingley et al., 2014). The model is less robust to potential confounders with a negative relationship to both the mediator and outcome, as all indirect effect estimates are positive in this scenario (contrary to the effect

(*a*) (*b*)




**Appendix C Figure 19** Sequential ignorability assumption check for (*a*) negative and (*b*) positive confounders.

observed in mediation analysis being checked here). However, it is not obvious what such a confounder would be, as this variable would need to correlate negatively with both felt energy and 5 km run times.

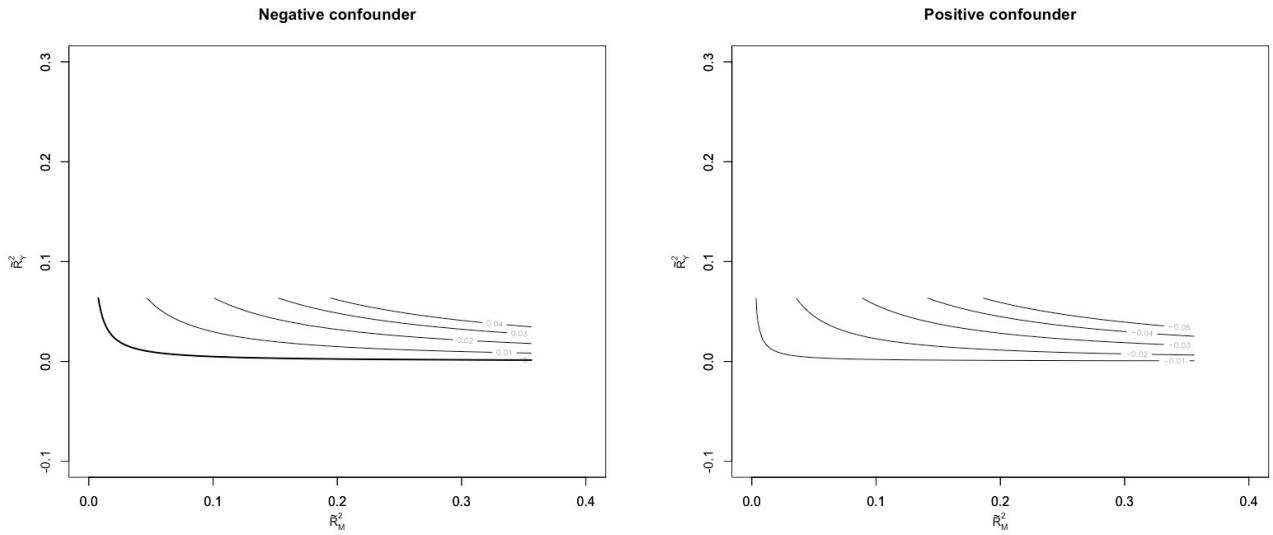
### 1.5 Felt energy as a mediator of the effects of pre-run sociality on run times

The assumption checks for this model gave similar results to those presented in Section 1.3.1 and 1.3.2 of this appendix, because the binary variable representing pre-run sociality had a similar structure and relationship to the outcome variables as the binary variable representing whether or not participants came or met up with friends. Thus, only the assumption check of the mediation analysis itself will be reported here.

#### 1.5.1 Mediation analysis

Regarding the additional assumption for mediation analyses (here, unobserved confounders), tests revealed that the model was robust to the sequential ignorability assumption (see Appendix C Figure 20) *if* the product for the coefficients for (potential) unobserved confounders and the mediator and outcome are positive, as indirect effects are estimated to be negative in this scenario, which is in accordance with the findings of the mediation analysis

(*a*) (*b*)




**Appendix C Figure 20** Sequential ignorability assumption check for (*a*) negative and (*b*) positive confounders.

being checked here (see Section 5.3.9.3, p. 172) (Imai et al., 2010; Tingley et al., 2014). The model is less robust to potential confounders with a negative relationship to both the mediator and outcome, as all indirect effect estimates are positive in this scenario (contrary to the effect observed in mediation analysis being checked here). Again, it is not obvious what such a confounder would be, as this variable would need to correlate negatively with both felt energy and 5 km run times.

## Tables

**Table C 1** Effects of who participants came or met up with on logged 5 km run times (Hypothesis 1.1)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 3.418 | 0.021 | 159.41 (357.3) | < .001 |
| Came or met up with family and/or friends | −0.007 | 0.006 | −0.47 (611.1) | .216 |
| Perceived exertion | −0.013 | 0.001 | −6.01 (608.3) | < .001 |
| Slowing down to run with running partner | 0.134 | 0.011 | 12.00 (605.9) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.004 | 0.193 | | |
| $R^2_m$ = 0.082, $R^2_c$ = 0.928 | | | | |

**Table C 2** Effects of parkrun community component on logged 5 km run times (Hypothesis 1.2)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 3.383 | 0.020 | 168.64 (291.8) | < .001 |
| Community component | 0.004 | 0.003 | 1.63 (170.8) | .108 |
| Perceived exertion | −0.010 | 0.001 | −9.04 (580.3) | < .001 |
| Slowing down to run with running partner | 0.136 | 0.026 | 5.28 (35.9) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.004 | 0.192 | | |
| Community component | < .001 | 0.007 | | |
| Slowing down to run with running partner | 0.018 | 0.135 | | |
| $R^2_m$ = 0.067, $R^2_c$ = 0.952 | | | | |

**Table C 3** Effects of pre-run sociality on logged 5 km run times (Hypothesis 1.3)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 3.413 | 0.021 | 159.15 (359.8) | < .001 |
| Pre-run sociality | −0.002 | 0.006 | 0.33 (607.2) | .742 |
| Perceived exertion | −0.014 | 0.001 | −10.41 (608.3) | < .001 |
| Slowing down to run with running partner | 0.132 | 0.011 | 11.80 (606.3) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.037 | 0.193 | | |
| $R^2_m$ = 0.082, $R^2_c$ = 0.928 | | | | |

**Table C 4** Effects of parkrun community component on perceptions of fatigue (Hypothesis 2.2)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 13.055 | 1.079 | 12.09 (173.8) | < .001 |
| Community component | 0.090 | 0.063 | 1.42 (74.9) | .159 |
| Logged 5 km run time | −2.513 | 0.327 | −7.69 (174.1) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.468 | 0.684 | | |
| Community component | 0.157 | 0.396 | | |
| $R^2_m$ = 0.132, $R^2_c$ = 0.451 | | | | |

**Table C 5** Effects of pre-run sociality on perceptions of fatigue (Hypothesis 2.3)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 10.706 | 1.449 | 7.39 (316.8) | < .001 |
| Pre-run sociality | −0.009 | 0.010 | −0.09 (280.4) | .925 |
| Logged 5 km run time | −1.794 | 0.441 | −4.07 (319.0) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 7.176 | 2.679 | | |
| Pre-run sociality | 0.122 | 0.349 | | |
| Logged 5 km run time | 9.082 | 3.014 | | |
| $R^2_m$ = 0.072, $R^2_c$ = 0.439 | | | | |

**Table C 6** Effects of who participants came or met up with on enjoyment levels (Hypothesis 3.1)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 5.574 | 0.081 | 68.54 (231.2) | < .001 |
| Came or met up with family and/or friends | 0.230 | 0.086 | 2.67 (714.2) | .008 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.360 | 0.611 | | |
| $R^2_m$ = 0.011, $R^2_c$ = 0.303 | | | | |

**Table C 7** Effects of parkrun community component on enjoyment levels (Hypothesis 3.2)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 5.709 | 0.056 | 101.59 (116.2) | < .001 |
| Community component | 0.439 | 0.039 | 11.21 (673.6) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.232 | 0.482 | | |
| $R^2_m$ = 0.161, $R^2_c$ = 0.360 | | | | |

**Table C 8** Effects of pre-run sociality on enjoyment levels (Hypothesis 3.3)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 5.479 | 0.085 | 65.75 (64.6) | < .001 |
| Pre-run sociality | 0.346 | 0.010 | 3.47 (80.8) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.304 | 0.552 | | |
| Pre-run sociality | 0.259 | 0.509 | | |
| $R^2_m$ = 0.023, $R^2_c$ = 0.336 | | | | |

**Table C 9** Motivation for attendance as a moderator of the effect of who participants came or met up with on logged 5 km run times (Hypothesis 4.1)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 3.178 | 0.031 | 101.60 (99.8) | < .001 |
| Came or met up with family and/or friends | −0.026 | 0.035 | −0.74 (274.6) | .458 |
| Motivation for attendance | 0.044 | 0.011 | 3.86 (91.9) | < .001 |
| Came or met up with family and/or friends × motivation for attendance | 0.013 | 0.014 | 0.89 (160.7) | .375 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.032 | 0.181 | | |
| Came or met up with family and/or friends | 0.004 | 0.065 | | |
| Motivation for attendance | 0.001 | 0.034 | | |
| Came or met up with family and/or friends × motivation for attendance | 0.002 | 0.043 | | |
| $R^2_m$ = 0.018, $R^2_c$ = 0.885 | | | | |

**Table C 10** Motivation for attendance as a moderator of the effect of the parkrun community component on logged 5 km run times (Hypothesis 4.2)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 3.158 | 0.027 | 115.24 (102.6) | < .001 |
| Community component | −0.023 | 0.020 | −1.14 (255.4) | .258 |
| Motivation for attendance | 0.053 | 0.009 | 5.91 (101.0) | < .001 |
| Community component × motivation for attendance | 0.011 | 0.008 | 1.42 (170.6) | .157 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.041 | 0.203 | | |
| Community component | 0.004 | 0.066 | | |
| Motivation for attendance | 0.002 | 0.043 | | |
| Community component × motivation for attendance | 0.001 | 0.031 | | |
| $R^2_m$ = 0.021, $R^2_c$ = 0.890 | | | | |

**Table C 11** Motivation for attendance as a moderator of the effect of pre-run sociality on logged 5 km run times (Hypothesis 4.3)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 3.142 | 0.034 | 93.08 (479.8) | < .001 |
| Pre-run sociality | 0.034 | 0.036 | −0.04 (393.0) | .356 |
| Motivation for attendance | 0.056 | 0.011 | 4.95 (467.7) | < .001 |
| Pre-run sociality × motivation for attendance | −0.008 | 0.013 | −0.61 (438.0) | .543 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.036 | 0.189 | | |
| Pre-run sociality | 0.003 | 0.052 | | |
| $R^2_m$ = 0.020, $R^2_c$ = 0.882 | | | | |

**Table C 12** Speeding up to run with a faster running partner as a moderator of the effect of who participants came or met up with on perceptions of fatigue (Hypothesis 4.4)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 4.859 | 0.076 | 63.92 (86.4) | < .001 |
| Came or met up with family and/or friends | −0.252 | 0.114 | −2.22 (98.0) | .029 |
| Speeding up to run with a faster running partner | 0.865 | 0.352 | 2.46 (582.5) | .014 |
| Came or met up with family and/or friends × speeding up to run with a faster running partner | −0.503 | 0.420 | − 1.20 (664.0) | .232 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.147 | 0.383 | | |
| Came or met up with family and/or friends | 0.330 | 0.574 | | |
| $R^2_m$ = 0.019, $R^2_c$ = 0.271 | | | | |

**Table C 13** Speeding up to run with a faster running partner as a moderator of the effect of the parkrun community component on perceptions of fatigue (Hypothesis 4.5)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 4.761 | 0.069 | 68.72 (104.7) | < .001 |
| Community component | 0.056 | 0.063 | 0.90 (74.0) | .372 |
| Speeding up to run with a faster running partner | 0.458 | 0.210 | 2.188 (29.1) | .038 |
| Community component × speeding up to run with a faster running partner | 0.214 | 0.211 | 1.01 (77.1) | .315 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.278 | 0.528 | | |
| Community component | 0.139 | 0.373 | | |
| Speeding up to run with a faster running partner | 0.576 | 0.759 | | |
| $R^2_m$ = 0.013, $R^2_c$ = 0.262 | | | | |

**Table C 14** Speeding up to run with a faster running partner as a moderator of the effect of pre-run sociality on perceptions of fatigue (Hypothesis 4.6)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 3.285 | 0.018 | 187.50 (138.6) | < .001 |
| Pre-run sociality | 0.017 | 0.010 | 1.70 (70.1) | .095 |
| Speeding up to run with a faster running partner | −0.012 | 0.311 | −0.40 (26. 9) | .692 |
| Pre-run sociality × speeding up to run with a faster running partner | −0.007 | 0.034 | −0.22 (46.0) | .831 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.036 | 0.191 | | |
| Pre-run sociality | 0.002 | 0.049 | | |
| Speeding up to run with a faster running partner | 0.003 | 0.057 | | |
| Pre-run sociality × speeding up to run with a faster running partner | 0.003 | 0.055 | | |
| $R^2_m$ = 0.002, $R^2_c$ = 0.874 | | | | |

**Table C 15** Effects of who participants came or met up with on felt energy (Hypothesis 5.1)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 5.819 | 0.190 | 30.96 (614.5) | < .001 |
| Came or met up with family and/or friends | 0.254 | 0.080 | 3.17 (678.3) | .002 |
| Slowing down to run with a slower running partner | −0.529 | 0.133 | −3.98 (670.3) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.366 | 0.605 | | |
| Came or met up with family and/or friends | 0.001 | 0.029 | | |
| $R^2_m$ = 0.027, $R^2_c$ = 0.394 | | | | |

**Table C 16** Effect of who participants came or met up with on logged 5 km run times, while controlling for felt energy (Hypothesis 5.1)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 3.131 | 0.029 | 37.85 (314.5) | < .001 |
| Felt energy | −0.007 | 0.003 | −2.31 (609.1) | .022 |
| Came or met up with family and/or friends | −0.003 | 0.008 | −0.40 (65.7) | .692 |
| Slowing down to run with a slower running partner | 0.188 | 0.011 | 17.84 (605.1) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.040 | 0.200 | | |
| Came or met up with family and/or friends | 0.001 | 0.033 | | |
| $R^2_m$ = 0.063, $R^2_c$ = 0.920 | | | | |

**Table C 17** Effects of parkrun community component on felt energy (Hypothesis 5.2)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 6.214 | 0.131 | 47.53 (645.9) | < .001 |
| Community component | 0.567 | 0.042 | 13.38 (678.3) | .002 |
| Slowing down to run with a slower running partner | −0.520 | 0.112 | −4.63 (724.0) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.137 | 0.370 | | |
| Community component | 0.073 | 0.270 | | |
| $R^2_m$ = 0.319, $R^2_c$ = 0.515 | | | | |

**Table C 18** Effect of parkrun community component on logged 5 km run times, while controlling for felt energy (Hypothesis 5.2)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 3.166 | 0.029 | 109.66 (642.6) | < .001 |
| Felt energy | −0.013 | 0.003 | −3.76 (582.7) | .002 |
| Community component | 0.012 | 0.004 | 3.04 (95.1) | .003 |
| Slowing down to run with a slower running partner | 0.181 | 0.011 | 17.16 (609.1) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.004 | 0.192 | | |
| Community component | < 0.001 | 0.007 | | |
| $R^2_m$ = 0.064, $R^2_c$ = 0.916 | | | | |

**Table C 19** Effects of pre-run sociality on felt energy (Hypothesis 5.3)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 5.646 | 0.207 | 27.34 (144.4) | < .001 |
| Pre-run sociality | 0.339 | 0.088 | 3.84 (60.6) | < .001 |
| Slowing down to run with a slower running partner | −0.517 | 0.132 | −3.93 (704.3) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.700 | 0.837 | | |
| Pre-run sociality | 0.109 | 0.330 | | |
| $R^2_m$ = 0.038, $R^2_c$ = 0.402 | | | | |

**Table C 20** Effect of pre-run sociality on logged 5 km run times, while controlling for felt energy (Hypothesis 5.3)

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 3.130 | 0.027 | 116.95 (548.1) | < .001 |
| Felt energy | −0.007 | 0.003 | −2.44 (612.6) | .015 |
| Pre-run sociality | 0.003 | 0.007 | 0.41 (70.4) | .686 |
| Slowing down to run with a slower running partner | 0.185 | 0.011 | 17.48 (608.2) | < .001 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.036 | 0.190 | | |
| Pre-run sociality | 0.001 | 0.026 | | |
| $R^2_m$ = 0.062, $R^2_c$ = 0.918 | | | | |

**Table C 21** Effect of survey response lag on perceptions of fatigue

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 4.912 | 0.193 | 25.44 (268.4) | < .001 |
| Log 5 km run time | −0.024 | 0.032 | −0.76 (612.6) | .449 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.253 | 0.503 | | |
| Log 5 km run time | < 0.001 | 0.015 | | |
| $R^2_m$ = < 0.001, $R^2_c$ = 0.209 | | | | |

**Table C 22** Effect of survey response lag on felt energy

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 5.919 | 0.163 | 36.42 (67.5) | < .001 |
| Log 5 km run time | −0.048 | 0.025 | −1.92 (68.1) | .060 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.566 | 0.752 | | |
| Log 5 km run time | 0.002 | 0.047 | | |
| $R^2_m$ = 0.005, $R^2_c$ = 0.397 | | | | |

**Table C 23** Effect of survey response lag on enjoyment levels

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | 5.906 | 0.166 | 36.44 (245.2) | < .001 |
| Log 5 km run time | −0.035 | 0.027 | −1.32 (730.8) | .186 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.359 | 0.599 | | |
| Log 5 km run time | < 0.001 | 0.002 | | |
| $R^2_m$ = 0.005, $R^2_c$ = 0.397 | | | | |

**Table C 24** Effect of survey response lag on parkrun community component

| **Variable** | ***b*** | ***SE*** | ***t*(*df*)** | ***p*** |
|---|---|---|---|---|
| Intercept | −0.006 | 0.153 | −0.04 (68.9) | .968 |
| Log 5 km run time | −0.007 | 0.024 | −0.28 (59.5) | .781 |
| **Random part** | **Variance** | ***SD*** | | |
| Intercept | 0.594 | 0.771 | | |
| Log 5 km run time | 0.005 | 0.073 | | |
| $R^2_m < 0.001$, $R^2_c = 0.488$ | | | | |

## Figures



UNIVERSITY OF OXFORD

APPROVED

**Information Sheet:**
**Sociality and the *parkrun* experience**

Thank you for your interest in participating in this study on the social experiences of *parkrunners*. The study is being conducted by researchers at the Institute of Cognitive and Evolutionary Anthropology at Oxford University. Before you decide to take part, please read the following information carefully.

**What is the study about?**

The investigation will entail a questionnaire-based study on a UK-based sample, and a cross-cultural analysis of the 'big data' available through the *parkrun* database, which covers over 11 million runs from 11 countries. *parkrun*'s success in encouraging participation appears, in large part, to be down to the fun and satisfaction derived from the community spirit in which the event is run and that it serves to promote. The proposed study will investigate how *parkrunners*' relationships with one another affect their overall experience at *parkrun* events. By better understanding the social factors that affect *parkrunners'* motivations and experiences, we hope to inform the future of community based, group exercise events.

**How can I participate?**

On each Saturday (following *parkrun* events) for the next four months you will be asked to answer a short questionnaire (approx. 2 minutes) on your running experience that day. This will involve answering questions about your social experience at *parkrun* as well as questions on your thoughts and feelings about your running experience that day. You can answer the questionnaire via the internet using a mobile phone, tablet, or laptop/desktop computer, or with paper and pen. On the back of this form you will be able to indicate which of these response methods you prefer.

As we are only interested in your typical *parkrun* experience, we do not want your participation in our study to affect your attendance or how you go about participating in *parkrun* when you are actually at events. Thus, you should attend only when you want to and participate in your usual way. You will only need to answer the questionnaire on days you choose to participate in *parkrun*.

As previously mentioned, we will also use data from the *parkrun* results database, which contains information already available on *parkrun* results webpages. We will gather the following information: age, sex, *parkrun* participation history, and run time information.

You do not have to take part in this study (or any part thereof) if you do not want to. If you decide to take part you may withdraw at any time without having to provide a reason. Withdrawing after deciding to take part is simply a matter of ceasing to respond to our weekly questionnaires.

Please feel free to ask any questions before you complete the consent form below. If you would like to discuss any other aspect of the research at any time, including after you have consented to participate, please contact Arran Davis via email at arran.davis@anthro.ox.ac.uk or via phone at +44(0) 7721 513026.

This study has been reviewed and approved by the School of Anthropology, University of Oxford internal ethical procedures. Nobody except the collaborators directly involved in this research will be allowed to see your files/questionnaires; furthermore, all your responses will be anonymous as you will be designated a participant number. Thus, all the information you provide will be completely confidential and will not be connected to your name or other identifying information. Furthermore, data will not be analysed at the individual participant level. Rather, all data will be analysed in aggregate form. In addition, participants will never be identified by name in any reports of the completed study. All data will be password-protected and only accessible to the principal investigator and co-investigators. Finally, this consent form will be stored separately from the anonymous information you provide.

**Figure C 1** Informed consent form.

**Questionnaire Response Method**

There are three ways to participate in the questionnaire portion of the study; via mobile phone, tablet, laptop/desktop computer, or with paper and pen. If you would like to answer the questionnaire via a mobile phone, tablet, or laptop/desktop computer you will need access to the internet. We will also need your mobile phone number and/or email address so that we can send you the survey link each Saturday. If you would like to answer with paper and pen, you will need to provide your mailing address. We will then send you paper-based questionnaires for the four month period as well as prepaid and addressed envelopes so that you can mail in your responses.

**Please indicate your preferred response method:**

□ Mobile phone, tablet, or laptop/desktop computer.

Please choose a method of contact: email, SMS (text) on mobile phone (free of charge with opt-out available with each text), or both. Only fill out the method(s) you'd like to be contacted by.

Email: _____ **(and/or)**

Mobile phone:_____

□ Paper and pen.

Please provide your mailing address here: _____

_____

_____

**Consent Form: Sociality and the *parkrun* experience**

You have been asked to participate in a study on the social experiences of *parkrunners*.

Please circle YES or NO to the following questions:

Have you read the information sheet about the study? YES NO

By agreeing to participate in this study you are indicating you are aware that you are participating in both this study and *parkrun* at your own risk and that it is your responsibility to ensure that you are fit and able to partake in physical activity. Do agree to participate in the study? YES NO

Signature: _____ Date: _____

Name (in block letters): _____

**Figure C 1** Informed consent form (continued).

## Appendix D

## 1 Experiment instructions

Below is the script used to deliver verbal and pictorial instructions to participants, it was read to participants after they read the information form and were brought into the experimental room. The script is split by exercise block condition to reflect the counterbalanced nature of the experiment. Split blocks (greyed) occur when the instructions differed based on whether the participant took the placebo (β-alanine) before the first or second exercise block.

| **β-alanine before Exercise Block One** | **β-alanine before Exercise Block Two** |
|---|---|
| "You will now begin the experiment, which is supposed to be transferable to fMRI (this is why you will be exercising using the hand-grip we have given you). You will first answer a series of questions that will tell us about your personality and how you relate to other people. Following this, you will complete two blocks of exercise trials." | |
| "Before the first block you, will take your dose of beta-alanine (in pill form), along with a glass of water. Before the second block, you will just drink a glass of water, so that you are equally hydrated before each block of exercise. We decided at random that you will take the beta-alanine before the first trial." | "Before the first block, you will just drink a glass of water. Before the second block, you will take your dose of beta-alanine (in pill form), along with a glass of water. The water before the first block of exercise trials is thus to ensure that you are equally hydrated before each block of exercise. We decided at random that you will take the beta-alanine before the second trial." |
| "The beta-alanine pill you are taking is relatively fast-acting – it will start to affect you about 20 minutes after you take it and these effects will last for about 45 minutes. This means that there will be a 30-minute break before the first trial and before the second trial, as you can see in this diagram." | |

This diagram was shown to participants who took beta-alanine before Exercise Block One:

| | | | |
|---|---|---|---|
| **Break 1**<br>**(30 minutes)**<br>• Take beta-alanine with water.<br>• It will take 20 minutes for your body to absorb the beta-alanine and for it to take effect.<br>• During this time, you will complete the memory task. | **Exercise Block One**<br>**(20 minutes)** | **Break 2**<br>**(30 minutes)**<br>• Drink water.<br>• During this time, you will again complete the memory task.<br>• During the 30-minute break, you should fully recover from the previous exercise block (muscle fatigue and lactic acid levels will return to baseline), so that you will be ready for the next block of exercise. The levels of beta-alanine in your system will also return to baseline. Since the effects will have worn off, you will do the second exercise block without the aid of beta-alanine. | **Exercise Block Two**<br>**(20 minutes)** |

This diagram was shown to participants who took beta-alanine before Exercise Block Two:

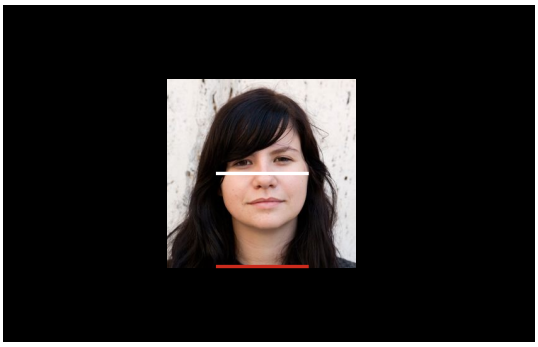
| | | | |
|---|---|---|---|
| **Break One (30 minutes)**<br>• Drink water.<br>• During this time, you will complete the memory task. | **Exercise Block One (20 minutes)** | **Break Two (30 minutes)**<br>• Take beta-alanine with water.<br>• It will take 20 minutes for your body to absorb the beta-alanine and for it to take effect.<br>• During this time, you will complete the memory task.<br>• During the 30-minute break, you should fully recover from the previous exercise block (muscle fatigue and lactic acid levels will return to baseline), so that you will be ready for the next block of exercise. | **Exercise Block Two (20 minutes)** |

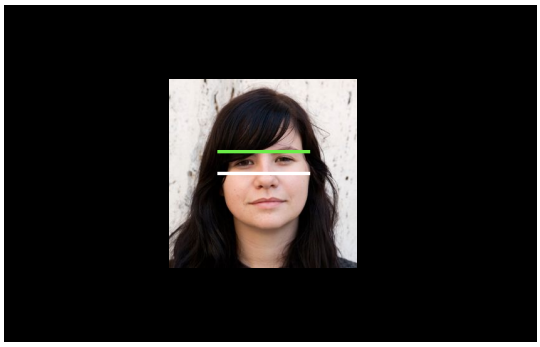
| | |
|---|---|
| "The 30-minute breaks are thus important for a few reasons. Since you will take your beta-alanine dose at the beginning of the first break, the 30 minutes will provide enough time for the drug to take effect before you begin the first block of exercise trials, as it will take about 20 minutes for you to absorb the beta-alanine. The second 30-minute break will allow you to recover fully from the first block of exercise trials, and it will allow for the effects of beta-alanine to wear off before you begin the second trial. If you remember, the effects will take 20 minutes to take hold, and will then last about 45 minutes. So, the effects of the beta-alanine will have worn off and you will have recovered from the first block of exercise trials before you begin the second block of exercise trials." | "The 30-minute breaks are thus important for a few reasons. Since you will take your beta-alanine dose at the beginning of the second break, the 30 minutes will provide enough time for the drug to take effect before you begin the second block of exercise trials, as it will take about 20 minutes for you to absorb the beta-alanine. The second 30-minute break will also allow you to recover fully from the first block of exercise trials before beginning the second block of exercise trials." |

"We are mainly interested in how the effects of beta-alanine on exercise performance differ from person to person. In some people, the effects are stronger than in others. We think that these effects might relate to peoples' personalities and how they relate to others. This is why you we will ask you the questions you will answer before the exercise trails. It is also why you will see the photo of the person you submitted to us and the photo of a stranger during the exercise trials. At the end of the experiment, we will ask you questions about how you felt about these people during the exercise trials.

So, the exercise trials will look something like this [the photos of the exercise task, below, are shown to participants]. As you can see, you will see a photo behind two lines – a coloured line (which is either red or green) and a stationary, white line. The harder you squeeze the handgrip, the higher the coloured line goes. Your goal is to keep the coloured line just above the white line 100% of the time (excluding the half-second at the beginning of the trial when you start squeezing and begin raising the line). When the coloured line moves above the white line, it changes from red to green. In some trials it will be harder than others to raise the coloured line above the white line. The order of the photos and the difficulty of the trials are randomly

generated. We will select a trail and time point within that trial at random, if the line is green at this time, you will be given an extra £5 for your effort.





After each trial, you will answer questions on how much effort you put in during the last trial and on how hard it was for you to keep the line green. Please answer these questions honestly and with the same criteria every time. You will have 5 seconds to answer each question, and you can move the circle from one end of the scale to the other by pressing the arrows on the keyboard."

The participant then does three practice runs of the 8-s exercise trial and post-trial questions.

"Like I said, when you are done with the exercise trials, you will answer some questions about the people you saw during the hand-grip trials and about your experience exercising under the influence of beta-alanine more generally. When you are done with these post-exercise questions, you will be done with the experiment. You will then be debriefed, have the option to sign a form giving us permission to use your data, and compensated for your time."

Participants are weighed and then answer the pre-exercise questions.

"As we explained previously, you will now be taking your dose of beta-alanine. This is a 430-milligram dosage, as you can see here [participants are shown their individualised version of the packet depicted in Figure D 5 (p. 388)] – this amount was calculated based on your body weight. Please take this pill along with all of the water in this glass. As I said before, this pill will take about 20 minutes to take effect. During this time, you will play a memory game, and once the pill has taken effect you will begin your exercise trials.

Most people feel less pain and fatigue and perform exercise better after having taken beta-alanine. You should feel this fatigue reduction and performance enhancement for about 45 minutes, so, throughout the exercise trial and into the break following it.

Beta-alanine is a certified performance-enhancer that has been shown to be effective in large clinical trials and is regularly used in both clinical settings by patients with chronic fatigue and in competitive settings by endurance

"Before this trial you will only drink a glass of water. This is because you will be asked to drink a glass of water along with your beta-alanine dose before the second exercise block, and we want to make sure you are equally hydrated before each block of exercise."

| | |
|---|---|
| athletes to reduce pain and fatigue and enhance performance.<br><br>Generally, beta-alanine is very well tolerated, particularly at the dosage used in this study. However, we will monitor you very carefully throughout the study and ask you to report any potential effects after the exercise trials." | |
| 30-min break during which participants played an unrelated memory task. | |
| "Okay, the beta-alanine should have taken effect by now, so you will begin your first block of exercise. Please follow the instructions on the screen. Remember, the goal is to keep the moving line green, so you don't need to raise the moving line too far above the stationary, white target line – if you do this, you will become fatigued more quickly, which will make the other trails harder. I will stay in the room with you, so just let me know if you have any questions or problems." | "You will now begin your first block of exercise. Please follow the instructions on the screen. Remember, the goal is to keep the moving line green, so you don't need to raise the moving line too far above the stationary, white target line – if you do this you will become fatigued more quickly, which will make the other trails harder. I will stay in the room with you, so just let me know if you have any questions or problems." |
| Exercise Block One | |
| "Okay, you have finished your first block of exercise. You will now have a 30-minute break where you will again complete the memory task. During this time, you should recover from the previous exercise block, so that you will be ready for the next block of exercise, and the effects of the beta-alanine dose you took will wear off or disappear completely.<br><br>Before the last block of exercise trials, you took a dose of beta-alanine along with a glass of water. This time, to make sure you are equally hydrated before each block of exercise, we ask that you again drink this glass of water." | "Okay, you have finished your first block of exercise. You will now have a 30-minute break where you will again complete the memory task. During this time, you should recover from the previous exercise trials, so that you will be ready for the next block of exercise.<br><br>As we explained previously, you will now be taking your dose of beta-alanine. This is a 430 milligram dosage, as you can see here [participants are shown their individualised version of the packet depicted in Figure D 5 (p. 388)] – this amount was calculated based on your body weight. Please take this pill along with all of the water in this glass. As I said before, this pill will take about 20 minutes to take effect. During this time, you will play the memory game again, and once the pill has taken effect you will begin your exercise trials.<br><br>Most people feel less pain and fatigue and perform exercise better after having taken beta-alanine. You should feel this fatigue reduction and performance enhancement for about 45 minutes, so, throughout the entire exercise trial. |

| | |
|---|---|
| | Beta-alanine is a certified performance-enhancer that has been shown to be effective in large clinical trials and is regularly used in both clinical settings by patients with chronic fatigue and competitive settings by endurance athletes to reduce pain and fatigue and enhance performance.<br><br>Generally, beta-alanine is very well tolerated, particularly at the dose used in this study. However, we will monitor you very carefully throughout the study and ask you to report any potential effects after the exercise trials." |
| 30-min break during which participants played an unrelated memory task | |
| "Okay, so you should have recovered from the previous exercise block and the effects of the beta-alanine dose you took should have worn off, so you won't experience its effects during the upcoming block. Please follow the instructions on the screen. I will stay in the room with you, so just let me know if you have any questions or problems." | "Okay, you should have recovered from the previous exercise block, and the effect of the beta-alanine should have taken effect by now, so you will begin the second block of exercise. Please follow the instructions on the screen. Remember, the goal is to keep the moving line green, so you don't need to raise the moving line too far above the stationary, white target line – if you do this, you will become fatigued more quickly, which will make the other trails harder. I will stay in the room with you, so just let me know if you have any questions or problems." |
| Exercise Block Two | |
| "Okay, you have finished your second block of exercise. You are now finished with the exercise portion of the study. Next, you will answer a few questions on your experience during the exercise trials, your opinions of the people in the photos you saw, and your relationship to them more generally. Please just follow the instructions on the screen." | |
| Participants answer the post-experiment questions, are debriefed, and paid. | |

## 2 Participant memories of feeling close to or supported by support figure

Below are five randomly chosen memories that participants provided of their support figures:

“When she helped me move house for the fourth time.” – Participant 25

“Every time I have felt bad in the past, from the moment I left home, I could call her and she would comfort me.” – Participant 30

“My sister sent me a package of thoughtful gifts in the post for my birthday.” – Participant 51

“Visiting Ely together on a sunny day. Feeling relaxed, comfortable and happy.” – Participant 82

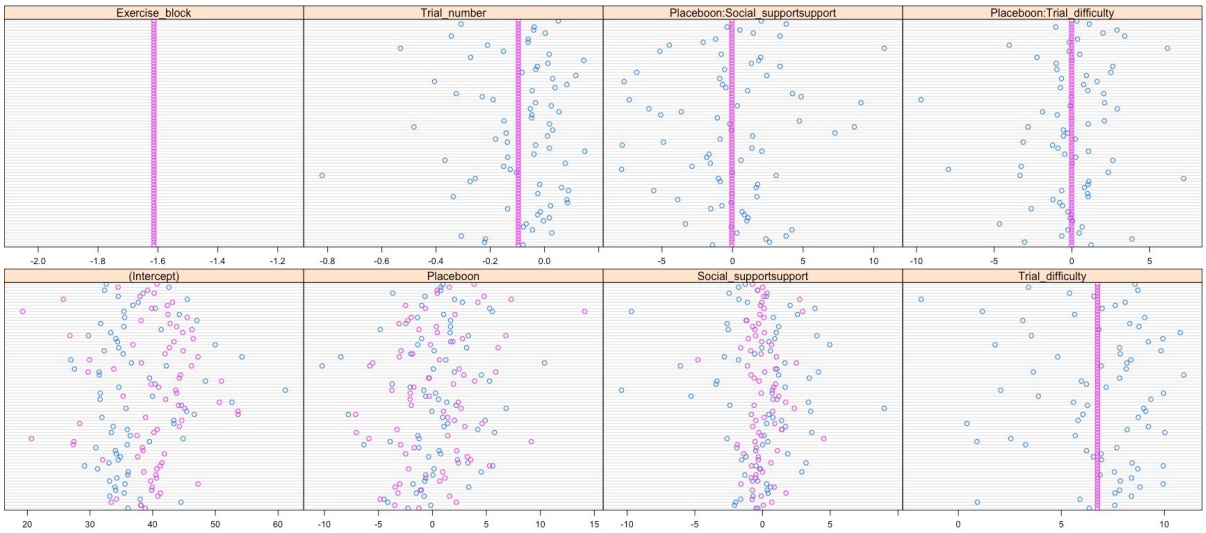
“When we worked together in Beirut (Lebanon) for an NGO. It was an especially tyring [sic] week but we motivated each other to keep going.” – Participant 97

## 3 Assumption checks

Model assumptions were checked in accordance with the procedures put forth my Snijders and Bosker (2012). These procedures are described in Section 1 of Appendix B (p. 295).

### 3.1 Multilevel models on participants' hand grip outputs

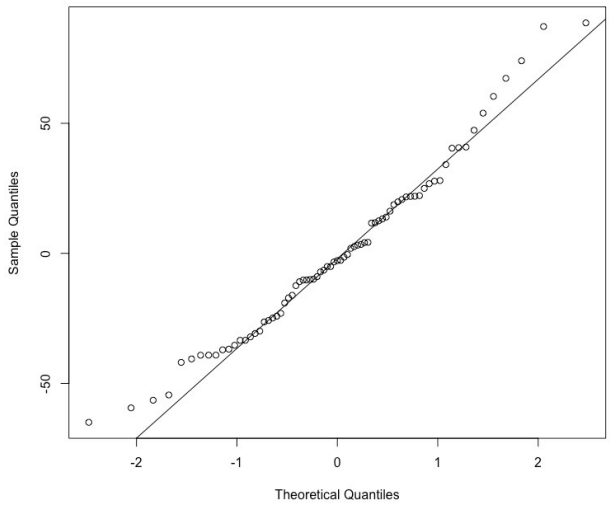
For level-one homoscedasticity, the variability of posterior means estimated by the multilevel model was similar to the variability of coefficients estimated by separate OLS regressions on data from each participant (level-two unit); see Appendix D Figure 1.




**Appendix D Figure 1** OLS coefficient estimates for each participant (blue) versus the posterior means for each participant in the multilevel model (pink). 'Exercise_block' represents the exercise block variable, 'Trial_number' represents the trial number variable, 'Placeboon:Social_supportsupport' represents the placebo condition × social support condition interaction, 'Placeboon:Trial_difficulty' represents the placebo condition × objective trial difficulty interaction, 'Placeboon' represents the placebo condition variable, ' Social_supportsupport' represents the social support condition variable, and 'Trial_difficulty' represents the trial difficulty variable.

For this model, the null hypothesis of homoscedasticity for level-one residuals was not rejected, $H$ = 83,463.57, $df$ = 1,007,325, $p$ = 1. Further, a Q-Q plot (see Appendix D Figure 2) of $d$ reveals that it is close to being normally distributed; it can be assumed that the model has an unproblematic amount of heteroskedasticity (Snijders & Bosker, 2012).

The normality of level-one residuals was checked by making a normal probability plot of the standardised OLS residuals. Appendix D Figure 3 shows that the normality assumption has

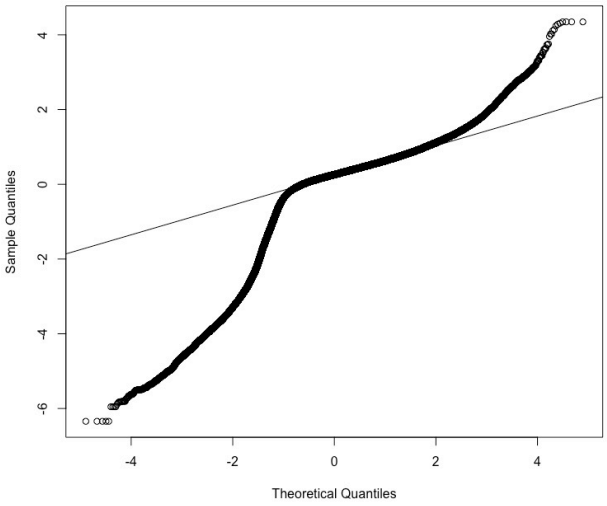



**Appendix D Figure 2** Q-Q plot of the standardised residual dispersion measure, *d*.

been violated, due to longer tails than what would be expected with the normal distribution. However, Seco et al. (2013) have demonstrated that fixed effects estimates are robust to violations of the normality assumption; multilevel models with non-normally distributed residuals do not produced biased fixed effect parameter estimates.

Normal Q-Q plots of standardised level-two residuals for random intercepts and slopes suggest deviations from normality for the random intercepts and slopes (see Appendix B Figure 4). However, Maas and Hox (2004) have shown that estimates of fixed effects and their standard errors are robust to non-normal level-two residual errors when there are at least 50 level-two units (this study had 75 participants). Given this, it can be assumed that the model's fixed effect estimates (and their standard errors) are unbiased.

Influential data points were checked using the *influence.ME* package in R (described in Appendix B, Section 1, p. 295). Results revealed that 15 participants (20%) had Cook's Distances greater than 1 ($M$ = 0.992, $SD$ = 2.798, range = 0.034 – 24.043). However, the exclusion of these participants (one at a time) did not change the significance of the interaction between trial difficulty social support. It can thus be concluded that no participant had an undue influence on the model.



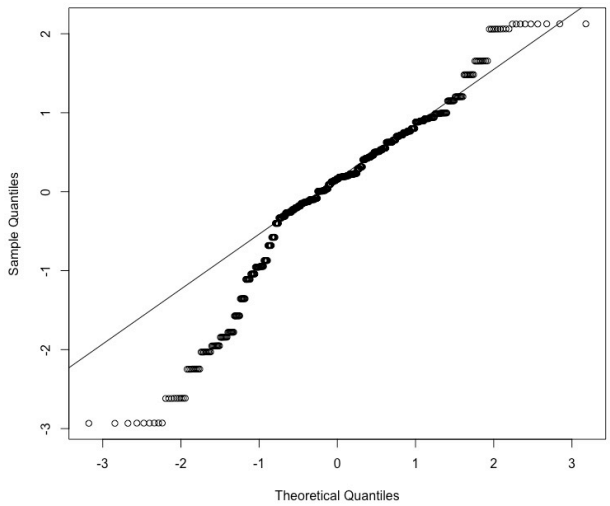

**Appendix D Figure 3** Standardised OLS level-one residuals versus the expected order statistics of a normal distribution (Q-Q plot) for multilevel model on participants' hand grip outputs.

### 3.2 Multilevel censored regression on perceptions of difficulty.

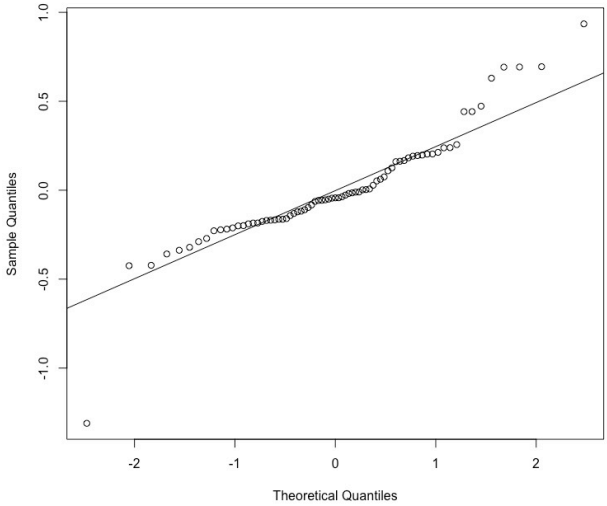
Given the nature of the response data for this question (hierarchical and heavily right censored) a multilevel censored regression model was chosen for analyses, as it would best fit these data structures. Multilevel censored regression models have the same assumptions as multilevel, random intercept models that use linear regression (Henningsen, 2010; McBee, 2010). However, the only way to estimate these models is through a series of procedures in R using the packages *censReg* and *plm*, and the model objects produced from these procedures do not offer model residuals (Croissant & Millo, 2008; Henningsen, 2010).

As an alternative means of understanding this model's fit and whether or not its assumptions were met, I analysed results from two simpler models for which residuals can be obtained: a censored regression model (ignoring the multilevel nature of the data) and a multilevel, random intercept model (ignoring the right censoring in the data). Specifically, I used the censored regression model to look at level-one residuals and the multilevel, random-intercept model to look at level-two residuals (i.e., posterior means of random, level-two effects).

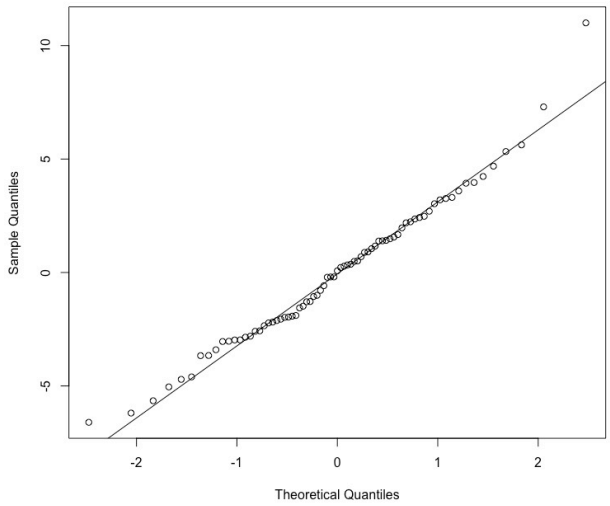
(*a*)




(*b*)



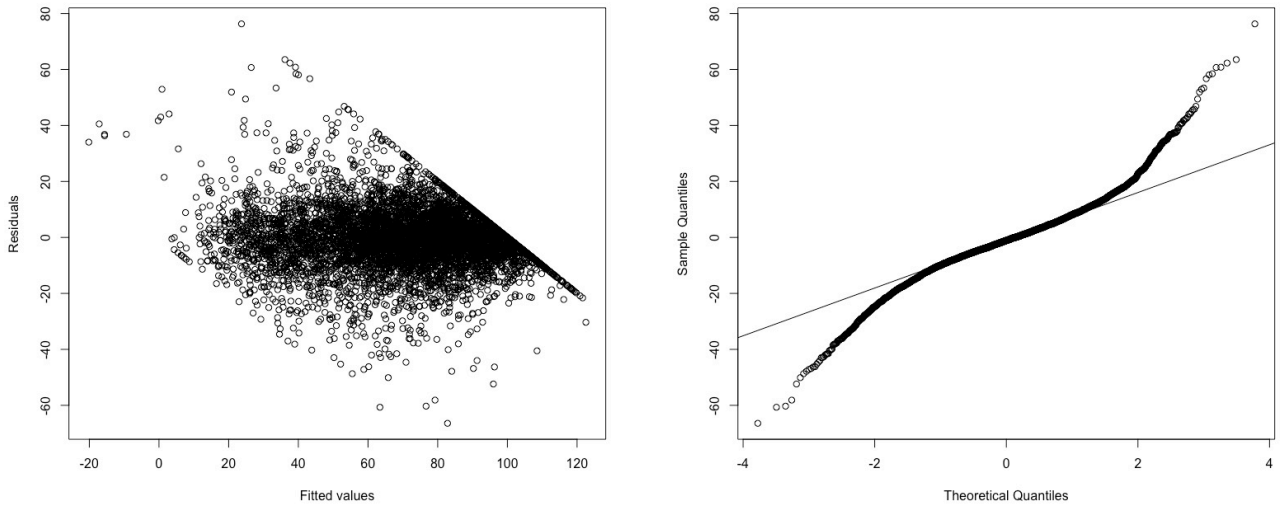

(*c*)




**Appendix D Figure 4** Checks of level-two residuals for multilevel model on participants' hand grip outputs: (*a*) intercept residuals and (*b*) social support and (*c*) placebo effect random slope residuals versus the expected order statistics of a normal distribution (Q-Q plots).

The censored regression model was estimated with the same predictors and covariates used for the multilevel censored regression, except with the addition of a participant variable as a factor (as a means of accounting for variance explained by repeated measures from participants) and the exclusion of the exercise block variable from the four-way interaction (the model would not converge due to singularity issues, since not all participants had taken placebo in both the first and second exercise block). This model was used to assess level-one

(*a*) (*b*)

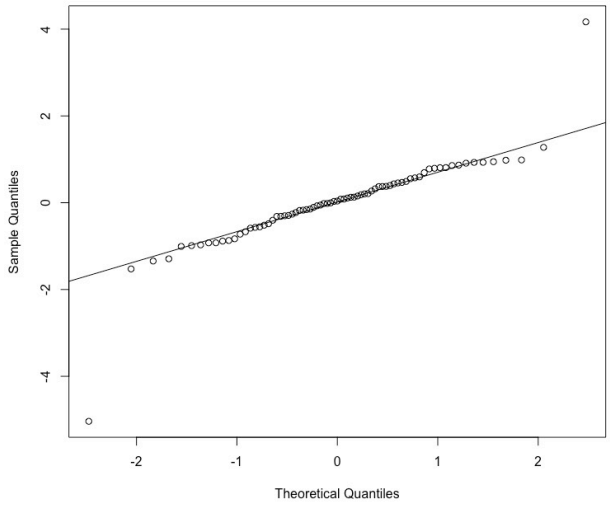



**Appendix D Figure 5** (*a*) Fitted v. residual plot and (*b*) normal Q-Q plot for censored regression on participants' perceived difficulty.

fit for the multilevel censored regression and was estimated using the *AER* package in R (Kleiber & Zeileis, 2009).

Regarding the level-one residuals, a fitted v. residual plot revealed that this model met the assumptions of linearity and homoscedasticity (see Appendix D Figure 5a). A normal Q-Q plot (see Appendix D Figure 5b), however, suggests that the normality assumption was broken, which may have an effect of biasing the results in the multilevel censored regression (Arabmazar & Schmidt, 1982). Variance inflation factors revealed that the model had no issues with multicollinearity ($M$ = 10.34, range = 1.01 – 21.64).

The multilevel model used the same covariates as the multilevel censored regression model (which did not include random slopes for any of the predictor variables) described in Section 6.2.3.4 (p. 208). This model was used to assess the level-two residuals and model fit of the multilevel censored regression and was estimated using the *lme4* function in R (Bates et al., 2014). I thus used the same model estimation procedures for this model as I used for the multilevel model on participants' hand grip outputs (see Section 6.2.3.3, p. 207), except with a simpler random effects structure (i.e., no random slopes).




**Appendix D Figure 6** Normal QQ plot for standardised level-two random intercept residuals for the multilevel model on participants' perceived difficulty.

Regarding the posterior means of random, level-two effects (i.e., predictions of the random intercepts), a Q-Q plot revealed that the normality assumption had been met (see Appendix D Figure 6), although this was not confirmed with a Shapiro-Wilks test ($W$ = 0.818, p < .001), likely due to the two outlying data points.

However, these outlying data points did not have an undue influence on the model. No groups of observations (i.e., participants) had Cook's Distances greater than 1 ($M$ = 0.05, $SD$ = 0.09, range = 0.003 – 0.66).

Given the fits of these test models, it is assumed that the more appropriate model on participants' answers to the question on how hard the previous trial was – the multilevel censored regression model reported in Section 6.3.5 (p. 214) – sufficiently met background assumptions about the distributions of observed and residual data points, and was not unduly influenced by outlying participants. The only issue is the lack of normality (especially at level-one). However, given the lack of ambiguity in Figure 6.7 (p. 216) – which shows clearly with raw data the main significant finding of the model (a placebo × exercise block interaction) – non-normality can be ignored in assessing the validity of this model's results.

## Tables

**Table D 1** Manipulation checks and descriptive statistics of relevant predictor variables

| Variable | Scale | *M* (*SD*) | Range | Test statistic (df) | *p* |
|---|---|---|---|---|---|
| β-alanine effects on performance | Sliding scale (0 – 100) | 58.12 (12.13) | 19 – 87 | $t$ = 5.80* (73) | < .001 |
| β-alanine effects on trial difficulty | Sliding scale (0 – 100) | 56.08 (16.60) | 10 – 95 | $t$ = 3.17* (73) | .002 |
| Closeness to support figure | Five-point Likert | 3.75 (1.09) | 1 – 5 | $W$ = 2098 | < .001 |
| Closeness to stranger | Five-point Likert | 1.73 (1.02) | 1 – 5 | | |
| Accuracy of support figure description | Seven-point Likert | 6.41 (0.72) | 4 – 7 | | |
| Duration of relationship with support figure | Years | 11.03 (9.97) | 0.25 – 40.83 | | |
| Need for social assurance | SAS[1] | 3.59 (0.79) | 1.75 – 6 | | |
| Ability to depend upon others | RAAS[2] | 3.52 (0.71) | 1.15 – 5 | | |
| Neuroticism | Big 5[3] | 2.82 (0.89) | 1.125 – 4.88 | | |
| Ratio of felt closeness to support figure (v. felt closeness to stranger) | Five-point Likert | 2.63 (1.32) | 0.25 – 5 | | |
| Fear of pain | FPQ[4] | 2.59 (0.59) | 1 – 4.1 | | |

* One-sample *t*-test comparing scores to no effects (50 on the scale)
[1] Lee and Robbins (1995)
[2] Collins and Read (1990) and Collins (1996)
[3] Rammstedt and John (2007)
[4] McNeil and Rainwater (1998)

**Table D 2** Self-reports of trial difficulty and effort levels (as percentage of sliding scale used for responses; see Section 6.2.2.4, p. 202)

| Target grip strength | Reported exercise trial difficulty | Reported exercise trial effort |
|---|---|---|
| 40% of maximum | 55.39% | 59.64% |
| 50% of maximum | 70.20% | 72.26% |
| 60% of maximum | 82.60% | 82.21% |
| **Exercise block** | | |
| 1 | 68.54% | 70.69% |
| 2 | 70.25% | 72.04% |

**Table D 3** Multilevel censored regression model on participants' answers to the question on how hard the previous trial was

| Variable | Coefficient | *SE* | *t* | *p* |
|---|---|---|---|---|
| Intercept | 0.299 | 1.076 | 0.28 | .781 |
| Placebo | −3.628 | 1.851 | −1.96 | .050 |
| Social support | −1.922 | 1.736 | −1.11 | .268 |
| Exercise block | −3.844 | 1.665 | −2.31 | .021 |
| Trial number | 0.174 | 0.008 | 21.61 | < .001 |
| Trial difficulty | 6.280 | 0.508 | 12.36 | < .001 |
| Placebo × social support | 0.423 | 0.930 | 0.46 | .991 |
| Placebo × trial difficulty | −0.923 | 0.934 | −0.99 | .323 |
| Social support × trial difficulty | 0.499 | 0.837 | 0.60 | .551 |
| Placebo × exercise block | 6.743 | 2.366 | 2.58 | .004 |
| Social support × exercise block | 1.136 | 2.943 | 0.39 | .699 |
| Trial difficulty × exercise block | −0.047 | 0.770 | −0.06 | .952 |
| Placebo × social support × trial difficulty | −0.301 | 1.509 | −0.20 | .842 |
| Placebo × social support × exercise block | −1.738 | 4.103 | −0.42 | .672 |
| Placebo × trial difficulty × exercise block | 1.523 | 1.112 | 1.37 | .170 |
| Social support × trial difficulty × exercise block | −0.506 | 1.330 | −0.38 | .704 |
| Placebo × social support × trial difficulty × exercise block | 1.161 | 1.935 | 0.60 | .548 |

**Table D 4** Linear model on observed social support effects on hand grip outputs with participants' need for social assurance as the main predictor variable of interest

| **Variable** | **Coefficient** | ***SE*** | ***t*** | ***p*** |
|---|---|---|---|---|
| Intercept | 0.402 | 0.731 | 0.55 | .584 |
| Need for social assurance | 0.007 | 0.197 | 0.04 | .972 |
| Participant sex (male) | 0.178 | 0.310 | 0.57 | .568 |
| Multiple $R^2$ = .005 | | | | |

**Table D 5** Linear model on observed social support effects on hand grip outputs with participants' neuroticism as the main predictor variable of interest

| **Variable** | **Coefficient** | ***SE*** | ***t*** | ***p*** |
|---|---|---|---|---|
| Intercept | −0.557 | 0.672 | −0.83 | .410 |
| Neuroticism | 0.306 | 0.120 | 1.54 | .129 |
| Participant sex (male) | 0.453 | 0.353 | 1.28 | .204 |
| Multiple $R^2$ = .036 | | | | |

**Table D 6** Linear model on observed social support effects on hand grip outputs with the ratio of how close participants felt to their support figure to how close they felt to the stranger as the main predictor variable of interest

| **Variable** | **Coefficient** | ***SE*** | ***t*** | ***p*** |
|---|---|---|---|---|
| Intercept | 0.044 | 0.394 | 0.112 | .911 |
| Closeness to support figure (v. stranger) ratio | 0.134 | 0.118 | 1.136 | .260 |
| Participant sex (male) | 0.245 | 0.313 | 0.782 | .437 |
| Multiple $R^2$ = .022 | | | | |

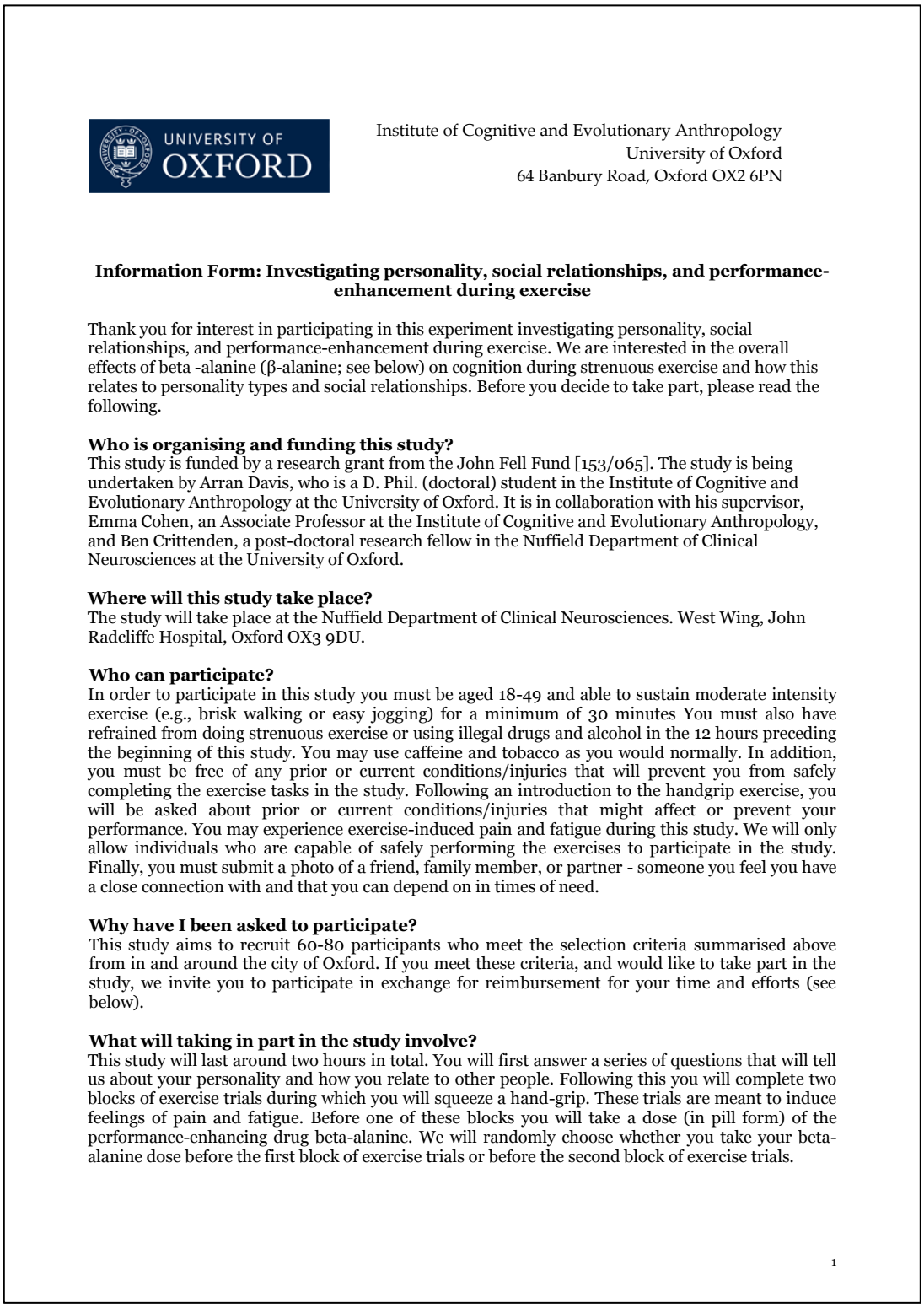
**Table D 7** Linear model on observed social support effects on hand grip outputs with the extent to which participants believe they can depend upon others when needed as the main predictor variable of interest

| **Variable** | **Coefficient** | ***SE*** | ***t*** | ***p*** |
|---|---|---|---|---|
| Intercept | 0.838 | 0.793 | 1.06 | .294 |
| Depend upon others | −0.117 | 0.217 | −0.54 | .593 |
| Participant sex (male) | 0.178 | 0.309 | 0.58 | .567 |
| Multiple $R^2$ = .009 | | | | |

**Figures**




**Figure D 1** Participant recruitment flyer.



Institute of Cognitive and Evolutionary Anthropology
University of Oxford
64 Banbury Road, Oxford OX2 6PN

**Information Form: Investigating personality, social relationships, and performance-enhancement during exercise**

Thank you for interest in participating in this experiment investigating personality, social relationships, and performance-enhancement during exercise. We are interested in the overall effects of beta -alanine (β-alanine; see below) on cognition during strenuous exercise and how this relates to personality types and social relationships. Before you decide to take part, please read the following.

**Who is organising and funding this study?**
This study is funded by a research grant from the John Fell Fund [153/065]. The study is being undertaken by Arran Davis, who is a D. Phil. (doctoral) student in the Institute of Cognitive and Evolutionary Anthropology at the University of Oxford. It is in collaboration with his supervisor, Emma Cohen, an Associate Professor at the Institute of Cognitive and Evolutionary Anthropology, and Ben Crittenden, a post-doctoral research fellow in the Nuffield Department of Clinical Neurosciences at the University of Oxford.

**Where will this study take place?**
The study will take place at the Nuffield Department of Clinical Neurosciences. West Wing, John Radcliffe Hospital, Oxford OX3 9DU.

**Who can participate?**
In order to participate in this study you must be aged 18-49 and able to sustain moderate intensity exercise (e.g., brisk walking or easy jogging) for a minimum of 30 minutes You must also have refrained from doing strenuous exercise or using illegal drugs and alcohol in the 12 hours preceding the beginning of this study. You may use caffeine and tobacco as you would normally. In addition, you must be free of any prior or current conditions/injuries that will prevent you from safely completing the exercise tasks in the study. Following an introduction to the handgrip exercise, you will be asked about prior or current conditions/injuries that might affect or prevent your performance. You may experience exercise-induced pain and fatigue during this study. We will only allow individuals who are capable of safely performing the exercises to participate in the study. Finally, you must submit a photo of a friend, family member, or partner - someone you feel you have a close connection with and that you can depend on in times of need.

**Why have I been asked to participate?**
This study aims to recruit 60-80 participants who meet the selection criteria summarised above from in and around the city of Oxford. If you meet these criteria, and would like to take part in the study, we invite you to participate in exchange for reimbursement for your time and efforts (see below).

**What will taking in part in the study involve?**
This study will last around two hours in total. You will first answer a series of questions that will tell us about your personality and how you relate to other people. Following this you will complete two blocks of exercise trials during which you will squeeze a hand-grip. These trials are meant to induce feelings of pain and fatigue. Before one of these blocks you will take a dose (in pill form) of the performance-enhancing drug beta-alanine. We will randomly choose whether you take your beta-alanine dose before the first block of exercise trials or before the second block of exercise trials.

1

**Figure D 2** Information form.

Each of the blocks will last around 20 minutes, during which you will do the handgrip exercise for 10 seconds and then rest for 10 seconds. This will last for the entirety of each 20-minute block. During the 10-second rest period you will answer questions on how hard you tried during the last 10 seconds of hand-gripping and on how hard it was for you to maintain the grip strength we set for you. The breaks in-between the two exercise blocks will last 30 minutes. These breaks will serve three functions: 1.) to allow enough time for your beta-alanine dose to take effect before you begin exercising, 2.) to allow you to recover from the first exercise block (in the case of the second break), and 3.) to allow enough time for the effects of beta-alanine to wear off before you begin the second exercise block (should you take your beta-alanine dose before the first exercise block).

During these 30-minute breaks you will play a memory game; certain personality characteristics have been shown to be related to the ways people remember things. You will also answer several computer-based questionnaires before and after the two blocks of exercise trials. The pre and post-trial questionnaires will take around 10-20 minutes each to complete and they will ask about your personality, how you relate to other people, and your experience of the effects of beta-alanine.

As stated above, before one of the exercise blocks you will take a dose of beta-alanine along with a glass of water. Your dosage will be dependent on your body weight, which we will take before the exercise trials. You will drink glasses of water before the other exercise block as well, in order to control for the effects of hydration on exercise performance.

Large clinical trials have shown that beta-alanine supplementation leads to enhanced performance by delaying the onset of muscle fatigue and pain during exercise. Beta-alanine reduces concentrations of molecules that lead to feelings of pain and fatigue during exercise, thereby altering perceptions and enhancing performance (specifically, beta-alanine in muscle cells is necessary for the synthesis of carnosine, a molecule that reduces intramuscular acidosis, an important cause of pain and fatigue during exercise). The beta-alanine pill you are taking is relatively fast-acting – it will start to affect you about 20 minutes after you take it and these effects will last for about 45 minutes.

Beta-alanine is a naturally occurring amino acid and, generally, it is very well tolerated (most individuals experience no side effects), particularly at the dose used in this study. However, we will monitor you carefully after you have taken your dose and we will ask you to report any potential side-effects at the end of the study. Beta-alanine is legal and not restricted in the UK.

Also, please note that exercise trials will be performed individually and are not competitive. While the effects of beta-alanine on exercise performance are well known, we are interested in how these effects vary between individuals. Research has shown that some people experience greater decreases in pain and fatigue and larger boosts in exercise performance after taking beta-alanine than do others. We are interested in how people with different personalities and social relationships are either more or less affected by the performance-enhancing qualities of beta-alanine. Thus, during the study you will answer questions about your personality and your relationship with the friend, family member, or partner you submitted a photo of. During the exercise trials you will also see photos of a stranger and the photo of the friend, family member, or partner you submitted to us. This will help us to determine how people with different personality and relationship styles are affected by beta-alanine.

Immediately upon completing the study you will be debriefed on our hypotheses and experimental methods. You will have the option to give your consent for your data to be used. Finally, you will be compensated for your time (regardless of your decision regarding the use of your data). You will then be free to leave the experiment cite. Debriefing and payment will last around 5 minutes.

**What is the purpose of this study?**
We are investigating personality, social relationships, and performance-enhancement during exercise. Thus, we would like to know how these factors affect peoples' experiences during the handgrip squeezing exercises. We hope that this study will provide the basis for future brain-imaging (fMRI) studies that will look at how these differing experiences are created in the brain.



**Figure D 2** Information form (continued).

**How will my information be used?**
All your responses from this study will be anonymous as you will be designated a participant number. Thus, all the information you provide will be completely confidential and not connected to any of your identifying information. Also, your data will not be analysed at the individual level. Rather, all data will be analysed in aggregate form. During analysis data will be stored on password-protected computer. In addition, you will never be identified by name in any reports of the completed study. All data will be password-protected and only accessible to the researchers involved in this study. We will keep this data for a minimum of three years and for as long as it is of value to the research team and wider research community. We may be required by publishers to make permanently available an open-access version of this data. In this case data would not include your name or your participant number – only the information collected on the variables you allowed us to measure today. Thus, it will also be completely anonymous. Consent and debriefing forms will be stored separately from the anonymised data you provide during the study and will be destroyed after five years.

**What should I do if I have any questions, concerns, or complaints?**
Potential participants should ask any questions they might have about the study before they decide to participate. These questions can be addressed to Arran Davis (arran.davis@anthro.ox.ac.uk). If you would like to discuss any further aspect of the research either during or after the study please ask the researchers present at the study or contact Arran Davis via email.

If you have a concern about any aspect of the project, please speak to or email Arran Davis, who will do his best to answer your query. The researcher should acknowledge your concern within 10 working days and give you an indication of how he intends to deal with it. If you remain unhappy or wish to make a formal complaint please contact either the chair of the School of Anthropology and Museum Ethnography Departmental Research Ethics Committee (email: HoD@anthro.ox.ac.uk) or the chair of the Research Ethics Committee at the University of Oxford (Chair, Social Sciences & Humanities Inter-Divisional Research Ethics Committee; email: ethics@socsci.ox.ac.uk; address: Research Services, University of Oxford, Wellington Square, Oxford OX2 2JD). The chair will seek to resolve the matter in a 'reasonably expeditious manner'.

This study has been reviewed and approved by the School of Anthropology, University of Oxford internal ethical procedures and the Central University Research Ethics Committee (CUREC).

**Do I have to participate and how will I be compensated for my time?**
You do not have to take part in this study (or any part thereof) if you don't want to. If you decide to take part you may withdraw at any time without having to provide a reason (this includes withdrawing because the exercise-induced pain and fatigue become too intense). You will not be penalised for withdrawing. You will still receive compensation for taking part in the study. All participants will be paid £25 for taking part in the study, with the opportunity of earning £5 more should they put forth maximum effort during the study.



**Figure D 2** Information form (continued).




Institute of Cognitive and Evolutionary Anthropology
University of Oxford
64 Banbury Road, Oxford OX2 6PN

Participant No. _____

**Consent Form: Investigating personality, social relationships, and performance-enhancement during exercise**

You have been asked to participate in a study investigating personality, social relationships, and performance-enhancement during exercise. The study is being undertaken by Arran Davis, who is a D. Phil. (doctoral) student in the Institute of Cognitive and Evolutionary Anthropology at the University of Oxford. It is in collaboration with his supervisor, Emma Cohen, an Associate Professor at the Institute of Cognitive and Evolutionary Anthropology, and Ben Crittenden, a post-doctoral research fellow in the Nuffield Department of Clinical Neurosciences at the University of Oxford (Level 6. West Wing, John Radcliffe Hospital, Oxford OX3 9DU).

Please feel free to ask any questions before you complete the consent form below, which will be stored separately from the confidential information you provide for the study. You must complete the consent for before participating.

If you would like to discuss any other aspect of the research please contact Arran Davis via email at arran.davis@anthro.ox.ac.uk or via phone at 07721 513026.

| | *Please initial each box* |
|---|---|
| 1. I confirm that I have read and understand the Information Form for the above study. I have had the opportunity to consider the information, ask questions and have had these answered satisfactorily. | ☐ |
| 2. I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason, without penalty or affecting my legal rights. | ☐ |
| 3. I understand that data collected during the study may be looked at by designated investigators from the University of Oxford and their co-investigators, and that it may be used – in anonymised form – for publications | ☐ |
| 4. I agree to take the dose of β-alanine that was described in the Information Form for this study. | ☐ |

**Figure D 3** Consent form.

5. I am free from any pre-existing medical conditions that could compromise my ability to participate fully in this study. ☐

6. I understand that this project has been reviewed by, and received ethics clearance through, the University of Oxford Central University Research Ethics Committee. ☐

7. I understand who will have access to personal data provided, how the data will be stored, and what will happen to the data at the end of the project. ☐

8. I understand how this research will be written up and published. ☐

9. I agree to participate in this study. ☐

**Signature and information of participant**

Signature: _____

Name (in block letters): _____ Date: _____

**Signature and information of researcher taking consent**

Signature: _____

Name (in block letters): _____ Date: _____

**Figure D 3** Consent form (continued).

The items listed below describe painful experiences. Please look at each item and think about how fearful you are of experiencing the pain associated with it. Chose one of the five options below to rate your fear of pain in relation to each event.

| | Not at all | A little | A fair amount | Very much | Extreme |
|---|---|---|---|---|---|
| Breaking your arm. | ○ | ○ | ○ | ○ | ○ |
| Having a foot doctor remove a wart from your foot with a sharp instrument. | ○ | ○ | ○ | ○ | ○ |
| Getting a paper-cut on your finger. | ○ | ○ | ○ | ○ | ○ |
| Receiving an injection in your mouth. | ○ | ○ | ○ | ○ | ○ |
| Getting strong soap in both your eyes while bathing or showering. | ○ | ○ | ○ | ○ | ○ |
| Having someone slam a heavy car door on your hand. | ○ | ○ | ○ | ○ | ○ |
| Gulping a hot drink before it has cooled. | ○ | ○ | ○ | ○ | ○ |
| Receiving an injection in your hip/buttocks. | ○ | ○ | ○ | ○ | ○ |
| Falling down a flight of concrete stairs. | ○ | ○ | ○ | ○ | ○ |
| Having a muscle cramp. | ○ | ○ | ○ | ○ | ○ |

**Figure D 4** Modified version of the short form of the Fear of Pain Questionnaire (McNeil et al., 2018).




**Figure D 5** Presentation of β-alanine (actually a placebo – 430 mg of sucrose placebo).



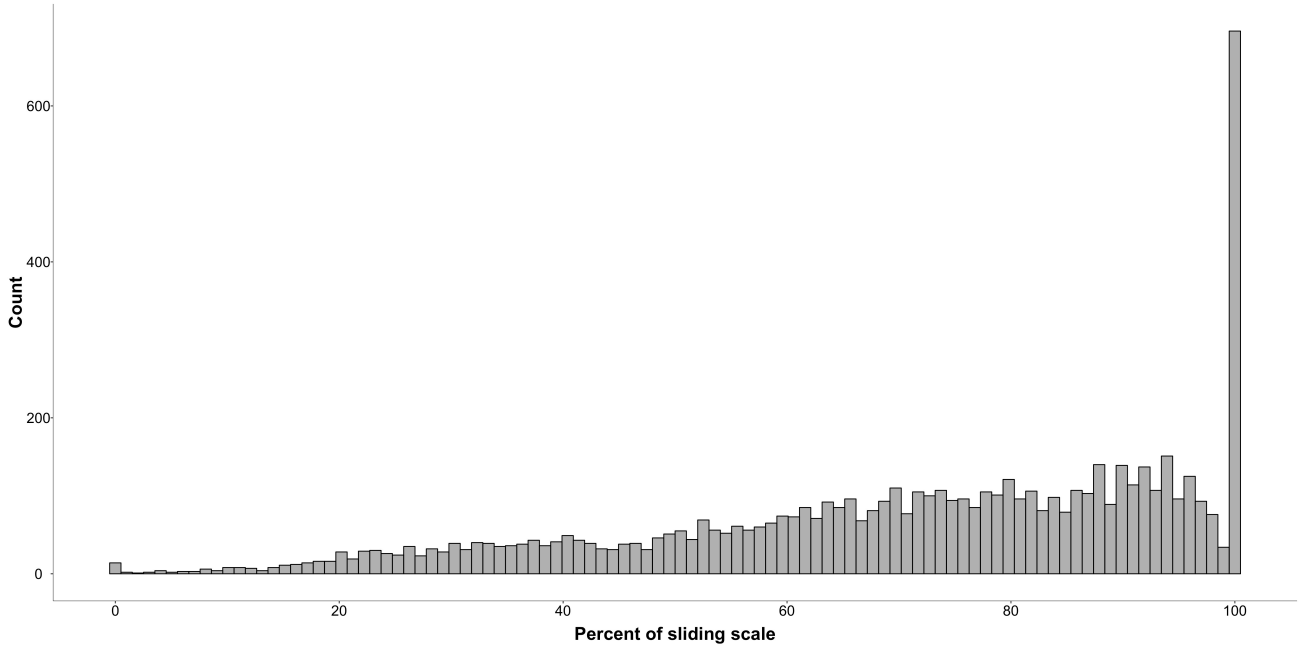



**Figure D 6** Histogram of participants' answers to the post-trial question on how hard the previous trial was (0 = *no effort at all*, 100 = *maximum effort*).

## References


Acevedo, B. P., Aron, A., Fisher, H. E., & Brown, L. L. (2012). Neural correlates of long-term intense romantic love. *Social Cognitive and Affective Neuroscience, 7*(2), 145-159. doi:10.1093/scan/nsq092

Adreani, C. M., Hill, J. M., & Kaufman, M. P. (1997). Responses of group III and IV muscle afferents to dynamic exercise. *Journal of Applied Physiology, 82*(6), 1811-1817.

Agresti, A., & Finlay, B. (1997). *Statistical Methods for the Social Sciences* (3rd ed.). Upper Saddle River, NJ: Prentice Hall, Inc.

Almeida, T. F., Roizenblatt, S., & Tufik, S. (2004). Afferent pain pathways: a neuroanatomical review. *Brain research, 1000*(1), 40-56.

Amann, M., Proctor, L. T., Sebranek, J. J., Pegelow, D. F., & Dempsey, J. A. (2009). Opioid‐mediated muscle afferents inhibit central motor drive and limit peripheral muscle fatigue development in humans. *The Journal of Physiology, 587*(1), 271-283. doi:10.1113/jphysiol.2008

Arabmazar, A., & Schmidt, P. (1982). An investigation of the robustness of the Tobit estimator to non-normality. *Econometrica*, 1055-1063.

Ariel, G., & Saville, W. (1971). Anabolic steroids: the physiological effects of placebos. *Medicine & Science in Sports & Exercise*(4).

Axelrod, R., & Hamilton, W. D. (1981). The Evolution of Cooperation. *Science, 211*(4489), 1390-1396. doi:Doi 10.1126/Science.7466396

Baecke, J., Burema, J., & Frijters, J. (1982). A short questionnaire for the measurement of habitual physical activity in epidemiological studies. *The American Journal of Clinical Nutrition, 36*(5), 936-942.

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist, 37*(2), 122.

Bar-Or, O. (1987). The Wingate anaerobic test an update on methodology, reliability and validity. *Sports Medicine, 4*(6), 381-394.

Barclay, P. (2016). Biological markets and the effects of partner choice on cooperation and friendship. *Current Opinion in Psychology, 7*, 33-38.

Barkley, J. E., Salvy, S.-J., & Roemmich, J. N. (2012). The effect of simulated ostracism on physical activity behavior in children. *Pediatrics, 129*(3), e659-e666.

Barr, D. J., Levy, R., Scheepers, C., & Tily, H. J. (2013). Random effects structure for confirmatory hypothesis testing: Keep it maximal. *Journal of Memory and Language, 68*(3), 255-278.

Barrot, M., Wallace, D. L., Bolaños, C. A., Graham, D. L., Perrotti, L. I., Neve, R. L., . . . Nestler, E. J. (2005). Regulation of anxiety and initiation of sexual behavior by CREB in the nucleus accumbens. *Proceedings of the National Academy of Sciences of the United States of America, 102*(23), 8357-8362.

Bates, D., Kliegl, R., Vasishth, S., & Baayen, H. (2015). Parsimonious mixed models. *arXiv preprint arXiv:1506.04967*.

Bates, D., Maechler, M., Bolker, B., & Walker, S. (2014). lme4: Linear mixed-effects models using Eigen and S4. *R package version, 1*(7), 1-23.

Bauer, D. J., Preacher, K. J., & Gil, K. M. (2006). Conceptualizing and testing random indirect effects and moderated mediation in multilevel models: new procedures and recommendations. *Psychological Methods, 11*(2), 142.

Beedie, C. J., & Foad, A. J. (2009). The placebo effect in sports performance. *Sports Medicine, 39*(4), 313-329.

Beedie, C. J., Lane, A. M., & Wilson, M. G. (2012). A Possible Role for Emotion and Emotion Regulation in Physiological Responses to False Performance Feedback in 10 Mile Laboratory Cycling. *Applied Psychophysiology and Biofeedback, 37*(4), 269-277. doi:10.1007/s10484-012-9200-7

Beedie, C. J., Stuart, E. M., Coleman, D. A., & Foad, A. J. (2006). Placebo effects of caffeine on cycling performance. *Medicine and Science in Sports and Exercise, 38*(12), 2159-2164.

Bell, B. A., Ferron, J. M., & Kromrey, J. D. (2008). *Cluster size in multilevel models: the impact of sparse data structures on point and interval estimates in two-level models.* Paper presented at the Proceedings of the Joint Statistical Meetings.

Benedetti, F. (2009). *Placebo effects: understanding the mechanisms in health and disease*. New York: Oxford University Press.

Benedetti, F. (2013). Placebo and the new physiology of the doctor-patient relationship. *Physiological reviews, 93*(3), 1207-1246.

Benedetti, F., Amanzio, M., Rosato, R., & Blanchard, C. (2011). Nonopioid placebo analgesia is mediated by CB1 cannabinoid receptors. *Nature Medicine, 17*(10), 1228-1230. doi:10.1038/nm.2435

Benedetti, F., Carlino, E., & Pollo, A. (2011). How Placebos Change the Patient's Brain. *Neuropsychopharmacology, 36*(1), 339-354. doi:10.1038/npp.2010.81

Benedetti, F., Frisaldi, E., Carlino, E., Giudetti, L., Pampallona, A., Zibetti, M., . . . Lopiano, L. (2016). Teaching neurons to respond to placebos. *The Journal of Physiology, 594*(19), 5647-5660.

Benedetti, F., Lanotte, M., Lopiano, L., & Colloca, L. (2007). When words are painful: unraveling the mechanisms of the nocebo effect. *Neuroscience, 147*(2), 260-271.

Benedetti, F., Pollo, A., & Colloca, L. (2007). Opioid-Mediated Placebo Responses Boost Pain Endurance and Physical Performance: Is It Doping in Sport Competitions? *The Journal of Neuroscience, 27*(44), 11934-11939. doi:10.1523/jneurosci.3330-07.2007

Benjamini, Y., & Hochberg, Y. (1995). Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society: Series B (Methodological), 57*(1), 289-300.

Benjamini, Y., & Yekutieli, D. (2001). The control of the false discovery rate in multiple testing under dependency. *The Annals of Statistics, 29*(4), 1165-1188.

Best, E. (1924). Maori: Volume 2 *Memoirs Of The Polynesian Society* (Vol. vol. 5, pp. x, 638). Wellington, N.Z.: Printed by H.H. Tombs, limited.

Bhalla, M., & Proffitt, D. R. (1999). Visual–motor recalibration in geographical slant perception. *Journal of Experimental Psychology: Human Perception and Performance, 25*(4), 1076.

Bilbo, S. D., Drazen, D. L., Quan, N., He, L., & Nelson, R. J. (2002). Short day lengths attenuate the symptoms of infection in Siberian hamsters. *Proceedings of the Royal Society of London. Series B: Biological Sciences, 269*(1490), 447-454. doi:10.1098/rspb.2001.1915

Bingel, U., & Tracey, I. (2008). Imaging CNS Modulation of Pain in Humans. *Physiology, 23*(6), 371-380.

Boecker, H., Sprenger, T., Spilker, M. E., Henriksen, G., Koppenhoefer, M., Wagner, K. J., . . . Tolle, T. R. (2008). The Runner's High: Opioidergic Mechanisms in the Human Brain. *Cerebral Cortex, 18*(11), 2523-2531. doi:10.1093/cercor/bhn013

Boesch, C., Crockford, C., Herbinger, I., Wittig, R., Moebius, Y., & Normand, E. (2008). Intergroup conflicts among chimpanzees in Taï National Park: lethal violence and the female perspective. *American Journal of Primatology, 70*(6), 519-532.

Bolger, N., & Amarel, D. (2007). Effects of social support visibility on adjustment to stress: experimental evidence. *Journal of Personality and Social Psychology, 92*(3), 458.

Bonferroni, C. (1936). Teoria statistica delle classi e calcolo delle probabilita. *Pubblicazioni del R Istituto Superiore di Scienze Economiche e Commericiali di Firenze, 8*, 3-62.

Boogert, N. J., Farine, D. R., & Spencer, K. A. (2014). Developmental stress predicts social network position. *Biology Letters, 10*(10), 20140561.

Borg, G. A. (1982). Psychophysical bases of perceived exertion. *Medicine & Science in Sports & Exercise, 14*(5), 377-381.

Bornstein, G., & Goldschmidt, C. (2008). Post-scoring behaviour and team success in football. In P. Anderson, P. Ayton, & C. Schmidt (Eds.), *Myths and Facts about Football: The*

*Economics and Psychology of the World's Greatest Sport* (pp. 113-123). Newcastle upon Tyne: Cambridge Scholars Publishing.

Boutcher, S. H., & Trenske, M. (1990). The effects of sensory deprivation and music on perceived exertion and affect during exercise. *Journal of Sport and Exercise Psychology, 12*(2), 167-176.

Bowlby, J. (1969). *Attachment*: Basic books.

Bowlby, J. (2008). *A secure base: Parent-child attachment and healthy human development*. New York: Basic Books.

Box, G. E. (1949). A general distribution theory for a class of likelihood criteria. *Biometrika, 36*(3/4), 317-346.

Bramble, D. M., & Lieberman, D. E. (2004). Endurance running and the evolution of Homo. *Nature, 432*(7015), 345-352. doi:10.1038/Nature03052

Bramble, D. M., Lieberman, D. E., & Daley, M. A. (2000). Mechanics of head-neck stabilization in running humans: implications for hominid evolution. *American Zoologist, 40*(6), 953-953.

Brent, L. J., Chang, S. W., Gariépy, J. F., & Platt, M. L. (2014). The neuroethology of friendship. *Annals of the New York Academy of Sciences, 1316*(1), 1-17.

Brown, J. L., Sheffield, D., Leary, M. R., & Robinson, M. E. (2003). Social support and experimental pain. *Psychosomatic Medicine, 65*(2), 276-283.

Brysbaert, M., & Stevens, M. (2018). Power analysis and effect size in mixed effects models: A tutorial. *Journal of Cognition, 1*(1).

Burke, S. M., Carron, A. V., & Shapcott, K. M. (2008). Cohesion in exercise groups: an overview. *International Review of Sport and Exercise Psychology, 1*(2), 107-123.

Bützer, T. L., Rinderknecht, M. D., Johannes, G. H., Popp, W. L., Lehner, R., Lambercy, O., & Gassert, R. (2016). Design and Evaluation of a Fiber-Optic Grip Force Sensor with Compliant 3D-Printable Structure for (f) MRI Applications. *Journal of Sensors*.

Cacioppo, J. T., Cacioppo, S., & Boomsma, D. I. (2014). Evolutionary mechanisms for loneliness. *Cognition & emotion, 28*(1), 3-21.

Cacioppo, S., Capitanio, J. P., & Cacioppo, J. T. (2014). Toward a neurology of loneliness. *Psychological Bulletin, 140*(6), 1464-1504.

Carmichael, M. D., Davis, M. J., Murphy, A. E., Brown, A. S., Carson, J. A., Mayer, E. P., & Ghaffar, A. (2006). Role of brain IL-1β on fatigue after exercise-induced muscle damage. *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology, 291*(5), R1344-R1348.

Carrier, D. R., Kapoor, A., Kimura, T., Nickels, M. K., Satwanti, Scott, E. C., . . . Trinkaus, E. (1984). The energetic paradox of human running and hominid evolution [and comments and reply]. *Current Anthropology*, 483-495.

Carron, A. V., Brawley, L. R., & Widmeyer, N. W. (1998). The measurement of cohesiveness in sport groups. In J. L. Duda (Ed.), *Advances in Sport and Exercise Psychology Measurement* Morgantown, WV: Fitness Information Technology (FIT).

Carron, A. V., Colman, M. M., Wheeler, J., & Stevens, D. (2002). Cohesion and performance in sport: a meta-analysis. *Journal of Sport and Exercise Psychology, 24*, 168-188.

Carron, A. V., Widmeyer, W. N., & Brawley, L. R. (1985). The development of an instrument to assess cohesion in sport teams: The Group Environment Questionnaire. *Journal of Sport Psychology, 7*(3), 244-266.

Carter, C. S., Grippo, A. J., Pournajafi-Nazarloo, H., Ruscio, M. G., & Porges, S. W. (2008). Oxytocin, vasopressin and sociality. *Progress in Brain Research, 170*, 331-336.

Chang, M. Y., Wang, S. Y., & Chen, C. H. (2002). Effects of massage on pain and anxiety during labour: a randomized controlled trial in Taiwan. *Journal of Advanced Nursing, 38*(1), 68-73.

Chiang, J. J., Eisenberger, N. I., Seeman, T. E., & Taylor, S. E. (2012). Negative and competitive social interactions are related to heightened proinflammatory cytokine activity. *Proceedings of the National Academy of Sciences, 109*(6), 1878-1882. doi:10.1073/pnas.1120972109

Chiang, J. J., Saphire-Bernstein, S., Kim, H. S., Sherman, D. K., & Taylor, S. E. (2012). Cultural differences in the link between supportive relationships and proinflammatory cytokines. *Social Psychological and Personality Science*, 1948550612467831.

Choi, J.-K., & Bowles, S. (2007). The Coevolution of Parochial Altruism and War. *Science, 318*(5850), 636-640. doi:10.1126/science.1144237

Christensen, U., Schmidt, L., Budtz-Jørgensen, E., & Avlund, K. (2006). Group cohesion and social support in exercise classes: Results from a Danish intervention study. *Health education & behavior, 33*(5), 677-689.

Coan, J. A., Kasle, S., Jackson, A., Schaefer, H. S., & Davidson, R. J. (2013). Mutuality and the social regulation of neural threat responding. *Attachment & human development, 15*(3), 303-315. doi:10.1080/14616734.2013.782656

Coan, J. A., Schaefer, H. S., & Davidson, R. J. (2006). Lending a Hand: Social Regulation of the Neural Response to Threat. *Psychological Science 17*(12), 1032-1039. doi:10.1111/j.1467-9280.2006.01832.x

Cohen, E. (2015). Group exercise and social bonding. In N. J. Enfield & P. Kockelman (Eds.), *Distributed Agency*. New York: Oxford University Press.

Cohen, E. (2017). Group exercise and social bonding. *Distributed Agency*, 141.

Cohen, E., Ejsmond-Frey, R., Knight, N., & Dunbar, R. (2010). Rowers' high: behavioural synchrony is correlated with elevated pain thresholds. *Biology Letters, 6*(1), 106-108. doi:10.1098/rsbl.2009.0670

Cohen, S., Janicki-Deverts, D., Turner, R. B., & Doyle, W. J. (2015). Does Hugging Provide Stress-Buffering Social Support? A Study of Susceptibility to Upper Respiratory Infection and Illness. *Psychological Science, 26*(2), 135-147. doi:10.1177/0956797614559284

Cohen, S., & Wills, T. A. (1985). Stress, social support, and the buffering hypothesis. *Psychological Bulletin, 98*(2), 310.

Cole, S., Balcetis, E., & Zhang, S. (2013). Visual perception and regulatory conflict: Motivation and physiology influence distance perception. *Journal of Experimental Psychology: General, 142*(1), 18.

Collins, N. L. (1996). Working models of attachment: Implications for explanation, emotion, and behavior. *Journal of Personality and Social Psychology, 71*(4), 810.

Collins, N. L., & Read, S. J. (1990). Adult attachment, working models, and relationship quality in dating couples. *Journal of Personality and Social Psychology, 58*(4), 644.

Colloca, L., & Benedetti, F. (2005). Placebos and painkillers: is mind as real as matter? *Nature Reviews Neuroscience, 6*(7), 545-552.

Colloca, L., Klinger, R., Flor, H., & Bingel, U. (2013). Placebo analgesia: psychological and neurobiological mechanisms. *PAIN, 154*(4), 511.

Cook, D., & Koltyn, K. (2000). Pain and exercise. *International Journal of Sport Psychology, 31*(2), 256-277.

Corbett, J., Barwood, M. J., Ouzounoglou, A., Thelwell, R., & Dicks, M. (2012). Influence of competition on performance and pacing during cycling exercise. *Medicine & Science in Sports & Exercise, 44*(3), 509-515.

Cosmides, L., & Tooby, J. (2000). Evolutionary Psychology and the Emotions. In M. Lewis, J. M. Haviland-Jones, & L. F. Barrett (Eds.), *Handbook of Emotions* (3rd ed.). New York: Guilford.

Courneya, K. S., & McAuley, E. (1995). Cognitive mediators of the social influence-exercise adherence relationship: A test of the theory of planned behavior. *Journal of Behavioral Medicine, 18*(5), 499-515.

Cribbie, R. A. (2007). Multiplicity control in structural equation modeling. *Structural Equation Modeling, 14*(1), 98-112.

Crockford, C., Wittig, R. M., Whitten, P. L., Seyfarth, R. M., & Cheney, D. L. (2008). Social stressors and coping mechanisms in wild female baboons (Papio hamadryas ursinus). *Hormones and Behavior, 53*(1), 254-265.

Croissant, Y., & Millo, G. (2008). Panel data econometrics in R: The plm package. *Journal of Statistical Software, 27*(2), 1-43.

D'Amato, F. R., & Pavone, F. (1996). Reunion of separated sibling mice: neurobiological and behavioral aspects. *Neurobiology of Learning and Memory, 65*(1), 9-16.

Datta, S. (1983). Relative power and the maintenance of rank. In R. A. Hinde (Ed.), *Primate Social Relationships* (pp. 103-112). Cambridge, UK: Cambridge University Press.

Davis, A., & Cohen, E. (2018). The Effects of Social Support on Strenuous Physical Exercise. *Adaptive Human Behavior and Physiology, 4*(2), 171-187.

Davis, A., Hettinga, F. J., & Beedie, C. (in press). Social and environmental factors: people as placebos. *European Journal of Sport Science*.

Davis, A., Taylor, J., & Cohen, E. (2015). Social Bonds and Exercise: Evidence for a Reciprocal Relationship. *Plos One, 10*(8), e0136705. doi:10.1371/journal.pone.0136705

Davis, A. J., Hettinga, F., & Beedie, C. (2019). You don't need to administer a placebo to elicit a placebo effect: Social factors trigger neurobiological pathways to enhance sports performance. *European Journal of Sport Science*, 1-11.

Davis, M. J., & Bailey, S. P. (1997). Possible mechanisms of central nervous system fatigue during exercise. *Medicine & Science in Sports & Exercise*(29), 45-57.

Davitz, J. R., & Mason, D. J. (1955). Socially facilitated reduction of a fear response in rats. *Journal of Comparative and Physiological Psychology, 48*(3), 149.

De Block, A., & Dewitte, S. (2009). Darwinism and the cultural evolution of sports. *Perspectives in biology and medicine, 52*(1), 1-16.

De Kloet, E. R., Joëls, M., & Holsboer, F. (2005). Stress and the brain: from adaptation to disease. *Nature reviews. Neuroscience, 6*(6), 463.

de Waal, F. B., & Suchak, M. (2010). Prosocial primates: selfish and unselfish motivations. *Philosophical Transactions of the Royal Society of London B: Biological Sciences, 365*(1553), 2711-2722.

Devanandan, M., Eccles, R. M., & Westerman, R. (1965). Single motor units of mammalian muscle. *The Journal of Physiology, 178*(2), 359-367.

Di Blasi, Z., Harkness, E., Ernst, E., Georgiou, A., & Kleijnen, J. (2001). Influence of context effects on health outcomes: a systematic review. *The Lancet, 357*(9258), 757-762.

Dietrich, A., & McDaniel, W. F. (2004). Endocannabinoids and exercise. *British Journal of Sports Medicine, 38*(5), 536-541. doi:Doi 10.1136/Bjsm.2004.011718

Dunbar, R., Launay, J., Wlodarski, R., Robertson, C., Pearce, E., Carney, J., & MacCarron, P. (2017). Functional benefits of (modest) alcohol consumption. *Adaptive Human Behavior and Physiology, 3*(2), 118-133.

Dunbar, R. I. M. (1980). Determinants and Evolutionary Consequences of Dominance among Female Gelada Baboons. *Behavioral Ecology and Sociobiology, 7*(4), 253-265. doi:10.2307/4599339

Dunbar, R. I. M. (2010). The social role of touch in humans and primates: Behavioural function and neurobiological mechanisms. *Neuroscience & Biobehavioral Reviews, 34*(2), 260-268. doi:http://dx.doi.org/10.1016/j.neubiorev.2008.07.001

Dunbar, R. I. M. (2012). Bridging the bonding gap: the transition from primates to humans. *Philosophical Transactions of the Royal Society B: Biological Sciences, 367*(1597), 1837-1846. doi:10.1098/rstb.2011.0217

Dunlop, B. W., Thase, M. E., Wun, C.-C., Fayyad, R., Guico-Pabia, C. J., Musgnung, J., & Ninan, P. T. (2012). A meta-analysis of factors impacting detection of antidepressant efficacy in clinical trials: the importance of academic sites. *Neuropsychopharmacology, 37*(13), 2830-2836.

Durkheim, E. m. (1912/1965). *The Elementary Forms of Religious Life* (J. W. Swain, Trans.). New York: Free Press.

Ebner, K., Bosch, O. J., Krömer, S. A., Singewald, N., & Neumann, I. D. (2005). Release of oxytocin in the rat central amygdala modulates stress-coping behavior and the release of excitatory amino acids. *Neuropsychopharmacology, 30*(2), 223-230.

Edgerton, R. B. (1989). *Like lions they fought: the Zulu War and the last black empire in South Africa*: Ballantine Books.

Eippert, F., Finsterbusch, J., Bingel, U., & Büchel, C. (2009). Direct evidence for spinal cord involvement in placebo analgesia. *Science, 326*(5951), 404-404.

Eisenberger, N. I. (2012a). The neural bases of social pain: evidence for shared representations with physical pain. *Psychosomatic medicine, 74*(2), 126.

Eisenberger, N. I. (2012b). The pain of social disconnection: examining the shared neural underpinnings of physical and social pain. *Nature Reviews Neuroscience, 13*(6), 421-434.

Eisenberger, N. I. (2013a). An empirical review of the neural underpinnings of receiving and giving social support: implications for health. *Psychosomatic medicine, 75*(6), 545-556.

Eisenberger, N. I. (2013b). Social ties and health: a social neuroscience perspective. *Current Opinion in Neurobiology, 23*(3), 407-413. doi:http://dx.doi.org/10.1016/j.conb.2013.01.006

Eisenberger, N. I. (2015). Social Pain and the Brain: Controversies, Questions, and Where to Go from Here. *Annual Review of Psychology, 66*, 601-629.

Eisenberger, N. I., Jarcho, J. M., Lieberman, M. D., & Naliboff, B. D. (2006). An experimental study of shared sensitivity to physical pain and social rejection. *PAIN, 126*(1), 132-138.

Eisenberger, N. I., & Lieberman, M. D. (2004). Why rejection hurts: a common neural alarm system for physical and social pain. *Trends in Cognitive Sciences, 8*(7), 294-300. doi:http://dx.doi.org/10.1016/j.tics.2004.05.010

Eisenberger, N. I., Lieberman, M. D., & Williams, K. D. (2003). Does Rejection Hurt? An fMRI Study of Social Exclusion. *Science, 302*(5643), 290-292. doi:10.1126/science.1089134

Eisenberger, N. I., Master, S. L., Inagaki, T. K., Taylor, S. E., Shirinyan, D., Lieberman, M. D., & Naliboff, B. D. (2011). Attachment figures activate a safety signal-related neural region and reduce pain experience. *Proceedings of the National Academy of Sciences of the United States of America, 108*(28), 11721-11726. doi:10.1073/pnas.1108239108

Eisenberger, N. I., Taylor, S. E., Gable, S. L., Hilmert, C. J., & Lieberman, M. D. (2007). Neural pathways link social support to attenuated neuroendocrine stress responses. *NeuroImage, 35*(4), 1601-1612. doi:10.1016/j.neuroimage.2007.01.038

Estabrooks, P. A. (2000). Sustaining exercise participation through group cohesion. *Exercise and Sport Sciences Reviews, 28*(2), 63-67.

Estabrooks, P. A., & Carron, A. V. (1999). Group cohesion in older adult exercisers: Prediction and intervention effects. *Journal of behavioral medicine, 22*(6), 575-588.

Evans, D. (2002). Pain, evolution, and the placebo response. *Behavioral and Brain Sciences, 25*(04), 459-460.

Evans, D. (2003). *Placebo: Mind over matter in modern medicine*. Oxford: Oxford University Press.

Falk, A., Fehr, E., & Fischbacher, U. (2008). Testing theories of fairness—Intentions matter. *Games and Economic Behavior, 62*(1), 287-303.

Fattore, L., Melis, M., Fadda, P., Pistis, M., & Fratta, W. (2010). The endocannabinoid system and nondrug rewarding behaviours. *Experimental Neurology, 224*(1), 23-36.

Fessler, D. M., & Holbrook, C. (2014). Marching into battle: synchronized walking diminishes the conceptualized formidability of an antagonist in men. *Biology Letters, 10*(8), 20140592.

Field, A., Miles, J., & Field, Z. (2012). *Discovering Statistics Using R*. London: Sage.

Field, T., Hemandez-Reif, M., Taylor, S., Quintino, O., & Burman, I. (1997). Labor pain is reduced by massage therapy. *Journal of Psychosomatic Obstetrics & Gynecology, 18*(4), 286-291.

Figueredo, A. J., Vásquez, G., Brumbach, B. H., Sefcek, J. A., Kirsner, B. R., & Jacobs, W. J. (2005). The K-factor: Individual differences in life history strategy. *Personality and Individual Differences, 39*(8), 1349-1360.

Filho, E., Dobersek, U., Gershgoren, L., Becker, B., & Tenenbaum, G. (2014). The cohesion–performance relationship in sport: a 10-year retrospective meta-analysis. *Sport Sciences for Health, 10*(3), 165-177. doi:10.1007/s11332-014-0188-7

Firth, R. (1959). *Economics of the New Zealand Maori*. Wellington, Nz.: R. E. Owen, Govt.Printer.

Fischer, R., Callander, R., Reddish, P., & Bulbulia, J. (2013). How do rituals affect cooperation? *Human Nature, 24*(2), 115-125.

Frankenhuis, W. E., Panchanathan, K., & Nettle, D. (2016). Cognition in harsh and unpredictable environments. *Current Opinion in Psychology, 7*, 76-80.

Fraser, S. N., & Spink, K. S. (2002). Examining the role of social support and group cohesion in exercise compliance. *Journal of behavioral medicine, 25*(3), 233-249.

Freeman, P., & Rees, T. (2008). The effects of perceived and received support on objective performance outcome. *European Journal of Sport Science, 8*(6), 359-368. doi:10.1080/17461390802261439

Freeman, P., & Rees, T. (2009). How does perceived support lead to better performance? An examination of potential mechanisms. *Journal of Applied Sport Psychology, 21*(4), 429-441.

Freeman, P., & Rees, T. (2010). Perceived social support from team-mates: Direct and stress-buffering effects on self-confidence. *European Journal of Sport Science, 10*(1), 59-67. doi:10.1080/17461390903049998

Friedson, S. M. (1996). *Dancing prophets: Musical experience in Tumbuka healing*: University of Chicago Press.

Fritz, T. H., Hardikar, S., Demoucron, M., Niessen, M., Demey, M., Giot, O., . . . Leman, M. (2013). Musical agency reduces perceived exertion during strenuous physical performance. *Proceedings of the National Academy of Sciences, 110*(44), 17784-17789. doi:10.1073/pnas.1217252110

Fuller, R. A., Irvine, K. N., Devine-Wright, P., Warren, P. H., & Gaston, K. J. (2007). Psychological benefits of greenspace increase with biodiversity. *Biology Letters, 3*(4), 390-394.

Galdino, G., Romero, T. R., Silva, J. F. P., Aguiar, D. C., de Paula, A. M., Cruz, J. S., . . . Di Marzo, V. (2014). The endocannabinoid system mediates aerobic exercise-induced antinociception in rats. *Neuropharmacology, 77*, 313-324.

Gearing, F. O. (1962). Priests And Warriors: Social Structures For Cherokee Politics In The 18Th Century *Memoir* (pp. viii, 124). [Menasha, Wis.]: American Anthropological Association.

Gilbert, W. H. (1978). Eastern Cherokees *Bulletin ; Anthropological Papers* (pp. 169-413). New York: AMS Press.

Glass, G. V., Peckham, P. D., & Sanders, J. R. (1972). Consequences of Failure to Meet Assumptions Underlying the Fixed Effects Analyses of Variance and Covariance. *Review of Educational Research, 42*(3), 237-288. doi:10.2307/1169991

Gleason, M., & Iida, M. (2015). Social support. *APA Handbooks in Psychology. APA handbook of personality and social psychology, 3*, 351-370.

Gleason, M. E., Iida, M., Bolger, N., & Shrout, P. E. (2003). Daily supportive equity in close relationships. *Personality and Social Psychology Bulletin, 29*(8), 1036-1045.

Goodwin, M. H. (2017). Haptic Sociality: The Embodied Interactive Constitution of Intimacy through Touch. In C. Meyer, J. Streeck, & J. S. Jordan (Eds.), *Intercorporeality: Emerging Socialities in Interaction*. Oxford, UK: Oxford University Press.

Gorka, S. M., Fitzgerald, D. A., de Wit, H., & Phan, K. L. (2015). Cannabinoid modulation of amygdala subregion functional connectivity to social signals of threat. *International Journal of Neuropsychopharmacology, 18*(3).

Gotaas, T. (2012). *Running: A Global History*. London: Reaktion Books.

Gould, D., Guinan, D., Greenleaf, C., Medbery, R., & Peterson, K. (1999). Factors affecting Olympic performance: Perceptions of athletes and coaches from more and less successful teams. *The Sport Psychologist, 13*(4), 371-394.

Gould, S. J., & Lewontin, R. C. (1979). The Spandrels of San Marco and the Panglossian Paradigm: A Critique of the Adaptationist Programme. *Proceedings of the Royal Society of London. Series B, Biological Sciences, 205*(1161), 581-598. doi:10.2307/77447

Gracia, A., Arsuaga, J. L., Martínez, I., Lorenzo, C., Carretero, J. M., de Castro, J. M. B., & Carbonell, E. (2009). Craniosynostosis in the Middle Pleistocene human cranium 14 from the Sima de los Huesos, Atapuerca, Spain. *Proceedings of the National Academy of Sciences, 106*(16), 6573-6578.

Green, P., & MacLeod, C. J. (2016). SIMR: an R package for power analysis of generalized linear mixed models by simulation. *Methods in Ecology and Evolution, 7*(4), 493-498.

Greer, F., McLean, C., & Graham, T. (1998). Caffeine, performance, and metabolism during repeated Wingate exercise tests. *Journal of Applied Physiology, 85*(4), 1502-1508.

Grinnell, G. B. (1889). *Pawnee Hero Stories And Folk-Tales, With Notes On The Origin, Customs And Character Of The Pawnee People*. New York: Forest and Stream Publishing Company.

Grove, J. R., & Prapavessis, H. (1992). Preliminary evidence for the reliability and validity of an abbreviated profile of mood states. *International Journal of Sport Psychology*.

Gumprecht, B. (2003). Stadium culture: College athletics and the making of place in the American college town. *Southeastern Geographer, 43*(1), 28-53.

Hagen, E., & Bryant, G. (2003a). Music and dance as a coalition signaling system. *HUman Nature, 14*(1), 21-51. doi:10.1007/s12110-003-1015-z

Hagen, E. H., & Bryant, G. A. (2003b). Music and dance as a coalition signaling system. *HUman Nature, 14*(1), 21-51.

Hamilton, W. D. (1964). The genetical evolution of social behaviour. II. *Journal of Theoretical Biology, 7*(1), 17-52. doi:http://dx.doi.org/10.1016/0022-5193(64)90039-6

Hashish, I., Hai, H. K., Harvey, W., Feinmann, C., & Harris, M. (1988). Reduction of postoperative pain and swelling by ultrasound treatment: a placebo effect. *PAIN, 33*(3), 303-311.

Hawkley, L. C., & Capitanio, J. P. (2015). Perceived social isolation, evolutionary fitness and health outcomes: a lifespan approach. *Phil. Trans. R. Soc. B, 370*(1669), 20140114.

Hawkley, L. C., Thisted, R. A., & Cacioppo, J. T. (2009). Loneliness predicts reduced physical activity: cross-sectional & longitudinal analyses. *Health Psychology, 28*(3), 354.

Hayes, A. F. (2013). *Introduction to Mediation, Moderation, and Conditional Process Analysis*. London: The Guilford Press.

Heinrichs, M., Baumgartner, T., Kirschbaum, C., & Ehlert, U. (2003). Social support and oxytocin interact to suppress cortisol and subjective responses to psychosocial stress. *Biological Psychiatry, 54*(12), 1389-1398.

Hennessy, M. B., Deak, T., & Schiml, P. A. (2014). Sociality and sickness: Have cytokines evolved to serve social functions beyond times of pathogen exposure? *Brain, Behavior, and Immunity, 37*(0), 15-20. doi:http://dx.doi.org/10.1016/j.bbi.2013.10.021

Hennessy, M. B., Kaiser, S., & Sachser, N. (2009). Social buffering of the stress response: diversity, mechanisms, and functions. *Frontiers in Neuroendocrinology, 30*(4), 470-482.

Hennessy, M. B., Mendoza, S. P., Mason, W. A., & Moberg, G. P. (1995). Endocrine sensitivity to novelty in squirrel monkeys and titi monkeys: species differences in characteristic modes of responding to the environment. *Physiology & Behavior, 57*(2), 331-338.

Henningsen, A. (2010). Estimating censored regression models in R using the censReg Package. *R package vignettes*.

Henrich, J. (2015). *The Secret of Our Success: How Culture Is Driving Human Evolution, Domesticating Our Species, and Making Us Smarter*. Princeton, NJ: Princeton University Press.

Hettinga, F. J., Konings, M. J., & Pepping, G.-J. (2017). The science of racing against opponents: Affordance competition and the regulation of exercise intensity in head-to-head competition. *Frontiers in Physiology, 8*, 118.

Hindley, D. (2018). “More Than Just a Run in the Park”: An Exploration of Parkrun as a Shared Leisure Space. *Leisure Sciences*. doi:10.1080/01490400.2017.1410741

Holmes, L. D. (1958). *Ta'U: Stability And Change In A Samoan Village*. The Polynesian Society, Inc.: Wellington, N.Z.

Holt-Lunstad, J., Birmingham, W., & Light, K. C. (2011). The influence of depressive symptomatology and perceived stress on plasma and salivary oxytocin before, during and after a support enhancement intervention. *Psychoneuroendocrinology, 36*(8), 1249-1256.

Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social relationships and mortality risk: a meta-analytic review. *PLoS medicine, 7*(7), e1000316.

Holt-Lunstad, J., & Uchino, B. (2008). Social Support and Health. In K. Glanz, B. K. Rimer, & K. Viswanath (Eds.), *Health behavior and health education: theory, research, and practice*: John Wiley & Sons.

Hrdy, S. B. (2007). Evolutionary Context of Human Development: The Cooperative Breeding Model. In C. A. Salmon & T. K. Shackelford (Eds.), *Family relationships: An evolutionary perspective* (pp. 39-68). New York: Oxford University Press.

Hruschka, D. J. (2010). *Friendship: Development, ecology, and evolution of a relationship* (Vol. 5): Univ of California Press.

Hublin, J.-J. (2009). The prehistory of compassion. *Proceedings of the National Academy of Sciences, 106*(16), 6429-6430.

Hughes, S., Jaremka, L. M., Alfano, C. M., Glaser, R., Povoski, S. P., Lipari, A. M., . . . Carson, W. E. (2014). Social support predicts inflammation, pain, and depressive symptoms: Longitudinal relationships among breast cancer survivors. *Psychoneuroendocrinology, 42*, 38-44.

Humphrey, N. (2002). Great expectations: The evolutionary psychology of faith-healing and the placebo effect. *Psychology at the turn of the millennium, 2*, 225-246.

Humphrey, N. (2013). Placebos at large: the power of society's symbols. *New Scientist*.

Humphrey, N., & Skoyles, J. (2012). The evolutionary psychology of healing: A human success story. *Current Biology, 22*(17), R695-R698. doi:10.1016/j.cub.2012.06.018

Hutchison, W. D., Davis, K. D., Lozano, A. M., Tasker, R. R., & Dostrovsky, J. O. (1999). Pain-related neurons in the human cingulate cortex. *Nature neuroscience, 2*(5), 403.

Iannetti, G. D., Salomons, T. V., Moayedi, M., Mouraux, A., & Davis, K. D. (2013). Beyond metaphor: contrasting mechanisms of social and physical pain. *Trends in Cognitive Sciences, 17*(8), 371-378.

Imai, K., Keele, L., & Yamamoto, T. (2010). Identification, inference and sensitivity analysis for causal mediation effects. *Statistical Science, 25*(1), 51-71.

Inagaki, T. K., & Eisenberger, N. I. (2013). Shared neural mechanisms underlying social warmth and physical warmth. *Psychological Science, 24*(11), 2272-2280.

Inagaki, T. K., Muscatell, K. A., Irwin, M. R., Moieni, M., Dutcher, J. M., Jevtic, I., . . . Eisenberger, N. I. (2015). The role of the ventral striatum in inflammatory-induced approach toward support figures. *Brain, Behavior, and Immunity*(0). doi:http://dx.doi.org/10.1016/j.bbi.2014.10.006

Inagaki, T. K., Ray, L. A., Irwin, M. R., Way, B. M., & Eisenberger, N. I. (2016). Opioids and social bonding: Naltrexone reduces feelings of social connection. *Social Cognitive and Affective Neuroscience, 11*(5), 728-735. doi:https://doi.org/10.1093/scan/nsw006

Ishak, W. W., Kahloon, M., & Fakhry, H. (2011). Oxytocin role in enhancing well-being: a literature review. *Journal of Affective Disorders, 130*(1), 1-9.

Jiang, H., & Eskridge, K. M. (2000). Bias in principal components analysis due to correlated observations.

John, O. P., & Srivastava, S. (1999). The Big Five trait taxonomy: History, measurement, and theoretical perspectives. *Handbook of Personality: Theory and Research, 2*(1999), 102-138.

Judge, T. A., Simon, L. S., Hurst, C., & Kelley, K. (2014). What I experienced yesterday is who I am today: Relationship of work motivations and behaviors to within-individual variation in the five-factor model of personality. *Journal of Applied Psychology, 99*(2), 199.

Julien, D., Brault, M., Chartrand, É., & Bégin, J. (2000). Immediacy behaviours and synchrony in satisfied and dissatisfied couples. *Canadian Journal of Behavioural Science/Revue canadienne des sciences du comportement, 32*(2), 84. doi:10.1037/h0087103

Junod, H. A. (1927a). Life Of A South African Tribe: Vol. 1. London: Macmillan and Co., Limited.

Junod, H. A. (1927b). *Life Of A South African Tribe: Vol. 2*. London: Macmillan and Co., Limited.

Kalasountas, V., Reed, J., & Fitzpatrick, J. (2007). The effect of placebo-induced changes in expectancies on maximal force production in college students. *Journal of Applied Sport Psychology, 19*(1), 116-124.

Kalin, N. H., & Shelton, S. E. (1989). Defensive behaviors in infant rhesus monkeys: environmental cues and neurochemical regulation. *Science, 243*(4899), 1718-1722.

Kaptchuk, T. J. (2002). The placebo effect in alternative medicine: can the performance of a healing ritual have clinical significance? *Annals of Internal Medicine, 136*(11), 817-825.

Kaptchuk, T. J. (2011). Placebo studies and ritual theory: a comparative analysis of Navajo, acupuncture and biomedical healing. *Philosophical Transactions of the Royal Society B: Biological Sciences, 366*(1572), 1849-1858. doi:10.1098/rstb.2010.0385

Kaptchuk, T. J., Kelley, J. M., Conboy, L. A., Davis, R. B., Kerr, C. E., Jacobson, E. E., . . . Nguyen, L. T. (2008). Components of placebo effect: randomised controlled trial in patients with irritable bowel syndrome. *BMJ, 336*(7651), 999-1003. doi:10.1136/bmj.39524.439618.25

Karremans, J. C., Heslenfeld, D. J., Van Dillen, L. F., & Van Lange, P. A. (2011). Secure attachment partners attenuate neural responses to social exclusion: An fMRI investigation. *International Journal of Psychophysiology, 81*(1), 44-50.

Kavanagh, D., & Hausfeld, S. (1986). Physical performance and self-efficacy under happy and sad moods. *Journal of Sport Psychology, 8*(2), 112-123.

Kelley, J. M., Kraft-Todd, G., Schapira, L., Kossowsky, J., & Riess, H. (2014). The influence of the patient-clinician relationship on healthcare outcomes: a systematic review and meta-analysis of randomized controlled trials. *Plos One, 9*(4), e94207. doi:10.1371/journal.pone.0094207

Kennell, J., Klaus, M., McGrath, S., Robertson, S., & Hinkley, C. (1991). Continuous emotional support during labor in a US hospital: a randomized controlled trial. *Jama, 265*(17), 2197-2201.

Kikusui, T., Winslow, J. T., & Mori, Y. (2006). Social buffering: relief from stress and anxiety. *Philosophical Transactions of the Royal Society B: Biological Sciences, 361*(1476), 2215-2228. doi:10.1098/rstb.2006.1941

Kinzler, K. D., Shutts, K., DeJesus, J., & Spelke, E. S. (2009). Accent Trumps Race in Guiding Children's Social Preferences. *Social Cognition, 27*(4), 623-634. doi:10.1521/soco.2009.27.4.623

Kirsch, I., & Sapirstein, G. (1998). Listening to Prozac but hearing placebo: A meta-analysis of antidepressant medication. *Prevention & Treatment, 1*(2), 2a.

Kirschner, S., & Tomasello, M. (2010). Joint music making promotes prosocial behavior in 4-year-old children. *Evolution and Human Behavior, 31*(5), 354-364. doi:http://dx.doi.org/10.1016/j.evolhumbehav.2010.04.004

Kiyokawa, Y., Kikusui, T., Takeuchi, Y., & Mori, Y. (2004). Partner's stress status influences social buffering effects in rats. *Behavioral Neuroscience, 118*(4), 798.

Klaus, M. H., Kennell, J. H., Robertson, S. S., & Sosa, R. (1986). Effects of social support during parturition on maternal and infant morbidity. *Br Med J (Clin Res Ed), 293*(6547), 585-587.

Kleiber, C., & Zeileis, A. (2009). AER: Applied Econometrics with R. R package version 1.1.

Konings, M. J., Schoenmakers, P. P., Walker, A. J., & Hettinga, F. J. (2016). The behavior of an opponent alters pacing decisions in 4-km cycling time trials. *Physiology & Behavior, 158*, 1-5.

Krahé, C., Springer, A., Weinman, J. A., & Fotopoulou, A. (2013). The social modulation of pain: others as predictive signals of salience–a systematic review. *Frontiers in Human Neuroscience, 7*.

Kraus, M. W., Huang, C., & Keltner, D. (2010). Tactile Communication, Cooperation, and Performance: an Ethological Study of the NBA. *Emotion, 10*(5), 745-749. doi:10.1037/a0019382

Kulik, J. A., & Mahler, H. I. (1989). Social Support and Recovery From Surgery. *Health Psychology, 8*(2), 221-238.

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2015). Package 'lmerTest'. *R package version, 2*(0).

Lakens, D., & Stel, M. (2011). If they move in sync, they must feel in sync: Movement synchrony leads to attributions of rapport and entitativity. *Social Cognition, 29*(1), 1-14. doi:10.1521/soco.2011.29.1.1

Lambert, E., Gibson, A. S. C., & Noakes, T. (2005). Complex systems model of fatigue: integrative homoeostatic control of peripheral physiological systems during exercise in humans. *British Journal of Sports Medicine, 39*(1), 52-62.

Lane, A., Soos, I., Leibinger, E., Karsai, I., & Hamar, P. (2005). Emotional intelligence, mood states and successful and unsuccessful performance. *Journal of Sports Sciences, 23*, 1254.

Lane, A. M., Devonport, T. J., Soos, I., Karsai, I., Leibinger, E., & Hamar, P. (2010). Emotional intelligence and emotions associated with optimal and dysfunctional athletic performance. *Journal of sports science & medicine, 9*(3), 388.

Lane, A. M., Terry, P. C., Beedie, C. J., Curry, D. A., & Clark, N. (2001). Mood and performance: test of a conceptual model with a focus on depressed mood. *Psychology of Sport and Exercise, 2*(3), 157-172. doi:http://dx.doi.org/10.1016/S1469-0292(01)00007-3

Lane, A. M., Wilson, M. G., Whyte, G. P., & Shave, R. (2011). Physiological correlates of emotion-regulation during prolonged cycling performance. *Applied Psychophysiology and Biofeedback, 36*(3), 181-184.

Lang, M., Bahna, V., Shaver, J. H., Reddish, P., & Xygalatas, D. (2017). Sync to link: Endorphin-mediated synchrony effects on cooperation. *Biological Psychology, 127*, 191-197.

Lardelli, D., Mauger, A., & Mealamu, K. (2007). Kapo o Pango explained: All Blacks.

Launay, J., Dean, R. T., & Bailes, F. (2013). Synchronization can influence trust following virtual interaction. *Experimental Psychology, 60*(1), 53.

Lazarus, R. S. (2000). How emotions influence performance in competitive sports. *The Sport Psychologist, 14*, 229-252.

Lazarus, R. S., & Folkman, S. (1984). *Stress, appraisal, and coping*. New York: Springer Publishing Company, Inc.

LeDoux, J. (1998). *The emotional brain*. London: Orion.

Lee, R. M., & Robbins, S. B. (1995). Measuring belongingness: The Social Connectedness and the Social Assurance Scales. *Journal of Counseling Psychology, 42*(2), 232-241.

Lenth, R., Love, J., & Hervé, M. (2018). Package emmeans.

Lepore, S. J. (1992). Social conflict, social support, and psychological distress: Evidence of cross-domain buffering effects. *Journal of Personality and Social Psychology, 63*(5), 857.

Li, N. P., van Vugt, M., & Colarelli, S. M. (2018). The evolutionary mismatch hypothesis: Implications for psychological science. *Current Directions in Psychological Science, 27*(1), 38-44.

Lieberman, D. E., Bramble, D. M., Raichlen, D. A., & Shea, J. J. (2007a). The evolution of endurance running and the tyranny of ethinography: A reply to Pickering and Bunn (2007). *Journal of Human Evolution, 53*(4), 439-442. doi:Doi 10.1016/J.Jhevol.2007.07.002

Lieberman, D. E., Bramble, D. M., Raichlen, D. A., & Shea, J. J. (2007b). The evolution of endurance running and the tyranny of ethnography: a reply to Pickering and Bunn (2007).

Lieberman, D. E., Bramble, D. M., Raichlen, D. A., & Shea, J. J. (2009). Brains, brawn, and the evolution of human endurance running capabilities *The First Humans–Origin and Early Evolution of the Genus Homo* (pp. 77-92): Springer.

Linden, W., Chambers, L., Maurice, J., & Lenz, J. W. (1993). Sex differences in social support, self-deception, hostility, and ambulatory cardiovascular activity. *Health Psychology, 12*(5), 376.

Lindsey, K. P., Glaser, S. T., & Gatley, S. J. (2005). Imaging of the brain cannabinoid system *Cannabinoids* (pp. 425-443): Springer.

Liu, H., & Yuan, T.-F. (2016). Physical Interaction Is Required in Social Buffering Induced by a Familiar Conspecific. *Scientific reports, 6*, 39788.

Long, S. J. (1997). *Regression models for categorical and limited dependent variables*. Thousand Oaks, CA.

Lordkipanidze, D., Vekua, A., Ferring, R., Rightmire, G. P., Agusti, J., Kiladze, G., . . . Tappen, M. (2005). Anthropology: the earliest toothless hominin skull. *Nature, 434*(7034), 717-718.

Lyby, P. S., Aslaksen, P. M., & Flaten, M. A. (2010). Is fear of pain related to placebo analgesia? *Journal of Psychosomatic Research, 68*(4), 369-377.

Lyons, D. M., Price, E. O., & Moberg, G. P. (1993). Social grouping tendencies and separation‐induced distress in juvenile sheep and goats. *Developmental Psychobiology: The Journal of the International Society for Developmental Psychobiology, 26*(5), 251-259.

Lyons, M., Caldwell, T., & Shultz, S. (2010). Mind-reading and manipulation—Is Machiavellianism related to theory of mind? *Journal of Evolutionary Psychology, 8*(3), 261-274.

Maas, C. J., & Hox, J. J. (2004). Robustness issues in multilevel regression analysis. *Statistica Neerlandica, 58*(2), 127-137.

Macdonald, G., & Kingsbury, R. (2006). Does physical pain augment anxious attachment? *Journal of Social and Personal Relationships, 23*(2), 291-304. doi:10.1177/0265407506062481

Machin, A. J., & Dunbar, R. I. (2011). The brain opioid theory of social attachment: a review of the evidence. *Behaviour, 148*(9-10), 9-10.

MacKinnon, D. P., Fairchild, A. J., & Fritz, M. S. (2007). Mediation analysis. *Annu. Rev. Psychol., 58*, 593-614.

Maganaris, C. N., Collins, D., & Sharp, M. (2000). Expectancy effects and strength training: do steroids make a difference? *Sport Psychologist, 14*(3), 272-278.

Marlowe, F. W. (2005). Hunter‐gatherers and human evolution. *Evolutionary Anthropology: Issues, News, and Reviews: Issues, News, and Reviews, 14*(2), 54-67.

Marshall, L. (1976). *!Kung Of Nyae Nyae*. Cambridge, Mass.: Harvard University Press.

Master, S. L., Eisenberger, N. I., Taylor, S. E., Naliboff, B. D., Shirinyan, D., & Lieberman, M. D. (2009). A Picture's Worth: Partner Photographs Reduce Experimentally Induced Pain. *Psychological Science, 20*(11), 1316-1318. doi:10.1111/j.1467-9280.2009.02444.x

McArdle, W. D., Katch, F. I., & Katch, V. L. (2010). *Exercise Physiology: Nutrition, Energy, and Human Performance*. Philadelphia: Lippincott Williams & Wilkins.

McBee, M. (2010). Modeling outcomes with floor or ceiling effects: An introduction to the Tobit model. *Gifted Child Quarterly, 54*(4), 314-320.

McCormick, A., Meijen, C., & Marcora, S. (2015). Psychological determinants of whole-body endurance performance. *Sports Medicine, 45*(7), 997-1015.

McNair, D. M. (1971). *Manual profile of mood states*: Educational & Industrial testing service.

McNeil, D. W., Kennedy, S., Randall, C., Addicks, S., Wright, C., Hursey, K., & Vaglienti, R. (2018). Fear of Pain Questionnaire‐9: Brief assessment of pain‐related fear and anxiety. *European Journal of Pain, 22*(1), 39-48.

McNeil, D. W., & Rainwater, A. J. (1998). Development of the fear of pain questionnaire-III. *Journal of Behavioral Medicine, 21*(4), 389-410.

McNeil, W. H. (1995). *Keeping together in time*. Cambridge, MA: Harvard University Press.
McPherron, S. P., Alemseged, Z., Marean, C. W., Wynn, J. G., Reed, D., Geraads, D., . . . Bearat, H. A. (2010). Evidence for stone-tool-assisted consumption of animal tissues before 3.39 million years ago at Dikika, Ethiopia. *Nature, 466*(7308), 857-860. doi:http://www.nature.com/nature/journal/v466/n7308/abs/nature09248.html#supplementary-information
McQuay, H., Carroll, D., & Moore, A. (1996). Variation in the placebo effect in randomised controlled trials of analgesics: all is as blind as it seems. *PAIN, 64*(2), 331-335.
Merskey, H., & Bogduk, N. (1994). *Classification of Chronic Pain, IASP Task Force on Taxonomy*. Seattle, WA: International Association for the Study of Pain Press.
Miller, G. (1999). *The Mating Mind*. New York: Doubleday.
Miller, G., Chen, E., & Cole, S. W. (2009). Health psychology: Developing biologically plausible models linking the social world and physical health. *Annual Review of Psychology, 60*, 501-524.
Mitford, B. (1883). *Through the Zulu Country: Its Battlefields and Its People*: Kegan Paul, Trench & Company.
Moerman, D. (2002). *Meaning, medicine and the 'placebo effect'*. Cambridge: Cambridge University Press.
Morrison, D. F. (1998). *Multivariate analysis, overview*: Wiley Online Library.
Nakagawa, S., & Schielzeth, H. (2013). A general and simple method for obtaining R2 from generalized linear mixed‐effects models. *Methods in Ecology and Evolution, 4*(2), 133-142.
Nangle, D. W., Erdley, C. A., Newman, J. E., Mason, C. A., & Carpenter, E. M. (2003). Popularity, Friendship Quantity, and Friendship Quality: Interactive Influences on Children's Loneliness and Depression. *Journal of Clinical Child & Adolescent Psychology, 32*(4), 546-555. doi:10.1207/S15374424JCCP3204_7
Nash, J. C. (1970). *In the Eyes of the Ancestors: Belief and Behavior in a Mayan Community*. New Haven, CT: Yale University Press.
Nieuwenhuis, R., te Grotenhuis, H., & Pelzer, B. (2012). Influence. ME: tools for detecting influential data in mixed effects models.
Noakes, T. D. (2012). Fatigue is a brain-derived emotion that regulates the exercise behavior to ensure the protection of whole body homeostasis. *Frontiers in Physiology, 3*(82), 1-13. doi:10.3389/fphys.2012.00082
Noakes, T. D., Gibson, A. S. C., & Lambert, E. V. (2005). From catastrophe to complexity: a novel model of integrative central neural regulation of effort and fatigue during exercise in humans: summary and conclusions. *British Journal of Sports Medicine, 39*(2), 120-124.
Numuendaju, C. (1979). *The Serente: Translated from the Manuscript by Robert H. Lowie*: AMS Press.
O'Connor, P. J., & Puetz, T. W. (2005). Chronic physical activity and feelings of energy and fatigue. *Medicine & Science in Sports & Exercise, 37*(2), 299-305.
Okun, M. A., Ruehlman, L., Karoly, P., Lutz, R., Fairholme, C., & Schaub, R. (2003). Social support and social norms: Do both contribute to predicting leisure-time exercise? *American Journal of Health Behavior, 27*(5), 493-507.
Ossipov, M. H., Dussor, G. O., & Porreca, F. (2010). Central modulation of pain. *The Journal of Clinical Investigation, 120*(11), 3779-3787. doi:10.1172/JCI43766
Page, A. E., Chaudhary, N., Viguier, S., Dyble, M., Thompson, J., Smith, D., . . . Migliano, A. B. (2017). Hunter-gatherer social networks and reproductive success. *Scientific Reports, 7*(1), 1153.
Panksepp, J. (2004). *Affective neuroscience: The foundations of human and animal emotions*: Oxford university press.
Panksepp, J., Bean, N. J., Bishop, P., Vilberg, T., & Sahley, T. L. (1980). Opioid blockade and social comfort in chicks. *Pharmacology Biochemistry and Behavior, 13*(5), 673-683.

Panksepp, J., Herman, B., Vilberg, T., Bishop, P., & DeEskinazi, F. (1981). Endogenous opioids and social behavior. *Neuroscience & Biobehavioral Reviews, 4*(4), 473-487.

Park, J., Kitayama, S., Karasawa, M., Curhan, K., Markus, H. R., Kawakami, N., . . . Ryff, C. D. (2013). Clarifying the links between social support and health: Culture, stress, and neuroticism matter. *Journal of Health Psychology, 18*(2), 226-235. doi:10.1177/1359105312439731

Pearce, E., Launay, J., & Dunbar, R. I. (2015). The ice-breaker effect: singing mediates fast social bonding. *Royal Society Open Science, 2*(10), 150221.

Peciña, M., Azhar, H., Love, T. M., Lu, T., Fredrickson, B. L., Stohler, C. S., & Zubieta, J.-K. (2013). Personality trait predictors of placebo analgesia and neurobiological correlates. *Neuropsychopharmacology, 38*(4), 639.

Petrovic, P., Kalso, E., Petersson, K. M., & Ingvar, M. (2002). Placebo and opioid analgesia--imaging a shared neuronal network. *Science, 295*(5560), 1737-1740.

Pinker, S. (2011). *The better angels of our nature: The decline of violence in history and its causes*: Penguin UK.

Pinker, S. (2019). *Enlightenment now: The case for reason, science, humanism, and progress*: Penguin Books.

Pollak, K. A., Swenson, J. D., Vanhaitsma, T. A., Hughen, R. W., Jo, D., Light, K. C., . . . Light, A. R. (2014). Exogenously applied muscle metabolites synergistically evoke sensations of muscle fatigue and pain in human subjects. *Experimental Physiology, 99*(2), 368-380. doi:10.1113/expphysiol.2013.075812

Pollo, A., Carlino, E., & Benedetti, F. (2008). The top-down influence of ergogenic placebos on muscle work and fatigue. *European Journal of Neuroscience, 28*(2), 379-388. doi:10.1111/j.1460-9568.2008.06344.x

Pollo, A., Carlino, E., & Benedetti, F. (2011). Placebo mechanisms across different conditions: from the clinical setting to physical performance. *Philosophical Transactions of the Royal Society of London B: Biological Sciences, 366*(1572), 1790-1798.

Power, E. A. (2017). Social support networks and religiosity in rural South India. *Nature Human Behaviour, 1*(3), 0057.

Putnam, R. D. (1995). Bowling alone: America's declining social capital. *Journal of Democracy, 6*(1), 65-78.

Quené, H., & Van den Bergh, H. (2004). On multi-level modeling of data from repeated measures designs: A tutorial. *Speech Communication, 43*(1), 103-121.

Radcliffe-Brown, A. R. (1922). *The Andaman Islanders*. New York: Free Press.

Raichlen, D. A., Foster, A. D., Gerdeman, G. L., Seillier, A., & Giuffrida, A. (2012). Wired to run: exercise-induced endocannabinoid signaling in humans and cursorial mammals with implications for the 'runner's high'. *Journal of Experimental Biology, 215*(8), 1331-1336. doi:Doi 10.1242/Jeb.063677

Raichlen, D. A., Foster, A. D., Seillier, A., Giuffrida, A., & Gerdeman, G. L. (2013). Exercise-induced endocannabinoid signaling is modulated by intensity. *European Journal of Applied Physiology, 113*(4), 869-875. doi:10.1007/s00421-012-2495-5

Raichlen, D. A., Keeney, B. K., Gerdeman, G., Meek, T. H., Wijeratne, R. S., & Garland, T. J. (2008). Wired to run? The evolution of novel locomotor behaviors in hominins. *American Journal of Physical Anthropology*, 176-177.

Rammstedt, B., & John, O. P. (2007). Measuring personality in one minute or less: A 10-item short version of the Big Five Inventory in English and German. *Journal of Research in Personality, 41*(1), 203-212. doi:10.1016/j.jrp.2006.02.001

Rathschlag, M., & Memmert, D. (2013). The influence of self-generated emotions on physical performance: an investigation of happiness, anger, anxiety, and sadness. *J Sport Exerc Psychol, 35*(2), 197-210.

Rathschlag, M., & Memmert, D. (2014). Self-Generated Emotions and Their Influence on Sprint Performance: An Investigation of Happiness and Anxiety. *Journal of Applied Sport Psychology*.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (Vol. 1): Sage.

Reddish, P., Bulbulia, J., & Fischer, R. (2013). Does synchrony promote generalized prosociality? *Religion, Brain & Behavior, 4*(1), 3-19. doi:10.1080/2153599X.2013.764545

Reddish, P., Fischer, R., & Bulbulia, J. (2013). Let's Dance Together: Synchrony, Shared Intentionality and Cooperation. *Plos One, 8*(8), e71182. doi:10.1371/journal.pone.0071182

Rees, T., & Freeman, P. (2010). Social support and performance in a golf-putting experiment. *Sport Psychologist, 24*(3), 333.

Rees, T., & Hardy, L. (2004). Matching social support with stressors: Effects on factors underlying performance in tennis. *Psychology of Sport and Exercise, 5*(3), 319-337.

Rees, T., Hardy, L., & Freeman, P. (2007). Stressors, social support, and effects upon performance in golf. *Journal of Sports Sciences, 25*(1), 33-42.

Richardson, J. D. (2000). Cannabinoids modulate pain by multiple mechanisms of action. *The Journal of Pain, 1*(1), 2-14.

Rittenhouse, M., Salvy, S.-J., & Barkley, J. E. (2011). The effect of peer influence on the amount of physical activity performed in 8-to 12-year-old boys. *Pediatric Exercise Science, 23*(1), 49-60.

Roberts, M. H., Klatzkin, R. R., & Mechlin, B. (2015). Social Support Attenuates Physiological Stress Responses and Experimental Pain Sensitivity to Cold Pressor Pain. *Annals of Behavioral Medicine, 49*(4), 557-569. doi:10.1007/s12160-015-9686-3

Robles, T. F., Slatcher, R. B., Trombello, J. M., & McGinn, M. M. (2014). Marital quality and health: A meta-analytic review. *Psychological Bulletin, 140*(1), 140.

Robson-Ansley, P. J., Milander, L. d., Collins, M., & Noakes, T. D. (2004). Acute Interleukin-6 Administration Impairs Athletic Performance in Healthy, Trained Male Runners. *Canadian Journal of Applied Physiology, 29*(4), 411-418. doi:10.1139/h04-026

Rubenstein, D. I. (1978). On predation, competition, and the advantages of group living *Social Behavior* (pp. 205-231): Springer.

Rucker, D. D., Preacher, K. J., Tormala, Z. L., & Petty, R. E. (2011). Mediation analysis in social psychology: Current practices and new recommendations. *Social and Personality Psychology Compass, 5*(6), 359-371.

Ryon, H., & Gleason, M. (2018). Reciprocal support and daily perceived control: Developing a better understanding of daily support transactions across a major life transition. *Journal of Personality and Social Psychology*.

Saltelli, A., Tarantola, S., Campolongo, F., & Ratto, M. (2004). Sensitivity analysis in practice: a guide to assessing scientific models. *Chichester, England*.

Samuni, L., Preis, A., Mundry, R., Deschner, T., Crockford, C., & Wittig, R. M. (2016). Oxytocin reactivity during intergroup conflict in wild chimpanzees. *Proceedings of the National Academy of Sciences*, 201616812.

Sanchez, M. M., Mccormack, K. M., & Howell, B. R. (2015). Social buffering of stress responses in nonhuman primates: Maternal regulation of the development of emotional regulatory brain circuits. *Social Neuroscience*, 1-15.

Sanders, C., & Vail, D. A. (2009). *Customizing the body: The art and culture of tattooing*: Temple University Press.

Sapolsky, R. M., Romero, L. M., & Munck, A. U. (2000). How do glucocorticoids influence stress responses? Integrating permissive, suppressive, stimulatory, and preparative actions. *Endocrine Reviews, 21*(1), 55-89.

Scheffer, J. (1704). The history of Lapland: containing a geographical description, and a natural history of that country; with an account of the inhabitants, their original, religion, customs, habits, marriages, conjurations, employments, etc. (pp. 24). London: Printed for Tho. Newborough, at the Golden-Ball in St. Paul's-Church-Yard:

And R. Parker under the Royal-Exchange.

Schiphof-Godart, L. S.-G., Roelands, B., & Hettinga, F. J. (2018). Drive in sports: How mental fatigue affects endurance performance. *Frontiers in Psychology, 9*, 1383.

Schnall, S., Harber, K. D., Stefanucci, J. K., & Proffitt, D. R. (2008). Social support and the perception of geographical slant. *Journal of Experimental Social Psychology, 44*(5), 1246-1255.

Schülke, O., Bhagavatula, J., Vigilant, L., & Ostner, J. (2010). Social bonds enhance reproductive success in male macaques. *Current Biology, 20*(24), 2207-2210.

Seco, G. V., García, M. A., García, M. P. F., & Rojas, P. E. L. (2013). Multilevel bootstrap analysis with assumptions violated. *Psicothema, 25*(4), 520-528.

Semaw, S., Rogers, M. J., Quade, J., Renne, P. R., Butler, R. F., Dominguez-Rodrigo, M., . . . Simpson, S. W. (2003). 2.6-Million-year-old stone tools and associated bones from OGS-6 and OGS-7, Gona, Afar, Ethiopia. *Journal of Human Evolution, 45*(2), 169-177.

Seyfarth, R. M., & Cheney, D. L. (2012). The Evolutionary Origins of Friendship. *Annual Review of Psychology, 63*(1), 153-177. doi:doi:10.1146/annurev-psych-120710-100337

Sgherza, A. L., Axen, K., Fain, R., Hoffman, R. S., Dunbar, C. C., & Haas, F. (2002). Effect of naloxone on perceived exertion and exercise capacity during maximal cycle ergometry. *Journal of Applied Physiology, 93*(6), 2023-2028.

Shariff, A. F., & Tracy, J. L. (2011). What Are Emotion Expressions For? *Current Directions in Psychological Science, 20*(6), 395-399. doi:10.1177/0963721411424739

Shintel, H., Cacioppo, J. T., & Nusbaum, H. (2006). *Accentuate the negative, eliminate the positive? Individual differences in attentional bias to positive and negative information.* Paper presented at the 47th Annual Meeting of the Psychomatic Society, Houston, TX.

Silk, J. B., Alberts, S. C., & Altmann, J. (2003). Social Bonds of Female Baboons Enhance Infant Survival. *Science, 302*(5648), 1231-1234. doi:10.1126/science.1088580

Silk, J. B., Beehner, J. C., Bergman, T. J., Crockford, C., Engh, A. L., Moscovice, L. R., . . . Cheney, D. L. (2010). Strong and consistent social bonds enhance the longevity of female baboons. *Current Biology, 20*(15), 1359-1361.

Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2011). False-positive psychology: Undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychological Science, 22*(11), 1359-1366.

Simpson, E. H. (1951). The interpretation of interaction in contingency tables. *Journal of the Royal Statistical Society: Series B (Methodological), 13*(2), 238-241.

Snijders, T. A. B., & Bosker, R. J. (2012). *Multilevel analysis: an introduction to basic and advanced multilevel modeling* (2nd ed.): Sage.

Somerville, L. H., Heatherton, T. F., & Kelley, W. M. (2006). Anterior cingulate cortex responds differentially to expectancy violation and social rejection. *Nature Neuroscience, 9*(8), 1007.

Spanier, G. B. (1976). Measuring dyadic adjustment: New scales for assessing the quality of marriage and similar dyads. *Journal of Marriage and the Family*, 15-28.

Sparling, P. B., Giuffrida, A., Piomelli, D., Rosskopf, L., & Dietrich, A. (2003). Exercise activates the endocannabinoid system. *Neuroreport, 14*(17), 2209-2211. doi:Doi 10.1097/01.Wnr.0000097048.56589.47

Spink, K. S., & Carron, A. V. (1994). Group cohesion effects in exercise classes. *Small Group Research, 25*(1), 26-42.

Stanley, D., Beedie, C., Lane, A., Friesen, A., & Devonport, T. (2012). Emotion regulation strategies used by runners prior to training and competition. *International Journal of Sport and Exercise Psychology, 10*(3), 159-171.

Stanton, M. E., Patterson, J. M., & Levine, S. (1985). Social influences on conditioned cortisol secretion in the squirrel monkey. *Psychoneuroendocrinology, 10*(2), 125-134.

Stein, D. J., Collins, M., Daniels, W., Noakes, T. D., & Zigmond, M. (2007). Mind and muscle: the cognitive-affective neuroscience of exercise. *CNS Spectrums, 12*(01), 19-22.

Steinkopf, L. (2015). The Signaling Theory of Symptoms An Evolutionary Explanation of the Placebo Effect. *Evolutionary Psychology, 13*(3), 1474704915600559.

Stevinson, C., & Hickson, M. (2013). Exploring the public health potential of a mass community participation event. *Journal of Public Health, 36*(2), 268-274.

Stevinson, C., Wiltshire, G., & Hickson, M. (2014). Facilitating Participation in Health-Enhancing Physical Activity: A Qualitative Study of parkrun. *International journal of behavioral medicine*, 1-8.

Sullivan, P., & Rickers, K. (2013). The effect of behavioral synchrony in groups of teammates and strangers. *International Journal of Sport and Exercise Psychology, 11*(3), 286-291. doi:10.1080/1612197X.2013.750139

Sullivan, P., Rickers, K., & Gammage, K. L. (2014). The Effect of Different Phases of Synchrony on Pain Threshold. *Group Dynamics: Theory, Research, and Practice, 18*(2), 122-128. doi:10.1037/gdn0000001

Tanaka, M., & Watanabe, Y. (2012). Supraspinal regulation of physical fatigue. *Neuroscience & Biobehavioral Reviews, 36*(1), 727-734.

Tarr, B., Launay, J., Benson, C., & Dunbar, R. I. (2017). Naltrexone Blocks Endorphins Released when Dancing in Synchrony. *Adaptive Human Behavior and Physiology, 3*(3), 241-254. doi:10.1007/s40750-017-0067-y

Tarr, B., Launay, J., Cohen, E., & Dunbar, R. (2015a). *Let's dance! The role of synchrony and exertion in social bonding during group movement*. Paper presented at the European Human Behaviour and Evolution Association Annual Conference, Helsinki, Finland.

Tarr, B., Launay, J., Cohen, E., & Dunbar, R. (2015b). Synchrony and exertion during dance independently raise pain threshold and encourage social bonding. *Biology Letters*.

Tarr, B., Launay, J., & Dunbar, R. (2016). Silent Disco: Dancing in synchrony leads to elevated pain thresholds and social closeness. *Evolution and Human Behavior*.

Thomas, S., Reading, J., & Shephard, R. J. (1992). Revision of the Physical Activity Readiness Questionnaire (PAR-Q). *Canadian Journal of Sport Sciences, 17*(4), 338-345.

Tingley, D., Yamamoto, T., Hirose, K., Keele, L., & Imai, K. (2014). Mediation: R package for causal mediation analysis.

Tobin, J. (1958). Estimation of relationships for limited dependent variables. *Econometrica: journal of the Econometric Society*, 24-36.

Tomasello, M. (2014). The ultra‐social animal. *European Journal of Social Psychology, 44*(3), 187-194.

Tomasello, M., Carpenter, M., Call, J., Behne, T., & Moll, H. (2005). Understanding and sharing intentions: The origins of cultural cognition. *Behavioral and Brain Sciences, 28*(05), 675-691. doi:doi:10.1017/S0140525X05000129

Tomasello, M., Melis, A. P., Tennie, C., Wyman, E., & Herrmann, E. (2012). Two Key Steps in the Evolution of Human Cooperation: The Interdependence Hypothesis. *Current Anthropology, 53*(6), 673-692. doi:10.1086/668207

Tomazini, F., Pasqua, L. A., Damasceno, M. V., Silva-Cavalcante, M. D., de Oliveira, F. R., Lima-Silva, A. E., & Bertuzzi, R. (2015). Head-to-head running race simulation alters pacing strategy, performance, and mood state. *Physiology & Behavior, 149*, 39-44.

Tooby, J., & Cosmides, L. (1990). The past explains the present: Emotional adaptations and the structure of ancestral environments. *Ethology and Sociobiology, 11*(4-5), 375-424.

Totterdell, P. (2000). Catching moods and hitting runs: mood linkage and subjective performance in professional sport teams. *Journal of Applied Psychology, 85*(6), 848.

Trezza, V., Baarendse, P. J., & Vanderschuren, L. J. (2010). The pleasures of play: pharmacological insights into social reward mechanisms. *Trends in Pharmacological Sciences, 31*(10), 463-469.

Trimmer, P. C., Marshall, J. A. R., Fromhage, L., McNamara, J. M., & Houston, A. I. (2013). Understanding the placebo effect from an evolutionary perspective. *Evolution and Human Behavior, 34*(1), 8-15. doi:10.1016/j.evolhumbehav.2012.07.004

Trinkaus, E., & Villotte, S. (2017). External auditory exostoses and hearing loss in the Shanidar 1 Neandertal. *Plos One, 12*(10), e0186684.

Trinkaus, E., & Zimmerman, M. (1982). Trauma among the Shanidar Neandertals. *American Journal of Physical Anthropology, 57*(1), 61-76.

Tsang, J.-A. (2006). The effects of helper intention on gratitude and indebtedness. *Motivation and Emotion, 30*(3), 198-204.

Turnbull, C. M. (1962). The forest people (pp. 120). New York: Simon and Schuster.
Turnbull, C. M. (1965). The Mbuti Pygmies: an ethnographic survey (pp. [p.263-a]). New York: American Museum of Natural History.
Tuttle, A. H., Tohyama, S., Ramsay, T., Kimmelman, J., Schweinhardt, P., Bennett, G. J., & Mogil, J. S. (2015). Increasing placebo responses over time in US clinical trials of neuropathic pain. *PAIN*. doi:10.1097/j.pain.0000000000000333
Uchida, Y., Kitayama, S., Mesquita, B., Reyes, J. A. S., & Morling, B. (2008). Is perceived emotional support beneficial? Well-being and health in independent and interdependent cultures. *Personality and Social Psychology Bulletin, 34*(6), 741-754.
Uchino, B. N. (2009). Understanding the links between social support and physical health: A life-span perspective with emphasis on the separability of perceived and received support. *Perspectives on Psychological Science, 4*(3), 236-255.
Valdesolo, P., Ouyang, J., & DeSteno, D. (2010). The rhythm of joint action: Synchrony promotes cooperative ability. *Journal of Experimental Social Psychology, 46*(4), 693-695. doi:http://dx.doi.org/10.1016/j.jesp.2010.03.004
van 't Veer, A. E., & Giner-Sorolla, R. (2016). Pre-registration in social psychology—A discussion and suggested template. *Journal of Experimental Social Psychology, 67*, 2-12.
Van Schaik, C. P. (1983). Why are diurnal primates living in groups? *Behaviour, 87*(1), 120-144.
Vase, L., Nørskov, K. N., Petersen, G. L., & Price, D. D. (2011). Patients' direct experiences as central elements of placebo analgesia. *Philosophical Transactions of the Royal Society B: Biological Sciences, 366*(1572), 1913-1921.
Wager, T. D., Atlas, L. Y., Lindquist, M. A., Roy, M., Woo, C.-W., & Kross, E. (2013). An fMRI-Based Neurologic Signature of Physical Pain. *New England Journal of Medicine, 368*(15), 1388-1397. doi:doi:10.1056/NEJMoa1204471
Wager, T. D., Rilling, J. K., Smith, E. E., Sokolik, A., Casey, K. L., Davidson, R. J., . . . Cohen, J. D. (2004). Placebo-induced changes in FMRI in the anticipation and experience of pain. *Science, 303*(5661), 1162-1167.
Wager, T. D., Scott, D. J., & Zubieta, J.-K. (2007). Placebo effects on human μ-opioid activity during pain. *Proceedings of the National Academy of Sciences of the United States of America, 104*(26), 11056-11061. doi:10.1073/pnas.0702413104
Walker, P. L. (2001). A bioarchaeological perspective on the history of violence. *Annual review of Anthropology, 30*(1), 573-596.
Wall, P. D. (1999). *Pain: The Science of Suffering*. London: Weidenfeld & Nicolson.
Wall, P. D., & Melzack, R. (2004). Textbook of pain: P3-P35.
Watts, D. P., & Mitani, J. C. (2001). Boundary patrols and intergroup encounters in wild chimpanzees. *Behaviour, 138*(3), 299-327.
Wei, D., Allsop, S., Tye, K., & Piomelli, D. (2017). Endocannabinoid signaling in the control of social behavior. *Trends in Neurosciences, 40*(7), 385-396.
Wei, D., Lee, D., Cox, C. D., Karsten, C. A., Peñagarikano, O., Geschwind, D. H., . . . Piomelli, D. (2015). Endocannabinoid signaling mediates oxytocin-driven social reward. *Proceedings of the National Academy of Sciences, 112*(45), 14084-14089.
Weinstein, D., Launay, J., Pearce, E., Dunbar, R. I., & Stewart, L. (2015). Group music performance causes elevated pain thresholds and social bonding in small and large groups of singers. *Evolution and Human Behavior*.
Weinstein, D., Launay, J., Pearce, E., Dunbar, R. I., & Stewart, L. (2016). Singing and social bonding: changes in connectivity and pain threshold as a function of group size. *Evolution and Human Behavior, 37*(2), 152-158.
Weller, A., & Feldman, R. (2003). Emotion regulation and touch in infants: the role of cholecystokinin and opioids. *Peptides, 24*(5), 779-788.
Whannel, G. (1995). Sport, national identities and the tale of Big Jack. *Critical Survey*, 158-164.
Wheatley, T., Kang, O., Parkinson, C., & Looser, C. E. (2012). From Mind Perception to Mental Connection: Synchrony as a Mechanism for Social Understanding. *Social and*

*Personality Psychology Compass, 6*(8), 589-606. doi:10.1111/j.1751-9004.2012.00450.x

Wilcox, R. R. (2012). *Introduction to Robust Estimation and Hypothesis Testing*. Cambridge, MA: Academic Press.

Wills, T. A., & Shinar, O. (2000). Measuring perceived and received social support. *Social support measurement and intervention: A guide for health and social scientists*, 86-135.

Wilson, M. G., Lane, A. M., Beedie, C. J., & Farooq, A. (2012). Influence of accurate and inaccurate 'split-time'feedback upon 10-mile time trial cycling performance. *European Journal of Applied Physiology, 112*(1), 231-236.

Wiltermuth, S. S., & Heath, C. (2009). Synchrony and Cooperation. *Psychological Science, 20*(1), 1-5. doi:Doi 10.1111/J.1467-9280.2008.02253.X

Wiltshire, G., Fullagar, S., & Stevinson, C. (2018). Exploring parkrun as a social context for collective health practices: running with and against the moral imperatives of health responsibilisation. *Sociology of Health & Illness, 40*(1), 3-17.

Winslow, J. T., Noble, P. L., Lyons, C. K., Sterk, S. M., & Insel, T. R. (2003). Rearing effects on cerebrospinal fluid oxytocin concentration and social buffering in rhesus monkeys. *Neuropsychopharmacology, 28*(5), 910-918.

Wittig, R. M., Crockford, C., Langergraber, K. E., & Zuberbühler, K. (2014). Triadic social interactions operate across time: a field experiment with wild chimpanzees. *Proceedings of the Royal Society B: Biological Sciences, 281*(1779), 20133155.

Wittig, R. M., Crockford, C., Lehmann, J., Whitten, P. L., Seyfarth, R. M., & Cheney, D. L. (2008). Focused grooming networks and stress alleviation in wild female baboons. *Hormones and Behavior, 54*(1), 170-177.

Wittig, R. M., Crockford, C., Weltring, A., Langergraber, K. E., Deschner, T., & Zuberbühler, K. (2016). Social support reduces stress hormone levels in wild chimpanzees across stressful events and everyday affiliations. *Nature Communications, 7*.

Woo, K. Y. (2012). Exploring the effects of pain and stress on wound healing. *Advances in Skin & Wound Care, 25*(1), 38-44.

Woodman, T. I. M., & Hardy, L. E. W. (2003). The relative impact of cognitive anxiety and self-confidence upon sport performance: a meta-analysis. *Journal of Sports Sciences, 21*(6), 443-457. doi:10.1080/0264041031000101809

Wu, X.-J., Schepartz, L. A., Liu, W., & Trinkaus, E. (2011). Antemortem trauma and survival in the late Middle Pleistocene human cranium from Maba, South China. *Proceedings of the National Academy of Sciences, 108*(49), 19558-19562.

Yeoman, S. (2015). Arizona Wildcats to stop pre-game haka. *The New Zealand Herald*. Retrieved from http://www.nzherald.co.nz/sport/news/article.cfm?c_id=4&objectid=11522837

Young, C., Majolo, B., Heistermann, M., Schülke, O., & Ostner, J. (2014). Responses to social and environmental stress are attenuated by strong male bonds in wild macaques. *Proceedings of the National Academy of Sciences, 111*(51), 18195-18200.

Zimet, G. D., Dahlem, N. W., Zimet, S. G., & Farley, G. K. (1988). The Multidimensional Scale of Perceived Social Support. *Journal of Personality Assessment, 52*(1), 30-41.

Zubieta, J.-K., Bueller, J. A., Jackson, L. R., Scott, D. J., Xu, Y., Koeppe, R. A., . . . Stohler, C. S. (2005). Placebo effects mediated by endogenous opioid activity on μ-opioid receptors. *The Journal of Neuroscience, 25*(34), 7754-7762.

Zupan, M. F., Arata, A. W., Dawson, L. H., Wile, A. L., Payn, T. L., & Hannon, M. E. (2009). Wingate anaerobic test peak power and anaerobic capacity classifications for men and women intercollegiate athletes. *The Journal of Strength & Conditioning Research, 23*(9), 2598-2604.