Investigating the cognitive characteristics of positive mental health and resilience



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Abstract

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Mental health is distinct to emotional vulnerability, and can be characterised by wellbeing and functioning well in life. Cognitive-affective approaches have been widely used to investigate emotional vulnerability, however, research investigating the cognitive characteristics of mental health and resilience is in its infancy. Research in this thesis examined emotional information processing biases in positive mental health. Chapters Two and Three present cross-sectional data that support the continued exploration of the role of emotional cognitive biases in mental health. Chapter Two found associations between positive attention biases and psychological flexibility, and between the recognition of facially expressed emotions and mental health. Chapter Three found that the interrelationships amongst biases in attention, interpretation, and memory differed between high mental health and low mental health samples of adolescents. In Chapters Four and Five, attention bias modification was used to train attention bias towards positive information and away from negative information. Training-induced shifts in attentional bias were found to associate with positive emotions and happiness 12 weeks later in Chapter Four, but not in the replication and extension in Chapter Five. In Chapter Six a cognitive model of psychological resilience is introduced to draw together the largely disparate fields of emotional information-processing in emotional vulnerability, and resilience approaches. Chapter Seven was a proof-of-principle study of one hypothesis drawn from the cognitive model outlined in Chapter Six. Data from a novel attention bias alignment assessment task supported the hypothesis that individuals are capable of aligning attentional bias to threat as a function of whether displaying such a bias is adaptive or maladaptive in the current context. The studies in this thesis contribute to the understanding of emotional information-processing in mental health and resilience. Future studies investigating the adaptive directing of cognitive biases in differing contexts may be especially useful moving forward.

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Declaration

This thesis comprises work conducted by Sam Parsons for the degree of Doctor of Philosophy from the University of Oxford. Sam Parsons has contributed significantly to the design, recruitment, and data collection of the work contributing to each Chapter in this thesis. Sam Parsons has led all of the work included in this thesis. Several Chapters contain content that is published (Chapter Six) or currently under review (Chapters Three and Four) in peer-reviewed journals, but these Chapters have been edited and formatted for this thesis. Below each Chapter with co-authors is described in more depth.

Chapter Three. Recruitment and data collection for Chapter Three was completed as part of the CogBIAS longitudinal project. Sam has assisted with study design and data collection for the duration of this project. Chapter Three presents a subset of the complete data-set; the conception of the data analysis and narrative in this Chapter was led by Sam Parsons. The study reported in this Chapter has been submitted for publication in Clinical Psychological Science. Prof. Fox, Charlotte Booth, and Annabel Songco are co-authors on this paper and provided feedback on the manuscript prepared for publication. The material has been revised and reformatted for this thesis.

Chapter Four. Chapter Four presents a study that has been submitted and is currently under review for publication in Emotion. Both supervisors (Prof. Fox and Dr. Kruijt) are co-authors on this paper. The study conception, data collection, data analysis, and drafting of the manuscript were led by Sam and the material has been revised and reformatted for this thesis.

Chapter Six. Chapter Six presents revised and reformatted material from "A cognitive model of Psychological Resilience" published in the Journal of Experimental Psychopathology. Sam is the first author on this paper, and it was co-authored by both supervisors (Prof. Fox and Dr. Kruijt). The material has been reformatted and reworked for inclusion in this thesis.

Chapter Seven. Recruitment and data collection for Chapter Seven was completed at the University of Western Australia in Perth, Western Australia. Sam was situated in Perth for the duration of these stages and worked with Matthew Herbert on these stages. This data is currently in preparation for publication and Sam will be an author on this paper. For the purposes of this thesis, Sam has performed separate analyses of the data collected and this Chapter has been edited and formatted for this thesis.

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Chapter 1

1

Introduction

The severe impact of emotion vulnerability

Improving mental health is crucial for many individuals, families, and society as a whole to thrive. In England alone, it has been estimated that over 16 million people suffer from a disorder each year with an estimated yearly cost of over £77 billion (Sainsbury Centre for Mental Health, 2003). The World Health Organisation states that "Depression is the leading cause of disability worldwide, and is a major contributor to the overall global burden of disease" (WHO, 2017). The mental health research charity, MQ, estimates that 75% of people with a mental health condition start developing it before the age of 18, yet only a tiny proportion of the national research budget is spent on mental health issues in young people ("The MQ manifesto for young people's mental health," 2016).

In the face of this crisis, a commendable body of research has been conducted examining the mechanisms of emotional disorders, such as anxiety and depression. Working in tandem with clinical practitioners, great progress has been made in our understanding and treatment of emotional vulnerability. For example, Cognitive Behavioural Therapy (CBT) has been shown to be an effective treatment as a stand-alone intervention or as an addition to pharmaceutical approaches (Aaron T Beck & Dozois, 2011), though there is significant room for improvement of response and remission rates (for overviews of CBT efficacy see

Driessen & Hollon, 2010; Hofmann, Asnaani, Vonk, Sawyer, & Fang, 2012). However, given the scope of the problem of emotional vulnerability, a substantially greater investment is necessary in order to improve current treatments and to help alleviate the burden of emotional disorders on the individual, and society.

Positive Psychology

Positive psychology centres on examining and developing the patterns of psychological strengths and protective factors associated with wellbeing and has heralded a distinct approach to explaining and treating emotional vulnerability (e.g. Csikszentmihalyi, 2014; Seligman, 2011; Seligman & Csikszentmihalyi, 2000). The increasing focus on wellbeing in research and policy is further reflected in the World Health Organisation definition of mental health as "a state of well-being in which the individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community" (WHO, 2004, p.12). It is encouraging that focus has transitioned from an almost exclusive focus on emotional vulnerability to include an investigation of psychological strengths and wellbeing. However, these two bodies of literature have remained largely independent (Huta & Hawley, 2010), and only relatively recently has a combined approach to complete mental health been proposed, comprising wellbeing and mental illness as two discrete, albeit related, constructs emerged (Keyes, 2002; 2005a; 2007).

A singular focus on alleviating emotional distress and treating mental illness is unlikely to improve positive mental health and build individuals towards flourishing in life. As such, work is needed to examine the mechanisms that promote and protect mental health. The purpose of this thesis is to examine the cognitive components of mental health and resilience within an emotional information-processing framework. The work presented here in this

thesis is amongst the first to draw together these previously disparate research streams. The following sections introduce the fundamental theoretical frameworks underpinning the research in this thesis. First, positive mental health and resilience approaches are discussed to demonstrate the importance of investigating positive mental health as something beneficial of itself. Next, the emotional information-processing approach is introduced to highlight how this approach and associated methodologies have been used to investigate emotional vulnerability. Finally, this Chapter outlines the research undertaken in this thesis that integrates these approaches.

Positive mental health

Mental health has been characterised as a syndrome of symptoms of positive feeling and positive functioning in life (Keyes, 2002). Keyes operationalises mental health as a combination of emotional, psychological, and social wellbeing. Emotional wellbeing is comprised of feelings of happiness, interest in life, and life satisfaction. Psychological wellbeing is comprised of aspects of self-acceptance, mastery, positive relations, personal growth, autonomy, and purpose in life. Social wellbeing is comprised of social contribution, social integration, social actualization, social acceptance, and social coherence. Keyes' "Dual Continua" model of mental health and mental illness (Keyes, 2005a) challenges the assumption that the absence of mental illness equates to mental health. Instead, this model characterises mental health and mental illness as two separate, albeit negatively correlated, dimensions. Support for the dual model comes from confirmatory factor analyses conducted on data from large-scale population studies - the Midlife in the United States (MIDUS; Keyes, 2005a) and the 2008 Health and Wellbeing Survey sample of Canadian students (Peter, Roberts, & Dengate, 2011). Both analyses support the hypothesis that mental health and emotional vulnerability comprise two distinct factors. One of the central findings of

Keyes' initial study (2002) was that individuals with low mental health (but no mental illness) reported comparable real-world functionality and psychosocial impairment (e.g. poorer emotional health, more days lost at work etc.) to mentally ill individuals (depressed, but with average mental health). This pivotal finding demonstrates the dualism between positive mental health and emotional vulnerability. Even without a mental illness diagnosis, an individual can be functioning poorly in life.

Further evidence for a dual continua model of mental health and mental illness can be drawn from two additional lines of research. First, Huta and Hawley (2010) examined self-reported character strengths and cognitive vulnerabilities (dysfunctional attitudes) in a student sample and a clinically depressed sample (n = 241 and 54 respectively). Strengths were found to have a stronger and more consistent relationship with positive well-being, and cognitive vulnerabilities had a stronger relationship with ill-being. Perhaps most importantly, strengths were found to negate the adverse effects of vulnerabilities. In the depressed sample, higher self-reported strengths during active depression, prospectively predicted greater improvement in depression post-treatment (group CBT), whereas vulnerabilities had no such relationship. The evidence supports a position in which strengths and vulnerabilities are not merely opposites and instead serve as discrete contributors to overall wellbeing. Second, Ryff and colleagues (2006) examined the relationship between well-being (positive relations, positive affect) and ill-being (negative affect, depressive symptomology) with a range of biological markers (ten in total, including cortisol, norepinephrine, blood pressure, etc.). Only two of these biomarkers were associated with a measure of both well-being and ill-being, whereas seven biomarkers in total were associated with either well-being or ill-being only. The authors argue that the data further support the hypothesis of well-being and ill-being being associated with distinct patterns of biology. Measures of well-being were found to have a more pervasive and distinct biological signature. Together, these studies demonstrate the

importance of a dual complementary approach to mental health and mental illness as modelled by Keyes dual continua model (Keyes, 2002, 2005a).

Flourishing

Conceptualising mental illness or emotional vulnerability as distinct from positive mental health could be considered a purely hypothetical exercise without an examination of the separate implications each has on the individual. It is therefore important to consider flourishing mental health. Flourishing mental health is the pinnacle of positive mental health; a desirable state that epitomises functioning well in life and high levels of wellbeing. Mirroring DSM-IV classification criteria for major depression, Keyes proposes that a categorisation of flourishing mental health can be made if individuals meet clearly defined criteria across emotional, psychological, and social wellbeing; along with no diagnosis of mental illness (Keyes, 2002, 2005a, 2005b). Flourishing individuals have been found to have the best psychosocial outcomes overall (e.g. better emotional health, less days lost at work etc.). On the other hand, individuals with a comorbid diagnosis of mental illness and low mental health reported the poorest psychosocial outcomes overall and were significantly worse than languishing or mental illness alone. Further, another study reporting data from the MIDUS study reported that flourishing individuals reported the greatest productivity and lowest healthcare use and conversely fully mentally ill individuals reported the lowest productivity, greatest workdays lost and greatest healthcare use (Keyes & Grzywacz, 2005).

The benefits of flourishing mental health reach beyond psychosocial functioning and into life expectancy. Keyes and Simoes (2012) explored individuals' mental health status in 1995 as a predictor of all-cause mortality in 2005, using the 10 years follow-up data from the MIDUS study. A hundred-and-one participants enrolled at baseline passed away during the initial 10 years of the study (6.3% of n=3032). The likelihood of mortality was increased by

as much as 62% for those classified at baseline as non-flourishers compared to flourishers, even after adjusting for other known causes of death (Age, gender, race, education, smoking, physical inactivity, cardiovascular disease, and HIV/AIDS). Therefore, pursuing positive mental health appears to be integral for increased longevity. Analyses of the second decade follow-up data of the MIDUS study found that improvements in mental health between 1995 and 2005 predicted declines in mental illness, whereas losses of mental health predicted increases in mental illness (Keyes, Dhingra, & Simoes, 2010). Relative to individuals who maintained flourishing, people who became languishing or stayed languishing were more than 7 times as likely to have developed a mental illness.

Together, the research presented here support Keyes' (2007) proposition that anything short of flourishing mental health is associated with increased burdens to self (disease, psychological functioning etc.) and society (e.g. work days missed, health care utilization). This is particularly damning when we consider that flourishing individuals are in the minority with a mere 17% prevalence in the MIDUS sample. Approaching mental illness purely from a model of treatment and reduction of vulnerability overlooks the beneficial effects of the promotion and protection of mental health. It is essential that research and practice takes into consideration the beneficial consequences of flourishing mental health, in addition to the burden of mental illness.

Psychological resilience

Early understanding of the concept of resilience was influenced by a pioneering research programme called 'Project Competence' (Garmezy, Masten, & Tellegen, 1984; Masten & Tellegen, 2012). The results of Project Competence revealed a key set of personal attributes that promoted resilience in childhood that involved the enhancement of a sense of personal agency or self-efficacy (Garmezy et al., 1984). Being able to focus attention, avoid

distraction, rapidly shift mental set, and challenge negative thoughts and ideas in a reflective way were generally found to be critical for the development of personal agency and coping well in a complex world. It was concluded that deficits in these cognitive functions, induced by early social deprivation, prevented people from capitalizing on life opportunities

Psychological resilience is a dynamic process in which individuals show adaptive functioning and recovery following adversity or trauma (Luthar, Cicchetti, & Becker, 2000), and is an important factor in promoting positive mental health. Resilience has been previously described as; positive outcomes despite adversity, continued positive or effective functioning in adversity, and recovery after trauma (Schoon, 2006). Schoon asserts that resilience is a two-way construct between exposure to adversity and successful adaptation. As such, for an individual to display resilience there must be some risk factor that would predict poorer outcomes. For example; socio-economic disadvantage, significant trauma, disability predict poorer outcomes overall in wellbeing and functioning. Carver (1998) describes four potential outcomes following an adverse event; Succumbing, in which individuals' continue in a downward spiral of dysfunction; Survival with impairment, such that individuals recover some functioning following adversity but do not return to their level of functioning prior to the event; Recovery (resilience), in which individuals regain their baseline functioning following adversity; and Thriving, in which individuals' functioning is improved following adversity. It is important to note that there is debate around conceptualising resilience. Some define resilience as having relatively good or normal outcomes despite adversity (e.g. Carver, 1998), whereas others view resilience as the ability to bounce back, recover, and grow from difficult conditions (Truffino, 2010). Importantly, resilience should not be considered as invulnerability or immunity to stress and adversity, but rather as an adaptive process requiring modification as new risks and/or strengths emerge within changing life

circumstances allowing an individual to successfully adapt to changing circumstances, stress and trauma (Carver, 1998).

Many of the themes emerging in the developmental literature have also been reflected in adult research especially in the pioneering work of George Bonanno (Bonanno, 2004). Investigating reactions to major life trauma such as death of a spouse or being part of a major natural disaster or terrorist attack reveals that multiple pathways to resilience are also apparent in adulthood and that resilience is actually much more normative than might be expected (e.g. Masten, 2001). While this latter point has recently been debated (Galatzer-Levy & Bonanno, 2016; Infurna & Luthar, 2016a, 2016b), a large body of research demonstrates that certain personal attributes, such as self-enhancement, are important for the expression of resilience in adulthood (Bonanno, 2004).

Regardless of whether resilience is conceptualised as a process by which individuals exhibit relatively normative outcomes in spite of adversity, the process of recovery from said adversity, or the building of strengths and thriving in the face of adversity; resilience appears to buffer mental health and provide groundwork for flourishing in life. For instance, one conceptualisation describes resilience as counteracting emotional vulnerability as growth and a predictor of positive outcomes despite adversity, comprising all aspects of personal competence; emotional, cognitive, and social (Truffino, 2010). These areas of personal competence closely match Keyes' description of flourishing mental health (2002, 2005a) and suggest that psychological resilience could be an important underlying factor in flourishing. An individual must first recover from stress or trauma and subsequently build the resources to meet similar adverse circumstances in the future in order to ultimately flourish.

Promoting positive approaches

In this section, mental health and resilience approaches have been introduced as distinct to an emotional vulnerability framework. Research has been presented making a case for a conceptual distinction between positive mental health and emotional vulnerability. Further to this, the role of resilience in adapting to adversity and providing the groundwork for flourishing has also been expanded upon. Research which investigates the cognitive processes underlying mental health and resilience is still in its infancy. Therefore, in the following section, cognitive approaches to emotional vulnerability are introduced alongside an overview of the cognitive tasks used in this thesis.

Cognitive-affective mechanisms in emotion vulnerability

Cognitive models of emotion vulnerability (Aaron T Beck, 1967, 1979) propose that the dysfunctional patterns of emotional experience observed in emotion disorders, such as depression and anxiety, result from maladaptive patterns of emotional information-processing (Mathews & MacLeod, 1994, 2005; Williams, Watts, MacLeod, & Mathews, 1988). There is a wealth of research examining the role of biased emotional information-processing in the etiology, development, and maintenance of emotional psychopathology (for reviews, see Cisler & Koster, 2010; Gotlib & Joormann, 2010; Yiend, 2010). It is thought that investigating these processes may elucidate the underlying mechanisms of emotion dysfunction, and enable the development of novel cognitive therapies, such as cognitive bias modification interventions that target these dysfunctional processing styles (Colin MacLeod & Holmes, 2012).

In the following sections, the emotional information-processing approach is discussed to lay the foundations for the investigations of the role of cognitive biases in positive mental health presented throughout this thesis. First, the role that specific cognitive biases play in

emotional vulnerability is discussed. Second, an overview is given of the combined cognitive bias hypothesis, which proposed that the relationships and interactions amongst cognitive biases are important in emotional vulnerability. Finally, cognitive bias modification procedures are briefly discussed as powerful experimental methodologies to examine the causal role of cognitive biases in emotional vulnerability.

Cognitive biases and emotional vulnerability

The studies in this thesis used a range of cognitive bias tasks that have previously been used to examine emotional vulnerability. Here, three areas of cognitive bias are introduced; attention bias, emotion recognition bias, and memory bias. Each Chapter provides a more in-depth discussion of the biases assessed; therefore the present aim is to highlight prior research demonstrating the role of cognitive biases in emotional vulnerability. Figure 1.1 highlights the cognitive biases that are assessed in each Chapter.

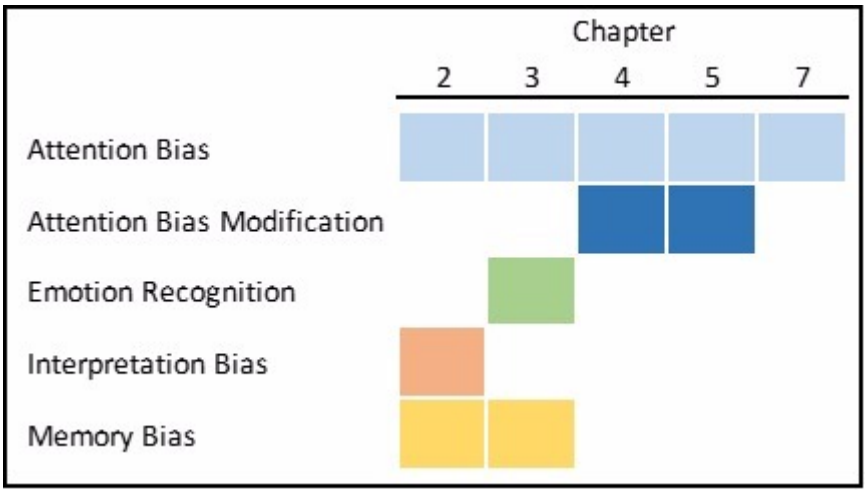


Figure 1.1. The cognitive biases assessed in each Chapter of this thesis.

Attention bias refers to the process of allocating additional resources towards certain stimuli to allow for additional processing, at the expense of other stimuli in the environment. For example, automatically allocating resources to be vigilant to threatening information.

Emotional or arousing stimuli in particular draw attentional resources, and therefore, stimuli with greater emotional significance would be predicted to draw and hold attention more than stimuli of lesser emotional significance. A number of tasks and experimental paradigms have been utilised to examine attention bias, including; the emotional stroop task, the dot-probe task, the visual search task, and the spatial cueing task (Cisler & Koster, 2010). The fact that attentional bias has been observed across numerous tasks suggests that attentional bias is not an artefact of a particular experimental procedure.

The emotional dot-probe task (Colin MacLeod, Mathews, & Tata, 1986), is used in several of the studies in this thesis and the use of the dot probe methodology has grown exponentially over the last decade (see Kruijt, Field, & Fox, 2016, supplemental figure 1). In the task, two stimuli (words or images) are presented on a computer screen, one in the top half and the other in the bottom half (the stimuli may alternatively be presented on the left and the right of the screen). Typically, one item will be neutral and the other will be emotionally salient (e.g. threat-related). Following a brief presentation (e.g. 500ms) the stimuli are removed and a probe is presented in the location previously occupied by one of the stimuli. Participants are tasked to respond to the probe as quickly as possible. It is assumed that faster responses will be made to probes in the location of previously attended stimuli due to the additional time required to shift attention towards the previously unattended location. Systematic allocation of attention to emotional stimuli is therefore highlighted by shorter response latencies in emotion-congruent trials (probes appear in the same location as emotional items) than emotion-incongruent trials (probes appear in the opposite location to emotional items).

The emotional dot-probe is perhaps the most widely used attention bias task, and has been used extensively to examine threat-related attentional biases thought to characterise

anxiety (Cisler & Koster, 2010). For example, selective attention to threatening stimuli has been shown to causally contribute towards anxiety responses to laboratory induced (Colin MacLeod, Rutherford, Campbell, Ebsworthy, & Holker, 2002) and naturally occurring stress (Clarke, Macleod, & Shirazee, 2008). Additionally, attentional biases towards threat-related images have been shown to be associated with enhanced physiological responses (cortisol reactivity) to a laboratory stress task up to eight months later (Fox, Cahill, & Zougkou, 2010). Although one meta-analysis reports some evidence for negative attentional biases in depression (Peckham, Mchugh, & Otto, 2010) and one study suggests that depression is associated with an attentional bias to mood-congruent stimuli presented for longer exposure times (Gotlib et al., 2004), it has been suggested that depressed individuals are not vigilant for negative information, but rather have difficulties in disengaging attention from negative information (Gotlib & Joormann, 2010).

There is some evidence suggesting that there might be a selective attentional component of positive mental health. For example, biases towards positive information have been found to associate with positive mood states and reward-seeking behaviour (Tamir & Robinson, 2007) and passive viewing of positive images has also been associated with trait happiness and life satisfaction (Raila, Scholl, & Gruber, 2015). Chapters 2 and 3 will examine the potential relationship between biased attention and mental health.

Emotion recognition refers to the ability to accurately distinguish emotional information, for example interpreting subtle facial cues to infer the expressed emotion. Accurate recognition of facial expressions of emotion is important in social interactions. Impairments in emotion recognition may have a profound impact on an individual's interpretation of social interactions and their subsequent behaviour, ultimately impacting interpersonal relationships. Biases in the perception of emotional facial expressions have been suggested to play a causal

role in subjective anger and aggressive behaviour (Penton-Voak et al., 2013). Further, these biases have been shown to be modifiable. Adolescents reported as being at high-risk of committing crime viewed composite images of emotional faces taken from the Karolinska Directed Emotional Faces (Lundqvist, Flykt, & Ohman, 1998) and made forced-choice ratings for each expression as happy or angry. Each image was a composite of happy and angry faces, and a 'balance point' was calculated for each participant such that they were equally likely to perceive the expression as happy or angry. In the training condition, participants were trained such that the ambiguous expressions would be interpreted as happy rather than angry. Participants in the training condition showed increased happy perceptions of emotion expressions and also displayed a decline in self-rated and staff-rated aggressive behaviour at 7 and 14 days post-training, relative to controls. In a similar study, undergraduates that were trained to perceive emotional expressions as happy rather than sad reported lower depressive symptoms and negative mood, and there was some evidence for an increase in positive mood (Penton-Voak, Bate, Lewis, & Munafò, 2012). Modification of emotion recognition biases may positively affect social interactions, which then serves to facilitate greater shifts in emotion recognition bias reciprocally, in what has been described as a "virtuous cycle" (Penton-Voak et al., 2012, pp.72).

The effect of emotion recognition on emotion regulation has been shown to extend to social anxiety in the form of general biases in emotion regulation (Button, Lewis, Penton-Voak, & Munafò, 2013). More specifically, social anxiety was associated with differences in the decoding of ambiguous facial expressions, more often classifying low intensity expressions as emotions, and more often the wrong ones. Generalised difficulties to interpret facial expressions in social circumstances may therefore underlie social anxiety, rather than a specific tendency to interpret individuals as more threatening. Socially anxious individuals also reported higher social cost to emotional expressions, rating that it would be worse for

them to interact with the person in the picture, particularly for negative emotions. When anxious individuals therefore interpret ambiguous expressions as emotional, they are open to perceiving more expressions (at very low intensities) as costly to themselves, reciprocally increasing social anxiety.

Facial emotion recognition has also been shown to be sensitive to antidepressant medication. A single dose of the noradrenergic antidepressant Reboxetine has been shown to bias perception of facial expressions towards greater recognition of happy facial expressions, compared to placebo controls (Harmer, Hill, Taylor, Cowen, & Goodwin, 2003). More specifically, following Reboxetine administration participants reported greater recognition of happy faces at low levels of expression intensity. This change in emotion recognition bias is suggested to occur early in antidepressant treatment, however interaction with the environment is required before the subsequent improvement in mood. This suggests that information processing biases in emotion recognition influence social interactions reciprocally. Emotion recognition at low levels of expressed emotion is therefore suggested to be important in social interactions and mood disorders.

Memory bias is regarded as an increased capacity to recall particular categories of information. Memory enhancements for negative information are particularly pronounced in depression (Mathews & MacLeod, 2005). In a meta-analysis of mood-congruent recall Matt, Vazquez, and Campbell (1992) reported that individuals with major depression remembered 10% more negative words than positive words, whereas non-depressed individuals typically showed a memory bias for positive information relative to negative information. In addition, sub-clinically depressed individuals did not tend to differ in preferential recall of positive versus negative items. Induced mood was also found to be important as induced

depressed/sad individuals showed negative memory bias, whereas induced elated individuals showed memory bias for positive information.

In contrast, there is inconsistent supporting evidence for memory bias in anxiety, except for panic disorders (for a review, see Coles & Heimberg, 2002). it has been proposed that his may be due to anxious individuals not processing or elaborating on threatening information in the same way as depressed individuals do with negative information. More specifically, the relative lack of memory bias in anxiety would be due to an avoidance of semantic elaboration (Brewin, 2001). It is also possible that depression related worry may not involve elaborate connections with other information in memory, and therefore doesn't make threat representations more retrievable (Mathews & MacLeod, 2005).

Depression related deficits in memory bias for positive words and facilitated recall of negative words may be due in part to differences in the elaboration of the emotional material (Gotlib & Joormann, 2010). Implicit memory has been found in depressed individuals for negative items, but has been most frequently observed when items have been semantically encoded or made self-referential (Watkins, 2002), and as such biased memory in depression may reflect increased conceptual processing of negative information. In a review of the implicit memory literature, Watkins concluded that depressed participants do not display memory bias when the encoding or recall of stimulus depends purely on perceptual processing. Rather, semantic processing is necessary to elicit memory biases relating to depression. For example, encoding the stimuli as self-relevant by indicating whether an item refers to the self, assists with recall of items regardless of the self-referential judgement (Rogers, Kuiper, & Kirker, 1977). Memory biases for positive and negative words were assessed in Chapters Two and Three to examine the plausible relationship between memory

biases and positive mental health directly (Chapter Two) and the relationships amongst other biases between high and low mental health samples (Chapter Three).

The combined cognitive bias hypothesis

Much of the research into cognitive bias in psychopathology has examined a single process in isolation with few studies investigating more than one bias in a single study (Hirsch, Clark, & Mathews, 2006). The combined cognitive bias hypothesis proposes that cognitive biases influence each other and interact to impact other variables, such as the disorder itself, which may result in the maintenance of a given emotional disorder (though the authors focus on social phobia). As such, it is not only the individual cognitive biases that causally influence vulnerability to emotional disorders, but also (and perhaps just as importantly) the interactions between cognitive processes. Hirsch and colleagues (2006) found that interpretation bias was found to influence later self-imagery, anticipated social anxiety, and estimated social performance. To investigate the hypothesis that emotional biases in attention, interpretation, and memory do not operate as isolated processes another study utilised eye tracking while participants engaged in a task that required them to unscramble emotional sentences to measure attention and interpretation and followed this with a memory task (Everaert, Duyck, & Koster, 2014). The study design allowed for a path analysis of the data which suggested that memory depended upon the manner to which emotional information is attended and interpreted. In a separate study, attentional bias did not directly influence memory bias, but did influence interpretation bias which subsequently affected memory bias (Everaert, Tierens, Uzieblo, & Koster, 2013). Though it should be noted that neither study can establish causation, there is general support for the combined cognitive bias hypothesis due to the interplay between biases. There is additional evidence that associations between biases in attention and memory may differ between clinical groups (formerly depressed) and non-clinical groups (sad mood induction) – coherence was found

only in non-depressed individuals (Vrijsen, van Oostrom, Isaac, Becker, & Speckens, 2014). It is possible that 'biased processing' alone may not be a global vulnerability factor for emotional disorders, and that the functional relationships between these different processes may also be a contributory factor. Conceptualising cognitive vulnerability to emotional disorders as a collection of different (interacting) cognitive biases in line with the combined cognitive bias hypothesis is a valid step forward. In Chapter Three, to test the combined cognitive bias hypothesis in positive mental health, the interrelationships amongst attention, interpretation, and memory biases were examined using a network analysis approach.

Modification of cognitive biases

One of the founders of social psychology, Kurt Lewin, is credited with the quote "if you want to truly understand something, try to change it". The ability to experimentally induce, reduce, or enhance a cognitive process provides a powerful experimental tool to examine the causal relations between cognitive processes and a range of outcome measures (Hertel & Mathews, 2011). Experimental methods known collectively as "cognitive bias modification" (CBM) procedures have been developed to selectively modify automatic biases in attention (ABM: MacLeod, Rutherford, Campbell, Ebsworthy, & Holker, 2002) and interpretation of ambiguity (CBMi: (Mathews & Mackintosh, 2000)). In the flagship attention bias modification (ABM) paradigm the emotional dot-probe is tailored to train attention bias away from threatening stimuli (Colin MacLeod et al., 2002). A stimuli-probe contingency is introduced to the task, such that the probe appears most frequently (or always) in the same location as the non-threatening stimuli. The implication is that this contingency implicitly trains participants to automatically attend to the non-threatening stimuli and/or away from the threatening stimuli, as this will lead to improved task performance by speeding responses to the probe. The shifts in attention bias can be assessed as the difference between a standard emotional dot-probe assessment before, and after the ABM procedure. Some have argued that

when these biases are successfully modified (e.g., when a negative bias is reduced) this reduction is associated with changes in emotional vulnerability (Clarke, Notebaert, & MacLeod, 2014; Hertel & Mathews, 2011). Within this context it is interesting to note that the experimental induction of an attentional bias towards positive stimuli, relative to negative stimuli, (using a CBMa procedure) has been shown to be associated with improved physiological recovery from a stressor (Baert, Casier, & De Raedt, 2012) and reduced emotional reactions to a laboratory stressor (MacLeod et al., 2002). Likewise, training emotion recognition processes to interpret ambiguous faces as being relatively more happy than angry results in reductions in anger and actual aggressive behaviours (Penton-Voak et al., 2013). These CBM procedures can be powerful experimental tools that provide an opportunity to examine the relationship between mental health and cognitive biases.

It is worth noting that there are concerns regarding the efficacy and mechanism of cognitive bias modification as a clinical tool. A recent meta-analysis (Heeren, Mogoaşe, Philippot, & McNally, 2015) concluded that there is some evidence that attention bias modification can make small but significant reductions in social anxiety disorder symptoms, reactivity to speech challenge, and attention bias. However, the authors argue that prior research has been substandard and that attention bias modification (ABM) is not ready for use as a clinical intervention for anxiety. A separate meta-analysis including randomised controlled trials of various CBM interventions for various mood disorders concluded that there are considerable problems with CBM interventions (Cristea, Kok, & Cuijpers, 2015), including; a lack of an established protocol, the wide variety of CBM interventions and the typically small sample sizes in such studies (Mogoaşe, David, & Koster, 2014). In contrast, a recent meta-analysis found that positive interpretation bias modification was associated with increased positive interpretation bias and reduced negative mood, concluding that CBM-I may have clinical potential (Menne-Lothmann et al., 2014).

It is not the aim of this thesis to argue for or against the clinical utility of CBM. Instead, it is proposed that CBM and cognitive control training procedures are useful as experimental manipulations in examining the causal mechanisms associating information-processing styles and psychological resilience. To this end, it is worth pointing out that several of the meta-analyses report that ABM does indeed modify bias (Heeren et al., 2015; Mogoaşe et al., 2014), and the report most critical of ABM does not report data on actual change in bias (Cristea et al., 2015). The first dot-probe based ABM procedure (Mathews & MacLeod, 2002) was designed to experimentally induce a bias in attention, i.e. the task was intended to provide an experimental tool to examine the mechanisms associating attention bias towards threatening stimuli and emotional vulnerability. The task was not designed to reduce anxiety (also see Hakamata et al., 2010), but rather, to serve as an experimental manipulation. It is important to recognise within discussing the efficacy of CBM a distinction between the *process* of bias change and the *procedure* intended to induce such a change (Colin MacLeod & Grafton, 2016). More reliable methods of measuring and modifying the information processing biases of interest are needed, and the utility of such techniques as direct clinical interventions requires further examination.

Individual differences in susceptibility to attention bias modification towards threat has been associated with a naturalistic increase in attentional bias towards threat and an increase in trait anxiety over a period of extended mild stress (Clarke et al., 2008). In addition, greater malleability of attention bias towards positive information has also been associated with reductions in anxiety to a lab stressor (Taylor, Bomyea, & Amir, 2011). Individual differences in susceptibility to acquire bias influences stress reactivity and may be important in the development of resilience. Cognitive bias modification procedures represent an important experimental tool in the examination and testing of the associations between cognitive processes and resilience. In Chapters 4 and 5 an attention bias modification

procedure is used to induce a more positive relative-to negative attention bias in order to examine the prospective relationship between shifts in attention bias as a result of the training and future wellbeing-related factors.

Integrating cognitive approaches and positive mental health approaches

The previous section provides a brief overview of the body of evidence supporting cognitive models of emotional vulnerability. In particular, focus was given to the importance of emotional information processing biases. Emotional disorders are thought to comprise of distinct patterns of biased emotional information processing (Cisler & Koster, 2010; Gotlib & Joormann, 2010; Mathews & MacLeod, 1994, 2005). Mental health and emotional vulnerability are not polar opposites on a single continua (Keyes, 2002, 2005a). Moreover, positive mental health is thought to protect against emotional vulnerability (Keyes, 2007; Keyes et al., 2010; Keyes & Simoes, 2012; Provencher & Keyes, 2011) and therefore the promotion of mental health is likely to prove to be a fruitful companion to the treatment and amelioration of mental illness and emotional vulnerability. It is plausible that mental health, or flourishing, is characterised by a specific pattern of cognitive bias. As such, the role that selective processing of emotional information plays in positive mental health is an important research question.

Current cognitive-experimental approaches have examined mental illness and the absence of mental illness, however, research has yet to utilise the cognitive-experimental approach to investigate the continua comprising flourishing and languishing. There has been a previous call for the integration of cognitive-experimental approaches to emotional dysfunction and research on normal emotion regulation processes (Macleod & Bucks, 2011). The authors argue that although these parallel research streams have similar theoretical

positions the transfer between them has not been optimal. Convergence of these fields would yield reciprocal benefits in the transfer of theoretical frameworks of emotion regulation and methodological strengths of information-processing paradigms. This integration of approaches is proposed to facilitate the understanding of normal and abnormal emotion processes. This proposal begins to extend the emotional information-processing approach from an exclusive focus on emotional vulnerability, towards a more holistic examination of emotion regulation.

In this Chapter, a similar argument has been made for the application of emotional information-processing methodologies to the examination of mental health and flourishing, as something distinct to emotional vulnerability. Investigating the cognitive processes that help push individuals towards improved mental health is a complementary approach to the treatment of emotional vulnerability (Keyes, 2007). Chapter Six furthers this line of argument and presents a theoretical account of how cognitive-experimental approaches to emotional dysfunction may be applied within a resilience framework. This thesis is intended to act as an initial examination of the emotional information-processing biases associated with mental health.

Summary and key questions

The research presented in this introductory Chapter makes a case for the importance of positive mental health research in filling gaps left by the exceptional work increasing our understanding of emotional vulnerability and improving treatments. Indeed, cognitive models of emotional disorders have been developed and tested with a wide range of tasks and methodologies. These information-processing approaches have thrived in examining the cognitive bias mechanisms implicated in emotional vulnerability. In this Chapter, positive mental health has been described as distinct (albeit related) to emotional vulnerability and

may therefore be explained by a distinct pattern of cognitive bias. However, to date, little research has sought to examine the role of emotional information-processing bias in positive mental health leaving this field of research in its infancy. The aim of this thesis is to investigate the role of cognitive biases, as well as flexibility in applying those biases, in positive mental health. The studies presented in this thesis address three related questions:

Research Question 1. Are there specific cognitive biases, and specific patterns of relationships amongst cognitive biases that are associated with positive mental health?

Research Question 2. Is attention bias malleability (the capacity to shift attention bias due to contextual demands) associated with positive mental health and wellbeing?

Research Question 3. Are cognitive biases more or less adaptive in certain situational contexts, and are individuals able to shift their bias to be more adaptive?

These issues will be addressed in the following Chapters.

Chapter Two will address Research Question One. Specifically, it presents the results of an exploration of the relationships between mental health, and cognitive biases in attention, emotion regulation, and memory. Positive and negative stimuli were used in the attention and memory bias tasks to expand beyond assessing only negative biases.

Chapter Three also addresses Research Question One by investigating the direct relationships amongst cognitive biases using a psychological network analysis approach to examine the combined cognitive bias hypothesis in mental health, in adolescence. While the combined cognitive bias hypothesis suggests that distinct patterns of connectivity among attention, interpretation, and memory biases, contribute to psychopathology, little is known about the interrelationships amongst cognitive biases in relation to mental health. In this study, data from the CogBIAS project (Booth, Songco, Parsons, Heathcote, Vincent, Keers,

& Fox, 2017) were analysed from a sample of adolescents with high (n = 103) and low (n = 104) levels of self-reported mental health.

Chapter Four addresses Research Question Two. Individual differences in the ease with which attentional bias is modified in response to attention bias modification training have been shown to prospectively predict emotion vulnerability. This study examined whether ABM training-induced shifts in attentional bias towards positive and away from negative stimuli would prospectively associate with self-reported measures of positive emotions, happiness, and mental health assessed 12 weeks later.

Chapter Five continues to address Research Question Two. This Chapter presents a replication and extension of Chapter Four in which participants were assigned to one of three training conditions; no training, control training, and ABM training. As in Chapter Four, participants completed two testing sessions approximately 12 weeks apart. These conditions allowed for an examination of the role of task practice and bias training in the prospective associations between attentional bias, and future positive emotions and happiness. Further, the reliability of attention bias assessments were estimated in order to examine the role of the consistency of bias in the prospective associations.

Chapter Six addresses Research Question Three. In this Chapter a preliminary cognitive model of resilience is outlined in order to facilitate the application of cognitive approaches to the investigation of resilience in the face of adversity. This Chapter proposes that a cognitive approach has the potential to guide studies investigating the relationships between adversity, stress, and resilience. Specifically, it is argued that the situationally appropriate application of flexibility or rigidity in affective-cognitive systems is a key element in promoting resilience. This model is intended to provide an initial theoretical framework to guide research on the

development of cognitive functions that are considered to be important in the resilience process.

Chapter Seven also addresses Research Question Three by building on the theoretical position put forward in Chapter Six. A novel attentional bias alignment task comprised of two block types; in high control blocks it was adaptive to attend to threat, as participants were highly likely to control avoidance of danger, whereas, in low control blocks it was maladaptive to attend to threat, as the danger was unlikely to be avoided. The degree of control that 160 participants had in avoiding exposure to a danger (loss of money) signalled by a threatening cue was manipulated in order to test the hypothesis that individuals align attentional biases towards threat cues depending on whether such a bias is adaptive or maladaptive.

Chapter 2

2

An exploration of the associations between selective processing biases and positive mental health

Cognitive theories propose that emotion dysfunction is characterised by patterns of selective emotional information-processing. Positive mental health or wellbeing has been argued to be a separate dimension to emotional vulnerability. This exploratory study in 84 individuals examined relationships between various self-reported wellbeing factors, and information processing biased towards positive and negative information in the domains of attention, emotion recognition, and memory. Psychological flexibility was found to interact with anxiety severity to predict biases towards positive in a dot-probe task, yet the interaction pattern differed between positive stimuli paired with negative or neutral stimuli. For positive over negative information, those with higher flexibility and low anxiety showed bias away, while those with high flexibility and anxiety showed relatively strong bias towards positive. When positive information was paired with neutral information, those with low flexibility and low anxiety symptoms showed bias towards positive information, while those with low flexibility and high symptoms oriented away from positive information. No associations were found for negative-neutral bias. Positive mental health was found to associate with mild differences in emotion recognition accuracy with increasing emotion severity. No associations with self-reported mental health were found in the explicit memory task, although self-reported ability to imagine scenes described by positive words associated strongly with positive mental health and resilience. We discuss these results with respect to the guiding of future research examining the relationship between patterns of emotional information-processing and positive mental health.

Introduction

Cognitive models of emotion vulnerability (Aaron T Beck, 1967, 1979) propose that maladaptive patterns of emotional information-processing lead to dysfunctional patterns of emotional experience observed in emotional disorders, such as depression and anxiety (Mathews & MacLeod, 1994, 2005). There is a wealth of research examining the role of biased emotional information-processing in the etiology, development, and maintenance of emotional psychopathology (for reviews, see Cisler & Koster, 2010; Gotlib & Joormann, 2010; Yiend, 2010). It is thought that investigating these processes may elucidate the underlying mechanisms of emotion dysfunction, and enable the development of novel cognitive therapies, such as cognitive bias modification interventions that target these dysfunctional processing styles (Colin MacLeod & Holmes, 2012).

What is missing from these approaches is an examination of the role of biased emotional information processing in mental health and wellbeing. In the present study, we present an initial exploration of the relationships amongst positive mental health and cognitive biases in attention, emotion recognition, and memory. First, we introduce positive mental health and the related wellbeing factors of resilience and psychological flexibility. We then describe three domains of cognitive bias that have been shown to associate with emotional vulnerability and may demonstrate a relationship with mental health. Finally, we describe the present study, in which we sought to explore these plausible relationships.

Positive mental health

The dual continua model of complete mental health proposes that mental health and mental illness are two distinct, albeit inversely correlated continua (Keyes, 2002, 2005a). Low mental health, referred to as languishing in life, has been found to be as damaging to psychosocial functioning as mental illness (Keyes & Grzywacz, 2005). Further, mental illness

and low mental health have additive adverse effects on an individual's functioning in life, including academic impairment and suicidal ideation (Keyes et al., 2012), as well as all-cause mortality (Keyes & Simoes, 2012). There is converging evidence that there is a distinction between positive and negative factors in complete mental health. In one study, psychological strengths were found to predict positive wellbeing, whereas cognitive vulnerabilities predicted ill-being, and most often, the relationships with well-being or ill-being and strengths or vulnerabilities were unique (Huta & Hawley, 2010). A further study (Ryff et al., 2006) examined the associations between well-being, ill-being, and a range of biomarkers (e.g. cortisol, norepinephrine, blood pressure). Most biomarkers associated with only well-being or ill-being, supporting the view that well-being and ill-being are associated with distinct processes, at a biological level. It has been argued that, positive mental health practice and research should be promoted as a promising and complementary strategy to the treatment of mental illness (Keyes, 2007). Similarly, resilience and psychological flexibility are considered to be separate promoters of wellbeing and positive mental health.

Resilience theory (Fergus & Zimmerman, 2005) is concerned with investigating how individuals utilise protective and promotive factors or strengths in order to overcome the negative effects of risk or adversity, and avoid the negative outcomes usually associated with these stressors. We have presented an information processing model of resilience in which resilience is characterised by the appropriate allocation of cognitive control resources and selective emotional processing to the situation (Chapter Six). A dynamic information-processing-based model of resilience is an important first step in enabling the examination of the pattern of information-processing associated with positive mental health and resilience. Research has begun to examine resilience within a cognitive-experimental framework (e.g. Schäfer et al., 2015). For example, more resilient individuals have been shown to recover

more effectively following stress (Sanchez, Vazquez, Gomez, & Joormann, 2014; Tugade & Fredrickson, 2004) and attention bias modification has been shown to improve recovery from stress (Baert et al., 2012).

Psychological flexibility has been proposed to be a fundamental aspect of positive mental health, and that psychological inflexibility is characteristic of psychopathology (Kashdan & Rottenberg, 2010). The model of psychological resilience presented in Chapter Six incorporates psychological flexibility as a core element. Psychological flexibility refers to an individual's capability to adapt to changing circumstances and environments, involving a number of processes, such as positive emotion regulation, heightened executive control, optimism, mindfulness and so on. In essence, psychological flexibility is an umbrella term for those capabilities that allow an individual to adapt successfully to changing circumstances, and therefore promote positive mental health.

Information-processing approaches to emotion dysfunction

Positive mental health, resilience, and psychological flexibility represent aspects of wellbeing that are not merely the opposite or absence of emotional vulnerability. To date, little research has examined the role of emotional information-processing biases in wellbeing. However, a large body of research has investigated the cognitive biases underpinning emotional vulnerability. In this section, we briefly highlight three well-researched areas of information-processing bias which may be of relevance to the positive mental health factors discussed in the prior section; attention bias, emotion recognition bias, and memory bias. We cover how the prior research has established the role of the processing bias in emotion dysfunction and propose that each bias may plausibly be related to positive mental health factors.

Attention Bias. A wealth of research has investigated the role of selective attention in emotion dysfunction (see Mathews & MacLeod, 2005 for review). Anxiety in particular is thought to be characterized by selective attentional processing of threatening attention (Cisler & Koster, 2010). Selective attention to threatening stimuli for example, has been shown to causally contribute towards anxiety responses to laboratory induced (Colin MacLeod et al., 2002) and naturally occurring stress (Clarke et al., 2008). However, there is less evidence for the role of negative attentional biases in depression (Gotlib & Joormann, 2010), although some studies suggest that depression is associated with an attentional bias to mood-congruent stimuli presented for longer exposure times (Gotlib et al., 2004). There is emerging evidence of relationships between 'positive' biases and mental health, either directly, or as a protective factor against vulnerability. For example, impairments in positive mood processing and the down-regulation of positive emotions have been implicated across pathologies (e.g. Carl, Soskin, Kerns, & Barlow, 2013). Biases favouring positive information have been found to associate with positive mood states and reward-seeking behaviour (Tamir & Robinson, 2007) and passive selective viewing of positive images has also been associated with trait happiness and life satisfaction (Raila et al., 2015), suggesting that there might be a selective attentional component of positive mental health. Positive attentional deployment may increase goal-directed and reward directed behaviours leading to increased happiness and life satisfaction.

The current study sought to extend this research and directly examine the relationship between attention bias and positive mental health factors. Biases in attention were assessed with the dot-probe task (Colin MacLeod et al., 1986). Most dot-probe based studies have employed only negative and neutral stimuli and it has been suggested that research should directly contrast attentional responses to negative, positive, and neutral stimuli in order to address this issue (Grafton, Watkins, & MacLeod, 2012). While there is preliminary evidence

that individual differences in selective attentional responses to positive information might contribute to positive affectivity (Grafton, Ang, & MacLeod, 2012; Taylor et al., 2011), relatively little is known about the role of positive emotion processing in mental health. Therefore, in order to assess the relationship between positive mental health and attention bias in greater depth, three stimuli pairs were utilised as target trials; positive-negative, positive-neutral, and negative-neutral. This allowed for a direct assessment of biases towards positive or negatively valenced stimuli, with respect to the simultaneously presented stimuli.

Emotion recognition. Impairments in emotion recognition may have a profound impact on an individual's interpretation of social interactions and their subsequent behaviour, ultimately impacting interpersonal relationships (Penton-Voak et al., 2012). For example, biased processing of facial emotion expressions has been implicated in depression (Bourke, Douglas, & Porter, 2010), and these biases are somewhat dependent on mood (Anderson et al., 2011). Biases in the perception of emotional facial expressions have been suggested to play a causal role in subjective anger and aggressive behaviour (Penton-Voak et al., 2013). Modification of these biases may positively affect social interactions, facilitating improvements in emotion recognition bias reciprocally, in a "virtuous cycle" (Penton-Voak et al., 2012, p. 72). In addition, in one study social anxiety was found to impair emotion recognition accuracy. Specifically, increases in the intensity of an emotional expression were found to improve emotion recognition accuracy, however this was the case more for less anxious individuals than more anxious individuals (Button et al., 2013). More socially anxious individuals were more likely to classify low intensity expressions as emotional, and with a higher social cost to negatively valenced expressions. It is possible therefore that the interaction of biased emotion recognition processing, and cost attributions contribute to social anxiety. It has been suggested that early changes in emotional processing produced by

psychopharmacological treatment drive and predict therapeutic outcomes (Harmer & Cowen, 2013). In support of this proposition, a single dose of the norepinephrine reuptake inhibitor Reboxetine has been shown to bias perception of facial expressions resulting in greater recognition of happy facial expressions two hours following administration, compared to placebo controls (Harmer, Hill, Taylor, Cowen, & Goodwin, 2003, also see Harmer et al., 2009). Taken together, biases in emotion recognition appear to play an important role in emotional vulnerability. More accurate emotion recognition might be expected to facilitate social interactions and promote social well-being (Penton-Voak et al., 2012). It is also possible that positive mental health may be characterised by a distinct pattern of biased emotion recognition processing. Alternatively, facilitated recognition of positive expressions might be expected to promote a positivity bias, which may also be important to mental health. We sought to explore the relationship between emotion recognition and positive mental health. We used morphed images ranging from ambiguously emotional, to unambiguously emotional over six emotion categories. This allowed us to examine the role of intensity of emotion in accurate emotion recognition, in relation to positive mental health.

Memory bias. Memory enhancements for negative information are pronounced in depression (for reviews, see Gotlib & Joormann, 2010; Mathews & MacLeod, 2005; Watkins, 2002). In a meta-analysis of mood-congruent recall Matt, Vazquez, and Campbell (1992) reported that individuals with major depression remembered 10% more negative words than positive words, whereas non-depressed individuals typically show the opposite pattern of memory bias for positive information. It has been proposed that enhanced elaboration of the emotional material (particularly negative material) may account for the depression linked bias (Gotlib & Joormann, 2010). However, the evidence for anxiety related memory biases is mixed (e.g. Coles & Heimberg, 2002; Watkins, 2002). For example, two studies found

evidence for depression-congruent memory biases, but found no evidence for anxiety-congruent biases in memory (Bradley, Mogg, & Williams, 1994; Bradley, Mogg, & Williams, 1995). Similarly Dalgleish et al (2010) found no evidence of group differences (including; anxiety, depression, OCD, and healthy controls) in recall of positive or negative words.

While the research into emotion dysfunction related memory biases presents a mixed picture, we also explored the potential relationship between positive mental health and biased recall of positive and negative items. We examined memory bias with an incidental learning and free recall task (Gotlib et al., 2004; Vrijsen et al., 2014). Participants' encoded words by imagining themselves in a scene described by the word and rated the ease with which they were able to create the image. This allowed us to examine individual differences in self-reported mental imagery and explicit recall of positive and negative items.

Exploring the cognitive bias correlates of positive mental health

Positive mental health plays a key role in protecting against emotional vulnerability (Keyes, 2007; Keyes et al., 2010; Keyes & Simoes, 2012; Provencher & Keyes, 2011). An implication of the dual continua model is that just like the 'symptoms' of mental health and mental illness differ (Keyes, 2002, 2005a), they may be also be characterised by distinct patterns of selective processing. As such, the role that selective processing of emotional information plays in positive mental health is an important research question. The present study sought to utilise the emotional information processing approach, which has been successful in examining the cognitive mechanisms in emotional vulnerability, in an exploration of possible cognitive correlates of wellbeing.

Methods

Participants

Participants were 84 English-speaking adults (66 female, age; M = 21.90, SD = 5.64), reporting normal or corrected-to-normal vision. Participants were recruited through the University of Oxford SONA system and poster advertisements, and were compensated for their time with course credit, or £10. Participants gave their informed consent and were free to terminate the experiment at any time. Ethical approval for this study was granted by the University of Oxford Central University Research Ethics Committee (CUREC; Ref No: MS-IDREC-C1-2015-050).

Apparatus

The tasks were programmed and presented in INQUISIT Millisecond (Inquisit 4.0.8.0, 2013) on a Dell OptiPlex 9020 with 22-in colour monitor (1920x1080 resolution), and a standard keyboard and two-key mouse. INQUISIT measures RTs with millisecond accuracy (De Clercq, Crombez, Buysse, & Roeyers, 2003). Limesurvey 2.0 was used to record participants' responses to the self-report measures (Limesurvey Project Team & Casrten Schmitz, 2015).

Self-report measures

The primary measure of interest was positive mental health. Resilience and psychological flexibility measures were also included for the exploratory analyses. Measures of depression and anxiety were included in the exploratory analyses as secondary measures.

Mental Health. The Mental Health Continuum - Short Form (MHC-SF; Keyes, 2009) contains 14 items from three subscales; emotional wellbeing (this sample α = .81), social wellbeing (this sample α= .80) and psychological wellbeing (this sample α = .88) which load

onto a single overall mental health construct (this sample α = .92). Participants rate on a six point scale how often they have experienced or felt each of the items (e.g. "satisfied with life") in the past month.

Psychological flexibility. The Acceptance and Action Questionnaire – II (AAQ-II; Bond et al., 2011) is a 7 item self-report scale (this sample α = .91) designed to measure psychological inflexibility. Participants rate to what extent each item (e.g. "worries get in the way of my success") applies to them on a seven-point scale. Scores are reversed and summed to yield a psychological flexibility score.

Resilience. The Connor-Davidson Resilience Scale (CD-RISC; Connor & Davidson, 2003) is designed to quantify resilience and act as a clinical measure to assess response to treatment. Participants are asked to rate, on a 5-point scale how they feel each of the 25 items (e.g. "able to adapt to change") applied to them in the last month (this sample α = .92).

Depression. The Patient Health Questionnaire (PHQ-9; Kroenke & Spitzer, 2002) is a highly valid (this sample α = .83), self-administered inventory containing 9 items corresponding to the nine criteria on which a DSM-IV depressive disorder diagnosis is made. Participants rate how often over the last two weeks that they have been bothered by any of the nine problems (e.g. "little interest or pleasure in doing things") on a 4-point scale.

Anxiety. The Generalized Anxiety Disorder - 7 item scale (GAD-7; Spitzer, Kroenke, Williams, & Löwe, 2006) is a highly valid (this sample α = .89) brief self-administered measure designed to reflect DSM-IV symptom criteria for anxiety. Participants rate how often over the last two weeks that they have been bothered by any of the seven problems (e.g. "trouble relaxing") on a 4-point scale.

Participants also completed the Depression Anxiety Stress Scales (DASS; Lovibond & Lovibond, 1995), and the Attention Control Scale (ATC; Derryberry & Reed, 2002) as secondary measures for potential exploratory analyses. These data were not analysed and are not presented in this report.

Experimental Stimuli

Word Stimuli. We conducted a small pilot to develop the word stimuli for this study. 228 word stimuli were drawn from several sources, including; the Affective Norms for English Words database (ANEW; Bradley & Lang, 2010), and the Depth-of-Processing Self-Schema Task (Hammen & Zupan, 1984). These words were rated on a 1-9 scale for valence (negative to positive) and arousal (not arousing at all to very arousing). These ratings were used to create three categories of words; positive, negative, and neutral. Each category differed significantly in valence (all *p*s < .05). Positive and negative words did not differ significantly in arousal ($p > .05$), and both categories were rated significantly more arousing than neutral words (all *p*s < .05). For the dot-probe task, 80 word pairs (matched for word length) were selected from this sample. These were equally split between four categories of 20 word pairs; positive-negative, positive-neutral, negative-neutral, and neutral-neutral. 8 additional neutral-neutral word pairings were selected for use in practice trials. For the implicit learning and free recall task, a further 36 words were selected from the same word pool; 12 positive, 12 negative, and 12 neutral.

Face stimuli. Stimuli for the emotion recognition task were identical to those used in Bamford et al. (2015), with the addition that we included both male and female face stimuli. For a full description of the development of the stimulus set, see Bamford et al. (2015). In short, 12 young adult males and 12 young adult females posed emotional expressions (happy, sad, angry, disgust, fearful, surprised, and neutral), which were used to create composite male

and female images for each emotion. Prototypical emotional face stimuli were created by compositing all 12 individuals (separately for male and female models) in each of the six emotions plus neutral expressions. These stimuli are argued to be genuinely emotionally ambiguous rather than neutral. For both male and female stimuli, six 15-image morph sequences were created on a linear continuum from the emotional prototype to each of the full intensity emotions (totalling 180 stimuli) using standard techniques. To ensure that the first image in each sequence contained some emotional signal, the first image in each sequence was a morph 5% along the dimension of 'prototypical emotion' to 'full intensity emotion'.

Experimental Tasks

Dot probe. Each trial consisted of a fixation cross that was displayed in the centre of the screen for 500ms. This was followed by a random word pair with words above and below centre, separated by approximately 3cm from the centre of the screen. Words were presented in lower case black letters (16pt font) against a white background for 500ms with equal probability of appearing in the upper or lower location. Immediately following removal of the stimuli pair, a probe was presented in the location of one of the stimuli, with equal probability. The probe was a small (5 pixel) line oriented either horizontally or vertically

Participants were asked to respond as quickly and accurately as possible to the orientation of the probe by pressing one of two corresponding buttons. The probe was equally likely to appear in the location of either valence. The probe remained on screen until participants responded. Accuracy and latency of each response was recorded. The inter-trial interval was 500ms.

In order to encourage participants to focus on the fixation cross, nine catch trials were included in each block. In the catch trials, a number from 1 to 9 was presented in the centre of

the screen instead of the word pair. Participants were instructed to press the corresponding number on the keyboard as quickly as possible. Catch trials were randomly distributed within each block of trials with the only constraint being that no two catch trials were presented sequentially.

The dot-probe task consisted of four blocks of trials; each contained eight practice trials, 80 target trials, and nine catch trials. Each word pairing was presented four times, such that the stimuli location and probe location were counterbalanced. The four word-pair types were presented in separate blocks. The first block contained only neutral-neutral trials in order to fully acquaint participants with the task, and the last block contained positive-negative trials. The second and third block presented the positive-neutral trials, or the negative-neutral trials and these were counter-balanced between participants. The target trials within each block were presented randomly. Participants were offered a self-timed break following each block of trials. Before the first block, participants completed 16 practice trials to familiarise them with the task.

Emotion recognition task. Following Bamford and colleagues (Bamford et al., 2015), each trial began with a fixation cross presented in the centre of the screen for between 1500ms and 2500ms. A face stimulus was then presented for 150ms and followed by a 250ms pattern mask to disrupt any visual after-images (both 354x464 pixels). A circular array of the six emotion descriptors (happy, sad, angry, fearful, disgust, and surprise) was then presented, with each word spaced equally from the centre of the screen. Participants were instructed to identify the emotion expressed using the mouse to select the descriptor that they felt best described the facial expression. The 180 face stimuli were presented in random order and no breaks were given during the task.

Incidental learning task and free recall. The task followed Vrijsen et al. (2014), consisting of three phases; encoding, distractor, and recall. In the encoding phase, Participants were presented with 12 positive, 12 negative, and 12 neutral words in a random order, with the caveat that no more than two words in the same category were presented sequentially. Each word was presented in black lower-case letters (36pt) in the centre of the screen on a white background. In order that the words were made self-referential (Rogers et al., 1977) participants will be instructed to vividly imagine themselves in a scene with the presented word (Vrijsen et al., 2014). Following the 10s word presentation, participants were asked to rate how easily they were able to imagine themselves in the scene on a 5-point scale. The next word was presented 1s after participants made their response. In the distractor phase, participants completed a two-minute paper-based task (Raven matrices; Raven, 1958). Finally, in the third phase, participants were given a surprise recall test in which they were instructed to type in as many words as they could remember in 3 minutes.

Procedure

Each participant was tested individually. Participants were seated approximately 60cm in front of the computer screen. First, participants completed the three information-processing tasks in one of two orders, which were counterbalanced between participants. The dot-probe and the self-referential incidental learning and free recall task were counter-balanced to appear first or last in the order of information-processing tasks. The emotion decoding task was always presented second in order to alternate the type of stimulus used in the task (words or images). Following the information processing tasks, participants completed the self-report measures. Each testing session lasted approximately 60 minutes.

Data processing

Due to a technical error, no dot-probe data were collected for two participants. Additionally, two participants had more than 20% errors and were removed from the analyses. Error trials were excluded from the RT analysis, as were trials with RTs lower than 100ms, and higher than 1500ms to remove trials reflecting pre-emptive responses or delayed responses, respectively. Bias indices were calculated by subtracting the median RT in congruent trials from the median RT in incongruent trials for each participant in each word-pairing condition following the approach of Macleod et al. (2002). Negative bias, Positive Bias, and Positive-over-Negative bias indices were computed. Higher bias indices thus reflect speeded responses for probes in the location of the target valence. In the analysis of the dot-probe data, one participant was consistently found to be a multivariate outlier (standardised residuals >3) that was highly influential on the model (Cooks distance, and covariance) and was removed from the analyses (leaving n = 79).

Data analysis plan

We were primarily interested in exploring the associations between mental health and the attention bias measures. We therefore performed correlational analyses between each dot-probe bias index and mental health. We explored the dot-probe data by performing correlations between the other self-reported measures and attention bias indices. We further explored the significant correlations with hierarchical regressions predicting each attention bias index separately. We analysed data from the emotion recognition task in a similar procedure to Button et al. (2013). Specifically, we included emotion intensity, emotion, and mental health as main effects, and intensity by mental health, and emotion by mental health interactions as predictors in a multiple logistic regression predicting emotion recognition accuracy. We followed this analysis by performing the analysis separately for each emotion.

We explored the data from the incidental learning and free recall task by performing correlations between the self-reported measures, and the imagery self-reports and number of items recorded, separately for positive and negative items.

Results

Table 2.1 presents the means and standard deviations for the self-report measures and cognitive bias tasks.

Table 2.1. Means and Standard Deviations for self-report measures and cognitive bias tasks

Self-report scales (n = 84)		**M**	**SD**
Mental Health (MHC)		34.32	12.15
Resilience (CD-RISC)		66.54	13.74
Psychological Flexibility (AAQ-II)		31.43	8.76
Anxiety (GAD-7)		3.81	3.98
Depression (PHQ-9)		5.07	4.37
Cognitive bias task	**Stimuli type**	**M**	**SD**
Dot-Probe	Positive-Negative	4.96	25.13
(n=79)	Positive-Neutral	-.94	27.00
	Negative-Neutral	-.56	26.14
Emotion Recognition	Anger	62.02	48.54
(percent accurate,	Disgust	78.11	42.65
n=84)	Fear	53.06	49.92
	Happy	69.44	46.07
	Sad	75.32	43.12
	Surprise	72.66	45.58
	Total	68.10	46.61
Imagery ratings	Positive	3.74	1.05
(n=84)	Negative	3.86	.88
	Neutral	4.05	.77
Recall	Positive	5.05	1.95
(median items recalled,	Negative	4.79	2.08
n=84)	Neutral	5.31	1.79

Note. MHC = Mental Health Continuum, CD-RISC = Connor-Davidson Resilience Scale, AAQ-II = Action & Acceptance Questionnaire - II, GAD-7 = Generalized Anxiety Disorder - 7 item, PHQ-9 = Patient Health Questionnaire - 9 item.

Dot Probe Analysis

Two factors were found to be associated with positive-over-negative attention bias; anxiety – such that increased anxiety associated with attention bias more towards-positive and away-from negative stimuli (r = .26, p = .020), and psychological flexibility – such that increased psychological flexibility associated with attention bias more towards-negative and away-from positive stimuli (r = -.37, p < .001) (associations with mental health, resilience, and depression were not significant ps > .05). We therefore further explored these significant associations. A three step hierarchical multiple regression was performed for each bias index; the first step included only Anxiety, the second step added Psychological Flexibility, the third step added the interaction of these two factors. Regression tables and interaction plots are presented for each analysis.

Positive-over-Negative bias. Table 2.2 presents the results of the hierarchical regression analyses predicting positive-over-negative attention bias. In the first step, the model was statistically significant (p = .016) and accounted for 7.3% of the sample variance. Adding psychological flexibility to the model did not significantly improve the model (p = .156), and although the overall model remained significant (p = .022) neither predictor was significantly predictive of bias. Adding the interaction effect of anxiety and psychological flexibility significantly improved the model (p = .003), resulting in a highly significant model (p < .001) which explained 19.4% of the sample variance. In the final model, all three predictor variables were significant. Figure 2.1 displays this interaction between anxiety and psychological flexibility. Individuals with high psychological flexibility show the greatest impact of anxiety on attention bias. Individuals with low anxiety and high psychological flexibility demonstrated the lowest bias, whereas individuals with higher anxiety and high flexibility displayed the greatest bias overall.

Table 2.2. Hierarchical multiple regression analyses predicting positive-over-negative bias.

		R^2	ΔR^2	B	SE B	β	*P*
Step 1		.07	.07				.016*
	Constant			-1.53	3.80		.688
	GAD			1.67	.07	.27	.016*
Step2		.10	.03				.022*
	Constant			23.23	18.57		.215
	GAD			.62	1.02	.10	.541
	AAQ			-.66	.48	-.23	.177
Step 3		.19	.09**				<.001***
	Constant			54.89	20.52		.009**
	GAD			-5.46	2.23	-.89	.017*
	AAQ			-1.66	.57	-.57	.005**
	GAD*AAQ			.24	.08	.04	.003**

Note. GAD: Generalized Anxiety Disorder; AAQ: Acceptance and action questionnaire. * $p < .05$, ** $p < .01$, *** $p < .001$

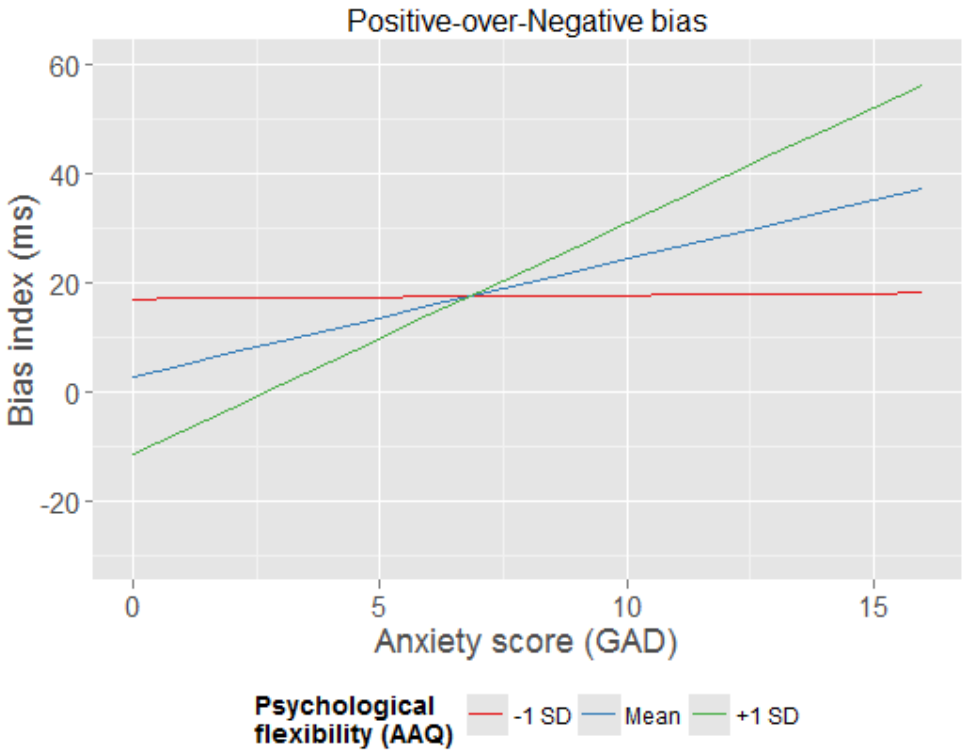


Figure 2.1. Positive-over-Negative bias index by anxiety and psychological flexibility. Positive indices indicate attentional bias towards positive, relative to negative, stimuli.

Positive bias. Table 2.3 presents the results of the hierarchical regression analyses predicting positive attention bias (relative to neutral stimuli). In the first step, the model was not statistically significant (p = .265) and accounted for only 1.6% of the sample variance. Adding psychological flexibility to the model significantly improved the model (p = .010), accounting for an additional 7.9% of the sample variance. Both predictors were significantly predictive within the model. Adding the interaction effect of anxiety and psychological flexibility as a predictor further improved the model (p = .025), explaining an additional 5.9% of the sample variance. The final model significantly predicted positive bias (p = .006) explaining 15.4% of the sample variance. In the final model, all three predictor variables were significant. Figure 2.2 displays this interaction between anxiety and psychological flexibility. Contrasting the interaction effect in Figure 2.1 predicting positive-over negative bias, individuals with high psychological flexibility showed the lowest impact of anxiety on bias. Individuals with low flexibility with low anxiety showed a vigilance for positive stimuli, whereas those with high anxiety demonstrated an avoidance of positive stimuli.

Table 2.3. Hierarchical multiple regression analyses predicting positive bias.

		R^2	ΔR^2	B	SE B	β	*P*
Step 1		.02	.02				.265
	Constant			2.33	4.20		.582
	GAD			-.84	.75	-.13	.265
Step2		.10	.08*				.023*
	Constant			52.52	19.96		.010*
	GAD			-2.95	1.09	-.45	.009**
	AAQ			-1.34	.52	-.43	.012*
Step 3		.15	.05*				.006**
	Constant			78.84	22.58		<.001***
	GAD			-8.01	2.46	-1.21	.002**
	AAQ			-2.17	.62	-.69	<.001***
	GAD*AAQ			.20	.09	.03	.025*

Note. GAD = Generalized Anxiety Disorder; AAQ = Acceptance and action questionnaire. * p < .05, ** p < .01, *** p < .001

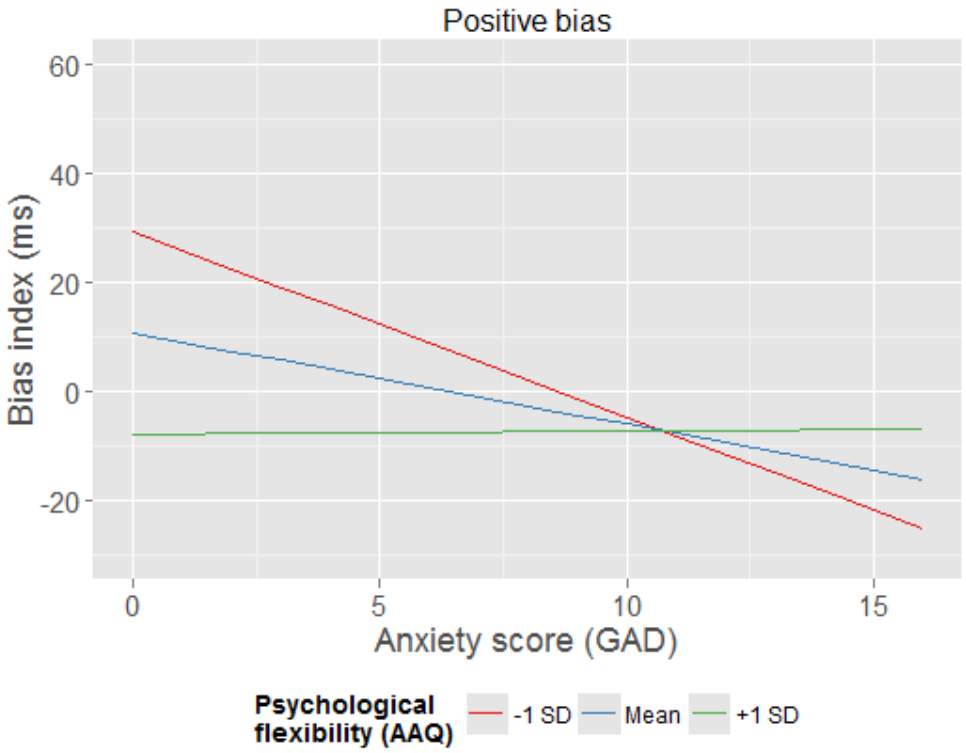


Figure 2.2. Positive bias index by anxiety and psychological flexibility. Positive bias indices indicate an increased attentional bias favouring positive stimuli.

Negative bias. Table 2.4 presents the results of the hierarchical regression analyses predicting negative attention bias (relative to neutral stimuli). In contrast to the prior positive bias and positive-over-negative bias analyses no model reached statistical significance, and none of the predictors entered significantly predicted bias. The final model explained only .8% of the sample variance in negative bias. For completeness, Figure 2.3 displays the interaction between anxiety and psychological flexibility.

Table 2.4. Hierarchical multiple regression analyses predicting negative bias.

		R^2	ΔR^2	B	SE B	β	*p*
Step 1		.00	.00				.667
	Constant			.66	4.10		.872
	GAD			-.31	.73	-.06	.667
Step2		.00	.00				.897
	Constant			-3.05	20.28		.881
	GAD			-.16	1.11	-.03	.888
	AAQ			.10	.53	.03	.852
Step 3		.01	.01				.886
	Constant			-10.93	23.66		.646
	GAD			1.36	2.57	.21	.600
	AAQ			.35	.65	.11	.597
	GAD*AAQ			-.06	.09	-.01	.516

Note. GAD: Generalized Anxiety Disorder; AAQ: Acceptance and action questionnaire. * $p < .05$, ** $p < .01$, *** $p < .001$

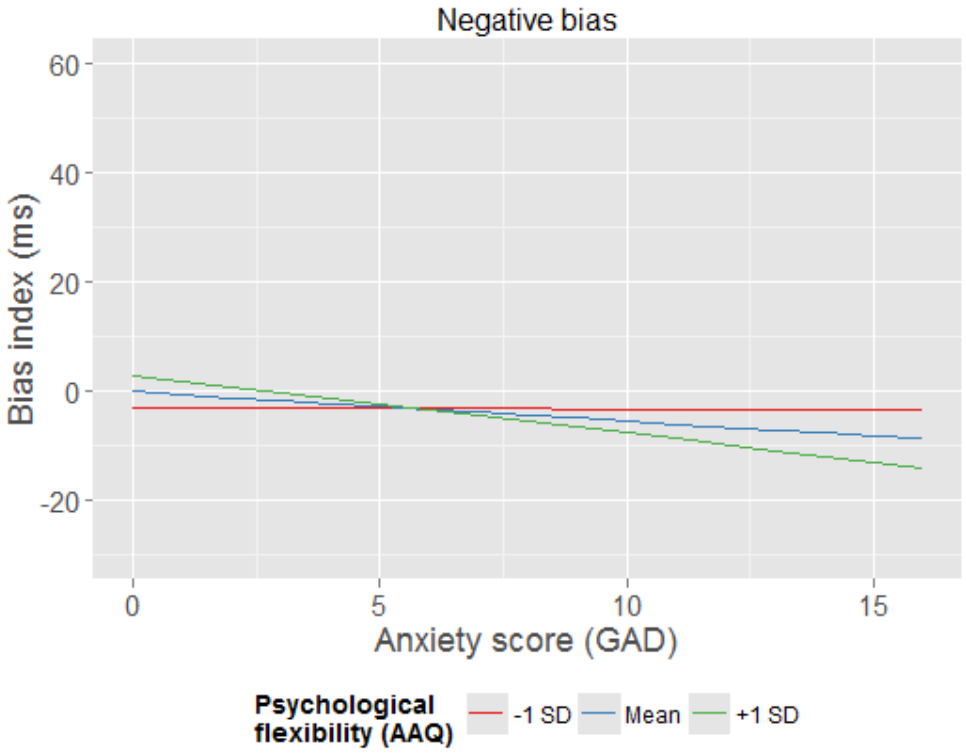


Figure 2.3. Negative bias index by anxiety and psychological flexibility. Positive indices indicate an attention bias favouring negative stimuli.

Emotion recognition task

A multiple logistic regression was performed to ascertain the effects of mental health, emotion intensity, and emotion type in predicting the likelihood of accurate emotion recognition. The overall model was significant $\chi^2(13) = 3012.81$, $p < .001$, explained 25% of the variance (Nagelkerke R^2) and correctly classified 74% of cases. Table 2.5 presents the model parameters and Figure 2.4 displays the predicted probability of accurate emotion recognition (collapsed across emotions) by the interaction between emotion intensity, and mental health. The significant mental health by emotion intensity interaction suggests that individuals with higher mental health were marginally more accurate at higher emotion intensities, but marginally worse at lower emotion intensities, compared to individuals with lower mental health. However, the effect is extremely small ($\beta \sim .001$), and should be interpreted with caution.

Table 2.5. Mixed-effects logistic regression predicting emotion recognition accuracy.

				95% CI		
Factor	**β**	**SE B**	**Odds Ratio**	**Lower**	**Upper**	***P***
Intercept	-.60	.17	.55	.39	.77	<.001
MHC	.00	.00	1.00	.99	1.01	.781
Intensity	.18	.01	1.19	1.16	1.23	<.001
Emotion						.013
Anger	-.20	.20	.82	.56	1.20	.312
Disgust	.19	.20	1.21	.82	1.81	.340
Fear	-.36	.19	.70	.48	1.51	.064
Happy	.02	.20	1.02	.69	1.51	.910
Sad	.27	.20	1.31	.88	1.95	.182
MHCxIntensity	.00	.00	1.00	1.00	1.00	<.001
MHCxEmotion						<.001

Note. R^2= .16 (Hosmer-Lemeshow), .18 (Cox-Snell), .25 (Nagelkerke). Model $\chi^2(13) = 3012.81$, $p < .001$. *p* values for variables with more than one level based on Wald's χ^2 test.

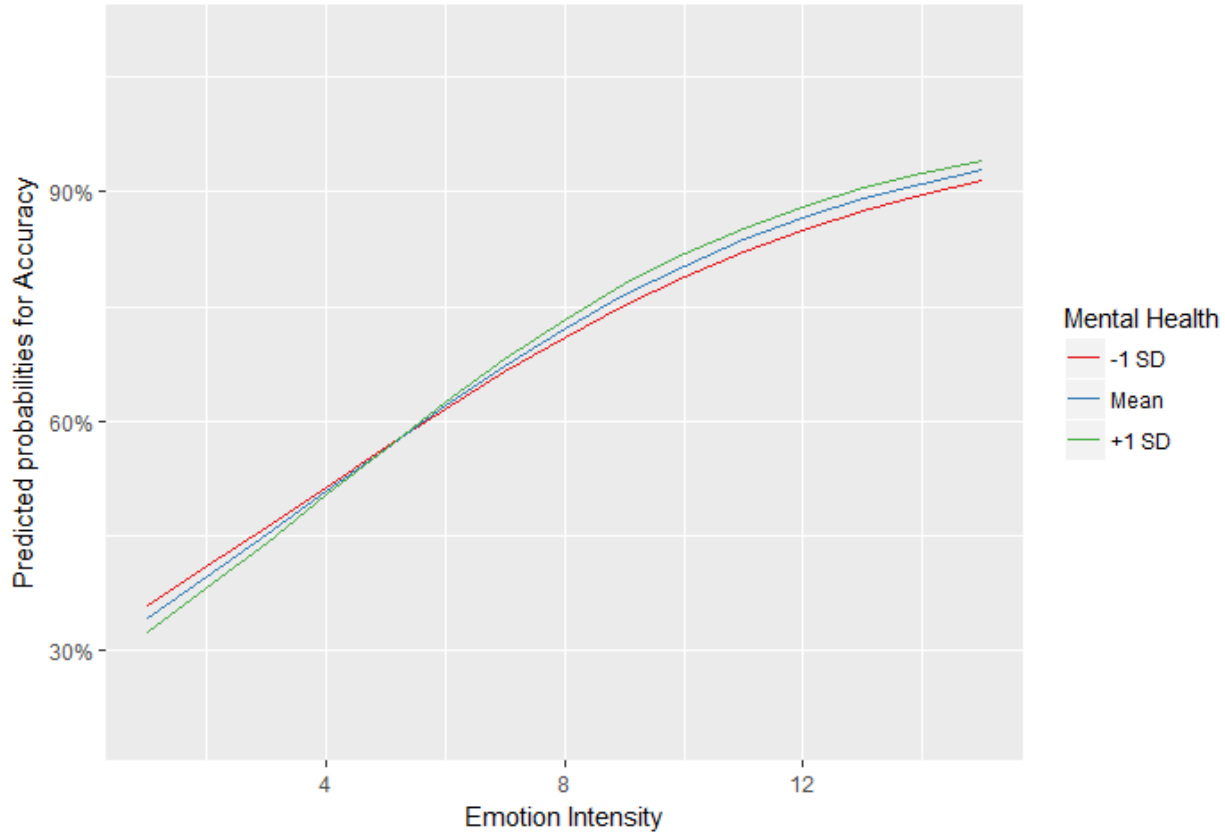


Figure 2.4. Predicted emotion recognition accuracy, predicted by intensity and mental health score. Note. Predicted values shown by mean and +/- 1 SD mental health score to illustrate the interaction.

The significant mental health x emotion interaction led us to explore the data further by performing separate regression analyses for each emotion. Table 2.6 presents the results of these analyses and Figure 2.5 presents the interactions visually. Each model significantly predicted recognition accuracy (all *p*s < .001). The angry, disgust, happy, and surprised models were similar; emotion intensity significantly predicted recognition accuracy (all *p*s < .001), whereas mental health and the interaction were not significant predictors. A significant mental health by intensity interaction was only observed in predicting accurate recognition of sad expressions (p = .006), along with the significant predictors of mental health and intensity. Emotion intensity did not significantly predict accurate recognition of fear

expressions, however, mental health was a significant predictor, and the interaction between these two factors approached significance.

Table 2.6. Multiple logarithmic regressions predicting correct recognition for each emotion, separately for each emotion type

Emotion	Factor	β	SE B	Odds Ratio	95% CI lower	95% CI upper	*p*
Angry	Constant	-1.69	.32	.18	.10	.34	<.001
	MHC	-.01	.01	.99	.97	1.00	.145
	Intensity	.30	.04	1.36	1.25	1.48	<.001
	MHC x Intensity	.00	.00	1.00	1.00	1.00	.162
R^2 = .28 (Hosmer-Lemeshow), .31 (Cox-Snell), .42 (Nagelkerke). $X^2(3) = 935.98$, $p < .001$							
Disgust	Constant	-.24	.27	.78	.46	1.34	.378
	MHC	.00	.01	1.00	.99	1.02	.784
	Intensity	.15	.04	1.17	1.09	1.25	<.001
	MHC x Intensity	.00	.00	1.00	1.00	1.00	.321
R^2 = .09 (Hosmer-Lemeshow), .10 (Cox-Snell), .15 (Nagelkerke). $X^2(3) = 261.29$, $p < .001$							
Fearful	Constant	.18	.25	1.20	.73	1.97	.481
	MHC	-.02	.01	.98	.97	1.00	.006
	Intensity	.03	.03	1.03	.97	1.08	.373
	MHC x Intensity	.00	.00	1.00	1.00	1.00	.054
R^2 = .02 (Hosmer-Lemeshow), .03 (Cox-Snell), .04 (Nagelkerke). $X^2(3) = 76.14$, $p < .001$							
Happy	Constant	-.45	.27	.64	.37	1.08	.094
	MHC	-.01	.01	.99	.98	1.01	.3477
	Intensity	.16	.03	1.17	1.10	1.25	<.001
	MHC x Intensity	.00	.00	1.00	1.00	1.00	.126
R^2 = .12 (Hosmer-Lemeshow), .14 (Cox-Snell), .19 (Nagelkerke). $X^2(3) = 365.96$, $p < .001$							
Sad	Constant	-.34	.29	.72	.41	1.25	.240
	MHC	-.02	.01	.98	.97	1.00	.033
	Intensity	.17	.04	1.19	1.10	1.29	<.001
	MHC x Intensity	.00	.00	1.00	1.00	1.01	<.001
R^2 = .20 (Hosmer-Lemeshow), .20 (Cox-Snell), .30 (Nagelkerke). $X^2(3) = 575.55$, $p < .001$							
Surprised	Constant	-1.54	.31	.21	.12	.39	<.001
	MHC	.00	.01	1.00	.98	1.02	.853
	Intensity	.32	.05	1.37	1.26	1.51	<.001
	MHC x Intensity	.00	.00	1.00	1.00	1.00	.224
R^2 = .27 (Hosmer-Lemeshow), .28 (Cox-Snell), .40 (Nagelkerke), $X^2(3) = 808.79$, $p < .001$							

Note. MHC = Mental Health Continuum.

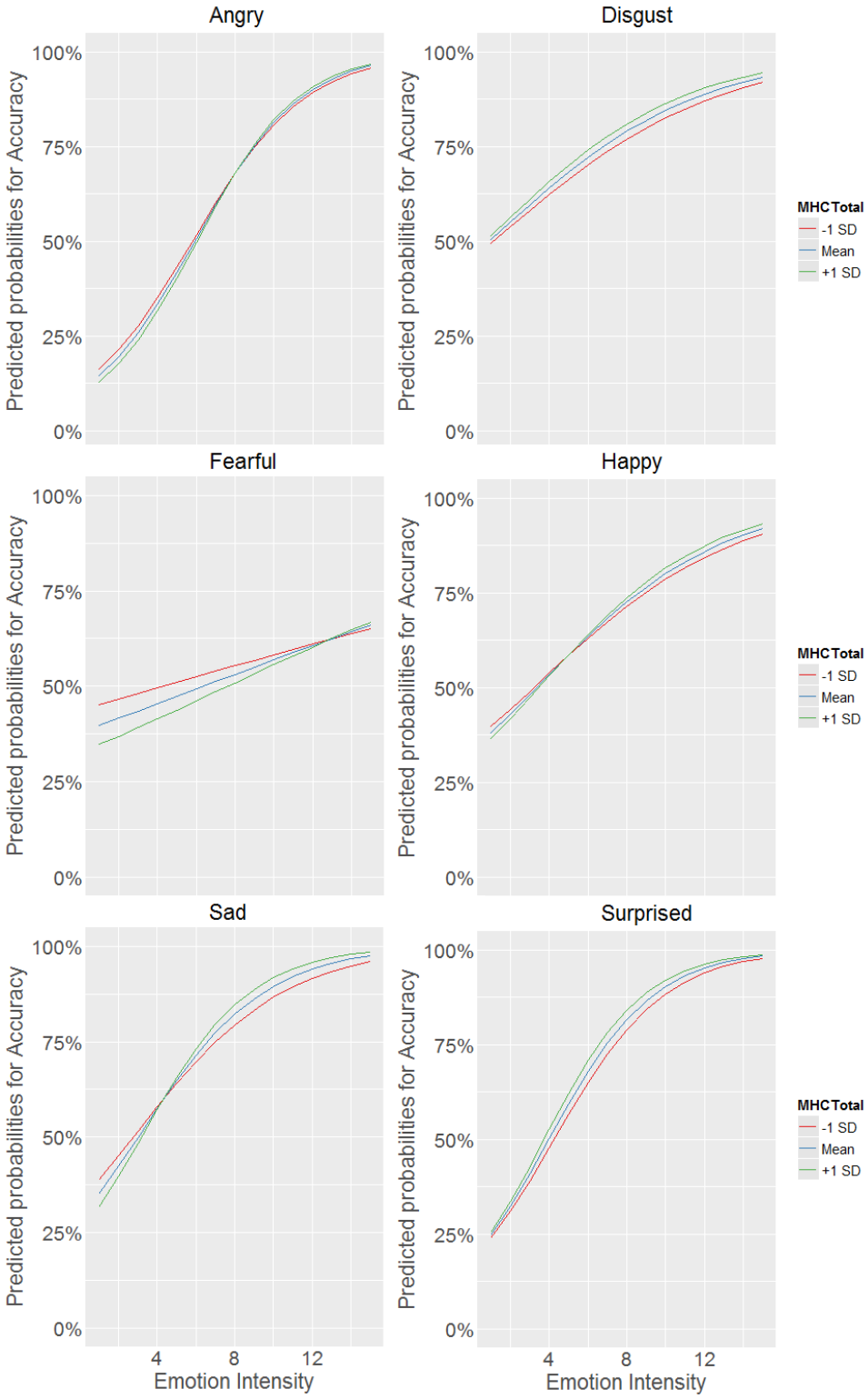


Figure 2.5. Predicted emotion recognition accuracy, predicted by intensity and mental health score, separately for each emotion. Note. Predicted values shown by mean and +/- 1 SD mental health score to illustrate the interaction.

Incidental learning and free recall task

Median imagery ratings and total words recalled in each word category were taken for each participant. Positive to negative imagery and recall ratios were calculated and used as the dependent variables. Table 2.7 displays the Pearson's correlations between the self-reported mental health factor scales and mental illness scales, and the imagery and recall ratios, for positive and negative items. Imagery ratings for positive items were significantly positively correlated with positive mental health measures, and significantly negatively correlated with mental illness measures. In contrast, the imagery ratings for negative items were only significantly correlated with psychological flexibility and depression. No significant correlations were found between self-report measures and recall of positive or negative items.

Table 2.7. Zero order correlations between self-reported measures, and Imagery and recall scores for positive and negative items

Self-report measure	Imagery		Recall	
	Positive	Negative	Positive	Negative
Mental Health (MHC)	.52***	.01	.20	.15
Resilience (CD-RISC)	.48***	-.01	.14	.03
Psychological Flexibility (AAQ-II)	.31*	-.23*	.12	-.04
Anxiety (GAD-7)	-.28*	.13	-.19	-.06
Depression (PHQ-9)	-.25*	.23*	-.21	-.12

Note. MHC = Mental Health Continuum, CD-RISC = Connor-Davidson Resilience Scale, AAQ-II = Action & Acceptance Questionnaire - II, GAD-7 = Generalized Anxiety Disorder - 7 item, PHQ-9 = Patient Health Questionnaire - 9 item. * $p > .05$, ** $p > .01$, *** $p > .001$.

Discussion

This study sought to investigate the relationships between positive mental health factors and information processing biases in attention, emotion recognition, and memory. Although exploratory, the current findings suggest that positive mental health factors associate with

biases in attention and emotion recognition. In the dot-probe task, psychological flexibility significantly interacted with anxiety to predict positive attention biases (relative-to negative, and neutral stimuli). In the emotion recognition task, mental health significantly interacted with emotion intensity to predict the probability of accurate recognition. Though positive mental health factors did not associate with the ratio of recalled positive over negative items, participants' ability to imagine themselves in a scene described by a positive word, was positively associated with mental health factors and negatively with mental illness. In the following sections we discuss the results from each cognitive bias task in greater detail.

Attentional bias

Trait-Anxiety and psychological flexibility were found to interact to predict attention biases towards positive stimuli. It is worth noting that the pattern of bias differed depending on whether the positive stimulus was paired with a negative, or a neutral stimulus. Increased psychological flexibility predicted greater attention bias towards positive stimuli, relative to paired negative stimuli, as anxiety increased. A possible explanation of these results is that increased psychological flexibility may facilitate the development of bias previously present, such as in anxiety. For example, one study demonstrated that later anxiety and attention bias was predicted by an increased readiness to adopt an attention bias in an attention bias modification procedure (Clarke et al., 2008). The ability to adapt an attentional bias readily to task demands might also be considered a marker of greater psychological flexibility. This might be thought to facilitate the acquisition of anxiety related bias over time. Unfortunately, this interpretation does not account for the differences between the positive bias indices. To contrast, when the positive stimuli were paired with neutral stimuli, higher levels of psychological flexibility predicted less (or no) change in bias with increasing anxiety. This suggests that maintaining no attentional bias towards positive stimuli (relative to neutral

stimuli) is protective, given increased anxiety. Given that the effects reported here are small and contradictory within an exploratory study, future work is needed to first support and then further investigate these contradictory results. An additional question is whether the positive-negative biases observed in this study reflect an increased attendance towards positive stimuli, or avoidance of negative stimuli. As no anxiety or psychological flexibility related bias towards negative information were observed, it would be tempting to assume that selective bias towards positive stimuli is the driving force behind these results. However, further investigation is needed into the influence of stimuli-pairs on attention biases. In particular, to examine the question of whether selective preference for positive over negative stimuli reflects attendance to the positive stimuli, or avoidance of the negative stimuli (e.g. (Koster, Crombez, Verschuere, & De Houwer, 2004) This would help elucidate the relationship between psychological flexibility and selective attention. Eye-tracking studies for example may be better able to demonstrate differences in overt attention during tasks such as the dot probe (Raila et al., 2015; Staugaard, 2009), within which the stimulus pairs can be manipulated for valence and arousal, in order to address this question.

Emotion Recognition

Our findings suggest that mental health may be characterized by subtle differences in emotion recognition accuracy, with respect to the intensity of the emotional expression expressed. The significant interaction suggests that individuals with higher positive mental health were found to benefit more from increasing emotional intensity in accurate recognition of emotional expressions. Moreover, this interaction appears to be driven by sad expressions, although the interaction in fear expressions also approached significance. Indeed, fearful and sad emotions also showed a main effect of mental health on accurate recognition, pointing to the role of emotion recognition in mental health. The results here suggest that mental health

more specifically associates with differences in the recognition of sad and fearful emotions. Prior research has demonstrated that social anxiety similarly affects recognition accuracy. However, unlike our data, these effects were generalised across emotions (Button et al., 2013). Although our task differed in that we did not have the option of a "neutral" expression response, the results presented here suggest that positive mental health may be associated with a more specific pattern of emotion recognition bias compared with social anxiety. Tentatively, this may suggest that positive mental health associates with a different pattern of emotion recognition to emotion dysfunction, supporting Keyes (2002, 2005a) dual continua model in emotion information-processing. Although it is important to note that the very small effect sizes warrant caution in interpretation of these results.

Imagery and memory bias

We found no associations between recall for positive or negative items and mental health or mental illness. This is in line with prior research that has found no evidence of group differences (between depresses, generally anxious, PTSD, and healthy controls) in recall of positive or negative words (Dalgleish et al., 2010). Future research might use implicit measures of memory bias in order to more fully explore the potential role of memory bias in positive mental health, and the role of conceptual elaboration of emotional information (Watkins, 2002). For example, while Bradley et al. (1994) found no evidence of depression-related explicit memory bias, they did find evidence of depression-related implicit memory biases. It is plausible that implicit biases in memory are associated with positive mental health, however, research is needed to test this hypothesis.

Participants' imagery ratings for positive items associated positively with self-reported mental health and negatively with mental illness. In contrast, only psychological flexibility and depression were associated with imagery ratings for negative items. The strongest

associations were between mental health and resilience, suggesting that ability to imagine more positive situations plays a role in mental health and resilience, or vice versa. Greater ability to generate vivid positive mental imagery of future events has been shown to associate with dispositional optimism (Blackwell et al., 2012). Together, this suggests that positive imagery could act as a positive mental health target for cognitive interventions, though more research is needed to establish the direction of causality.

Limitations and future directions

We acknowledge several limitations in this study. First, the cross-sectional design does not permit causal conclusions about the relationships between information processing biases and positive mental health factors. However, as little research has been undertaken in this area, it followed that an exploratory study was a reasonable first step in exploring the potential role of information processing biases in positive mental health. In addition, the design allowed for the examination of an extended range of selective processing, i.e. positive relative to negative or neutral stimuli. As such, we suggest that the results offer some support for future research investigating the information processing components of positive mental health.

Second, we did not utilise content-specific stimuli in either word-based task. The more general categories of positive, negative, and neutral words were used as stimuli categories. This may have hidden the effect of disorder specific biases, such as threatening stimuli in anxiety (Cisler & Koster, 2010). In addition, Tamir and Robinson (2007) found associations between positive attentional bias and positive affective states, in particular with reward related stimuli. Further probing of more specific attentional biases may be warranted to elucidate potential selective attentional characteristics of positive mental health. An image based attention task may also be used to explore the relationship between selective attention

to emotional information and positive mental health. We did not use emotional expressions as stimuli in the dot-probe task to avoid contaminating the data from the emotion recognition task, and vice versa. However, our finding that positive mental health was associated with subtle differences in the recognition of emotion, specifically in sad and fearful expressions, supports future examination of attentional biases towards facially expressed emotion.

Third, information-processing biases are not fixed phenotypes, and the adaptive benefit of selective information processing may depend on the context in which it is utilised (discussed in Chapter Six). For example, in situations of high threat, attentional bias towards threatening stimuli can be considered highly adaptive (e.g. Wald et al., 2015). It is likely that a laboratory testing session may not evoke the processing biases associated with emotional pathology and/or mental health. As such, in order to examine the role of selective processing in positive mental health and resilience different experimental designs are warranted. For example, some form of adversity or stress induction procedure might be necessary in order to examine a dynamic process such as resilience (e.g. Carver, 1998; Fergus & Zimmerman, 2005, this is also elaborated on in Chapter 6). It is perhaps unsurprising therefore that this study found no associations between trait-resilience measured as a self-report and cognitive biases assessed in a single low-stress session. The changes in bias across situations, such as periods of extended stress, or a laboratory induced stressor may reveal mechanisms relating context-specific adaptive information processing biases and positive mental health and resilience.

Finally, a potential limitation of the current sample is the small number of low mental health (languishing) individuals. This study is therefore limited in predicting the cognitive bias that may associate with low positive mental health. Keyes dual continua model typically classifies a small proportion of the sample as languishing (e.g. Fink, 2014; Keyes, 2002;

Peter, Roberts, & Dengate, 2011), which may explain the low prevalence in this sample, given that typically the samples are quite large. A strong approach would be to compare cognitive bias data from a sample of high mental health individuals to a sample of low mental health individuals. In Chapter Three, networks of cognitive biases are compared between of high and low mental health adolescents.

Conclusion

Despite some limitations, this study provides initial data on positive mental health related cognitive biases in attention and emotion recognition. The study intended to probe potential relationships between cognitive biases and mental health, in order to help guide future research in this area. While the exploratory nature of the study does not fully allow for conclusions to be drawn about these associations, the results presented support continued research in this area. Our key findings were that psychological flexibility interacted with anxiety to predict attention bias towards positive stimuli, and this pattern differed depending on the valence of the word with which the positive word was paired. Further, we found that positive mental health interacted (albeit mildly) with the intensity of a facially expressed emotion to predict the likelihood of accurate emotion recognition, with this effect being localised to sad and fearful expressions. Similarly, mental health and resilience were found to be strongly associated with the ability to generate images from positive, but not negative words. These results suggest that positive mental health may be characterized by a certain pattern of emotional information processing, which may also be distinct from patterns of cognitive bias observed in emotional vulnerability. The present results support continued investigation of the emotional information-processing characteristics of positive mental health, in addition to current work targeting emotional vulnerability.

2. An exploration of the associations between selective processing biases and positive mental health

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Chapter 3

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3

Cognitive correlates of mental health in adolescence: A network analysis approach

Selective cognitive processing biases for negative and positive material are important for mental health. While the combined cognitive bias hypothesis (CCBH) suggests that distinct patterns of connectivity among attention, interpretation, and memory biases, contribute to psychopathology, little is known about the interrelationships amongst cognitive biases in relation to positive mental health. In the current study, we used network analysis to estimate the interrelationships among cognitive biases in adolescents with high (n = 103) and low (n = 104) levels of self-reported mental health. We found greater connectivity amongst interpretation and memory biases in the low relative to the high mental health group suggesting that reducing connections between interpretation and memory biases may promote mental wellbeing in adolescents. This approach to visualizing connections amongst cognitive biases offers an informative way to visualize and investigate the combined cognitive bias hypothesis in adolescent mental wellbeing.

Introduction

Cognitive biases are important in the development and maintenance of emotional disorders (for reviews, see (Cisler & Koster, 2010; Gotlib & Joormann, 2010; Mathews & MacLeod, 1994, 2005). Automatic tendencies to selectively process negative, relative to benign or positive material, is associated with anxiety and depression, and these biases have been documented in attention, interpretation of ambiguity, as well as in memory. Studies examining selective processing biases in relation to emotional vulnerability have tended to examine a single process in isolation with few studies examining more than one bias in a single study (Everaert, Koster, & Derakshan, 2012; Hirsch et al., 2006). The combined cognitive bias hypothesis (CCBH: Hirsch et al., 2006), however, proposes that cognitive biases do not work in isolation to influence emotional vulnerability, but rather, they influence each other and interact to influence other variables, including emotional vulnerability. For example, increased attentional bias towards threatening stimuli might influence the degree to which less clearly negative information is interpreted more negatively, which in turn could plausibly influence memory for that stimulus. Such a series of causally related negative biases would be expected to propagate emotional vulnerability. The CCBH also suggests that targeting one process in order to produce a change in another is one way in which psychological interventions (e.g., cognitive behaviour therapy, cognitive bias modification) could be utilized to reduce emotional vulnerability. One study conducted in adults, for instance, concluded that memory bias may be more effectively modified by targeting emotional processing in another domain, such as interpretation bias (Vrijsen, van Oostrom, Isaac, Becker, & Speckens, 2014, also see Hertel & Mathews, 2011). A further study in adults investigated the functional relationships among cognitive biases in a subclinical depressed sample and found that while attentional bias was not directly associated with memory bias, there was an indirect association via interpretation bias (Everaert et al., 2013).

These results provide some indication that biased cognition in one domain may not act in isolation, but rather may influence other processing biases to ultimately influence emotional vulnerability.

In one study (Everaert et al., 2014) a novel computerised version of the scrambled sentences task (Wenzlaff & Bates, 1998) was used to investigate the direct impact of attention bias on interpretation bias to memory bias. Participants are required to unscramble a scrambled sentence to form a grammatically correct sentence of 5 or 6 words. Eye tracking is used to measure attentional bias to negative words based on fixation time on those words, while the ratio of negatively valenced to total unscrambled sentences is used to index interpretation bias. Finally, participants complete an incidental free recall test in which they recall as many of the sentences they constructed as possible, which provides an index of memory bias. From the theoretical framework of the CCBH, incorporating these biases into the same task allows more precise inferences to be made as to how attention bias directly influences interpretation bias, which directly influences memory bias. Two path models were tested, the first omitting relationships between each of the biases, and the second including paths between the biases. The results indicate that the models including functional relationships amongst cognitive biases provided a superior fit of the data. This supports the central notion of the CCBH, namely, cognitive biases in different domains do not act in isolation, but influence each other in sub-clinical depression. The authors conclude that future research should further investigate and take into account the interrelations among cognitive biases.

The research described thus far has addressed the CCBH in adults by examining modelled relationships between biases and symptoms, using tasks that specifically aim to capture the direct effects of one bias on another. Another approach to examine the CCBH is

to explore differences in the relationships between biases, in clinical and non-clinical groups. If cognitive biases are found to hold different relationships to one and another in a clinical sample, but not in a normative sample, this would suggest that the interrelationships and interactions among biases might contribute to the pathology itself. In one study, the factor structure of interrelations among cognitive bias measures in attention, inhibition, imagery, and memory were found to differ between a formerly depressed, and non-clinical sample (Vrijsen et al., 2014). Coherence between attention and memory bias was found in the non-clinical sample, but not in the formerly depressed sample. This suggests that functional relationships among cognitive biases may differ between vulnerable and less-vulnerable groups.

With substantive neural, cognitive and social changes occurring during adolescence, this period of development is a key stage for the first-onset and development of emotion disorders. Research to date has been performed in almost exclusively adult samples. To our knowledge only a single study to date has examined the combined cognitive bias hypothesis in an adolescent sample (Klein, de Voogd, Wiers, & Salemink, 2017). Three cognitive bias measures were used; an emotional visual search task, a dot-probe task, and the interpretation recognition task for children. The results indicate that each cognitive bias predicted unique variance in anxiety and depression, separately, supporting the CCBH proposition that cognitive biases in different domains contribute separately to emotional vulnerability. Further exploration of adolescent mental health from a CCBH perspective is likely to be highly informative and this is the aim of the current study.

Cognitive bias approaches to positive mental health and resilience

While information-processing approaches have been widely used to investigate the cognitive mechanisms of emotion dysfunction (for reviews, see Gotlib & Joormann, 2010;

Lau & Waters, 2017; Mathews & MacLeod, 2005; Yiend, 2010) relatively little research has examined the role of selective information processing in positive mental health in adults (Carl et al., 2013; Chapter Six) and even less in adolescents. Positive mental health and mental illness are considered to represent two distinct, albeit inversely correlated, continua (Keyes, 2002, 2005a). Mental illness and low mental health have been found to have additive adverse effects on an individual's functioning in life, including academic impairment and suicidal ideation (Keyes et al., 2012), as well as all-cause mortality (Keyes & Simoes, 2012). While some research has examined factors related to positive mental health within a cognitive-experimental framework, as with the CCBH, the majority of this research has been conducted in adults. Trait happiness and satisfaction with life, for example, which are both core components of positive mental health, have been associated with attentional biases towards positive images especially in the later stages of passive viewing (Raila et al., 2015). An implication of the dual continua model is that they may be characterised by distinct patterns of selective processing styles or biases, just as the 'symptoms' of mental health and mental illness differ from each other. A network approach is a useful methodology to explore whether or not distinct networks of cognitive biases distinguish between individuals with high and low levels of self-reported mental health. To our knowledge, this is the first study to use network analyses to examine the role that connections in selective processing of emotional information plays in positive mental health in an adolescent sample.

Psychological Network approaches

A network perspective on psychopathology views emotional disorders, such as anxiety and depression, as a system of interacting symptoms (Fried, 2017; Fried et al., 2017). As such, rather than individual symptoms acting alone to influence a disorder, the interrelations between them also play a key role. Borsboom and colleagues have been the driving force behind initiating network analyses in clinical psychology (Borsboom, Cramer, Schmittmann,

Epskamp, & Waldorp, 2011; Schmittmann et al., 2013), and this has resulted in an increasing application of network analysis approaches to psychopathology (e.g. Bernstein, Heeren, & McNally, 2017; Borsboom & Cramer, 2013; Heeren & McNally, 2016; McNally et al., 2015). A common aim of network approaches is to identify plausible, and potentially causal, connections amongst measured variables. Typically in examining psychopathology the relationships between individual symptoms of a disorder would be investigated (e.g. McNally et al., 2015). Of particular relevance to the current work are two studies that extended the network approach to investigate laboratory measures of cognition and behaviour (Bernstein et al., 2017; Heeren & McNally, 2016). Heeren and McNally investigated the interplay between symptoms, attentional bias, and attentional control in social anxiety disorder. Their analysis indicated that the orienting of attention was strongly linked to self-reported fear of social situations, which in turn was strongly related to avoidance of those situations. The network analysis has a potentially important clinical implication in that it suggests that interventions targeting attention orientation would positively influence other processes and propagate those benefits throughout the psychological network, resulting in therapeutic effects (McNally et al., 2015). Similarly, Bernstein et al. investigated components of executive control and components of rumination. The networks suggested that self-criticism was particularly central to the networks and had strong down-stream effects on negativity and brooding in particular. Thus, reducing self-criticism may have a wide reaching beneficial effect on other components of rumination, and represents a potentially useful therapeutic target. Network analysis approaches therefore provide an informative perspective of the interplay between cognitive processes and components of psychopathology and may help to inform the development of novel clinical interventions. In the current study, we employ network analyses to investigate the CCBH in relation to positive mental health and wellbeing in adolescence.

A network theory of mental disorders has recently been proposed, with several core principles (Borsboom, 2017). The *complexity* principle proposes that mental disorders are characterised in terms of the interactions among different components in a psychopathology network. That is to say that while the individual symptoms influence mental disorders, such symptoms are also related to one another. This relates to the *direct causal connections* principle, which states that direct causal connections among symptoms form the network structure. These principles are comparable to the, albeit less formal, core elements of the CCBH; namely that we would expect different biases to interact with one another to influence emotional vulnerability and that biases may reinforce one another reciprocally to influence emotional vulnerability. The similarities are such that theoretically applying the principles of the network approach may prove fruitful and provide a more formal and systematic approach to investigation of the CCBH. We propose that cognitive biases directly and indirectly influence one another (*direct causal connections*), and that these interactions among different biases are likely to influence emotional vulnerability as well as emotional wellbeing (*complexity*). Borsboom's fourth principle *mental disorders follow a network structure* can be described as the presence of symptoms that are more closely linked than others or as groups of symptoms that often arise together. Thus, we might expect that cognitive biases for negative information may be more highly clustered and interlinked in more vulnerable populations. Network analysis has been used to examine the structure amongst laboratory measures of attention bias and core symptoms of social anxiety disorder (Heeren & McNally, 2016), as well as functional relationships amongst components of executive control and rumination (Bernstein et al., 2017). In the current study, we sought to expand upon this work by utilising network approaches as a potentially informative theoretical and methodological framework to investigate the CCBH in adolescent mental health.

In a network, *nodes* that represent observed psychological variables (e.g. psychometric tests or indices of cognitive bias) are connected by *edges,* which represent some statistical relationship between them, such as the correlation. The strength, or *edge weight* of these edges can differ to incorporate information about the direction of the relationship, typically represented with positive associations in green and negative associations in red. Additionally, stronger relationships are represented with thicker edges, whereas weaker relationships are denoted with thinner less saturated edges. Visualising the network provides a detailed image of the multivariate dependencies that exist in the dataset. In contrast to correlational or latent variable approaches, inference methods from graph theory can then be used to assess the relative importance of each node with several *centrality indices*. This enables inferences to be made as to which symptoms have a greater effect on the network overall, or are potential targets for intervention (Fried et al., 2017; Fried & Cramer, 2017). Network approaches therefore differ from latent variable models that explain co-occurrence amongst symptoms, or biases as in the case of the CCBH, with an underlying unobserved latent variable as a common cause of the symptoms. Under this theoretical position, emotional disorders are denoted by a network in which some symptoms interact to stimulate or inhibit one another (Costantini et al., 2015). If we consider that cognitive biases represent a vulnerability factor for emotional disorders, similar to symptoms of a particular disorder, then this theoretical position is promising in the examination of the CCBH. Under the assumptions here, and the principles of network theory described above, a psychological network analysis approach is a valuable way to analyse cognitive bias data to examine the CCBH. We note that some authors have questioned the replicability of psychopathology networks (Forbes, Wright, Markon, & Krueger, 2017). However, this conclusion has been refuted strongly with evidence demonstrating the high degree of precision with which the networks were replicated (Borsboom et al., 2017).

In the current study, we employed a psychological network analysis approach to investigate the CCBH in positive mental health in adolescents. We were interested in differences between the networks of cognitive biases in adolescents reporting high and low mental health. Therefore, we selected two groups from a large sample of adolescents based on self-reported mental health scores with the aim of examining groups that differ in their self-reported mental health. The study focussed on attention, interpretation, and memory bias, to limit the scope to the processes previously implicated in the CCBH (Hirsch et al., 2006). Our primary aim was to explore differences in cognitive bias networks between adolescents reporting high mental health and those reporting low mental health on a standardized measure. To achieve this we computed weighted and directed networks of cognitive biases in high and low mental health samples to provide an initial investigation of the CCBH in positive mental health in adolescence, and to generate novel hypotheses for future research.

Methods

The data analysed and presented in this paper are drawn from the CogBIAS longitudinal study (Booth et al., 2017), which has recruited approximately five hundred 12-14 year old secondary school children in the UK. Each young person completed a series of cognitive bias measures (including attention, interpretation, and memory) are being followed up for two further waves of testing at the age of 14 and again at the age of 16. This project is the only one known to the authors to incorporate a longitudinal design, with a range of cognitive biases measured, and at three time-points in an adolescent sample. The CogBIAS project therefore presents an ideal opportunity to examine the CCBH as it applies to adolescents, specifically with respect to the role these cognitive biases play in positive mental health.

In this paper, we analyse only data from the Mental Health Continuum (MHC-SF; Keyes, 2002, 2009), which provides an assessment along the spectrum of languishing to

flourishing. To examine the cognitive biases of interest, we analysed data from the following tasks; the Dot-Probe task to assess attention bias (Colin MacLeod et al., 1986), the Adolescent Interpretation and Belief Questionnaire to assess interpretation bias (Miers, Blöte, Bögels, & Westenberg, 2008), and the Self-referential Encoding Task to assess memory bias (Hammen & Zupan, 1984). We present a brief description of these measures below, however, a complete description of the sample, methods, and design used in the project can be in the protocol paper (Booth et al, 2017).

Participants

We first excluded all participants without complete data in all of the measures described below, resulting in a sample of 448 students (from the original sample of 504). We selected two groups of participants for the network analyses based on scores on the Mental Health Continuum. To our knowledge there are no available normative mental health scores. Therefore, we aimed for a sample size in each group of approximately 100, in order to ensure that the groups represent individuals who represent high and low extremes of the mental health continuum, while ensuring an acceptable sample size for the network analysis. We selected 104 participants for the low Mental health group (corresponding to scores below 33, hereafter referred to as low-MH group), and 103 participants for the high Mental health group (corresponding to scores above 50, hereafter referred to as high-MH group). Note that scores of 33 and 50 correspond to the lower and upper quantile for the total sample. Table 3.1 presents the demographics and summary data from the study measures, for the high and low group separately. Ethical approval for this study was given by the National Research Ethics Service (NREC; REC reference: 14/SC/0128; IRAS project ID: 141833).

Table 3.1. Descriptive statistics of the high-MH and low-MH group

	low - MH	high-MH	*t*
N	104	103	

age	13.0	13.0	-0.37
gender (%F)	63.5	53.4	1.76[1]
MHC	22.5 (7.6)	55.6 (3.2)	-40.90*
Attention Bias			
Angry	-1 (38)	0 (40)	-0.27
Happy	7 (41)	-1 (47)	1.43
Pain	-3 (34)	-2 (30)	-0.08
Interpretation bias			
Positive – Social	2.2 (.6)	2.8 (.6)	-6.73*
Positive – Non-social	3.2 (.7)	3.9 (.6)	-7.02*
Negative – Social	3.6 (.8)	3.1 (.8)	4.36*
Negative – Non-social	3.3 (.7)	3.0 (.8)	2.53*
Memory bias			
Positive	5.2 (3.1)	8.0 (2.6)	-7.06*
Negative	4.0 (2.9)	1.4 (1.6)	7.92*

Note. [1] Chi-Squared goodness-of-fit test, * $p < .05$

Measures

Mental health. The MHC-SF contains 14 items that index emotional, psychological, and social wellbeing, in order to create a composite measure of positive mental health. Participants are asked to rate how often they have experienced each of the items in the past month, on a 6-point Likert scale from "never" to "every day". The MHC-SF has shown high internal consistency and discriminant validity (Keyes, 2009; Lamers, Westerhof, Bohlmeijer, ten Klooster, & Keyes, 2011; in the current sample, Cronbach's alphas for the emotion, social, and psychological wellbeing subscales, were .87, .87, and .89; Cronbach's alpha for the total score was .94).

Attention Bias. In the dot-probe task (Colin MacLeod et al., 1986), participants were presented with an emotional face, and a matched neutral face, both 230 x 230 pixels in size and presented to the left and right of the computer screen, separated by approximately 10^{o} visual angle. The face stimuli were chosen from the STOIC faces database, comprised of adult faces (Roy et al., 2007) and presented in grayscale, cropped to show no hair or jawline.

Both stimuli were presented for 500ms before being removed. Immediately following the removal of the face stimuli, a probe was presented in the location of one of the stimuli. The probe was either the letter Z or M, and participants were tasked to press this key as quickly and accurately as possible. Trials in which the probe appeared in the location of the emotional face were considered 'congruent' trials, and trials in which the probe appeared in the location of the neutral face were considered 'incongruent' trials. Following participant's response, or a maximum of 3000ms, the screen was cleared and the next trial began after a 500ms inter-trial interval and 500ms central fixation cross. Participants completed three blocks of 56 trials. In each block, the emotional face was either expressing an angry, happy, or pained expression and block order was counter-balanced between participants. Practice blocks of 8 and 16 trials were presented before the experimental blocks in order to familiarise participants with the task. Data from participants with greater than 30% errors was not analysed. Trials were removed in which an error was made, responses were less than 200ms or greater than 3000ms, or greater than 3 standard deviations from each participant's mean for each trial-type within each block. Bias indices were then calculated separately for the happy, angry, and pain blocks by subtracting the mean response time of congruent trials from the mean response time of incongruent trials.

Interpretation bias. The Adolescent Interpretation and Belief Questionnaire (AIBQ; Miers, Blöte, Bögels, & Westenberg, 2008) contains ten hypothetical situations, five of which are socially oriented and five are non-socially oriented, that are intended to reflect events that are likely to be experienced by adolescents. Participants read the scenario and are presented with a question that addresses a point of ambiguity in the scenario. A positive, a neutral, and a negative interpretation of the scenario are presented and participants rate how likely that interpretation would pop into their mind on a 5-point Likert scale. Participants then choose which interpretation of the situation they believe to be the most correct. Scenarios are

presented in a pseudo-random order. Bias scores were calculated by calculating the mean likelihood ratings for positive and negative interpretations of social and non-social situations separately, resulting in four bias indices – positive social; positive non-social; negative social; negative non-social.

Memory bias. In the Self-referential encoding task (SRET), participants were presented with 22 positive and 22 negative words in a random order (the word lists were drawn from Hammen & Zupan, 1984). Each word was presented for 200ms before a prompt "Describes me?" was presented on screen, after which participants responded 'yes' or 'no'. After all words had been presented a short distraction task was administered consisting of three simple mathematics questions. Finally, in the incidental recall phase, participants were given three minutes to recall and type in as many words as they could remember. Two bias indices were calculated. Positive and negative memory bias indices were calculated as the number of positive and negative words, respectively, that were endorsed (participants responded that the word described them) and subsequently recalled (Asarnow, Thompson, Joormann, & Gotlib, 2014).

Procedure

Participants were tested in groups of between 13 and 50 students in computer labs either in their own school, or at the University of Oxford. Testing consisted of two, one-hour sessions which were either back-to-back or on different days, depending on school availability. In each session, participants completed three tasks, in the same order, followed by a battery of questionnaires (see Booth et al, 2017, for further information on measures not analysed in this paper). Participants were asked to complete both sessions in exam conditions, i.e. not talking or looking at neighbours' computer screens. At least one researcher was

present throughout the testing sessions to answer any questions and ensure adequate testing conditions were maintained.

Network visualisation

We computed three types of networks using the *bootnet* R package (Epskamp, Borsboom, & Fried, 2017), which calls *qgraph* to estimate and plot the networks (Epskamp, Cramer, Waldorp, Schmittmann, & Borsboom, 2012). These networks were generated according to the Fruchterman and Reingold (1991) algorithm, which positions strongly related nodes in the middle of the figure, while weakly related nodes are presented further from the centre. To facilitate interpretations of the networks, and in particular, the differences between groups, the networks are displayed here as the average layout of the high-MH and low-MH groups. We first computed an association network, which included each variable of interest (the nodes) and the zero-order correlations between each variable (the edges). In this network, saturation of the edge represents the magnitude of the association, and the colour represents the direction of the correlation (green edges for positive correlations, and red edges for negative correlations). The association network is informative, however it can only approximate the underlying structure of the network in so far as the association between two nodes may be due to shared associations with a third node (Borsboom & Cramer, 2013; Maurage, Heeren, & Pesenti, 2013). Therefore, we computed a 'graphical LASSO' (glasso; Epskamp & Fried, 2016, also Friedman, Hastie, & Tibshirani, 2008) estimation procedure with EBIC model selection (Foygel & Drton, 2010). The glasso algorithm is implemented in the *glasso* package (Friedman, Hastie, & Tibshirani, 2014), and is called by the *bootnet* package (Epskamp et al., 2017), which we used for this paper. The glasso algorithm estimates a partial correlation network by directly penalising elements of the variance-covariance matrix. In order to maximise discovery in our analysis we set the tuning parameter gamma to 0. The graphical LASSO network is a sparser network, due to the removal of spurious

associations and therefore is thought to therefore be more representative of the network structure.

The association and graphical LASSO networks are weighted, which allows interpretation of the relationships between variables, however they are not directed. In order to make less limited inferences about the causal dynamics within a network, we computed a relative importance network (McNally et al., 2015; Robinaugh, LeBlanc, Vuletich, & Mcnally, 2014). Here, relative importance is an indicator of the non-normalised contribution that each predictor makes to R^2, taking into account the direct effect (its correlation with the criterion) and the effect in combination with the other variables in the regression equation model (Grömping, 2006; Johnson & Lebreton, 2004). As such, the relative importance networks are both weighted and directed, with the arrows indicating the direction of prediction. We used the *bootnet* package to estimate the relative importance network based on the graphical LASSO network structure, such that only edges that were included in the graphical LASSO were included in the relative importance network. To be clear, while the relative importance network can go some way to give an indication of the causal dynamics, the procedure cannot be used to infer causality.

Centrality analysis

Finally, we calculated four centrality indices (Costantini et al., 2015; Freeman, 1978) to examine the importance of each node in the relative importance network; *betweenness*, *closeness*, *in-strength*, and *out-strength*. Each index was calculated with the R package *qgraph* (Epskamp et al., 2012). Higher values for each index represent greater centrality within the network, the centrality plots depict these values graphically. *Betweenness* indicates the number of times the node lies on the shortest path length between any two other nodes. *Closeness* indicates the average distance of a node from the other nodes in the network, and is

computed as the inverse of the weighted sum of shortest path lengths of the node from all other nodes in the network (unconnected nodes have no variance in the distance from other nodes, and therefore closeness cannot be estimated for these nodes). *Strength* is calculated as the sum of edge weights connecting that node to the others in the network. The relative importance network, however, is directed and therefore we can separate in-strength from out-strength. As such, *In-strength* is an indication of the degree to which a node is influenced by the other nodes in the network, and is calculated as the sum of the directed edge weights directed to that node. On the other hand, *Out-strength* is an indication of the degree to which a node influences other nodes in the network, and is calculated as the sum of directed edges originating from that node.

Results

Network visualisation

Association networks. The association network presents the zero-order correlations between pairs of nodes (Figure 3.1). Some differences between the low-MH and high-MH networks are immediately apparent. The associations between memory and interpretation biases for social scenarios, for both positive and negative biases, for instance, are stronger in the low-MH group, compared to the high-MH group. Overall, the low-MH network appears more connected than the high-MH network. More specifically, a negative association between positive and negative memory bias can be seen in the low group (-.35), and a further negative association between positive and negative interpretation biases non-social scenarios is present only in the low-MH group (-.30). Common to both groups are strong connections between negative memory biases and negative social interpretation bias, and between negative social and negative non-social interpretation biases.

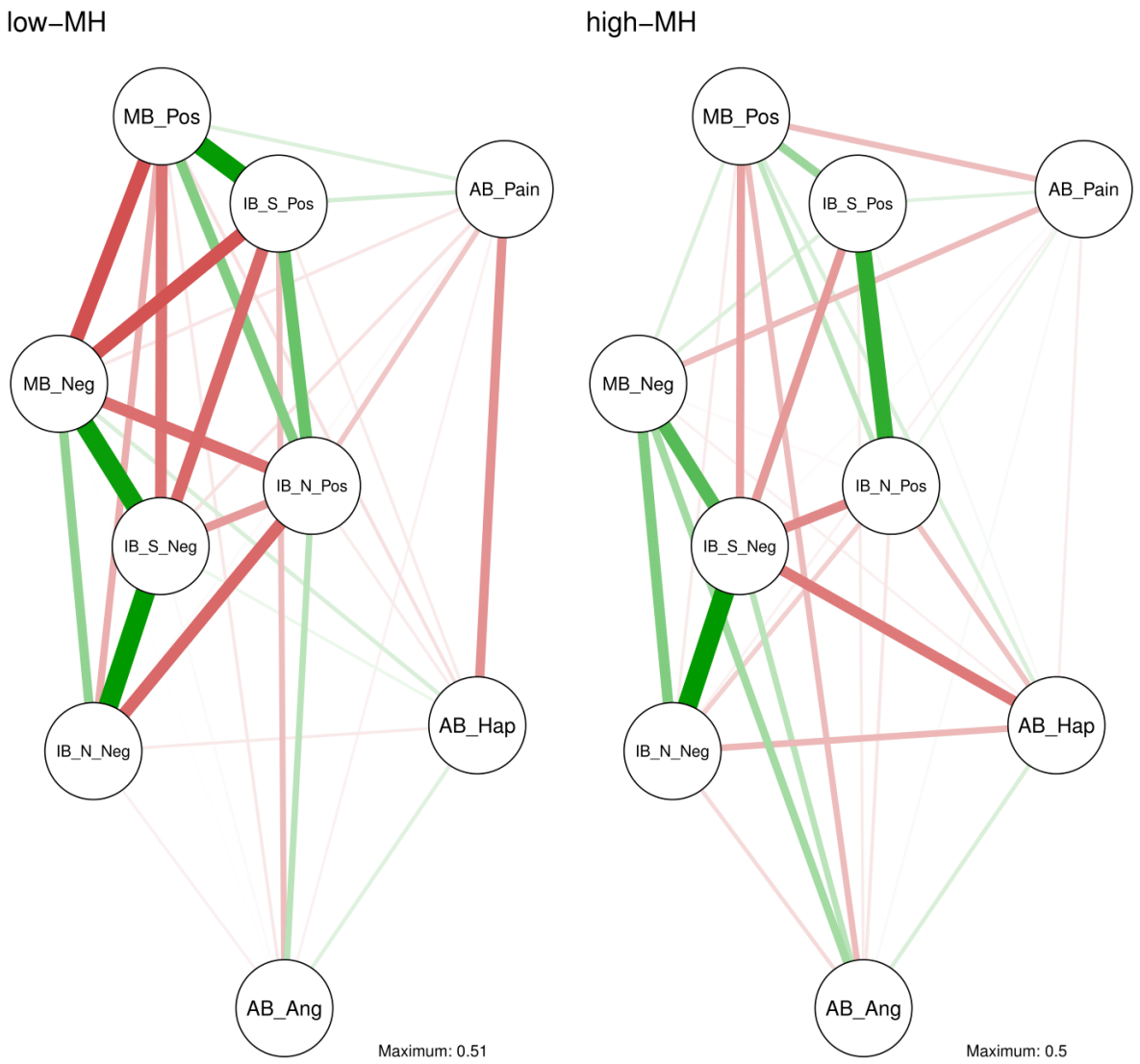


Figure 3.1. Association Networks. Note: The left panel presents the association network from the low mental health sample and the right panel presents the association network from the high mental health group. Each node represents a cognitive bias measure and each edge represents the (zero-order) correlation between the nodes it connects. The thickness of each edge represents the size of the association, such that thicker edges represent higher correlations. Green edges indicate positive correlations, whereas red edges indicate negative correlations.

AB_Ang = Attention bias for Angry faces in the Dot-Probe task; AB_Hap = Attention bias for Happy faces in the Dot-Probe task; AB_Pain = Attention bias for Pained faces in the Dot-Probe task; IB_S_Pos = Positive interpretation bias in social scenarios in the Adolescent Interpretation and Belief Questionnaire (AIBQ); IB_S_Neg = Negative interpretation bias in social scenarios in the AIBQ; IB_N_Pos = Negative interpretation bias in non-social scenarios in the AIBQ; IB_N_Neg = Negative interpretation bias in non-social scenarios in the AIBQ; MB_Pos = endorsed and recalled positive items from the self-referential encoding task; MB_Neg = endorsed and recalled negative items from the self-referential encoding task.

Graphical LASSO networks. The graphical LASSO networks present regularized partial correlations between nodes of cognitive biases (Figure 3.2). Importantly, this analysis creates a sparser network by controlling for the influence of other variables and leaving only direct associations between nodes, helping to confirm that the important relationships observed in the association network are less likely to be spurious. Similar patterns remain apparent from the association networks, in distinguishing between the low-MH and high-MH groups. The low-MH network contains more edges than the high-MH group, suggesting greater overall coherence between positive and negative biases in the low-MH group. There is a strong edge between positive memory bias and interpretation bias for positive social events in the low-MH group (.32), which was removed during the estimation in the high-MH group. The edge connecting positive interpretation biases for social and non-social scenarios is stronger in the high-MH group (.21), than the low-MH group (.10). Similarly, the edge connecting negative memory bias and negative social interpretation bias is stronger in the low-MH group (.29) compared to the high-MH group (.12).

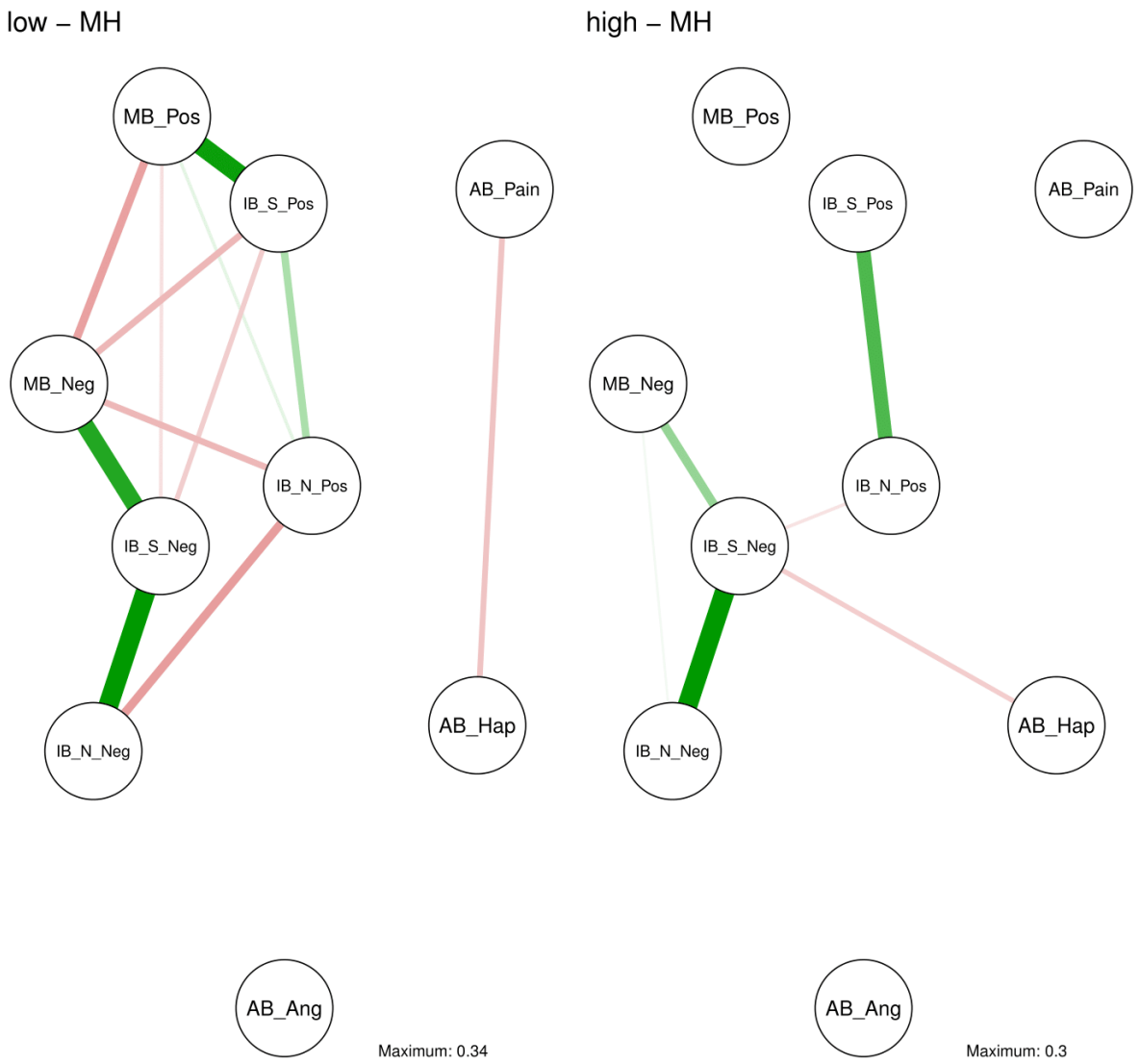


Figure 3.2. Graphical LASSO Networks. Note: The left and right panels present the graphical LASSO network from the low mental health and the high mental health groups, respectively. Each node represents a cognitive bias measure and each edge represents the (partial) correlation between the nodes it connects, after controlling for all other variables in the network. Larger correlations are represented by thicker edges. Green edges indicate positive correlations, whereas red edges indicate negative correlations.

AB_Ang = Attention bias for Angry faces in the Dot-Probe task; AB_Hap = Attention bias for Happy faces in the Dot-Probe task; AB_Pain = Attention bias for Pained faces in the Dot-Probe task; IB_S_Pos = Positive interpretation bias in social scenarios in the Adolescent Interpretation and Belief Questionnaire (AIBQ); IB_S_Neg = Negative interpretation bias in social scenarios in the AIBQ; IB_N_Pos = Negative interpretation bias in non-social scenarios in the AIBQ; IB_N_Neg = Negative interpretation bias in non-social scenarios in the AIBQ; MB_Pos = endorsed and recalled positive items from the self-referential encoding task; MB_Neg = endorsed and recalled negative items from the self-referential encoding task.

Relative importance networks. The relative importance network depicts the relative importance of one node as a predictor of another, controlling for the influence of all other nodes (Figure 3.3). These networks are directed, with the arrow indicating the direction of prediction. Both networks contain reciprocal predictive relationships between negative interpretation biases for social and non-social events (.19 - .23). Also similar across both networks is that interpretation bias for negative social scenarios is predictive of negative memory bias, however, this relationship is weaker in the high-MH group (.08) than the low-MH group (.17). In line with the association and graphical LASSO networks, the relationships between positive interpretation biases and positive memory bias appear to differ between groups. In the low-MH group, positive interpretation bias for social scenarios was predictive of positive memory bias, and vice versa (both .18). In contrast, in the high-MH group, these relationships were omitted during the glasso estimation. In the high-MH group, there was a reciprocal predictive relationship between positive interpretation biases for social and non-social scenarios (.15 - .16). We further examined the precision of the relative importance networks by bootstrapping confidence intervals of the edge weights (2500 bootstrap samples). These analyses indicate that in both low-MH and high-MH groups the strongest edges are fairly stable (respectively, Figures A1 and A2 in the Appendices).

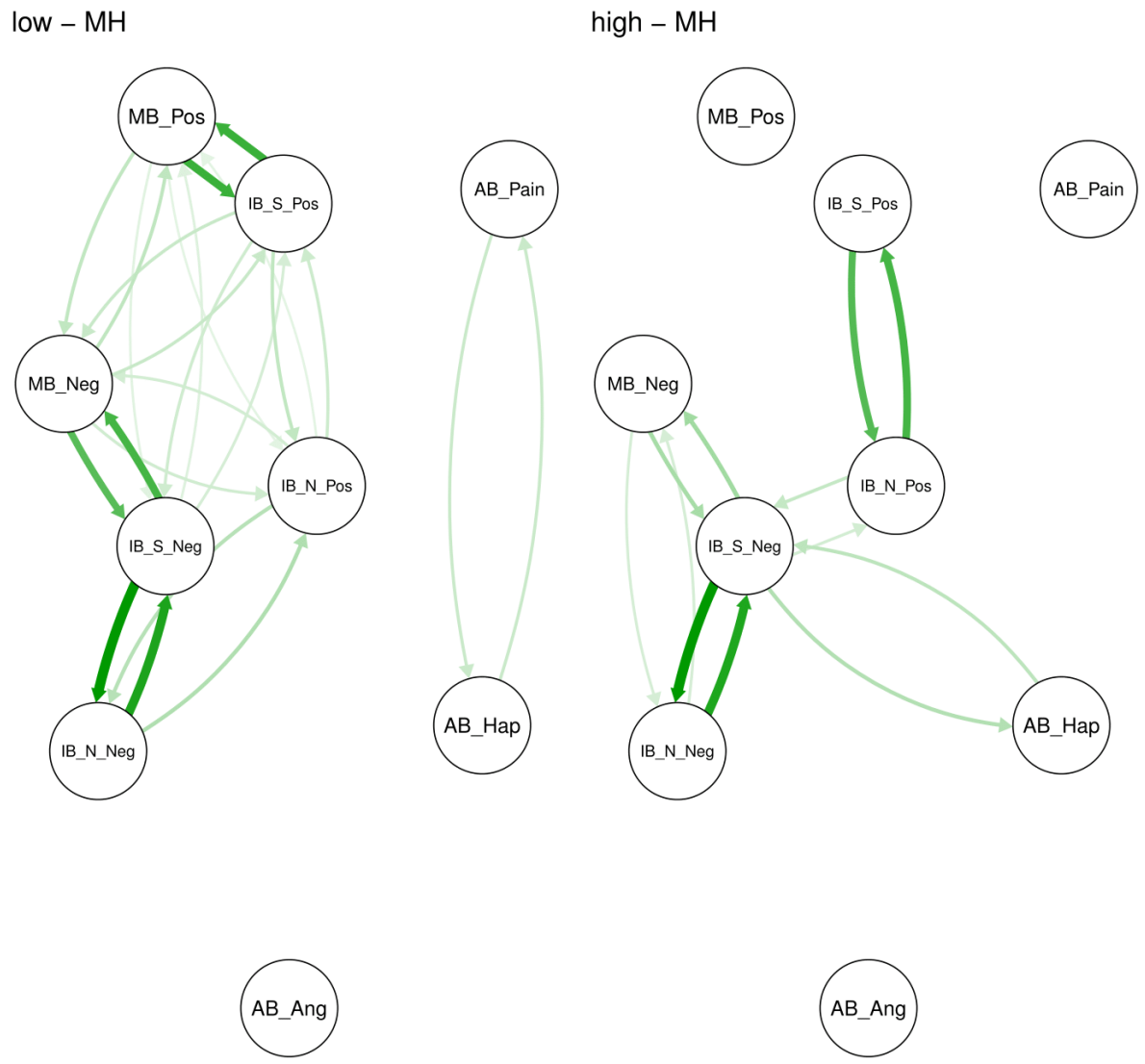


Figure 3.3. Relative importance Network. Note: The left panel presents the relative importance network from the low mental health sample and the right panel presents the relative importance network from the high mental health group. Each node represents a cognitive bias measure. Each edge represents the non-normalised relative importance of a node as a predictor of another node, with the edge thickness representing the magnitude and arrows indicating the direction of prediction.

AB_Ang = Attention bias for Angry faces in the Dot-Probe task; AB_Hap = Attention bias for Happy faces in the Dot-Probe task; AB_Pain = Attention bias for Pained faces in the Dot-Probe task; IB_S_Pos = Positive interpretation bias in social scenarios in the Adolescent Interpretation and Belief Questionnaire (AIBQ); IB_S_Neg = Negative interpretation bias in social scenarios in the AIBQ; IB_N_Pos = Negative interpretation bias in non-social scenarios in the AIBQ; IB_N_Neg = Negative interpretation bias in non-social scenarios in the AIBQ; MB_Pos = endorsed and recalled positive items from the self-referential encoding task; MB_Neg = endorsed and recalled negative items from the self-referential encoding task.

Centrality Indices

We also computed four centrality indices for the relative importance network to examine differences between high and low–MH groups. The centrality plot displays the normalised (z-scored) centrality indices (Figure 3.4). Perhaps most immediately evident are the differences in closeness and betweenness comparing the low-MH and high-MH groups. Negative memory bias showed higher levels of betweenness and closeness in the low-MH group, compared to the high-MH group. Negative interpretation bias for social events was highly central, showing the highest closeness and betweenness indices in both groups. In addition, negative interpretation bias for social events had the highest in-strength and out-strength, indicating that it was both the most predicted node by other nodes in the network and the most predictive of other nodes in the network. Together, this highlights negative social interpretation bias as most central to the networks. This suggests that modifying negative social interpretation bias would have the greatest potential impact on the other biases in the network. Both groups show similar patterns of in-strength (the amount to which a node is predicted by other nodes) and out-strength (how much a node is predictive of other nodes). One exception may be the node strength of positive memory bias, which appears to be less central in the high-MH group, perhaps due to there being fewer edges connecting that node to others. We further examined the stability of the centrality indices a person-dropping bootstrapping procedure (2500 bootstrap samples). These analyses indicate that the node strength is relatively stable, however the closeness and betweenness indices should be interpreted with some caution (for low-MH and high-MH groups respectively, see Figures A3 and A4 in the Appendices).

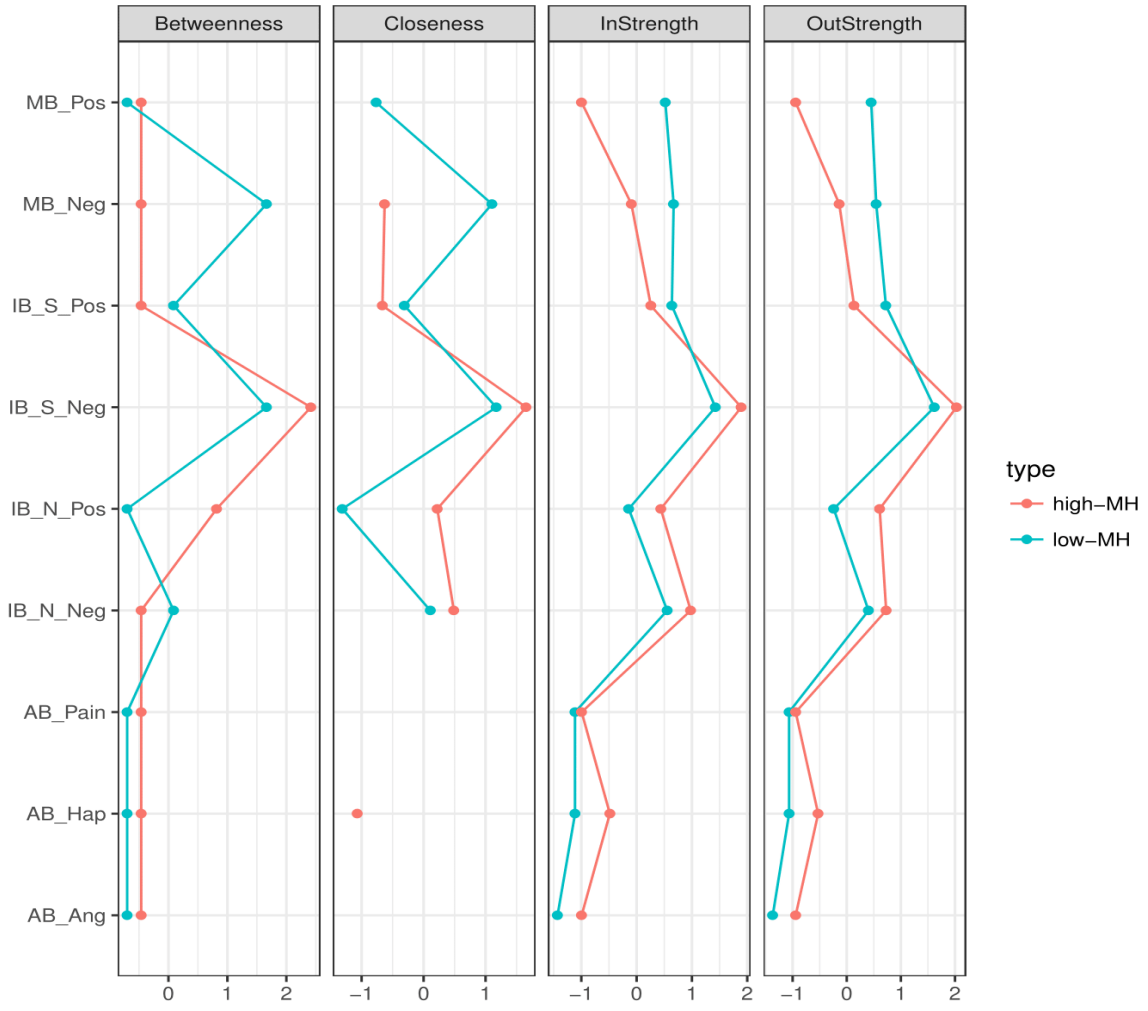


Figure 3.4. Centrality plots depicting betweenness, closeness, in-strength, and out-strength centrality indices for each variable in the relative importance network, separately for the high and low mental health sample. Note: The plot presents z-scores, rather than the raw centrality indices. Betweenness indicates the number of times the node lies on the shortest path length between any two other nodes. Closeness indicates the average distance of a node from the other nodes in the network, and is computed as the inverse of the weighted sum of shortest path lengths of the node from all other nodes in the network (unconnected nodes therefore have no index of closeness). In-strength is an indication of the degree to which a node is influenced by the other nodes in the network, and is calculated as the sum of the directed edge weights directed to that node. Out-strength indicates the degree to which a node influences other nodes in the network, and is calculated as the sum of directed edges originating from that node.

AB_Ang = Attention bias for Angry faces in the Dot-Probe task; AB_Hap = Attention bias for Happy faces in the Dot-Probe task; AB_Pain = Attention bias for Pained faces in the Dot-Probe task; IB_S_Pos = Positive interpretation bias in social scenarios in the Adolescent Interpretation and Belief Questionnaire (AIBQ); IB_S_Neg = Negative interpretation bias in social scenarios in the AIBQ; IB_N_Pos = Negative interpretation bias in non-social scenarios in the AIBQ; IB_N_Neg = Negative interpretation bias in non-social scenarios in the AIBQ; MB_Pos = endorsed and recalled positive items from the self-referential encoding task; MB_Neg = endorsed and recalled negative items from the self-referential encoding task.

Discussion

We computed weighted and directed networks consisting of positive and negative biases in attention, interpretation, and memory in order to investigate the CCBH (Hirsch et al., 2006) in high and low levels of mental health (Keyes, 2005a) in an adolescent sample using baseline data (at age 12-13 years) from a longitudinal study on the development of cognitive biases (the CogBIAS study; Booth et al, 2017). Support for the CCBH utilising the network approach comes from three main aspects of the networks. First, the networks we have presented highlight interconnectedness amongst biases in interpretation and memory. Second, these networks differ between groups displaying high and low mental health. Third, regardless of mental health group, negative social interpretation bias was the most central node in the networks.

Perhaps the most apparent difference between the mental health groups is the higher degree of connectedness between memory and interpretation biases in the low-MH group, compared to the high-MH group. In association networks, this can be seen as stronger edges connecting each of the interpretation and memory bias indices. In the graphical LASSO networks, stronger partial correlations can be seen between positive interpretation bias for social scenarios and positive memory bias, as well as between positive and negative interpretation biases for non-social scenarios. The relative importance networks show fewer and weaker connections between positive and negative biases in interpretation and memory. In the low-MH group, many more connections have remained in the model, following the glasso, compared to the high-MH group. This suggests that the connectedness between biases remains stronger in the low-MH group. Importantly, this also suggests a greater disconnect among positive and negative biases in interpretation and memory for the high-MH group. These observations support the CCBH in suggesting that low levels of mental health may be

characterised by higher interconnectivity amongst cognitive biases in interpretation and memory. This higher connectivity among negative biases may represent a risk factor for emotional vulnerability and offers a useful framework for future research. In contrast, the relative sparsity of connections between positive and negative biases in the high-MH group suggests that high mental health could be characterised by a relative independence (or disconnect) among positive and negative cognitive biases. Such an independence among biases might allow for greater flexibility in the implementation of biases in different contexts (cf., Chapter Six). Following the same logic, the increased connectedness between cognitive biases in the low-MH group might suggest that low mental health involves impairment in the ability to flexibly modify cognitive bias when necessary. In particular, the low-MH group showed increased connectivity between positive and negative biases, in conjunction with reduced positive biases and increased negative biases, compared to the high-MH group. So, it is possible that in low mental health, heightened negative biases in some domains may help to suppress positive biases in other domains, just as reductions in positive biases in one domain may help to amplify negative biases in other domains. This pattern is consistent with the notion that high mental health (i.e., psychological wellbeing) is characterised by increased psychological flexibility (e.g. Kashdan & Rottenberg, 2010), which is represented here as reduced direct connectedness among cognitive biases in the high-MH group. As such, the greater connectivity amongst biases in the low-MH group may lead to a degree of rigidity in the network of biases that does not allow for the flexibility associated with mental wellbeing and resilience Chapter Six. Future research investigating the relationship between positive mental health and flexibility in cognitive biases is warranted.

In the current sample, the high-MH group had greater positive biases and reduced negative biases, compared to the low-MH group as would be expected from previous research (for review see Lau & Waters, 2017). The network analysis extends previous work by

indicating that higher mutual reinforcement among biases, shown as greater connectivity in the networks, also associates with more pronounced negative biases and reduced positive biases in interpretation and memory. Future longitudinal research is warranted to investigate whether increased negative biases lead to reductions in positive biases or vice versa, in a pathway to low-MH. In particular, it will be important to directly examine the role of psychological flexibility in this causal system. This causal question is important to develop a longitudinal account of the development of cognitive biases in mental health.

One relationship that remained consistent across each network, and between low-MH and high-MH groups, was between negative interpretation biases for social and for non-social scenarios. This suggests that this association is fairly stable and relatively independent of mental health status. Similarly, the relationship between negative interpretation bias for social scenarios and negative memory bias appears relatively consistent across each network, although the relationship does appear to be stronger in the low-MH group. These results indicate that there is a robust coherence between both negative interpretation biases for social and non-social scenarios, and between negative interpretation biases for social scenarios and negative memory bias. The association between negative memory bias and interpretation bias for non-social scenarios in the association network is weaker in both the graphical LASSO and the relative importance networks, suggesting that the association is weak and potentially spurious in the association network. This is in line with the CCBH in that we see a fairly stable association between negative interpretation and negative memory biases. It is interesting to note that in the relative importance network, negative memory bias is less predictive of negative interpretation bias for social scenarios in the high-MH group. This may help explain why negative biases do not seem to proliferate and escalate in mentally healthy adolescents in the way they are thought to in those prone to emotional vulnerability. In line with the CCBH it is likely that in the low-MH group, memory bias feeds back into the

negative interpretation bias loop, whereas in the high-MH group, this relationship is much weaker. Although we cannot make causal predictions, it is plausible that feedback into negative interpretation biases from memory biases might serve to reinforce the bias. Whereas, if there is no or less feedback into negative interpretation bias from memory then this cycle is not reinforced, promoting positive mental health. Further experimental and longitudinal research is required to elucidate the role that these potentially reinforcing biases play in the development of positive mental health in adolescence.

In contrast to the stability of the negative interpretation and memory bias connections across MH groups, the connections between positive interpretation bias for social and non-social scenarios, and positive memory bias were distinctly different between the high-MH and low-MH groups. The relationship between positive interpretation bias for social scenarios and positive memory bias was weak in the low-MH group, and was absent in the high-MH relative importance network. The reverse was observed for the relationship between positive interpretation biases for social and non-social scenarios, with a much stronger relationship in the high-MH group and weaker connections in the low-MH group. In conjunction with the relationships observed between negative memory and interpretation biases, this pattern suggests that low-MH may be characterised by an enhanced coherence between memory and social interpretation biases. From a network and CCBH perspective, this indicates that mutual reinforcement of positive interpretation biases for social and non-social events may promote positive mental health outcomes.

Unlike prior research investigating the CCBH (e.g. Everaert et al., 2013; Hirsch et al., 2006; Vrijsen et al., 2014), the networks presented here do not support the hypothesis that biases in attention influence interpretation biases. The associations between attention biases and interpretation biases in the glasso and relative importance networks were either absent or

very weak. Studies using the dot-probe and Stroop tasks have shown mixed results in demonstrating a relationship between attention bias and anxiety in adolescence (e.g. Dalgleish et al., 2010; Rozenman, Amir, & Weersing, 2014; Waters, Bradley, & Mogg, 2014) and low reliabilities have been reported for this task (Schmukle, 2005; Staugaard, 2009; Waechter, Nelson, Wright, Hyatt, & Oakman, 2014). It is possible that the dot-probe task used in this study was not reliable enough to provide a stable measure of biased attention, rendering it difficult to discover the effects of interest (LeBel & Paunonen, 2011). Such a causal relationship may be best observed by utilising tasks developed specifically to assess multiple cognitive biases within the same assessment procedure (e.g. Everaert et al., 2014; Everaert & Koster, 2015), rather than using different tasks to measure biases in different domains (attention, interpretation, memory) as we have done in the current study. It is important for researchers to establish both the external validity as well as the reliability of all tasks designed to assess cognitive biases in relation to mental health. As we move forward an important challenge for researchers within this field is to develop tasks that are valid and reliable in order to assess biases in attention, interpretation and memory and to investigate their causal links.

Clinical implications.

In this study, we examined the interrelationships amongst cognitive biases in groups of adolescents who reported high and low levels of mental health on the mental health continuum (MHC: Keyes, 2002, 2005a). The MHC is associated with differential real-world functionality such that individuals reporting low mental health on this instrument and those with a diagnosed mental illness have the poorest outcomes, while those reporting high levels of wellbeing have positive real-life outcomes (Keyes, 2002). Since the roots of psychopathology typically emerge in adolescence it is essential to investigate mental health and associated cognitive mechanisms in adolescent populations. The current study

demonstrates that cognitive biases are more highly interrelated in adolescents with low mental health relative to those reporting high mental health, which has important clinical implications. Given that improvements in positive mental health at a population level have been found to predict declines in mental illness (Keyes et al., 2010), the promotion of positive mental health is likely to provide an important complementary strategy to treating mental illness in adolescent populations (Keyes, 2007).

Our results have several implications for future research using psychological and cognitive interventions to improve mental wellbeing. Since negative interpretation bias for social scenarios was found to be the most central node in the networks, with strong connections to other biases in the network, one implication is that cognitive interventions, such as cognitive bias modification procedures that directly target negative interpretation biases (CBM-I; Grey & Mathews, 2000; Lau & Pile, 2015; also see MacLeod & Mathews, 2012), specifically those targeting negative social scenarios, are likely to have the greatest impact on the cognitive bias networks overall with an on-going benefit to mental wellbeing. Adolescence is a period of fast social and interpersonal change and development (e.g. Nelson, Leibenluft, McClure, & Pine, 2005) and it is no surprise that the interpretation of social scenarios plays a central role in adolescent mental health. It is likely that reducing negative social interpretations will have a broader, positive impact on the complex network of cognitive biases, in particular negative memory biases. Our results go further and predict that the degree of transfer from CBM-I for negative-social scenarios on the network of cognitive biases is likely to be much stronger for individuals low in mental health relative to those reporting higher levels of mental wellbeing because of the tighter connections among cognitive biases in low mental health. This implies that CBM-I targeting negative social scenarios should be particularly effective in adolescents with low mental health relative to interventions targeting other biases. This is encouraging, and is in line with recommendations

for preventative interventions to target the most at-risk samples (e.g. Horowitz & Garber, 2006) and targeting a specific risk factor (e.g. Topper, Emmelkamp, Watkins, & Ehring, 2017)

Another implication of the current results is that targeting the relatedness among cognitive biases may offer a novel approach for improving mental health. In this study the high-MH group demonstrated a weaker relationship between positive memory and interpretation biases relative to those reporting low-MH. Similarly, the low-MH group showed stronger relationships between social interpretation biases and memory biases, for both positive and negative biases suggesting that tighter relationships between interpretation and memory biases may promote or maintain low mental health. The CCBH suggests that strongly connected biases are likely to reinforce one another cyclically. Interpreting an ambiguous social event as inherently negative, for example, is likely to then encourage more negative memory biases, which, in turn, influence future negative interpretations of social events. A key clinical implication of the network analysis applied in this study, as well as the CCBH more broadly, is that interactions and connections among different types of cognitive biases play an important role in mental health above and beyond the impact of those biases independently (Hirsch et al., 2006). If future studies establish such varying relatedness amongst cognitive biases as a common characteristic along the mental health continuum, a future avenue may be the development of experimental procedures aimed at weakening these links, which may eventually lead to new interventions.

The results of the current study and the clinical implications outlined indicate three recommendations for future research in clinical psychological science. Our first, and fundamental recommendation is for researchers to include multiple measures of cognitive bias in mental health research. Examining multiple cognitive biases is beneficial, not only to

gain traction on the role of individual biases, but also to provide a more complete account of how the connections and interrelationships among multiple cognitive biases impact on mental health outcomes (cf. Hirsch et al., 2006). Such research will build on the small, but emerging, research base investigating the CCBH in adolescence. Second, the current results indicate that it is beneficial to examine the sub-components of each bias separately to fully explore the interrelationships amongst cognitive biases. For instance, our analyses reveals a strong relationship between negative interpretation biases for social and non-social scenarios in both the high-MH and low-MH groups, suggesting a robust association between these biases. However, our data also suggest that social and non-social negative interpretation biases have very different relationships to other cognitive biases in the network, such as negative memory bias. Similarly, our results indicate that positive biases and negative biases are discrete components of interpretation and memory bias. This suggests that CBM-I targeting negative biases would be unlikely to impact positive interpretation biases. By examining components of cognitive biases as related-yet-distinct, the interrelated relationship of these biases with mental health can be explored in greater detail. Third, we recommend that future CBM-I research specifically targets negative interpretation bias for social events. Our results show that negative social interpretation bias is likely to have the greatest impact on other cognitive biases in an adolescent population. Therefore, cognitive interventions designed to target social interpretation biases have the potential to have the widest positive impact on a range of other cognitive biases. The CCBH offers an appropriate conceptual framework for examining CBM and other interventions by acknowledging that cognitive biases are highly interrelated and that these interconnections have important implications for mental health and mental health interventions. Research is needed to confirm consistency of the current findings in other samples, including clinical samples, which in turn may open up a venue of investigation

on the possibility that training interventions targeting one bias modality may also effect other biases through transfer of training.

Limitations

The current results should be interpreted in light of some limitations. The data reported here are cross-sectional, and therefore, while suggestive, the networks identified cannot be used to infer causality among cognitive biases. The data do however suggest that bi-directional associations between interpretation and memory biases are important cognitive factors in adolescent mental health. In light of the cross-sectional data, these observations are useful for generating hypotheses for future research. In relation to psychopathology and positive mental health, both longitudinal and experimental work is needed to uncover the causal connections among various cognitive biases. It is worth noting that the data analysed in this study has been drawn from the first wave of the CogBIAS longitudinal project (Booth et al., 2017), which will include two further testing waves, providing an ideal opportunity to examine the development of cognitive bias networks over time. The CogBIAS project follows a cohort of 500 children from the age of about 12/13 years to 16/17 years, the period of adolescence, which is a time of particular vulnerability to the development of emotional disorders (Fuhrmann, Knoll, & Blakemore, 2015; Lau & Waters, 2017). Further analyses of the CogBIAS data will help to elucidate how the CCBH applies to the development and maintenance of emotional dysfunction and positive mental health in young people. Further, network analysis typically requires large sample sizes in order to produce reliable network estimates. We removed many connections from our relative importance network through the Graphical LASSO, resulting in a reduced number of connections estimated relative to sample size. The networks therefore contained a lower ratio of nodes to participants, and the analyses of stability and robustness suggest that the networks are relatively stable. However, future

research investigating the combined cognitive bias hypothesis would benefit from larger sample sizes.

Despite some limitations, the results presented here provide valuable insight into the CCBH in relation to the mental health spectrum in adolescence. Network approaches to psychopathology (Borsboom, 2017; Borsboom & Cramer, 2013; Fried, 2017; Fried et al., 2017) offer a conceptual position that can help to unpack the CCBH in a systematic way. The CCBH predicts that the relationships among cognitive biases, as well as their co-occurrence, serve to influence emotional vulnerability. Using a psychological network analysis approach, we observed differences in the interrelatedness of cognitive biases between a low and high mental health sample. This suggests, in agreement with the CCBH, that connections among cognitive biases in interpretation and memory (but less so in attention in the present analysis) play a role in adolescent mental health. Network analysis offers a relatively new methodology to examine the relationships among biases in cross-sectional samples and provides a useful framework in order to elucidate the cognitive and neural processes that are particularly important (central) to mental health.

Chapter 4

An edited version of this Chapter has been submitted for publication as the following:

Parsons, Kruijt, & Fox (2017). *Induced attention bias favouring positive stimuli prospectively predicts happiness and positive emotions.* In review for publication in Emotion.

4

Attention bias trained away from negative and towards positive stimuli prospectively predicts happiness and positive emotions

Individual differences in the ease with which attentional bias can be modified may prospectively predict emotion vulnerability. Here we assessed whether ABM training-induced shifts in attentional bias towards positive and away from negative stimuli would prospectively associate with self-reported measures of positive emotions, happiness, and mental health assessed 12 weeks later. Forty-nine participants completed an initial session of dot-probe based ABM, including pre- and post-training measures of bias, and thirty-four participants returned for a follow-up assessment. Of our primary outcome measures, we found that training-induced shifts in attentional bias predicted self-reported positive emotions and happiness in the follow-up session, but was not associated with the other primary measures of resilience and positive mental health. The post-training bias was also not associated with measures of anxiety and depression, suggesting that the post-training bias prospectively associates with more transitory states of wellbeing, than dispositional mental health traits. Further exploration suggested that the post-training bias assessment, but not the pre-training bias assessment, was associated with future attention bias, positive emotions, and happiness. While shifts in bias from before to after ABM training were predictive of future positive emotions and happiness, the relationship was driven solely by the post-training bias. Implications for investigating the malleability of attentional bias and more reliable assessments of bias are discussed in relation to predicting indicators of positive mental health, such as positive emotion and happiness.

4. Attention bias trained away from negative and towards positive stimuli prospectively predicts happiness and positive emotions

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Introduction

Emotional reactions to events and circumstances typically facilitate responses that are adaptive for the conditions that caused them (Werner & Gross, 2010). For example, happy emotions promote approach and prosocial behaviours, whereas fear or anger promote behavioural strategies for dealing with threat (e.g. Fredrickson, 1998). Psychological disorders such as anxiety and depression, however, demonstrate that emotional processes can also be maladaptive, severely impacting an individuals' functioning and wellbeing. Cognitive models of emotion vulnerability propose that biased cognitive processing of emotional information is a key characteristic of emotional vulnerability (Aaron T Beck, 1967, 1979; Mathews & MacLeod, 2005). A wealth of research supports the proposition that certain patterns of biased cognitive processing of emotional information plays a central role in the development and maintenance of emotional pathology (Cisler & Koster, 2010; Gotlib & Joormann, 2010; Yiend, 2010).

Recently, research on mood disorders has begun to focus on positive emotion regulation (for review see Carl, Soskin, Kerns, & Barlow, 2013). This is an important step forward, and highlights the fact that positive mental health (and not just the absence of mental illness) has been somewhat neglected in previous work. The dual-continua model proposes that mental illness and positive mental health are distinct, albeit related, constructs (Keyes, 2002, 2005a). It follows that positive mental health research is essential to complement ongoing work investigating mental illness (Keyes, 2007). To provide a theoretically driven framework for the study of positive mental health an information-processing model of psychological resilience is proposed in Chapter Six. The model proposes that the ability to flexibly deploy information-processing biases favouring either positive or negative stimuli, depending on the context, can facilitate adaptive responses and promote resilience.

4. Attention bias trained away from negative and towards positive stimuli prospectively predicts happiness and positive emotions

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There is an emerging body of work examining the role of information-processing biases in positive mental health, such as positive emotions and happiness. For instance, increases in positive mood has been associated with broadening of visuospatial attention in the presence of self-related information/cues (Grol, Koster, Bruyneel, & De Raedt, 2014). Preferential processing of highly positive words in a colour-naming emotional-Stroop task has been associated with higher levels of positive emotions and lower levels of negative emotions (Strauss & Allen, 2006) and recently, it has been reported that attentional biases towards positive stimuli, particularly in the later stages of passive viewing, are associated with trait-happiness and satisfaction with life (Raila et al., 2015). Thus, individuals who are happy and satisfied with life may literally see the world in a more positive light. Similarly, more transient positive mood states have also been associated with selective attentional biases favouring positive (Sanchez et al., 2014), and rewarding (Tamir & Robinson, 2007) information. Moreover, Sanchez et al (2014) found that increased attentional deployment towards happy faces facilitated mood recovery following a negative mood induction suggesting that a positive attention bias serves to maintain a positive mood in the context of a negative event. Thus, there is a growing body of evidence suggesting that selective processing of positive emotional information may play an important role in promoting and maintaining positive mental health and resilience.

Experimental manipulation of processing biases that are thought to be important in emotion vulnerability and wellbeing provides an experimental methodology that allows researchers to directly examine the causal relationship between information processing biases and mental health outcomes (Hertel & Mathews, 2011). MacLeod and colleagues (Colin MacLeod et al., 2002) pioneered this field when they experimentally altered the contingency in what has become known as the "dot probe task" (Colin MacLeod et al., 1986) such that the

development of a selective attention bias is adaptive when it is conducive to increasing task performance. The original version of the dot-probe task provides an assessment of selective processing biases towards threat-related material (e.g. MacLeod et al., 1986). A threat stimulus and a neutral stimulus are presented simultaneously for a brief period (typically 500 ms) at two locations and participants respond to a neutral probe, which is presented shortly afterwards in the location of one of these stimuli. Speeded responses to probes that appeared in the location of the threat stimulus, compared to the neutral stimulus, are interpreted as representing a selective attentional bias towards threat. In an attention bias modification version of the dot-probe task (ABM), the contingency between a stimulus and the location of the probe is altered such that the probe reliably appears in the location of one category of stimuli most frequently. As a result, individuals should experience increased ease in performing their task if they implicitly learn that the probe reliably appears in the location following one category of stimuli (e.g. threatening pictures) rather than another (e.g., neutral pictures). Following this experimental manipulation, participants trained to attend towards threat typically report significantly greater increases in anxiety, and greater stress reactivity, relative to participants trained to selectively avoid threat and orient towards neutral stimuli (Mathews & MacLeod, 2002). These findings provide empirical support for a maintaining or causal role of selective attention in anxiety vulnerability. The modified dot-probe procedure has formed the basis of a large and rapidly growing field of ABM research.

In addition to being used as an effective experimental tool, the possible clinical utility of ABM procedures has also begun to be widely examined (Hakamata et al., 2010; Heeren et al., 2015; MacLeod & Holmes, 2012; MacLeod & Mathews, 2012), with a recent meta-analysis concluding that ABM procedures are largely ineffective in clinical contexts (Cristea, Kok, & Cuijpers, 2015, but see MacLeod & Grafton, 2016 for a contrasting perspective). Whatever

the clinical implications, from an experimental psychology point of view, ABM procedures are highly valuable as an experimental tool to allow examination of the directionality of cognition-emotion relationships in emotional vulnerability and mental health research (Colin MacLeod & Grafton, 2016). The current study uses ABM to investigate individual differences in the malleability of attention biases and asks whether these will predict future wellbeing and happiness.

Malleability refers to individual differences in the degree to which attentional bias changes as a result of some manipulation, such as a mood induction or ABM. Individual differences in attentional bias malleability have been shown to predict elevations in trait anxiety in response to an extended stressful environment in a study in which 26 students completed an ABM training procedure at the start of and at the end of their first university term (Clarke, Macleod, & Shirazee, 2008, study 1). Measures of bias and anxiety symptoms were taken pre- and post- training as well as at the end of term (Clarke et al., 2008). Individual differences in acquiring a bias in response to ABM were calculated by subtracting the pre-training bias from the post-training bias index. For the purposes of this paper, we term this pre- to post- training difference score as "training-induced shifts in attentional bias". At the twelve week, end of term, follow-up session those who had shown greater training-induced shifts in attentional bias towards threatening stimuli at the start of term, were found to report greater increases in anxiety over the course of the term, which the authors describe as a period of extended mild stress. This finding was subsequently replicated (Clarke et al, 2008, study 3) with a sample of 52 participants. The authors concluded that the magnitude of training-induced shifts in attentional bias towards threatening stimuli can be used as a proxy for the extent to which an individual adopts this biased processing style when environmental circumstances make it adaptive to do so, in this case to improve task performance. The

authors refer to this as attention bias malleability. Importantly, this research also found that training-induced shifts of bias away from threat did not predict subsequent increases in anxiety vulnerability (Clarke et al., 2008, study 2) indicating that it is only malleability in the direction of threat that is effective in relation to anxiety.

In an interesting follow-up study, attention bias malleability was examined in relation to the reduction in anxiety symptoms shown by socially anxious individuals following eight sessions of group cognitive behavioural therapy (CBT). The hypothesis put forward was that those who most readily acquired an attentional bias towards threat, using the technique described by Clarke et al (2008), when it was adaptive to do so, would also be more likely to acquire a bias away from threat when it is adaptive to do so (Clarke, Chen, & Guastella, 2012). In other words, the logic was that those with the highest degree of attention bias malleability (even though this was measured by the propensity to acquire a threat bias) would show the greatest reduction in anxiety vulnerability following CBT *because* these individuals would also be most likely to acquire a more positive attentional bias in response to a positive experience. This is exactly what was found. Larger training-induced shifts in attentional bias favouring threatening stimuli assessed prior to the first session of CBT predicted greater reductions in anxiety, but not depression, across an 8-week CBT treatment program for social anxiety (Clarke et al., 2012). The authors argue that this pattern supports a plasticity account of attentional bias acquisition in that the ease of acquiring an attentional bias (favouring threatening stimuli) following an experimental contingency manipulation (ABM) predicted reductions in anxiety during a positive experience such as cognitive behavioural therapy (Clarke et al., 2012). A limitation of this study, as the authors acknowledge, is that the propensity to acquire a more positive bias as anxiety levels start to decline – the proposed mechanism - was never actually measured. Nevertheless, taken together the results of Clarke

and colleagues (Clarke et al, 2008; 2012) indicate that the malleability of a person's capacity to acquire an attention bias appropriate to the current situation might be an important predictor of differences in the degree to which people respond to both positive and negative life experiences.

While previous research is informative, it has tended to focus on anxiety vulnerability and there is limited research on attention bias malleability and positive mental health. The role of positive emotional processing in modulating anxiety reactions to stress was examined in one study (Taylor et al., 2011). Similar to a plasticity account of attentional bias towards threat in anxiety vulnerability (Clarke et al., 2008), individual differences in the degree to which attention bias shifted in favour of positive stimuli predicted higher positive emotions, and lower anxiety, in response to a laboratory-based stressor (filmed speech: Taylor et al, 2011). Similarly, participants trained to attend to positive stimuli showed increased positive affect following a success experience induction, relative both to their own pre-training bias measures as well as to participants in a control condition who were trained to avoid positive stimuli (Grafton, Ang, et al., 2012),. Additionally, participants trained to attend to positive stimuli have been shown to attend less to negative images following a stress task (Wadlinger & Isaacowitz, 2008). It is promising that researchers have begun to utilise bias modification procedures as experimental tools to examine the cognitive processes involved in positive mental health and wellbeing. However, to our knowledge, no research has yet investigated this relationship longitudinally, specifically with positive mental health outcome measures. Therefore, the present research employed a prospective design to investigate an attention bias malleability account of factors relating to positive mental health and wellbeing.

We investigated the relationship between malleability of attentional bias and positive mental health characteristics by modifying the dot-probe procedure utilised by Clarke et al.

(2008). Instead of using negative-neutral word pairs as they did, we presented negative-positive word pairs. While biases for positive and negative information may be dissociable, rather than forming a continuum, it has been suggested that pairing positive and negative words in an ABM procedure may train attention towards positive stimuli and away from negative stimuli, simultaneously (Baert et al., 2012). While we cannot necessarily dissociate these mechanisms when using negative-positive pairs an advantage of this procedure is that we can match simultaneously presented words on arousal value, which is not possible with negative-neutral or positive-neutral pairs (see Fox, Zougkou, Ridgewell, & Garner, 2011). Participants completed an ABM procedure that included a pre- and post- training assessment of bias using the conventional dot-probe task. Training-induced shifts in attentional bias – or, the ease of acquiring an attentional bias that is adaptive for the situation - were calculated as the difference between biases pre- and post- training. Approximately 12 weeks later, participants returned to complete a re-assessment of attentional bias using the conventional dot-probe assessment task. In both sessions, participants also completed self-report measures of mental health, resilience, happiness, and positive and negative emotions. To our knowledge this is the first study to directly examine the prospective relationship between attention bias malleability and self-reported positive mental health. The astute reader will notice that, different from the bias malleability studies by Clarke et al, this study does not involve a specific period of elevated stress or engagement in therapy. The main reason is that it is very difficult to define a period of time in everyday life that is likely to be experienced as positive by the vast majority of individuals. As such, we focused here on investigating the impact of shifts in attention bias during a "normal" period regardless of specific created or assumed circumstances. Our central analyses explored the prospective relationships between training-induced shifts in attentional bias – attention bias malleability - and self-reported assessments of positive mental health.

Methods

Participants

49 participants completed session 1 (age; M= 20.43, SD = 3.01; 12 male, 36 female, 1 unknown), and 34 of these participants returned for a follow-up session (69% of original sample; age M= 20.24, SD = 3.08; 8 male, 25 female, 1 no response). The initial sample of 49 would have resulted in 80% power to detect an effect size of at least r = .39 in our main analysis. However, our final sample is smaller (n = 32) due to attrition between the initial training session and the follow-up session (n = 15) and removal of participants with high error rates (n=2). Had this been our planned sample size it would have allowed us to detect effect sizes of at least r = .47 with 80% power. Participants were recruited through the University of Oxford SONA system and poster advertisements, and were compensated for their time with course credit, or £8 per session. Ethical approval for this study was granted by the University of Oxford Central University Research Ethics Committee (CUREC; Ref No: MS-IDREC-C1-2015-202).

Experimental hardware and software

A Dell Optiplex 9010 computer with full-colour 24-inch monitor (1920x1080 resolution), and a standard keyboard and mouse were used to present the task and record participant responses. The ABM task was programmed and presented in INQUISIT Millisecond (Inquisit 4.0.8.0, 2013). INQUISIT measures RTs with millisecond accuracy (De Clercq et al., 2003). Limesurvey 2.0 was used to record participants' responses to the self-report measures (Limesurvey Project Team & Casrten Schmitz, 2015).

ABM task

Stimuli. 96 pairs of positive and negative words, matched for word length, were selected from the affective norms for English words (ANEW; Bradley & Lang, 2010). Word categories significantly differed in valence, $t(94) = -94.74$, $p < .001$, $d = 9.67$ (> 7.41 and < 2.67 for positive and negative words, respectively), and were not significantly different for arousal ratings $t(94) = .06$, $p = .949$, $d = .01$. Word pairs were split into two separate sets, set A and set B, which did not differ significantly by valence ($t(94) = .02$, $p = .988$, $d < .01$) or arousal ($t(94 = -1.93$, $p = .055$, $d = .28$). The word stimuli were presented in 32px lower case bold Arial font (approximately $.97^0$ vertical visual angle at 50cm from screen)

Trial structure. Participants were presented with a fixation cross in the centre of the screen for 500ms, followed immediately by a word pair, presented above and below the centre of the screen separated by approximately 3cm (approximately 6.9^0 visual angle). The word pair was presented for 1000ms and then replaced by a small probe in the location of one of the words. The stimuli presentation time of 1000ms was based on the procedure used by Clarke et al. (2008, p. 49) in order to "maximize the prospect of participants cognitively registering, and attentionally responding to, the bias induction contingency contained within the task". The probe was a 10 pixel long line presented in vertical or horizontal orientation. Participants were tasked to identify the rotation of the probe by pressing the appropriate key on the keyboard. The response cleared the screen and 500ms later the next trial began.

The contingency between the location of the positive word and the location of the probe differed between the assessment trials and the training trials. Specifically, in assessment blocks there was a 50% likelihood that the probe would appear in the location of the positive word (positive-probe trials) and a 50% likelihood that the probe would appear in the location of the negative word (negative-probe trials). In the training trials, there was a 91.7%

likelihood that probes appeared in the location of the positive stimuli (positive-contingency). This contingency was achieved by including a small proportion of incongruent trials (i.e., where the probe appeared in the location of the negative word), which allowed for calculation of a traditional bias index throughout the ABM procedure. Thus, in this situation acquiring a positive bias is adaptive in terms of improved performance on the task.

Following a practice session, participants completed a pre-training assessment block, which was followed, without a break, by the training blocks and finally participants completed the post-training assessment. Each assessment block consisted of 96 trials, while the ABM training (positive-contingency trials) consisted of 576 trials, split into six blocks. There were no breaks in between blocks, however, as the task took approximately 45 minutes, participants were given a forced two-minute break in the middle of the task, to help avoid fatigue.

Stimuli allocation. Based on participant numbers (odd/even), participants either viewed stimuli subset A in the first assessment block and the training blocks, and subset B in the second assessment block, or vice versa. Participants viewed the same word set in the first assessment block of session 1 and in the follow-up assessment. In each assessment block, the 48 word pairs in the allocated subset were presented twice. In the training trials, the 48 word pairs in the allocated subset were presented twelve times.

Self-report measures

The primary measures of interest were; positive mental health, resilience, happiness, and positive emotions. Measures of negative emotions, depression, anxiety, and psychological (in)flexibility were included as secondary measures. The secondary measures were included as demographic measures, and to conduct exploratory analyses to generate hypotheses for future research and are not considered in depth in the current report.

Mental Health. The Mental Health Continuum - Short Form (MHC-SF; Keyes, 2009) contains 14 items that index emotional, psychological, and social wellbeing, in order to create a composite measure of positive mental health. Participants are asked to rate how often they have experienced each of the items in the past month, on a 6 point Likert scale from "never" to "every day". The MHC-SF has shown high internal consistency and discriminant validity (Keyes, 2009; Lamers, Westerhof, Bohlmeijer, ten Klooster, & Keyes, 2011; in this sample, session 1 $\alpha = .92$; follow-up $\alpha = .91$).

Resilience. The 25 item Connor-Davidson Resilience Scale (CD-RISC; Connor & Davidson, 2003) is designed to quantify resilience and act as a clinical measure to assess response to treatment. Participants are asked to rate, on a 5-point scale how they feel each item applied to them in the last month. Scores are totalled with higher scores indicating higher resilience. The scale has demonstrated strong psychometric properties (Connor & Davidson, 2003, this sample session 1 $\alpha = .86$; follow-up $\alpha = .86$).

Happiness. The subjective Happiness Scale (SHS; Lyubomirsky & Lepper, 1999) is a 4 item scale assessing happiness on a global level containing items such as "In general, I consider myself" on a 7-point scale, from "not a very happy person" to "a very happy person". Internal consistency of the SHS in this study was $\alpha = .83$ in session 1, and $\alpha = .89$ at follow-up; the test retest reliability was $r = .67$).

Positive and negative emotions. The modified Differential Emotions Scale (mDES; Fredrickson, Tugade, Waugh, & Larkin, 2003) asks participants to rate, on a 5-point scale (from "never", to "most of the time"), how often they had felt each of 20 different emotions (10 positive, and 10 negative) in the past few weeks. Items include "What is the most joyful, glad, or happy you felt?" Internal consistency for the positive and negative scales were $\alpha = .84$, and $\alpha = .83$ in session 1, and $\alpha = .91$, and $\alpha = .84$ at follow-up.

Depression. The Patient Health Questionnaire (Kroenke & Spitzer, 2002) contains 9 items corresponding to the DSM-IV depressive disorder symptom criteria. Participants rate how often they have been bothered by any of nine problems (e.g. "little interest or pleasure in doing things") over the last two weeks, on a 4-point scale from "not at all", to "nearly every day". The PHQ-9 has shown strong validity as a brief measure of depression and good internal consistency (Kroenke, Spitzer, & Williams, 2001; this sample session 1 $\alpha = .89$; follow-up $\alpha = .89$).

Anxiety. The Generalized Anxiety Disorder – 7 item scale (Spitzer et al., 2006) is designed to reflect DSM-IV symptom criteria for anxiety. Participants rate how often over the last two weeks that they have been bothered by each of 7 problems (e.g. "trouble relaxing") on a 4-point scale from "not at all", to "nearly every day". The GAD-7 has shown excellent internal consistency and test-retest reliability (Spitzer et al., 2006; this sample session 1 $\alpha = .87$; follow-up $\alpha = .89$).

Psychological flexibility. The Acceptance and Action Questionnaire – II (Bond et al., 2011) contains seven items designed to assess psychological inflexibility. Participants rate to what extent each item (e.g. "I worry about not being able to control my worries and feelings") applies to them on a 7-point scale from "never true" to "always true". Scores are reversed and summed to create a continuous dimension score with higher scores indicating greater psychological flexibility. The AAQ-II has shown good reliability and test-retest reliability (Bond et al., 2011; this sample session 1 $\alpha = .91$; follow-up $\alpha = .91$; test-retest $r = .80$).

Day reconstruction method. The day reconstruction method was used to produce a detailed record of the prior day's events. This was intended to provide a rich and complementary measure of emotional experiences to the mDES, by reporting emotional responses to specific events during a typical day's events. Participants were asked to split the

prior day into a series of discrete events and report what they were doing, whom they were with, and to complete the mDES for that event. Participants reported a mean of 6.65 events (SD = 3.12). Participants were prompted to provide details about each event; including, when the event occurred, what they were doing, whom they were interacting with. Finally, for each discrete event, participants also completed the mDES to provide a more detailed description of the emotional experience.

Procedure

Following recruitment, participants were invited to one of several group testing sessions (between 1-14 participants). After giving informed consent, participants first completed the ABM procedure and then the questionnaire measures. Participants wore headphones during the ABM task to reduce the impact of noise distractions. Session 1 testing was conducted in October/November, which was early in the first term of the academic year. Participants were contacted by email to schedule their second session. Session 2 testing was conducted in January/February, which was early in the second term of the academic year; the mean time elapsing between testing sessions was 11.6 weeks. In the follow-up session, participants first completed an assessment block of the ABM procedure, followed by the questionnaire measures and the DRM.

Data processing

ABM Procedure. The data of two participants were discarded due to the high error rate (approximately 80% errors). In addition, one participant recorded median response time in the second assessment block more than 3 standard deviations from the group average median and was therefore excluded from the analyses. For the remaining participants, trials with incorrect responses were not analysed (6.6% of trials from the session 1 data, and 7.5% trials from the follow-up data), and trials with RTs below 100ms or above 1500ms were discarded

(a further 1% of trials and .3% trials from the follow-up data). Thus, analyses were based on 46 participants in session 1 and 32 in the follow-up session; for which 93.4% of trials from session 1 and 92.2% trials from the follow-up session data were included.

To create bias scores, each participant's median RT for the positive-probe trials was subtracted from their median RT for negative-probe trials, separately for each block of trials. Numerically positive attention bias scores therefore reflected speeded responses when the probe appeared in the location of the positive word compared to when the probe appeared in the location of the negative word, i.e. reflecting an attention bias favouring positive stimuli relative to negative stimuli. Of interest were the three separate assessment block bias indices; pre-training; post- training; and the follow-up assessment. From these indices, we calculated an index of training-induced shifts in attentional bias by subtracting the pre-training bias index from the post-training bias index. A numerically positive score indicates a larger shift in attention bias favouring positive relative to negative information as a result of ABM training. Finally, we created a bias change over time index by subtracting the pre-training bias index from the follow-up (not the post-training) bias index. Greater scores on this change score reflect larger changes in attentional bias towards favouring positive over negative stimuli from the baseline measurement, to the follow-up measure 12 weeks later.

Daily Reconstruction Method. Following prior research (Catalino & Fredrickson, 2011), we extracted events that included socializing, spiritual activity, exercising, intimate relations, playing, and learning. Unfortunately, the remaining 98 events reported were not sufficient to capture a detailed picture of participant's emotional experiences throughout a typical day. Therefore, we used only the mDES data as an indicator of positive and negative emotions.

Data Analysis

To examine prospective associations, we obtained Pearson's correlations between training-induced shifts in attentional bias (post-training bias minus pre-training bias) and the following primary measures at follow-up; happiness, positive emotions, positive mental health, and resilience, and the following secondary measures at follow-up; negative emotions, depression, anxiety, and psychological (in)flexibility. To explore the significant associations further we performed several multiple regressions with both pre-training and post-training biases as predictors of the follow-up self-report measures (positive emotions, and happiness). We then obtained the Pearson's correlations between attention bias and self-report measures within each testing session, to investigate potential overarching associations in these variables. Then, we investigated the pattern of prospective association in the bias assessments, firstly correlating training-induced shifts in bias with changes in bias over time, and secondly performing multiple regression with pre-training bias and post-training bias predicting attention bias at follow up. Finally, we examined the internal reliability of each attention bias assessment with a Monte Carlo split-half reliability estimation procedure.

Results

Table 4.1 presents the means and standard deviations of scores in the self-report measures, for both sessions. We performed a series of paired t-tests between session 1 and follow-up to probe changes in the self-reported measures over time. Between sessions, participants mean mental health ($t(31) = 2.29$, $p = .028$, $d = .41$) and trait-resilience ($t(31) = 2.06$, $p = .048$, $d = .36$) scores decreased, whereas anxiety increased ($t(31) = -2.04$, $p = .050$, $d = .36$). There were no significant differences between sessions, in any of the other scales (all ps $> .05$). In addition, independent t-tests were performed to assess for any possible differences on the session 1 self-report measures between participants who did and did not

return for the follow-up session. Participants who returned for the follow-up session reported higher positive emotions during session 1 ($t(18.71) = -2.58$, $p = .018$, $d = .95$) but did not appear to differ from those who dropped out of the study on any of the other self-report measures (all other *p*s > .05)

Table 4.1. Means and Standard deviations for self-report and cognitive measures taken in session 1 and follow-up.

	Session 1		Session 2	
	M	SD	M	SD
Mental Health	48.1	12.3	45.9*	11.2
Resilience	66.8	12.4	62.7*	15.1
Subjective Happiness	19.1	4.9	19.3	5.0
Positive Emotions	27.3	6.4	27.2	8.3
Negative Emotions	14.1	6.7	15.0	7.3
Depression	6.2	5.3	6.2	5.7
Anxiety	4.5	4.2	5.2*	4.8
Psychological Flexibility	35.5	9.3	36.4	9.7

Note: * indicates a significant (p < .05) difference between session 1 and session 2 (n = 32)

Associations between training induced shifts in bias and self-report measures: Prospective associations Session 1 –Session 2

Training-induced shifts in attentional bias during session 1, were significantly associated with subjective happiness ($r(30) = .37$, $p = .039$, 95% CI [.02, .63]), and self-reported positive emotions at follow-up ($r(30) = .38$, $p = .032$, 95% CI [.04, .64]). No associations were found between training-induced shifts in attentional bias and the self-report measure of positive mental health at follow-up ($r(30) = .26$, $p = .150$, 95% CI [-.10, .56]), or resilience at follow-up ($r(30) = .16$, $p = .386$, 95% CI [-.20, .48]). Training-induced shifts in attentional bias also did not associate with self-reported negative emotions at follow-up, $r(30) = .01$, $p = .947$, 95% CI [-.34, .36].

Next, we further explored the observed significant correlation between training-induced shifts in bias at session 1 and self-reported future happiness and positive emotions in session 2 by examining the two separate bias indices observed pre- and post- ABM training and including both as predictors of the session 2 measures in multiple regression analyses. In this model, both predictors compete directly to explain variance in the dependant variable. The pre-training bias was not predictive of subjective happiness at follow up (b = -.01, 95% CI [-.06, .04], $t(29)$ = -.28, p = .780), whereas the post-training bias was a significant predictor (b = .04, 95% CI [.01, .08], $t(29)$ = 2.54, p = .017). Similarly, the pre-training bias was not predictive of positive emotions at follow up (b = -.02, 95% CI [-.11, .06], $t(29)$ = -.55, p = .589), whereas the post-training bias was a significant predictor (b = .07, 95% CI [.01, .13], $t(29)$ = 2.47, p = .020). Figure 4.1 presents the association between the post-training attention bias and future happiness and positive emotions. For completeness, Table 4.2 reports the zero-order correlations between the attention bias measures, subjective happiness, and positive emotions for both testing sessions.

Table 4.2. Zero order correlations between each attention bias assessment, happiness, and positive emotions, for both testing sessions.

Variable	1	2	3	4	5	6
1. Pre-Training Bias[1]						
2. Post-Training Bias[1]	.12					
3. Follow-up Bias[2]	.06	.50**				
4. Happiness – S1[1]	.00	.13	.01			
5. Happiness – S2[2]	.02	.42*	.22	.58***		
6. Positive Emotions – S1[1]	.02	.16	.05	.49***	.40*	
7. Positive Emotions – S2[2]	-.03	.41	.15	.32	.71*	.53**

Note: * p < .05, ** p < .01, *** p < .001. [1] n = 46, [2] n = 32

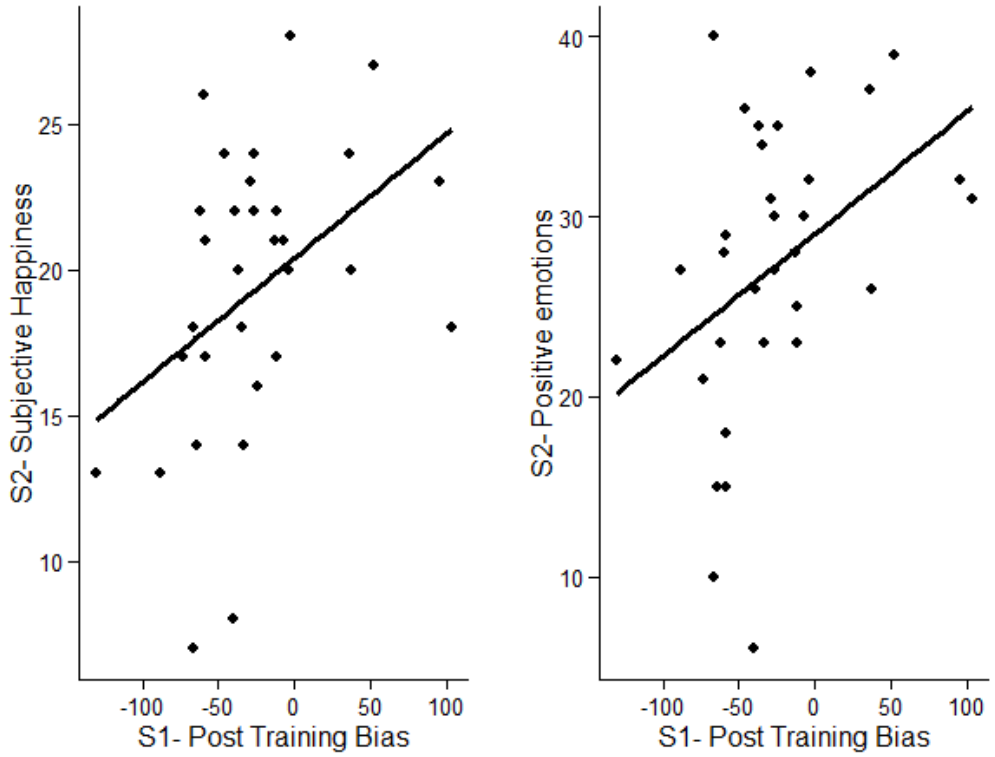


Figure 4.1. Panel a (left): session1 (S1) post-training bias predicting follow-up subjective happiness at session 2 (S2). Panel b (right) session 1 post-training bias predicting follow-up positive emotions.

Within-session Associations between attention bias and self-report items

To ensure that the observed prospective associations between the post-training bias and self-report measures at the follow-up session are not due to an overarching stable association, we also assessed associations between bias and self-report measures within each of the two testing sessions. No significant associations were observed between the session 1 self-report measures and biases assessed in the same session pre- and post- training (all *p*s > .266). Further, in the follow-up session, no significant associations were observed between the self-report measures and biases assessed at follow-up (all *p*s > .229). Importantly, no significant associations were observed between shifts in bias assessed in the first session, and changes in the primary self-report measures between the first session and follow-up (all *p*s > .273).

Further exploration of ABM task data

We also investigated associations between the various bias assessments. We observed no absolute effect of training at the group level; there was no significant difference between pre- and post- training bias assessments, $t(45) = -1.67$, p = .100, $d = .25$. Furthermore, the pre-training bias score was not predictive of the post-training bias ($r(44) = .12$, $p = .432$, 95% CI [-.18, .40]) and there was sizable variance in training-induced shifts in attentional bias (M = 12.73, SD = 51.64) ranging from -89.5 to 144. This suggests that there are substantial individual differences in the degree to which individuals shift their attentional bias in response to ABM training (i.e., bias malleability).

However, and similar to Clarke et al. (2008, study 3), training-induced shifts in attentional bias in a single session were found to significantly predict changes in bias from pre-training to the follow-up session twelve weeks later ($r(30) = .64$, $p < .001$, 95% CI [.38, .81]). Figure 4.2 displays a scatter plot of the positive relationship between training-induced shifts in attentional bias and change in bias over time.

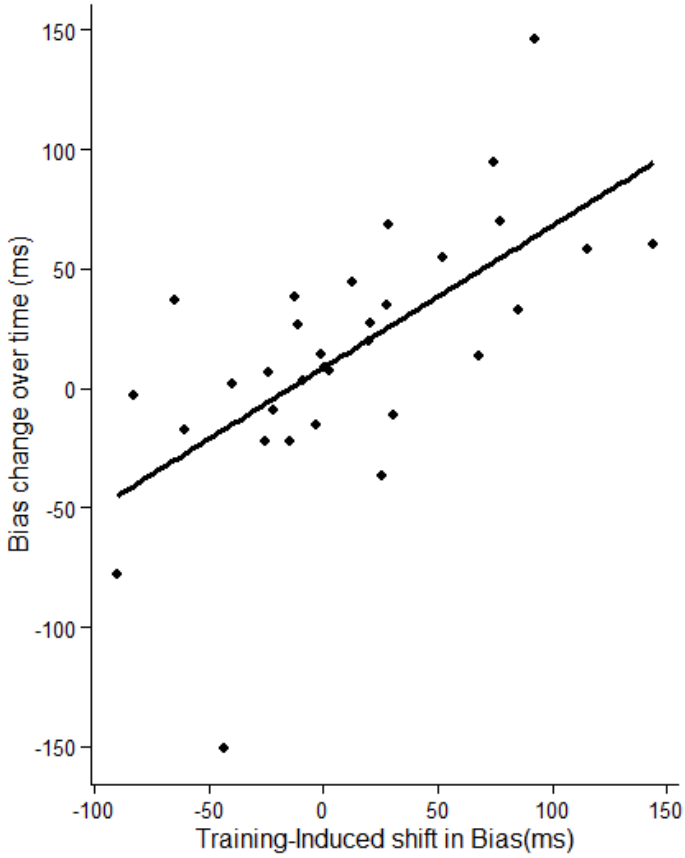


Figure 4.2. Scatterplot of the relationship between training-induced shifts in attentional bias, and changes in attentional bias from baseline to follow-up 12-weeks later. Training-induced shift in bias were calculated by subtracting pre-training attentional bias from post-training attentional bias. Changes in attentional bias were calculated by subtracting pre-training attentional bias from the follow-up attentional bias.

Next, we examined whether the separate pre- and post- training bias scores (as opposed to the training-induced shift in bias scores) predicted the bias scores at follow-up. Figure 4.3 presents the biases observed in each assessment block. We performed a multiple regression with pre-training bias and post-training bias as separate predictors of follow-up bias. The pre-training bias was not predictive of follow-up bias (b = -.02, 95% CI [-.42, .37], $t(29)$ = -.12, p = .908), whereas the post-training bias was a significant predictor of bias at follow-up (b = .42, 95% CI [.14, .69], $t(29)$ = 3.11, p = .004)

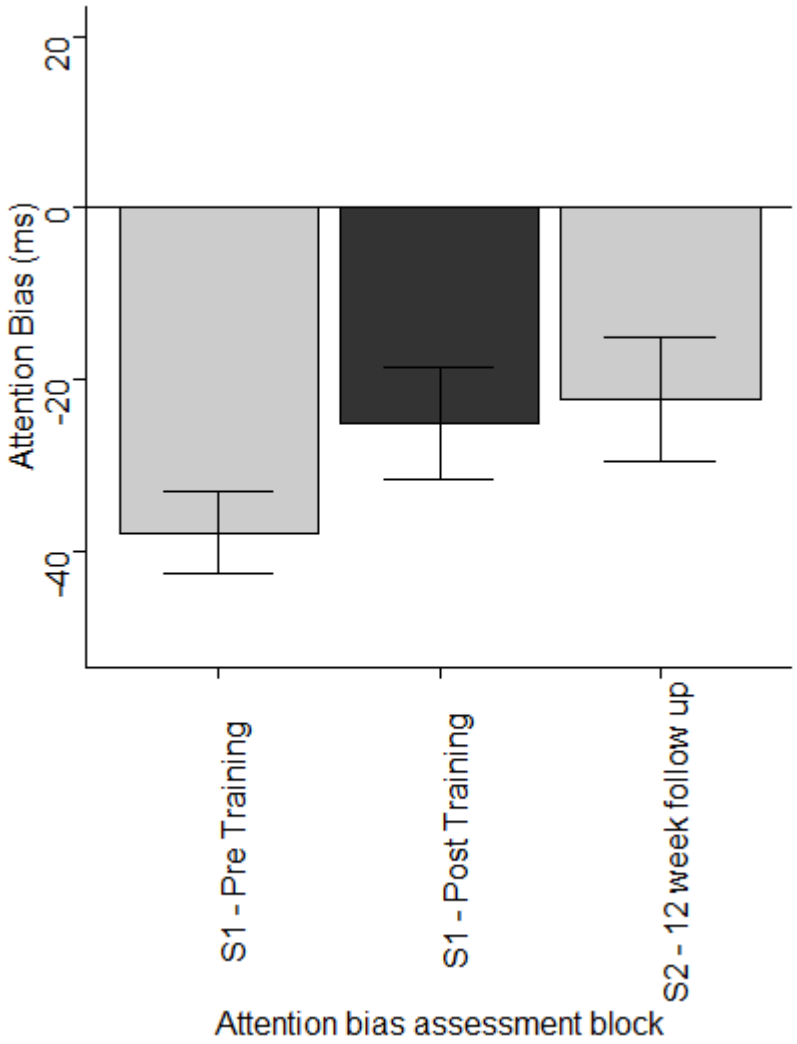


Figure 4.3. Attention bias scores observed in the assessment blocks. Positive scores indicate an attentional preference for positive stimuli, whereas negative scores indicate an attentional preference for negative stimuli. The colour of the bars represent the word lists used in the task. Error bars represent +/- 1SE.

Internal reliability of bias assessments

Given that there are increasing concerns regarding the reliability of the dot-probe task and since we observed that the prospective associations with bias malleability in this study were driven by the bias assessed post-training, we examined the reliability of each bias assessment block in a post-hoc analysis. To estimate the internal reliability of each bias assessment, we utilised a simulation process in which the data were randomly split in half and

split-half reliability calculated. The R package *splithalf* (Parsons, 2017) was developed for this purpose. A brief summary of the rationale for the development of this approach to estimating the reliability (internal consistency) of attention bias indices and a description of the Monte Carlo estimation procedure itself can be found in Appendix 5. This method has been argued to yield more stable estimates of bias score reliability (Enock, Hofmann, & McNally, 2014). The split-half reliability estimates were aggregated from 5000 simulations of this procedure and have been subject to the Spearman-Brown correction formula for estimating full-length reliability from split halves. The pre-training assessment was found to have a split half reliability of .42, whereas the post-training reliability was found to be .68. The reassessment of bias in the follow-up session was found to be .56.

Discussion

In this study, we examined prospective relationships between attention bias malleability and self-reported positive mental health. We assessed whether a shift in attention bias from pre- to post- a single baseline session of ABM predicted self-reported mental health and bias at a follow-up session around 12 weeks later. We replicated the findings of Clarke et al. (2008) in showing that training-induced shifts in attentional bias predict changes in bias from baseline (pre-training) to 12-weeks later. This is of theoretical importance to a malleability account of attention bias in indicating that shifts in attention bias in the laboratory are associated with naturalistic changes in attention bias over time. However, in contrast to prior findings (Cavanagh, Urry, & Shin, 2011; Clarke et al., 2012, 2008), we found no relationship between training-induced shifts in bias and naturalistic changes in self-reported measures from session 1 to session 2. We did observe prospective associations between the training-induced change in bias (attention bias malleability) and the scores on two out of four self-report measures related to positive mental health obtained at follow-up (subjective happiness

and positive emotions). Importantly, each of the prospective associations between self-reported happiness and positive emotions and training-induced shifts appeared to have been driven by the post-training bias. Post-training bias was associated with self-reported happiness and subjective happiness, as well as attention bias at the follow-up session twelve weeks following training, whereas pre-training bias was not.

Our results support prior literature suggesting a relationship between attention bias for positive information and trait happiness (e.g. Raila et al., 2015) and positive emotions (e.g. Strauss & Allen, 2006). It is important to note that the attention bias measured in this study reflects preferential allocation of attention to positive information relative-to negative information. Indeed, we did not find positive processing biases overall, but, rather, training-induced reductions in negative bias. We echo Grafton and colleagues' recommendation (Grafton, Ang, et al., 2012, p. 141) that future research is needed to disentangle the possibilities that training attention towards positive information, or away from negative information, or both, are important in the observed relationships between post-training attention bias and future positive emotions and happiness. Our data suggest that a reduction in selective processing of threat (i.e., a reduced negative attentional bias relative-to positive information) may prospectively associate with more transient experiences of positive emotion and happiness, rather than with trait-measures of mental health. This is similar to findings of attentional bias to highly positive stimuli associating with positive emotional states, but not trait positive emotion (Strauss & Allen, 2006). To our knowledge our research is the first to examine the prospective relationship between attention bias malleability in a short cognitive training intervention and outcome measures relating to positive mental health and wellbeing. Previous research has investigated changes in attention bias elicited by mood inductions. For example, Cavanagh et al. (2011) found that shifts in attentional bias as a result of happiness

mood inductions were predictive of changes in satisfaction with life over time (also see; Taylor et al., 2011). There is also some prior evidence for a prospective relationship between attentional bias and pathology. In a student population, for instance, biased attention to negative information has been found to predict cortisol reactivity to a laboratory-based stress task both at 4 (low-stress period) and 8 (high stress period) months later (Fox, Cahill, & Zougkou, 2010). In addition, MacLeod and (1992) found that automatic selective processing of threatening information predicted the degree of emotional distress in response to a diagnosis of cervical pathology several months later. All of these findings suggest that automatic processing biases can moderate emotional reactions to stressful 'real life' events. The current study's results extend this earlier work by suggesting that automatic attentional selectivity for positive information relative-to negative information may be similarly associated with future reports of positive emotional experiences.

It is worth noting that Clarke and colleagues examined changes in anxiety over very specific periods of time chosen because typical events occurring during these periods were expected to either elevate (2008) or reduce (2012) anxiety (first term of undergraduate study and group therapy respectively). In contrast, for this initial study we did not select a specific period of time in which we expected elevated positive emotions, not in the least because it is difficult to hypothesise a period of time to be typically characterised by positive emotions for most people. Instead, we were interested in investigating the variability in various indices of wellbeing and happiness and how these relate to a prior assessment of the malleability of attentional biases towards positive, relative to negative material without prior expectations of the emotional experiences during that time. The intervening period between testing sessions included the winter and Christmas holidays, which may contribute to increased positive affect among some, but not others, within our sample. We cannot fully account for individual

differences in emotional experiences between participants. In this light, an improvement to our methods would be to also assess the occurrence of positive and negative life events between the baseline and follow-up sessions, perhaps with a detailed experiential sampling approach (e.g. Larson & Csikszentmihalyi, 2014). This would facilitate our understanding of the role that emotional experiences over time plays in the observed relationships between post-training attentional bias and future positive emotions and happiness.

It is highly likely, indeed predicted, that the association between variations in cognitive processing biases and psychological wellbeing or vulnerability will be influenced by life events. Beevers and Carver (2003), for instance, have reported that changes in attention bias as a result of a sadness mood induction alone did not predict increases in dysphoria, while the interaction with life stress was significantly predictive. It is, of course, likely that individual variation in attention bias interacts with life experiences to influence pathology (Fox & Beevers, 2016, but see Kruijt, Putman, & Van der Does, 2014). For instance, the CogBIAS hypothesis (Fox & Beevers, 2016) proposes that cognitive biases may magnify the impact of positive and negative experiences so that the interaction between cognitive biases and life events influence the development of more negative or positive mental health outcomes. In the present study, it would have been useful to document the incidence of positive and negative experiences between testing sessions. The DRM was intended to provide some measure of this, however the data turned out not to be not viable for this purpose as, unlike Catalino et al. (2011) there was not sufficient data to provide a detailed account of daily emotional experiences. Future research may benefit by employing experiential sampling methodology (Csikszentmihalyi & Larson, 1987) in order to gain a more detailed picture of participants' life and emotional experiences over time. Further, an experiential sampling method would allow researchers to probe further into the prospective associations between attention bias

malleability and/or positive cognitive biases and future positive emotions and happiness, and provide important information as to when and for how long these prospective associations hold.

Although a change in bias over a training session was prospectively associated with happiness and positive emotions 12 weeks later, this effect was carried by the attentional bias assessed immediately after a single session of ABM training. This prompted us to examine the reliability of the dot-probe bias indices we observed in each assessment block. At .68 the split-half reliability of the post-training bias assessment was found to be very acceptable, while the reliabilities for the pre-training and follow-up assessments were relatively low (.42 and .56, respectively) although still quite high compared to dot-probe split-half reliabilities reported in other studies (e.g. Schmukle, 2005; Staugaard, 2009). Nonetheless, because of this relative unreliability of the pre-training block we cannot draw any strong conclusions as to whether or not the pre-existing/pre-training bias is or really is not associated with future positive emotions. This is a problematic observation, and it is certainly not confined to this specific study. Investigations into the reliability of dot-probe based attention bias assessments have typically revealed a pattern of low-reliability (Brown et al., 2014; Schmukle, 2005; Staugaard, 2009; Waechter et al., 2014), which is a problem with many different cognitive tasks (Hedge, Powell, & Sumner, 2017). The current study is among the few to report relatively good reliability of dot-probe based bias assessments (Bar-Haim et al., 2010; Enock et al., 2014; Waechter & Stolz, 2015). In Enock et al.'s study, participants completed dot-probe based ABM training three times daily, with an assessment of bias once per week. These weekly bias assessments showed a gradual increase in reliability to a spearman-brown corrected reliability of .53 in week 4. In combination with our results, this suggests that the reliability of the attention bias index as measured by the dot-probe task significantly

improves with ABM training. What remains unclear in the present study is whether the increase in reliability is simply a result of participants' practice on the task, or whether the specific training to preferentially attend towards positive stimuli during ABM is the critical factor. Some evidence for the latter comes from a study (Enock et al., 2014) in which control group participants completed an equivalent amount of practice on the dot-probe task without the training contingency. In this group the reliability of the bias index showed a less consistent pattern of improvement over time, with a spearman-brown corrected reliability of .31 in week 4. It is plausible that practice alone may not be enough to greatly improve the reliability of bias assessment, and that a high contingency between probe and emotional stimulus location may play an important role in increasing the reliability of dot-probe assessments of biased attention allocation. Further research is needed to investigate this question directly.

To summarise, in the present study we present data suggesting a prospective relationship between training-induced reductions in attentional biases towards negative stimuli (relative to positive stimuli) and future happiness and positive emotions. Post-hoc analyses suggested that this may in part be due to differences in the reliability of dot-probe bias assessment pre- and post- training, although further research is necessary to examine this directly. The current research indicates that the ability to adopt valence-specific attention bias to suit environmental or task demands may have important consequences for positive mental health outcomes.

4. Attention bias trained away from negative and towards positive stimuli prospectively predicts happiness and positive emotions

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Chapter 5

5

Investigating prospective associations of attentional biases following training with happiness and positive emotions: A replication and extension of Chapter Four

In Chapter Four, the results suggested that attention bias following Attention Bias Modification (ABM) training, but not attention bias at baseline, was prospectively associated with subjective happiness and positive emotions 12 weeks later. However, the results presented in Chapter Four left several questions open. First, it was important to test whether these results would replicate. Second, it was unclear whether the prospective associations were driven by the modification procedure, or the amount of time participants spent on the task. This study presents a replication and extension of Chapter Four. In addition to an ABM training group, the design was extended to include control-training and no-training groups. These additions enabled us to examine the prospective associations of attention biases with future happiness and positive emotions under varying degrees of attention bias training or exposure to attention bias assessment. We investigated the internal consistency of the attention bias indices for each attention bias assessment. The results are discussed in light of the previous Chapter to draw direct comparisons and make suggestions for future research.

Introduction

Attention Bias Modification (ABM) procedures implicitly promote the development of a selective attentional bias favouring one category of stimulus over another. An expanding research field has been built from the proposition that anxiety is characterised by an attentional bias towards threatening stimuli (Bar-haim, Lamy, Bakermans-kranenburg, & Ijzendoorn, 2007; Mathews & MacLeod, 2002, 2005) and the subsequent hypothesis that modifying this bias would reduce anxiety vulnerability. Although early research was encouraging (e.g. Hakamata et al., 2010), later work showed mixed results and a recent meta-analysis concluded that ABM procedures are largely clinically ineffective (Cristea, Kok, & Cuijpers, 2015). While agreeing that current ABM procedures have low clinical efficacy, it has been argued that this may be because the available procedures are not particularly good at actually inducing the required changes in attention bias (Grafton, MacLeod, Rudaiszky, Holmes, Salemink, Fox & Notebaert, 2017; MacLeod & Grafton, 2016). From this perspective, it is important to develop better methods of modifying attention biases before the clinical efficacy can be adequately tested. While much debate centres around the potential clinical utility of ABM, it is important to acknowledge that these procedures are extremely useful as an experimental tool to investigate the role of cognition-emotion relationships in emotional vulnerability and mental health outcomes (Hertel & Mathews, 2011; Colin MacLeod & Grafton, 2016). Manipulating the cognitive process of interest enables researchers to move beyond cross sectional designs in order to examine the causal relationship between emotional information processing biases and mental health (Hertel & Mathews, 2011).

Individual differences in the degree of change in attention bias resulting from ABM has been investigated previously as an index of attention bias malleability, or plasticity (see

Clarke, Chen, & Guastella, 2012; Clarke, Macleod, & Shirazee, 2008). Attentional bias (to threat) malleability has been found to predict increases in trait anxiety during a stressful period (Clarke et al., 2008), and reductions in trait anxiety during a more positive experience, in this case cognitive behavioural therapy (Clarke et al., 2012). Together, these studies suggest that readiness to alter attentional processing biases may underlie individual differences in responses to positive and negative experiences.

In the previous Chapter, we found that plasticity of attention bias towards positive information in a baseline session predicted self-reported positive emotions and happiness in a 12-week follow-up session. In further exploring these results, we found that the post-training bias was significantly prospectively associated with attention bias, happiness, and positive emotions at the follow-up session. In contrast, the pre-test bias was not prospectively associated with any of these variables. These results supported previous observations of a relationship between attention bias for positive information and trait happiness (e.g. Raila et al., 2015) and positive emotions (e.g. Strauss & Allen, 2006). Similar to Strauss and Allen, the results suggested that an attentional bias that had been trained away from negative information and more towards positive information may prospectively associate with more transient experiences of positive emotions (but not negative emotions) and happiness, rather than trait-measures of mental health. If these results are found to be robust, this has strong implications for the way that attention bias favouring positive information is examined in relation to positive experiential characteristics. It would suggest that ABM procedures would be useful in invoking the attention bias of interest and would have important implications for how studies investigating attention bias in positive mental health research should be conducted. However, until these results are replicated and further scrutinised, these possibilities are purely conjecture.

An important, yet under-reported and rarely discussed, characteristic of cognitive bias measures, such as the Emotional Dot-Probe is the internal consistency or reliability of the outcome measures calculated from task performance. While it is common practice to report the internal reliability of questionnaire measures in psychology (e.g. using Cronbach's alpha), it is the exception rather than the rule to report task reliability for cognitive measures (Gawronski, Deutsch, & Banse, 2011). Estimating and reporting the reliability of our tasks enables us to make more informed judgments about the implications of our analysis. As others have argued, "researchers should calibrate their confidence in their experimental results as a function of the amount of random measurement error contaminating the scores of the dependent variable." (LeBel & Paunonen, 2011, p. 578; but also see (De Schryver, Hughes, Rosseel, & De Houwer, 2016; Hedge et al., 2017). To illustrate, low levels of reliability indicate that there is a degree of measurement error that is likely to contaminate the measure's usefulness, in particular for individual differences or correlational analyses (De Schryver et al., 2016; Hedge et al., 2017). The importance of internal consistency of a measure's scores has led to the assertion that "Interpreting the size of observed effects requires an assessment of the reliability of the scores" (Wilkinson & APA Task Force on Statistical Inference, 1999, p. 596).

Given the importance of task reliability, in the previous study, we further examined the reliability of the dot-probe bias indices we observed in each assessment block. The R package *splithalf* (Parsons, 2017) was developed for this purpose. A brief summary of the rationale for the development of this approach to estimating the reliability (internal consistency) of attention bias indices and a description of the Monte Carlo estimation procedure itself can be found in Appendix 5. The reliability of the pre-training assessment (.42) was lower than the reliability of the post-training (.68) and the follow-up (.56) bias assessments. It is also worth noting that these estimates were amongst several higher estimates in the literature (Bar-Haim

et al., 2010; Enock et al., 2014; Waechter & Stolz, 2015) compared to other previously published estimates of dot-probe reliability (Brown et al., 2014; Schmukle, 2005; Staugaard, 2009; Waechter et al., 2014). It is possible that the pre-training block was not predictive of follow-up measures because it was a less reliable measure of bias. This may be a result of participants' lack of practice on the task, or alternatively, it may have something to do with the fact that participants were trained to preferentially attend towards positive stimuli during the ABM. To begin to disentangle these possibilities, we conducted a replication and extension of the previous study/Chapter.

Following the procedure in the previous Chapter, participants completed two testing sessions approximately 12 weeks apart. In the first session, for each condition, participants completed two blocks of assessment trials to provide an index of attention bias at the start and end of the task. For the remainder of the paper, we refer to the first or baseline bias assessment block as the pre-training bias assessment and the second assessment block as the post-training bias assessment. Approximately 12 weeks later all participants completed another assessment block, which we refer to as the follow-up bias assessment.

To replicate and extend the design from the prior Chapter, three experimental conditions were used; no-training, control training, and towards-positive ABM training. The ABM training followed the same procedure as the prior study. Briefly, participants completed 6 blocks of attention bias modification trials in between the pre-training bias assessment and the post-training bias assessment blocks. To examine whether the results in the prior study (both the changes in reliability of assessments, and the predictive capability of the post but not pre assessment) were a result of either the training contingency, or practice on the dot-probe task, we included a control training condition. In this condition, participants completed six blocks of attention bias assessment blocks in between the pre-training bias assessment and

the post-training bias assessment blocks. In this way, those participants were not trained towards a particular bias, but were as practiced in the task as those in the ABM training condition. It was important also to explore whether the amount of training was of importance. We therefore included a no-training condition, in which participants completed the post-training assessment immediately following the pre-training assessment.

The purpose of the present study is to replicate and extend the results of the previous study/Chapter. Firstly, given the current background of the replication crisis (Open Science Framework, 2015) and open science movements, it is important to investigate whether the key results from the previous study can be replicated in a larger sample. The results of the previous Chapter left several questions open. The addition of control training and no training groups allows us to determine whether the prospective associations between post-training attention bias and future positive emotions and happiness were due to the training the bias or simply due to increased familiarity with the task. Further, this is the first study to examine the reliability of bias assessments as an additional consideration in the relationships that baseline and post-training biases have in predicting future positive mental health experiences.

Methods

Participants

Participants were recruited from the subject pool on Prolific Academic, an online research recruitment system enabling online recruitment, testing, and payment of participants supported by Oxford University Innovation, part of the University of Oxford. English-speaking adults (18-65 years of age) with reported normal, or corrected to normal eyesight, self-selected to complete the first session. Approximately 12 weeks later (M = 12.00, SD = 1.37) participants were re-contacted through Prolific to complete a follow-up testing session. In total, 143 participants completed both testing sessions. This study received ethical

approval from the Medical Sciences Inter-Divisional Research Ethics Committee (Ref: R49423/RE001).

We based our sample size on the observed correlation in the previous study of $r \sim .4$ between post-training bias and follow-up happiness and positive emotions. We therefore aimed for 80% statistical power to detect an effect size of $r = .4$ with an alpha of .05. Forty-six participants were required for each group and we aimed to recruit 50 per group, for a total of 150 participants.

Questionnaire measures

Happiness. The subjective Happiness Scale (SHS; Lyubomirsky & Lepper, 1999) is a 4 item scale assessing happiness on a global level containing items such as "In general, I consider myself" on a 7-point scale, from "not a very happy person" to "a very happy person". Internal consistency of the SHS in this study was $\alpha = .87$ in session 1, and $\alpha = .88$ at follow-up. Test-retest reliability was $r = .86$.

Positive and negative emotions. The modified Differential Emotions Scale (mDES; Fredrickson, Tugade, Waugh, & Larkin, 2003) asks participants to rate, on a 5-point scale (from "never", to "most of the time"), how often they had felt each of 20 different emotions (10 positive, and 10 negative) in the past few weeks. Items include "What is the most joyful, glad, or happy you felt?" Internal consistency for the positive and negative scales were $\alpha = .89$, and $\alpha = .90$ in session 1, and $\alpha = .93$, and $\alpha = .89$ at follow-up. Test re-test reliability for the positive and negative scales was $r = .63$, and $r = .42$

Depression. The Patient Health Questionnaire (Kroenke & Spitzer, 2002) contains 9 items corresponding to the DSM-IV depressive disorder symptom criteria. Participants rate how often they have been bothered by any of nine problems (e.g. "little interest or pleasure in doing things") over the last two weeks, on a 4-point scale from "not at all", to "nearly every

day". The PHQ-9 has shown strong validity as a brief measure of depression and good internal consistency (Kroenke, Spitzer, & Williams, 2001; this sample session 1 α = .87; follow-up α = .89; test retest *r* = .67).

Anxiety. The Generalized Anxiety Disorder – 7 item scale (Spitzer et al., 2006) is designed to reflect DSM-IV symptom criteria for anxiety. Participants rate how often over the last two weeks that they have been bothered by each of 7 problems (e.g. "trouble relaxing") on a 4-point scale from "not at all", to "nearly every day". The GAD-7 has shown excellent internal consistency and test-retest reliability (Spitzer et al., 2006; this sample session 1 α = .90; follow-up α = .90; test retest *r* = .78).

Dot-Probe task

Stimuli. The stimuli pair lists used in the present study were identical to the previous study/Chapter. 96 pairs of positive and negative words, matched for word length, were selected from the affective norms for English words (ANEW; Bradley & Lang, 2010). Word categories significantly differed in valence, $t(94) = 94.74$, $p < .001$, $d = 9.67$ (> 7.41 and < 2.67 for positive and negative words, respectively), and were not significantly different for arousal ratings $t(94) = .06$, $p = .949$, $d = .01$. Word pairs were split into two separate sets, set A and set B, which did not differ significantly by valence ($t(94) = .02$, $p = .988$, $d < .01$) or arousal ($t(94 = 1.93$, $p = .055$, $d = .28$). The word stimuli were presented in 32px lower case bold Arial font (approximately $.97^0$ vertical visual angle at 50cm from screen). Based on participant numbers (odd/even), participants either viewed stimuli subset A in the first assessment block and the training blocks, and subset B in the second assessment block, or vice versa. Participants viewed the same word set in the first assessment block of session 1 and in the follow-up assessment.

Trial structure. The trial structure was identical to the previous study/Chapter. Participants were presented with a fixation cross in the centre of the screen for 500ms, followed immediately by a word pair, presented above and below the centre of the screen separated by approximately 3cm (approximately 6.9^0 visual angle). The word pair was presented for 1000ms and then replaced by a small probe in the location of one of the words. The stimuli presentation time of 1000ms was selected following the procedure Chapter Four, which followed Clarke et al. (Clarke et al., 2008, p. 50), to maximise the prospect that participants would cognitively register and respond to the bias induction in the training component of the task. The probe was a 10 pixel long line presented in vertical or horizontal orientation. Participants were tasked to identify the rotation of the probe by pressing the appropriate key on the keyboard. The response cleared the screen and 500ms later the next trial began.

The contingency between the location of the positive word and the location of the probe differed between the assessment trials, control training trials, and ABM trials. In assessment blocks and control training blocks, there was a 50% likelihood that the probe would appear in the location of the positive word (positive-probe trials) and a 50% likelihood that the probe would appear in the location of the negative word (probe-negative trials). In the training trials, there was a 91.7% likelihood that probes appeared in the location of the positive stimuli (positive-probe). This contingency was achieved by including a small proportion of incongruent trials, which allowed for calculation of a traditional bias index throughout the ABM procedure.

Procedure

Participants completed the study online, on their own computer. The task and questionnaires was programmed and presented in INQUISIT Millisecond (Inquisit 4.0.8.0,

2013). INQUISIT measures RTs with millisecond accuracy (De Clercq et al., 2003). After giving informed consent, participants first completed the questionnaire measures and then the Dot-Probe task. The task began with written instructions and practice trials to familiarise participants with the task. Participants were allocated to one of three conditions; no-training, control training, and ABM training. In the no-training condition, participants completed two assessment blocks. The first and last assessment block will hereafter be referred to as the pre-training and post-training blocks, respectively (each consisting of 96 trials). In the control training condition, participants completed the pre-training assessment, followed by six control training blocks (totalling 576 trials), and ending with the post-training assessment. In the ABM training condition, participants completed the pre-training assessment, followed by six ABM training blocks (576 trials), finishing with the post-training assessment. In the follow-up session, participants first completed the questionnaires and then a single assessment block.

We completed two waves of data collection, the first in February to May 2017 (n = 77), the second in May to August 2017 (n = 66). In short, the decision was made to increase the total sample size following a discussion of the necessary statistical power to adequately perform the analyses. Further details can be found in the pre-registration of the study analysis (https://osf.io/w5cmf/). Importantly, no data were analysed until the full sample data were collected, and the pre-registered analysis uploaded.

Data processing

Participants with greater than 30% errors on any block of trials in either session (including the ABM and control training blocks of trials) were removed from the analyses. This resulted in the removal of 13 participants' data. For the 130 participants remaining; incorrect trials were removed, resulting in a loss of 4.29% of the session 1 and 5.51% of the

session 2 data. Next, trials with response times greater than 1500ms and less than 150ms were removed, resulting in the loss of a further 2.52% from the session 1 and 1.24% from the session 2 data. Following the removal of these trials, 93.19% and 93.25% (session 1 and 2, respectively) of the data were retained for the analyses.

To create bias scores, each participant's median RT for the congruent trials was subtracted from their median RT for incongruent trials, separately for each block of trials. Of interest were the three separate assessment block bias indices; pre-training; post- training; and the follow-up assessment. From these indices, we calculated an index of training-induced shifts in attentional bias by subtracting the pre-training bias index from the post-training bias index.

Data analysis plan

The data analysis plan was pre-registered on the Open Science Framework (https://osf.io/w5cmf/; in particular, see the data analytic plan document) on the 22nd August 2017, before data collection was completed and importantly, before any of the data were processed and analysed. One worthwhile note is that rather than performing a series of correlational analyses, here we performed multiple regressions, in order to include the pre-training and post-training bias index in the same analysis. The raw data and the data analysis script can also be found on the OSF project page (https://osf.io/tsrhg/). The following is a brief summary of the data analytic plan.

First, we examined whether the groups differed on any of the self-report measures with a series of independent t-tests, and whether groups differed on the self-report scales with a series of dependant t-tests. We next explored whether the ABM-training procedure was successful in shifting attention bias at the group level, relative to the control-training and no-training conditions. We performed a mixed ANOVA with between-subjects factor of group

(3 levels; ABM training, control training, and no training), and within-subjects factor of time (2 levels; pre-training and post-training). We then sought to replicate our results from the previous study/Chapter by performing a series of multiple regressions with pre-training bias and post-training bias as predictors of the self-report measures of positive emotions and subjective happiness, in the ABM-training group only. To extend the analysis from the previous study, we performed the same analyses in the control-training and no-training groups. Finally, in order to examine the role of task reliability we estimated the internal consistency of each bias assessment block, for each group, using a Monte Carlo estimation procedure.

Results

Table 5.1 presents the means and standard deviations of each self-report measure taken, for sessions 1 and 2, separately for each experimental group. To test for group-level changes in scores between sessions, we performed paired t-tests between session 1 and session 2 scores, for each measure, separately for each group. In the no training group, negative emotions were significantly greater in session 1, compared to session 2 ($M_d = 3.57$, 95% CI [0.77, 6.37], $t(41) = 2.58$, $p = .014$, d = .40). There were no other within-subjects significant differences. Further, to test for differences between groups on these measures, in either session, a series of independent t-tests were performed. In session 1 the negative emotion reports were greater in the no training compared to the control training group ($\Delta M = -5.34$, 95% CI[1.49, 9.20], $t(81.16) = 2.76$, $p = .007$, d = .59). There were no other significant between-subjects differences.

Table 5.1. Mean (SD) scores in session 1 and session 2, stratified by experimental group

	ABM Training		Control Training		No Training	
	Session 1	**Session 2**	**Session 1**	**Session 2**	**Session 1**	**Session 2**
N	42	42	46	46	42	42
Subjective happiness	17.67 (5.96)	17.76 (5.49)	15.91 (5.38)	16.46 (5.18)	17.17 (5.57)	17.17 (6.34)
Positive Emotions	31.81 (8.82)	30.38 (9.49)	28.80 (7.99)	28.74 (8.95)	31.69 (8.76)	30.67 (9.00)
Negative Emotions	23.10 (9.08)	20.86 (8.44)	21.09 [2] (8.33)	21.20 (7.46)	26.43 [1,2] (9.72)	22.86 [1] (8.31)
Anxiety	13.98 (5.10)	13.88 (5.94)	14.00 (4.85)	13.65 (4.59)	14.19 (5.64)	14.17 (5.12)
Depression	17.90 (5.31)	17.21 (6.18)	18.13 (6.26)	17.98 (6.67)	16.60 (5.79)	17.33 (5.64)
Pre-Training Bias	-34.30 (35.34)	-	-37.14 (31.18)	-	-35.08 (38.20)	-
Post-Training Bias	-15.09 (29.36)	-	-37.57 (38.28)	-	-35.47 (38.12)	-
Follow-up Bias	-	-28.51 (38.03)	-	-31.83 (32.65)	-	-26.19 (28.99)

Note. [1] denotes a significant within-group difference from session 1 to session 2. [2] denotes a significant between-group difference in the same testing session. Negative attention biases indicate vigilance for negative relative to positive stimuli.

The effect of training

We first examined the correlations between pre-training and post-training bias, for each group, to provide an indication of the individual differences in response to each training condition. As would be expected given that bias was not modified, significant correlations were found in the no-training group (r = .31, 95% CI [.01, .57], $t(40) = 2.11$, p = .040), and the control training group (r = .35, 95% CI [.06, .58], $t(44) = 2.47$, p = .018) groups. Consistent with Chapter Four, there was no significant correlation in the ABM group (r = .15, 95% CI [-.16, .43], $t(40) = .94$, p = .353), suggesting variation in individual responses to the bias modification procedure.

To examine whether the ABM training resulted in a change in bias relative to the other conditions, we performed a mixed ANOVA with a within-subjects effect of training (pre and post training bias assessments) and a between subjects effect of group (no training, control training, and ABM training). Figure 5.1 presents the biases observed pre- and post- training in each group. There were no significant main effects of measure ($F(1,127) = 2.55$, $MSE = 897.19$, $p = .113$, $\eta_p^2 = .020$) or group ($F(2,127) = 2.49$, $MSE = 1{,}588.23$, $p = .087$, $\eta_p^2 = .038$). The interaction did not reach significance ($F(2,127) = 3.05$, $MSE = 897.19$, $p = .051$, $\eta_p^2 = .046$). We then ran three t-tests comparing the bias at pre- and post- training for each group. There was a significant difference in bias between pre- and post- training bias in the ABM group ($M_d = 19.21$, 95% CI [5.97, 32.45], $t(41) = 2.93$, $p = .006$, d = .45). There were no significant differences between pre-training and post-training bias assessments in the no training (p = .955) and control training (p = .942) groups.

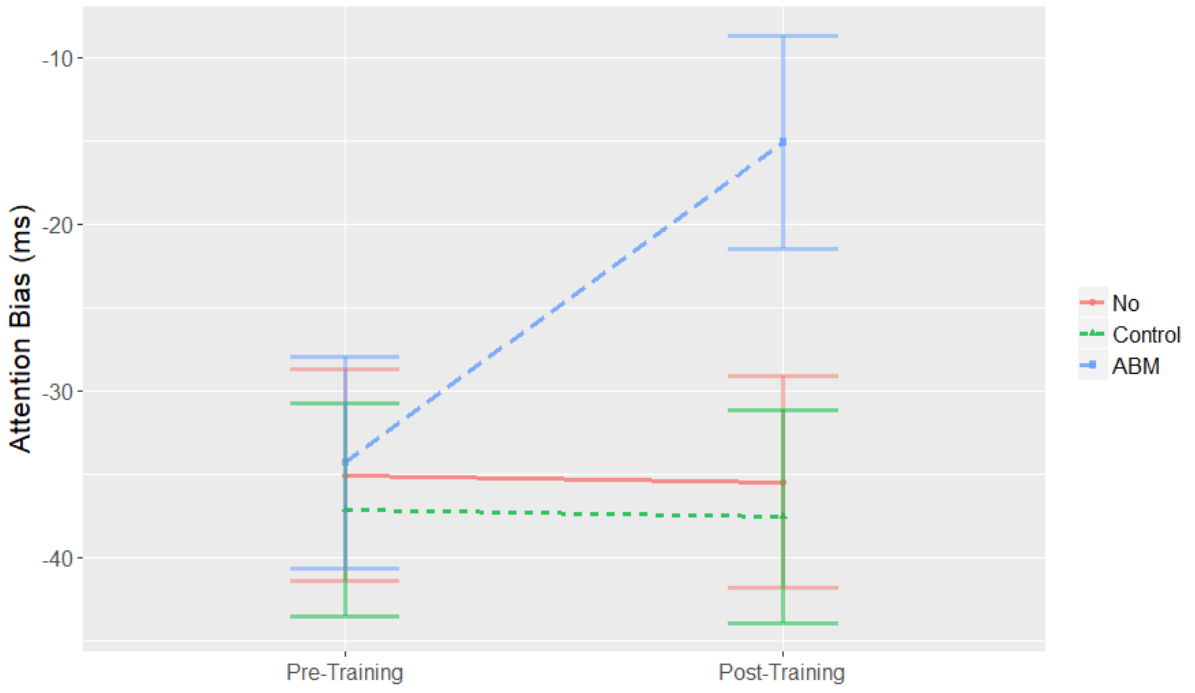


Figure 5.1. Attention bias indices from Pre- to Post- training, separately for each training condition. Negative attention biases indicate vigilance for negative relative to positive stimuli. Error bars represent one standard error of the mean

Prospective associations

To address the main research questions, we performed several multiple regressions. Pre-training bias and Post-training bias were used as predictors of the follow-up measures of happiness and positive emotions, separately. Analyses were performed separately for each experimental group. Tables 5.2 (subjective happiness) and 5.3 (positive emotions) present the results of these analyses. Figures 5.2 and 5.3 then present the associations, across each training condition, for Post-Training bias with future subjective happiness and positive emotions, respectively. Based on the results in Chapter Four, we predicted that in the ABM group, post-training bias, but not the pre-training bias, would significantly associate with future positive emotions and happiness. Neither pre-training bias, nor post-training bias was prospectively associated with future positive emotions or happiness (all *p*s > .05). We had no hypotheses regarding the prospective associations in the control and no training groups. In the control training group, post-training bias was prospectively associated with follow-up positive emotions ($p = .003$), but the pre-training bias was not significantly predictive ($p = .602$). Neither pre-training nor post-training bias were significantly prospectively related to happiness (*p*s > .05). In the no-training group, neither pre-training bias nor post-training bias were prospectively associated with follow-up happiness or positive emotions (*p*s > .05).

Table 5.2. Results of multiple regressions with pre-training bias and post-training bias predicting follow-up happiness, separately for each experimental group.

Group	Predictor	*b*	95% CI	T	*p*
ABM	Intercept	16.38	[13.93, 18.82]	13.53	< .001
	Bias Pre	-.04	[−.09, . 00]	-1.82	.076
	Bias Post	.01	[−.05, . 07]	.28	.783
Control	Intercept	18.35	[15.85, 20.84]	14.81	< .001
	Bias Pre	.01	[−.04, . 06]	.35	.731
	Bias Post	.04	[.00, . 08]	2.00	.052
No	Intercept	17.14	[14.09, 20.20]	11.36	< .001
	Bias Pre	-.02	[−.08, . 03]	-.87	.392
	Bias Post	.02	[−.03, . 08]	.83	.411



Figure 5.2. Scatter plot presenting the association between Post-training attention bias in session 1 and subjective happiness in session 2. Negative attention biases indicate vigilance for negative relative to positive stimuli.

Table 5.3. Results of multiple regressions with pre-training bias and post-training bias predicting follow-up positive emotions, separately for each experimental group.

Group	Predictor	*b*	95% CI	t	*p*
ABM	Intercept	29.26	[25.00, 33.52]	13.89	< .001
	Bias Pre	-.06	[−.14, . 03]	-1.38	.175
	Bias Post	.06	[−.04, . 16]	1.14	.260
Control	Intercept	31.92	[27.80, 36.04]	15.62	< .001
	Bias Pre	-.02	[−.11, . 06]	-.53	.602
	Bias Post	.11	[.04, . 18]	3.11	.003
No	Intercept	31.33	[26.97, 35.69]	14.53	< .001
	Bias Pre	-.01	[−.09, . 07]	-.32	.751
	Bias Post	.03	[−.05, . 11]	.79	.436

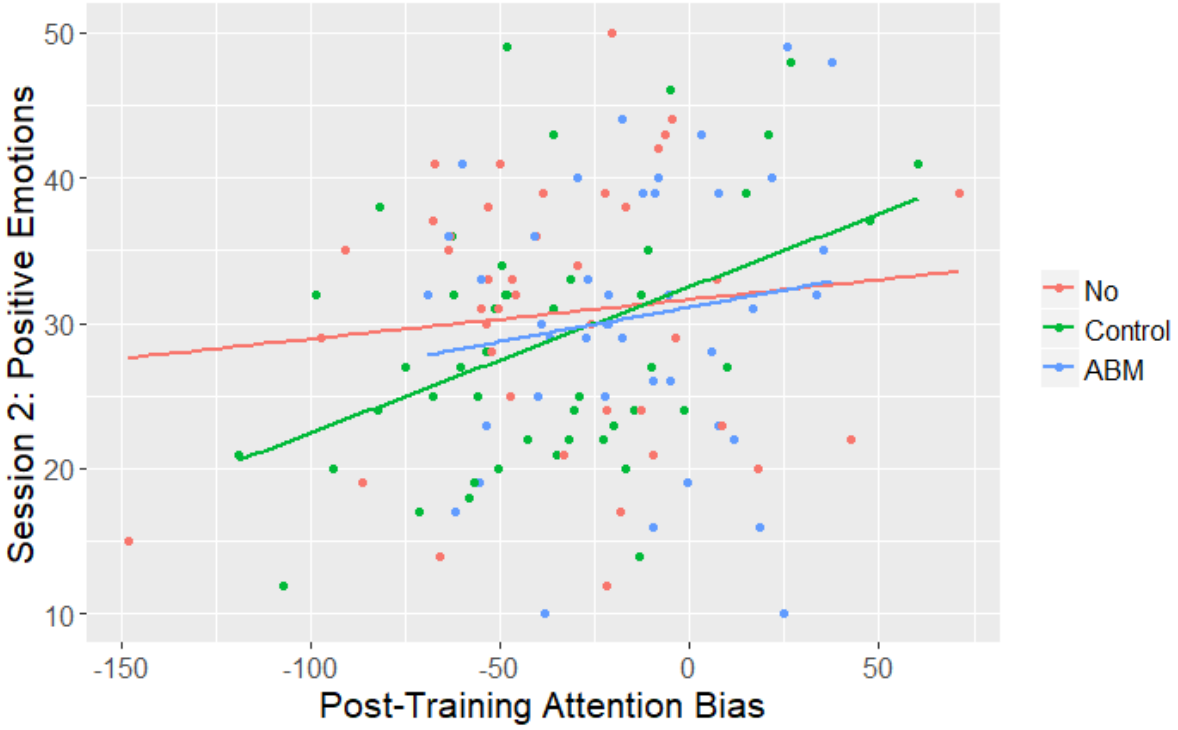


Figure 5.3. Scatter plot presenting the association between Post-training attention bias in session 1 and positive emotions in session 2. Negative attention biases indicate vigilance for negative relative to positive stimuli.

The relationship between biases in session 1 and session 2

To follow our prior results indicating that a post-ABM-training bias is predictive of future bias, we examined the associations between pre- and post- training biases and follow-up session bias, for each group, with multiple regressions. In each regression, pre-training and post-training bias were used as predictors of follow-up-bias. The results of these analyses can be found in Table 5.4, and a scatter plot of the association between post-training bias and follow-up bias is presented in Figure 5.4. In contrast to the results in Chapter Four, in the ABM training group, the post-training bias was not significantly associated with attention bias at follow-up, whereas the pre-training bias was significantly associated.

Table 5.4. Results of multiple regressions with pre-training bias and post-training bias predicting follow-up bias, separately for each experimental group

Group	Predictor	*b*	95% CI	t	*p*
ABM	Intercept	-20.05	$[-36.60, -3.50]$	-2.45	.019
	Pre-Training	.35	$[.02, .68]$	2.16	.037
	Post-Training	-.24	$[-.64, .16]$	-1.22	.230
Control	Intercept	-34.27	$[-49.96, -18.57]$	-4.40	< .001
	Pre-Training	.23	$[-.09, .56]$	1.46	.153
	Post-Training	-.30	$[-.56, -.03]$	-2.26	.029
No	Intercept	-17.88	$[-31.57, -4.18]$	-2.64	.012
	Pre-Training	.10	$[-.16, .35]$	0.77	.446
	Post-Training	.14	$[-.11, .39]$	1.13	.266

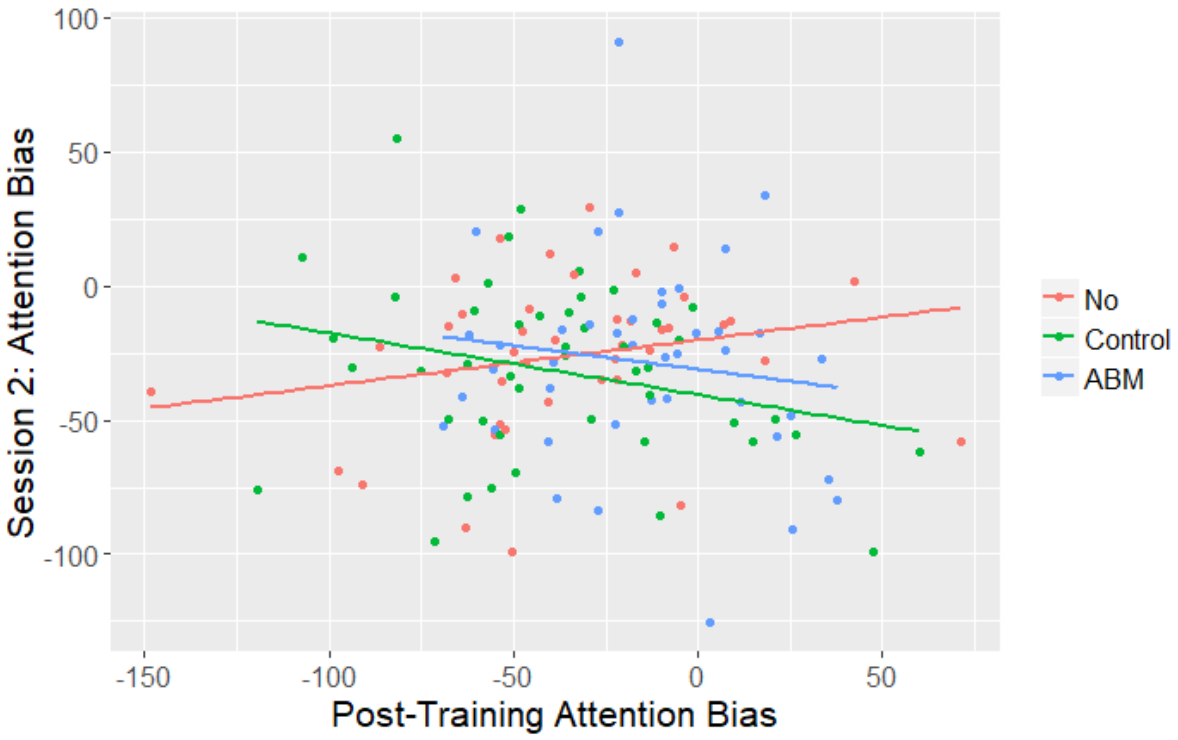


Figure 5.4. Scatter plot presenting the association between Post-training attention bias in session 1 and Follow-up attention bias in session 2. Negative attention biases indicate vigilance for negative relative to positive stimuli.

Investigating the reliability of bias assessment

The R package *splithalf* (Parsons, 2017) has been developed to robustly estimate the internal consistency of response time based task scores (A brief summary of the rationale for the development of this approach to estimating the internal consistency of attention bias indices and a description of the Monte Carlo estimation procedure itself can be found in appendix 5). The function *DPsplithalf* was used to estimate the internal consistency of the attention bias index scores. The Monte Carlo simulation procedure takes the following steps. Separately for each condition, within each bias assessment, and for each participant; the incongruent and congruent trials are randomly split into two halves and used to calculate two bias indices. Then, the Pearson correlation is calculated between the bias indices as a single split-half reliability estimate. This procedure is repeated a large number of times (5000 in this

study), and the mean estimate is taken as the robust split-half reliability (or internal consistency) estimate. This method has been argued to yield more stable estimates of bias score reliability (Enock, Hofmann, & McNally, 2014). Figure 5.2 presents the splithalf reliability estimates of each bias assessment, separately for the three training groups. Note that in the prior Chapter, the Spearman-Brown correction was used, however for the present study the raw Pearson correlations were used. For comparison, the non-Spearman-Brown corrected reliability estimates for the pre-training, post-training, and follow-up training assessments in Chapter Four were .27, .52, and .39, respectively. In all cases, the internal consistency estimates in Chapter Four were greater than those presented here. The ABM and control training groups showed an opposite pattern in the change in internal consistency from pre-training to post-training. While the control training group appears to show a less consistent bias following the task, the ABM training group appears to increase in reliability over time.

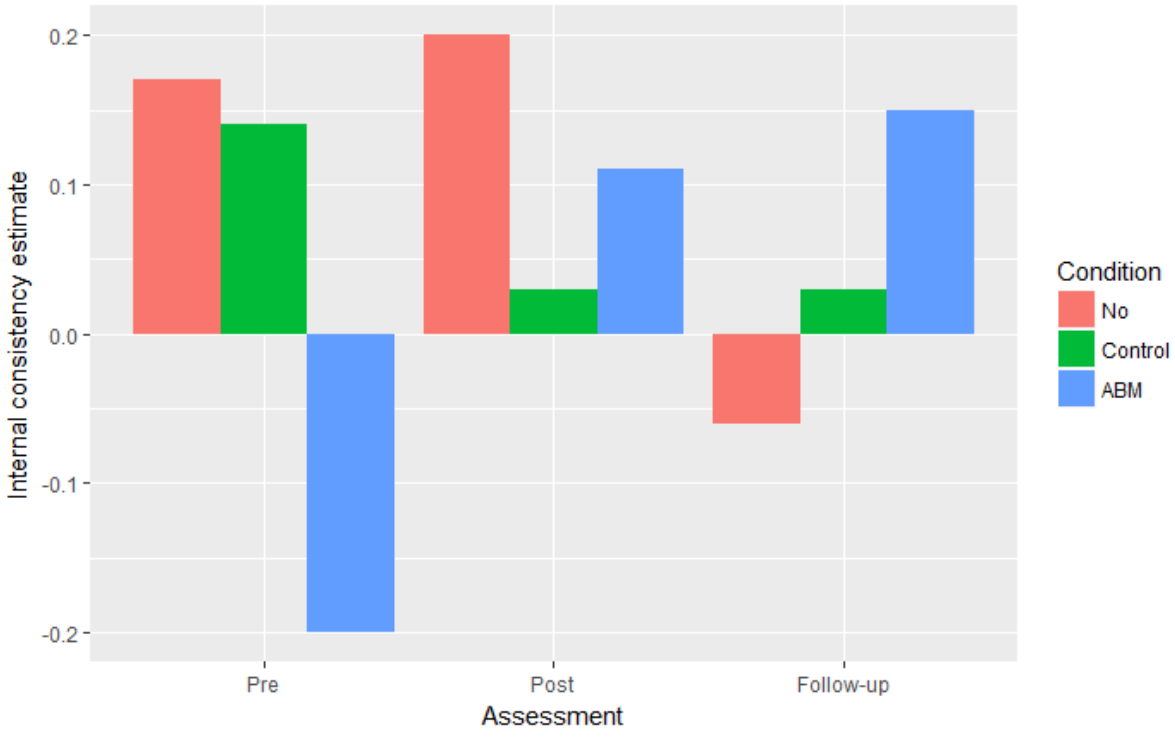


Figure 5.2. Robust estimates of the internal consistency of each attention bias assessment, separately for each group.

Discussion

Chapter Four left open several questions that this study sought to address. Perhaps most pressingly, will the results replicate? Following this, were the significant prospective associations in the post-training but not the pre-training (as well as the increase in task reliability) a result of training the attention bias, or a result of practice on the task? Further, does this act as a function of the amount of training? The current study was designed as a replication and extension of Chapter Four. We examined the prospective relationships between attention bias (pre-training and post-training) and self-reported positive emotions and subjective happiness. Participants were allocated to one of three training conditions; ABM-training, which repeated the procedure in Chapter Four, control training, and no training. This allowed us to extend the prior study and examine differences between the degree and type of training in prospective relationships between attention bias and future happiness and positive emotions. One of the limitations of the study presented in Chapter Four was the high drop-out rate and subsequent decline in statistical power. This study addressed this issue by recruiting a larger sample in each condition, and reducing overall attrition. First, we discuss the main results found in each condition.

ABM training group. The ABM procedure was successful in producing a group-level change in attention bias, though as expected there was substantial variation in individual responses to the ABM training. From results in the previous Chapter, we predicted that the post-training attention bias in the ABM group would predict future positive emotions and happiness. We did not replicate this effect in this study. We further predicted that the post-training bias, but not the pre-training bias, would significantly predict bias at follow up. The results were counter to these predictions; pre-training, but not post-training, bias was significantly predictive of future bias.

Control training group. We had no hypotheses regarding the prospective associations between pre-training and post-training biases and follow-up happiness and positive emotions. Interestingly, we found that post-training bias was significantly associated with future positive emotions. Further, it was only in this group that the post-training bias was prospectively associated with the bias at follow-up. These findings follow a similar pattern to those in Chapter Four, albeit this was not an ABM training group. They do seem to support a pattern in which prospective associations between attention bias post-training (whether ABM or practice) and future bias and positive emotions go hand in hand

No training group. The no-training group was included as a comparison group to the control-training group. Although we had no specific hypotheses for this group; it is worth noting that we found no significant associations between pre-training or post-training attention bias and future bias, positive emotions, or happiness. This suggests that the amount of practice on the task does indeed play a role in these prospective relationships.

Together, the results present a mixed picture of the prospective associations between an attention bias post-training, and future self-reports of positive emotions and happiness. The results of the previous Chapter were not replicated, finding no support in this sample for the hypothesis that a post-ABM-training attention bias away from negative and towards positive information would be prospectively associated with positive emotions and happiness. We did however find some evidence that such a prospective relationship existed in the control-training group, albeit only for positive emotions. This also co-occurred with a prospective association between the post-control-training attention bias and attention bias at follow-up, which is consistent with the previous Chapter. Further research is needed to evaluate the prospective relationship that attention bias may have with transient positive experiences, such as happiness and positive emotions. Moreover, it will be important to address the co-

occurrence of prospective associations between post-training attention biases and future bias and self-report measures.

The internal consistency of attention bias indices

One of the aims of this study was to explore the role that the internal consistency of the bias indices plays in the findings. The attention bias assessments reported in Chapter Four presented an uncharacteristically high internal consistency, relative to prior investigations of dot-probe reliability (Brown et al., 2014; Schmukle, 2005; Staugaard, 2009; Waechter et al., 2014, but also see Bar-Haim et al., 2010; Enock et al., 2014; Waechter & Stolz, 2015). Indeed, this high internal consistency was one result in the previous Chapter that warranted further investigation and replication. In addition, the findings suggested that training increased the internal consistency of the bias index, and this coincided with a significant prospective association with future positive emotions, happiness, and attention bias. The internal consistency of the attention bias indices in the present study did not follow the pattern observed in Chapter Four. The current estimates were consistently lower than those in the previous study. This is perhaps an indication that the dot-probe task is not best suited for use online testing and laboratory settings might be necessary to produce consistency in biased attention. Further work is needed that directly compares the reliability of attention bias, and cognitive bias tasks more broadly, in various settings.

Although the internal consistency estimates were low, some trends during the first testing session should be noted. We do observe a rise in internal consistency of the bias assessment in the ABM group. It is possible that as participants learn a strategy (i.e. it is more adaptive for task performance to attend to the positive stimulus) that they become more consistent overall in displaying an attention bias. This may also explain the decline in internal consistency in the control training group. Although the control-training task does not

implicitly try to shift bias in either direction, it may promote constant shifting of bias in order to either; maintain the current bias, or to gradually shift towards having no bias (depending on one's perspective on what the effects of completing the task without an experimental contingency are). Either route has the potential to result in a low internal consistency estimate. The no-training group also showed little change in internal consistency, suggesting that a certain degree of practice is necessary in the task itself to become less consistent in bias.

The internal consistency (often referred to as reliability) of a task score is important in calibrating confidence in statistical inferences drawn from using that task score in a particular analysis (LeBel & Paunonen, 2011). Though, it is important to note that lower reliability indices are not universally damaging to our analyses (De Schryver et al., 2016). More specifically, internal consistency estimates have distinct implications for one category of analysis, e.g. correlational, compared to another, e.g. experimental or between-group differences (Hedge et al., 2017). What is unclear are implications this has for attention bias modification, and cognitive bias modification procedures, more generally. For example, if training and control procedures push the internal consistency of our measures in opposite directions, we would expect a complex interaction between the analytic procedures and internal consistency across each measure in being able to judge the precision of the results of the analyses. A clearer understanding of the impact of various types of internal consistency of bias indices across a range of statistical analyses is required to more accurately evaluate the confidence that can be placed in the results.

Limitations

There are several limitations that are worth discussion. First, online participant recruitment and data collection in this study was used to compensate for time and participant

access constraints; however this does raise some issues. In standard laboratory conditions, ambient noise and distractions are limited and relatively constant across participants. Although the instructions clearly stated that the task should be completed in a quiet and distraction-free environment, with online testing we cannot be certain that these conditions were adhered to. It is plausible that the reduced environmental control was reflected in the low internal consistency of the bias indices. A previous study did report reasonable internal consistency (.53) of a smartphone based dot-probe task following 4 weeks of ABM training (Enock et al., 2014), suggesting that it may be possible to capture an internally consistent measure of attention bias under inopportune experimental conditions. Further research is needed to develop robust measures that are stable under different environmental conditions. This is especially important with cognitive bias training procedures that are administered at-home for research purposes, and if such interventions are thought to be potentially useful additions to clinical interventions (Colin MacLeod & Holmes, 2012).

Second, a limitation of the previous study (Chapter 4) is that a detailed account of emotional experiences between testing sessions was not taken. In Clarke and colleagues investigations of attention bias malleability; periods of prolonged stress (Clarke et al., 2008), or positive restorative experiences (Clarke et al., 2012) were used. This allowed for conclusions to be drawn regarding the relationship between bias malleability and anxiety as a function of more negative or positive emotional experiences. Given that we had no reason to expect that participants would have a more or less positive experience between testing sessions, we cannot draw any conclusions about the role of emotional experiences from our analyses. The control that experimenters have over prolonged periods in an individual's life is limited, regardless of assumptions about how restorative or stressful that period is, and we should expect considerable individual variation in experiences. Future research on attention bias malleability (and cognitive bias modification interventions more broadly) would benefit

from experiential sampling methodologies (e.g. Csikszentmihalyi & Larson, 1987; Larson & Csikszentmihalyi, 2014) throughout the periods between testing sessions. Typically these methods involve contacting participants several times throughout the day to record a current or recent emotional experience. This provides a rich account of an individual's emotional experience across a period of time. Importantly, this would allow researchers to draw better inferences on the interactive role of attention bias malleability and emotional experiences on mental health and emotional vulnerability, without a reliance on assumptions on expected emotional experiences over time.

Summary

The study presented in this Chapter is a replication and extension of Chapter Four. Although the key results of Chapter Four were not replicated, some evidence was found for post-training attention bias prospectively associating with positive emotions, in the control-training group. The low internal consistency estimates, in conjunction with the mixed findings in the prospective analyses leave little scope for making inferences about the impact of internal consistency of the bias indices on the prospective relationships between attention bias, and self-reported happiness and positive emotions. These results should therefore be interpreted with some caution. Further research is required to investigate the discrepant results in this and the prior study, and to elucidate the role of attention bias malleability in future positive experiences.

Chapter 6

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6

A Cognitive Model of Psychological Resilience

The previous empirical Chapters investigated the plausible relationships between positive mental health (and associated factors, such as happiness and positive emotions) and a range of emotional information-processing biases. Lacking from this approach is a guiding theoretical framework for future research. In this Chapter a cognitive model of psychological resilience is proposed. Resilience is considered to be the process by which individuals demonstrate more positive outcomes than would be expected, given the nature of the adversity experienced. We propose that a cognitive approach has the potential to guide studies investigating the relationships between adversity, stress, and resilience. We outline a preliminary cognitive model of resilience in order to facilitate the application of cognitive approaches to the investigation of resilience in the face of adversity. We argue that the situationally appropriate application of flexibility or rigidity in affective-cognitive systems is a key element in promoting resilient responses. We propose that this mapping of cognitive processing can be conceptualised as being undertaken by an overarching mapping system, which serves to integrate information from a variety of sources, including the current situation, prior experience, as well as more conscious and goal-driven processes. We propose that a well-functioning mapping system is an integral part of the cognitive basis for resilience to adversity. Our preliminary model is intended to provide an initial theoretical framework to guide research on the development of cognitive functions that are considered to be important in the resilience process.

Introduction

The previous empirical Chapters investigated the plausible relationships between positive mental health (and associated factors, such as happiness and positive emotions) and a range of emotional information-processing biases. One of the issues with developing experimental investigations of cognitive biases amongst positive mental health is the lack of a strong theoretical model. The previous studies in this thesis therefore relied on cognitive models of emotional vulnerability and cognitive bias tasks widely utilised to examine mental ill-health. This approach was sufficient to fuel early investigations, however, a beneficial next step is the development of a cognitive model that can be applied to positive mental health research. This Chapter outs forward a cognitive model of psychological resilience as a core element of positive mental health.

There are profound differences in how people respond to all sorts of environmental adversities. The fact that some people cope with stressful experiences better than expected, given the nature of adversity, is the essence of the concept of resilience. Thus, a reasonable working definition of resilience is the demonstration of a relatively good outcome given exposure to adverse circumstances (Rutter, 2006). Or, as defined by Masten (2011, p. 494) resilience can be viewed as "the capacity of a dynamic system to withstand or recover from significant threats to its stability, viability or development". As pointed out by Rutter (2012), such notions imply that resilience is an interactive concept that has to be inferred from individual variations in outcome among those who have been exposed to significant stress or adversity. In other words, resilience can only be understood in the context of responding to significant adversity. At a cognitive level, adversity is typically conceptualized as a perceived discrepancy between the situation an individual is confronted with and a desired conception

of reality specified by their goals, needs, investments, and aspirations for the future (e.g., Schwager & Rothermund, 2013).

Early understanding of the concept of resilience was influenced by a pioneering research programme called 'Project Competence' (Garmezy et al., 1984; Masten & Tellegen, 2012). The results of Project Competence revealed a key set of personal attributes that promoted resilience in childhood that involved the enhancement of a sense of personal agency or self-efficacy (Garmezy et al., 1984). Being able to focus attention, avoid distraction, rapidly shift mental set, and challenge negative thoughts and ideas in a reflective way were generally found to be critical for the development of personal agency and coping well in a complex world. It was concluded that deficits in these cognitive functions, induced by early social deprivation, prevented people from capitalizing on life opportunities. To illustrate, a qualitative study of people who had been hospitalized for a serious mental illness in adolescence found that what marked out those who were more resilient to this adversity in the longer term was a strong sense of personal agency that led them to assess what was and was not working for them, gave a determination to overcome adversity, and typically induced a commitment to relationships (Hauser, Allen, & Golden, 2006). Broadly speaking then, we can draw the conclusion that the personal mental qualities that characterize resilience relate to a sense of personal agency or self-efficacy, a high degree of cognitive- or executive control, cognitive flexibility, and the ability to self-regulate emotional reactivity. Further, given the range of processes that may contribute to resilient responses to adversity, it should be noted that there are likely many pathways to resilience and what works in one situation may not necessarily be as effective in other situations. From this perspective, resilience should be viewed as an interactive process, rather than a fixed trait or characteristic (Rutter, 2006).

Of course, an interactive process account of resilience does not mean that some individuals do not show better outcomes than others (resilience) in a wide set of circumstances, which is more supportive of a personality trait conception of resilience (Block & Block, 1980). We suggest that both approaches to resilience have their merits and that a science of resilience can benefit from integrating research from these different streams. Even from a trait perspective, however, it is important to point out that resilience should not be considered to be an all or none phenomenon. Rather, a probabilistic understanding of resilience seems more likely such that some individuals will be more resilient than others in a wider variety of circumstances. This is similar to theoretical conceptualizations of trait-anxiety (e.g., Spielberger, 1972), which does not assume that highly trait-anxious people are in a high state of anxiety all the time. Rather, high trait-anxious individuals are thought to experience a higher frequency of elevations in state anxiety over time relative to those with lower levels of trait-anxiety.

Many of the themes emerging in the developmental literature have also been reflected in adult research especially in the pioneering work of George Bonanno (Bonanno, 2004). Investigating reactions to major life trauma such as death of a spouse or being part of a major natural disaster or terrorist attack reveals that multiple pathways to resilience are also apparent in adulthood and that resilience is actually much more normative than might be expected (e.g. Masten, 2001). While this latter point has recently been debated (Galatzer-Levy & Bonanno, 2016; Infurna & Luthar, 2016a, 2016b), a large body of research demonstrates that certain personal attributes, such as self-enhancement, are important for the expression of resilience in adulthood (Bonanno, 2004). For instance, those high in the personality trait of hardiness (Maddi, 2002, 2006; Maddi & Khoshaba, 1994) - characterized by a commitment to finding a purpose in life, a sense of personal agency, and the belief that one can learn and grow from both positive as well as distressing life experiences – tend to be

more resilient than those low in this trait. Other researchers have focused on how individuals utilise positive factors and personal strengths, in order to protect against the negative effects of risk exposure and promote positive mental health (Fergus & Zimmerman, 2005; Zimmerman, 2014). Schwager and Rothermund (2013) have argued that the automatic regulation of fundamental processes such as selective attention and affective processing are critical for resilience as they lay the groundwork for motivational change and facilitate the expression of adaptive behaviours in situations of threat and adversity. In line with this approach, research has begun to investigate the cognitive processing styles associated with the trait concept of psychological resilience (e.g. Schäfer et al., 2015; Thoern, Grueschow, Ehlert, Ruff, & Kleim, 2016). A real problem, however, is that resilience research has remained relatively fragmented, which is due in part to the absence of a clear theoretical framework added to a lack of clarity over the concept of resilience itself (Luthar et al., 2000).

To summarize, a substantial body of research with children, adolescents and adults suggests that there are multiple pathways to resilience and that a combination of personal attributes, family circumstances, and the nature of supportive networks outside the immediate family are critical to the development of either resilience or vulnerability in the wake of severe life adversity. In this paper, we focus specifically on the role that personal attributes, especially aspects of cognitive functioning, might play in tipping the balance towards better than expected outcomes (i.e., resilience) in the face of severe stress and adversity. Given this focus, it is worth noting that we have made a conceptual distinction between external factors that have been found to support resilience, and internal, cognitive factors. For the purposes of the cognitive model we outline in this paper, we consider these external factors to be part of the current or past situation that can guide and influence cognitive processing.

There are a number of reasons for a focus on the cognitive aspects of resilience. First, whether a situation is deemed to be stressful or not is to a large extent determined by how an individual appraises the situation (Lazarus & Folkman, 1984). While many situations are considered to be universally adverse (e.g., death of a spouse), the impact of even these tragic events actually differs very widely across people (Bonanno, 2004). Therefore, an acknowledgement of individual variation in how people interpret and appraise different situations is important. Second, we note that there is a large body of experimental psychopathology research demonstrating the association between automatic negative cognitive biases (in attention, interpretation, and memory) and emotional vulnerability (Mathews & MacLeod, 2005 for review). For example, an automatic tendency to allocate attention selectively to negative cues relative to neutral or positively valenced material is a key cognitive characteristic of anxiety. Moreover, the tendency to selectively allocate attention towards more threat-related material in high trait-anxious people is increased when they are under stress (MacLeod & Mathews, 1988). Methods developed in experimental psychopathology research to assess selective processing biases have not yet been fully utilized in the field of resilience research, and we believe that using such methods will be advantageous in furthering resilience research. Third, there is substantial evidence that anxious mood states and generally feeling stressed has a negative impact on a variety of executive functioning abilities. Executive functions (also termed executive- or cognitive-control) refer to a group of top-down mental processes consisting of inhibitory control, working memory, and cognitive flexibility and are supported largely by the pre-frontal cortex (Diamond, 2013, for review). Collectively, these executive functions allow us to remain focused, avoid distraction from temptations, as well as facilitating the ability to flexibly adjust to changing demands and circumstances. Critically for the current context, these executive functions are disproportionately impaired when people are stressed or in highly

anxious mood states (Arnsten, 1998; Eysenck, Derakshan, Santos, & Calvo, 2007; Liston, McEwen, & Casey, 2009).

Thus, cognitive functions are critical at every stage of how we cope and react to stressful situations. First, whether or not a situation is psychologically stressful for a particular individual is influenced by cognitive appraisals of that situation alongside the presence of automatic processing biases to allocate cognitive resources towards the more negative or difficult aspects of the situation. Second, if the situation is stressful then the automatic processing of negativity (and the simultaneous ignoring of more positive or hopeful aspects of the situation) tends to intensify. Third, in this situation the very executive functions that are likely to help in developing appropriate coping responses are selectively impaired. Thus, there is a perfect "cognitive" storm of increasing automatic biases and appraisals towards negativity alongside a decrease in executive control functions when faced with stress (See Eysenck et al, 2007 for similar view in relation to trait-anxiety and worry). We would predict that individuals with an increased capacity to guide automatic biases, appraisals, and executive functioning, towards processing styles that are adaptive in that specific situation are more likely to develop resilience in a wide range of situations. Further, an important mechanism in this adaptive system is the capacity to promote flexibility or rigidity in the cognitive processing system when it is appropriate to do so. Given the disparate nature of resilience research we argue that a focus on personal attributes from a cognitive perspective will facilitate the investigation of the underlying cognitive mechanisms involved in the unfolding process of resilience as people deal with stress and adversity.

A Cognitive Model of Resilience

On the basis of considerable success in enhancing our understanding of the cognitive aspects of emotional vulnerability (e.g. Hertel & Mathews, 2011; Mathews & MacLeod,

2005; Williams, Watts, MacLeod, & Mathews, 1988) we propose that a cognitive approach has the potential to guide studies of the relationships between adversity, stress, and resilience. An advantage of combining a cognitive model with an experimental psychopathology approach is that it allows us to derive and test specific hypotheses regarding the selective processing of emotional information. (Fox, Mackintosh, & Holmes, 2014; Macleod & Bucks, 2011). Controlled experimental task environments and methodologies allow researchers to predict specific patterns of observable behaviours, e.g. response latencies between experimental conditions or between participant groups. To date, this approach has been oriented primarily towards emotional vulnerability. Here, we develop a preliminary cognitive model of resilience in order to facilitate the application of cognitive approaches to the investigation of resilience in the face of adversity. We accept that much of the key research has not yet been conducted but argue that the provision of a coherent model will help to integrate the various distinct approaches to resilience. We hope that this theoretical framework will enable researchers to develop novel hypotheses and approaches to the measurement and development of psychological resilience and positive mental health.

As shown in Figure 6.1, our proposed model of resilience focuses on the ability to flexibly apply appropriate cognitive processing that is relevant to the current situation. Common to other cognitive models (e.g. Beck & Bredemeier, 2016; Beck & Clark, 1997; Beck & Clark, 1988; Schwager & Rothermund, 2013; Teasdale, 1988), at the core of our model are cognitive processes, which would typically be considered to be implicit and not under conscious control; including executive control, information processing biases, and active cognitions. The novel element in our model is an overarching mapping system that guides the flexible application of information processing, relevant to current situational demands and perceived needs and goals. The function of the mapping system is to integrate information about the current situation and evaluate whether current responses are

appropriate or not. If the resultant behavioural responses are not meeting the specified aim (e.g. dealing effectively with stress) then the mapping system would promote flexibility in the cognitive processing systems and facilitate the appropriate calibration of these systems. The exception to this would be when prior experience supports the use of the current processing style to promote a more adaptive outcome in the longer term. It stands to reason that some processing strategies may take time to achieve the desired result, and that a functional mapping system would take prior experiences of cognitive styles that have been effective in similar situations into account. Alternatively, if the current approach is believed to be appropriate in achieving the currently held goal or desired state (or shift towards that state), then the mapping system would be expected to inhibit changes in the cognitive system in order to promote the desired outcome.

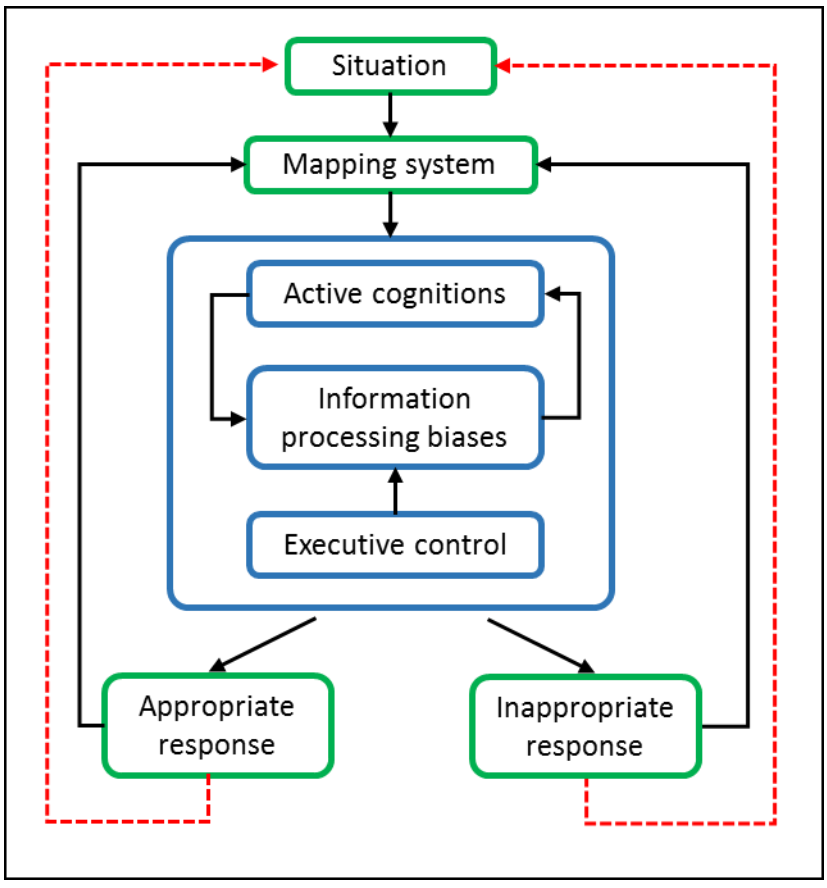


Figure 6.1. An information-processing model of psychological resilience.

It is important to note that we are not arguing that flexibility in the cognitive system is universally adaptive. Rather, we propose that processing styles may be adaptive or maladaptive depending on the situation, and subsequently that transitioning between flexibility and rigidity in processing style is particularly important in promoting adaptive cognitive processing. For instance, when a particular information processing strategy is appropriate, for example in a combat scenario, the mapping system might promote a rigid selective attentional bias towards threat, then this form of processing will be maintained until such a time as that strategy has become inappropriate. Following the removal of the threat, the mapping system would be expected to promote flexibility in the cognitive processing system and guide the shifting of processing strategy. The mapping system is proposed to function closer to a conscious threshold than automatic implicit information-processing. At this level of functioning, the mapping system is theoretically capable of integrating conscious goal-driven processing as well as previous experience in order to guide flexible processing of emotional information. It is also plausible that this system would be capable of taking into account indirect experiences, such as observations of other people's reactions to similar adverse situations. We might speculate that this is one mechanism through which external support systems, such as a supportive family, might promote resilient outcomes (Garmezy, Masten, & Tellegen, 1984). For example, exposure to a nurturing home environment may help to build a cognitive representation in the mapping system that promotes positive mood, rest, and recovery from other, more stressful environments. Taking this into account, a functioning mapping system would be expected to become better equipped to direct cognitive processing in line with this promotive state. This integration allows for development and long term adaptation within the model given individual difference in exposure to adversity and the learning of which processing styles are adaptive or maladaptive given the situation and timeframe.

The mapping system is therefore a key factor in our model that is proposed to tip the balance away from vulnerability and towards resilience in the face of stress and adversity. This occurs via the allocation of contextually appropriate information processing. We believe that the applied flexibility of cognitive processing styles is best conceptualised at this stage as being guided by an overarching system. Research is needed to investigate the model's central hypothesis that the mapping system guides flexibility of information processing strategies, with respect to situational feedback, and can be guided by conscious, goal driven processes. We propose that, due to its unconscious and highly dynamic nature, the interplay between active cognitions/schemata and biased information processing is near impossible to disentangle experimentally. To some extent this extends to the concept of executive control. It is possible to derive quantitative indices of individual levels of executive control separate from emotional evaluation/valenced information processing biases. It is, however, difficult to determine whether executive control affects the activation of cognitions, controls the expression of information processing biases, or both. We propose that this triad (cognitions/biases/executive control) may be regarded as a closed system and it should be possible to test whether this system in its entirety gets more active or shifts in certain directions as a function of situational demands and the availability of guiding information that can be consciously perceived by the individual. We propose that those for whom indices of executive control indicate that more or less resources are allocated when available information indicates such a necessity may also display more appropriate biases given situational demands. We further propose that these individuals will exhibit more resilience when faced with real life adversities.

In the remainder of this paper we aim to a) further elucidate our cognitive model of resilience to provide an integrative framework, which we hope can guide a research agenda in resilience science, b) review the resilience literature with a focus on identifying cognitive

styles and processes that are associated with resilience, and c) outline how cognitive approaches may be used to examine resilience. The key cornerstones of our cognitive model are: cognitive processes (including selective information processing biases, executive control processes, and active cognitions), an overarching mapping and monitoring system, and feedback loops.

Processing biases as implicit emotion regulation strategies

As mentioned before, whether or not a particular situation is stressful or adverse is determined, not only by the purely objective situation, but also by how the situation is subjectively appraised in light of an individual's personal goals and identity. Lazarus and Folkman (1984), for instance, defined a stressful situation as consisting of a perceived discrepancy between a desired state of reality that is determined by the person's goals, needs, motives, desires and aspirations and the reality of the situation actually confronting them at a given moment. How people cope and what they do when such a discrepancy is perceived is an important part of the resilience process. Our model builds on the work of Brandtstädter and Rothermund (2002) who have made an important distinction between what they call assimilative and accommodative coping responses. Assimilative responses are those where an individual tries to actively change an adverse situation to bring it into line with personal goals and aspirations. In contrast, accommodative coping responses are those where the individual attempts to change the subjective evaluation of the situation or tries to downgrade the personal importance of the goals that are threatened. The latter ultimately leads to more positive appraisals of the situation without actually changing it.

It is important to note that neither of these coping responses (assimilative or accommodative) are always the more adaptive. Which type of coping response fosters resilience depends on aspects of the situation as well as the person. For instance, assimilation

will be most effective when the situation is modifiable, opportunities and resources to change the situation are available, and the goals that are affected are important to the person. However, when the situation is uncontrollable, the possibility of changing the situation is unlikely, and alternative goals can be substituted for the goals affected by the critical event, then accommodative coping responses are likely to be the more efficient. An important point for the current discussion is the assumption that efficient coping "cannot be understood adequately without recourse to basic mechanisms in automatic processing that help to adjust cognition, affect, and motivation to superordinate self-regulatory needs" (Schwager & Rothermund, 2013, p. 58). Schwager and Rothermund argue that automatic processing mechanisms are critical for resilience because they provide the basis for an increase in the importance of a threatened goal and thereby support the self-regulatory stabilization of motivational commitment in the face of adversity. For example, there is evidence for an automatic focusing mechanism such that threat to a cherished goal leads to preferential processing of goal-related information while information that is unrelated to the goal becomes inhibited (Fishbach, Friedman, & Kruglanski, 2003). Such a focusing mechanism helps to keep people focused on new or existing goals when going through difficulties and adversity. Similarly, accommodative responses such as disengaging from a blocked goal do not always come about through a process of rational deliberation. Instead, the development of positive reappraisals of a situation requires a change in the cognitive accessibility of information that is relevant to the reappraisal or re-evaluation of the new situation. These changes can only come about by automatic information processing mechanisms that facilitate self-regulation by highlighting the positive aspects and benefits of a given situation (Schwager & Rothermund, 2013). In other words, the flexible adjustment of automatic processing biases towards the positive and negative aspects of a situation is a vital component of efficient self-regulation in difficult circumstances.

Similar notions are apparent in the literature on emotion dysfunction, which has also examined fundamental information processing biases that are largely deemed to be automatic (for reviews see, Cisler & Koster, 2010; Gotlib & Joormann, 2010; Mathews & MacLeod, 2005). Likewise, in the emotion regulation literature, processes such as biased attention allocation have been described as implicit or automatic emotion regulation strategies (Gyurak, Gross, & Etkin, 2011). Our model attempts to bring together these overlapping elements of work in the disparate fields of experimental psychopathology, emotion regulation and coping processes to deepen our understanding of resilience. We conceptualise these automatic processes as strategies for processing emotional and goal-relevant information and propose that these biases may be situationally appropriate or inappropriate, in so far as they can result in appropriate or inappropriate responses to the situation, and that this relationship between circumstance and bias is an integral factor in the development of resilience. We refer to these processes as processing biases for the purposes of the model.

One of the founders of social psychology, Kurt Lewin, is credited with the quote "if you want to truly understand something, try to change it". The ability to experimentally induce, reduce, or enhance a cognitive process provides a powerful experimental tool to examine the causal relations between cognitive processes and a range of outcome measures. Experimental methods known collectively as "cognitive bias modification" (CBM) procedures have been developed to selectively modify automatic biases in attention (CBMa: MacLeod, Rutherford, Campbell, Ebsworthy, & Holker, 2002) and interpretation of ambiguity (CBMi: Mathews & Mackintosh, 2000). When these biases are successfully modified (e.g., when a negative bias is reduced) this reduction has been shown to be associated with changes in emotional vulnerability (Clarke, Notebaert, & MacLeod, 2014; Hertel & Mathews, 2011). To illustrate, attentional biases towards threat-related images have been shown to be associated with enhanced physiological responses (cortisol reactivity) to a laboratory stress task up to eight

months later (Fox, Cahill, & Zougkou, 2010). Within this context it is interesting to note that the experimental induction of an attentional bias towards positive stimuli, relative to negative stimuli, (using a CBMa procedure) has been shown to be associated with improved physiological recovery from a stressor (Baert, Casier, & De Raedt, 2012) and reduced emotional reactions to a laboratory stressor (MacLeod et al., 2002). Likewise, training emotion recognition processes to interpret ambiguous faces as being relatively happier than angry results in reductions in anger and actual aggressive behaviours (Penton-Voak et al., 2013). Penton-Voak et al. argue that the modification of emotion recognition biases might positively affect social interactions, thus facilitating a more positive emotion recognition bias reciprocally, in a "virtuous cycle" (p.163). This supports the notion discussed earlier that automatic information processing biases could activate specific cognitions and behaviours that subsequently influence the original processing bias in a dynamic feedback loop. Such CBM procedures provide a powerful experimental tool that has not yet been fully utilized in the resilience field. The on-going development of CBM procedures provides an excellent opportunity to test some of the hypotheses generated by our information-processing model of resilience. We propose that our model of resilience offers the opportunity to examine the causal role of cognitive processing styles in promoting resilient responses, benefiting from this wide literature on the cognitive basis of emotional vulnerability.

Executive Control processes

In addition to specific automatic strategies such as information-processing biases, goal-directed implementation of cognitive control has also been hypothesised to be a form of emotion regulation (Saunders, Milyavskaya, & Inzlicht, 2015) and the executive functions of inhibitory control, working memory capacity and cognitive flexibility are considered crucial for adequate functioning (Diamond, 2013). For example, difficulties in switching between self-generated thoughts to environmental information has been found to mediate the

relationship between dysphoria and the frequency of rumination, self-blame, and catastrophizing (Rochat, Billieux, & Van der Linden, 2012). Rumination, a crucial vulnerability factor for depression (Nolen-Hoeksema, Wisco, & Lyubomirsky, 2008), has been associated with impaired filtering of currently irrelevant task instruction information and reduced flexibility to adapt behaviour to task demands (Owens & Derakshan, 2013). Importantly, these studies utilised non-valenced stimuli in the cognitive tasks and therefore, these results cannot be attributed to emotional bias. The results are likely due to cognitive inflexibility, characterised by active maintenance and tendency to perform a dominant task regardless of whether the behaviour is adaptive. In contrast, psychological flexibility is described as the ability to utilise a variety of cognitive and behavioural strategies to promote adaptation and is considered to be a fundamental component of resilience and positive mental health (Kashdan & Rottenberg, 2010). Non-emotional executive control training has also been found to affect neural mechanisms in that this type of cognitive training reduces amygdala reactivity to negative information (Cohen et al., 2016). This suggests that recruitment of executive control influences biases to irrelevant (though emotionally salient) information. We suggest that executive control processes and information processing biases play different (though interacting) roles in resilience (and vulnerability) to emotional disorders.

There is some promising research demonstrating that cognitive control or executive control functions can be trained with cognitive tasks requiring memory updating (Jaeggi, Buschkuehl, Jonides, & Perrig, 2008; Owens, Koster, & Derakshan, 2013), task switching (Karbach & Kray, 2009), or working memory (Klingberg, 2010). Working memory training improvements have been associated with reductions in stress reactivity, dysphoria and anxiety following training (respectively, Hoorelbeke, Koster, Vanderhasselt, Callewaert, & Demeyer, 2015; Owens, Koster, & Derakshan, 2013; Sari, Koster, Pourtois, & Derakshan,

2015). In a recent meta-analysis, Motter et al. (2016) found that computer-based cognitive control training was associated with improvements in depressive symptoms and everyday functioning. The results suggest that adaptive working memory training can lead to attention control improvements and serve a protective function against emotional vulnerability. Inconsistent effects of cognitive control training on cognitive measure were also observed however, highlighting the need for further research in this area. In particular, it is important to establish a) the transfer effects of targeted cognitive training programs on other cognitive control domains (e.g. Karbach & Kray, 2009) and b) the possible mechanisms that might underlie such transfer. For instance, executive control training with non-emotional stimuli might reduce the effects of irrelevant emotional information via influencing emotion-regulation neurological circuits (Cohen et al., 2016). Executive control training procedures offer a valuable experimental tool to investigate the potential role of cognitive control processes in resilience. These training procedures may allow us to examine the hypothesis that improved executive control facilitates shifts in processing bias strategy and importantly, how this affects resilience.

Active cognitions

Cognitive models of emotional vulnerability propose that maladaptive cognitive biases (which we describe here as biased information-processing) give rise to dysfunctional cognitions which are activated by stressful events (Beck, 1967, 2008; Beck & Clark, 1988). Dysfunctional conditions are typically considered to be automatic negative thoughts about the self, the world, and the future. The culmination of maladaptive cognitive biases and dysfunctional active cognitions is proposed to be central to emotional vulnerability. In addition, maladaptive cognitive biases and dysfunctional cognitions are proposed to reinforce one another reciprocally, leading to increased vulnerability (e.g. Muris & Field, 2008). Drawing from cognitive theories of emotional vulnerability, we propose that mental

wellbeing is characterised by the reciprocally reinforcing processes of active positive cognitions, and adaptive cognitive biases. Examples of active positive cognitions might include the belief that a difficult situation is a challenge rather than a threat leading to positive beliefs about one's capacity to cope in even very difficult situations – e.g., a sense of personal agency. Positive cognitions and emotions influence positive reappraisals and adaptive information-processing (e.g., selective processing of positive relative to negative cues) leading to further active positive cognitions in an upward spiral (Garland et al., 2010). With respect to resilience, we would predict that adaptive emotional responses to adverse situations arise from appropriate guidance of the cognitive systems achieved by the mapping system. Emotion regulation frameworks propose a similar reciprocal relationship between biased attentional deployment and cognitive appraisals in producing adaptive or maladaptive emotional responses to situations (Gross, 2015; Gross & Thompson, 2007; Siemer, Mauss, & Gross, 2007). Our cognitive model of resilience therefore incorporates a reciprocal relationship between processing biases and active cognitions. As such, active cognitions that have been activated by the current situation influence, and are influenced by, biased information processing ultimately impacting emotional responses.

Feedback loops

Situations and their outcomes do not exist in isolation, but as a dynamic interplay between the individual and their environments (both internal and external). The modal model of emotion regulation (Gross, 2015) proposes a cyclical nature of processing, whereby the actions taken as a result of processing situational information directly influences the following situation ad infinitum. Our model incorporates two feedback loops (see Figure 6.1). The situation feedback loop, which feeds from the individual's response to the situation, indicates that the individual's response to the present situation affects the following situation. The subsequent environmental information is the product of both the original information

processing and the responsive coping processes undertaken. In turn this is proposed to be monitored by the mapping system in order to further guide processing. The monitoring loop feeds from the individual's responses to the mapping system. This monitoring is proposed to be undertaken by the mapping system in order to guide the further mapping of the cognitive system. Importantly, both feedback loops in the model enable the development of adaptive processing styles via the monitoring of successful and unsuccessful strategies. We propose that these system loops, in combination with the mapping system, allow an individual greater cognitive autonomy over their circumstances and responses to them, rather than the cognitive system merely being submissive to circumstance.

Mapping appropriate cognitive processing

Our model hypothesises that a central predictor of positive outcomes is the appropriate mapping of processing bias strategies to the context. Just as in the coping processes literature (e.g., Schwager & Rothermund, 2013), an implication of this is that most processing styles should not be considered to be universally adaptive, or maladaptive. To illustrate this, a tendency for attention to gravitate towards cues signalling potential danger can be highly dysfunctional as this tendency occurs far more frequently even under conditions of little danger, as in anxiety disorders (MacLeod & Mathews, 2012). This bias can also, however, be highly functional in contexts of high threat and serves to facilitate adaptive emotional responses. For example, soldiers exposed to greater levels of threat while on active duty have been shown to display increased threat related attentional bias (Wald et al., 2015). This attentional bias towards threat in dangerous situations is likely to allow the individual to better address the combat environment more appropriately. Moreover, while an attention bias towards threat before military training was associated with post-traumatic stress disorder (PTSD) symptoms, an attention bias avoiding threat during actual training has been

associated with PTSD symptoms (Wald et al., 2015) implying that vigilance for threat is associated with positive outcomes in threatening situations.

This research supports an evolutionary developmental approach, which supports the proposition that cognitive processing styles presumed to be maladaptive, are in fact an adaptation to situational demands, particularly in early life (Ellis et al., 2012; Frankenhuis & de Weerth, 2013; Frankenhuis & Del Giudice, 2012). Several mechanisms by which an adaptive developmental mechanism may result in a maladaptive outcome have been proposed (Frankenhuis & Del Giudice, 2012). One plausible mechanism is that the process itself is not maladaptive, but rather a mismatch between the situation and the strategy employed results in maladaptive outcomes. It follows that appropriate mapping of information processing strategies to situational demands would predict more positive outcomes and associate with resilience. Our cognitive model predicts that the appropriate mapping of information processing to contextual demands promotes adaptive responses and positive outcomes, reflecting resilience.

Several criteria for the study of resilience are of note. First, resilience must be clearly operationalised. For example, resilience has been described as the ability to "bounce back" from negative experiences (e.g. Bonanno, 2004; Tugade & Fredrickson, 2004). A valid index of resilience would be the efficiency with which an individual recovers psychologically and physiologically following a stressful event (also see Baert, Casier, & De Raedt, 2012). Therefore, we might operationalise resilience as the rate of decrease of a particular stress-marker in the period following a stress induction. Heart rate, heart rate variability, self-reported mood or anxiety are among the viable measures that might be used in such a design. Second, an initial stress response is necessary. Individuals resistant to stress cannot be said to recover from it or react resiliently. It will be important to capture a range of responses to

induced stress and their trajectories. As such, baseline measures are necessary in addition to the measures taken during or immediately following the stress induction and the multiple measures during the recovery period. We have proposed this cognitive model of resilience to highlight how methods from cognitive science may be applied to resilience research. A specific hypothesis of our model is that the mapping of an appropriate pattern of information processing during the period will predict faster psychophysiological recovery following a stress induction procedure. To examine shifts in processing bias from baseline to during a stressor, and finally during a recovery period, multiple measurements, if not continuous measures, of the cognitive process in question are needed during each stage of the design. Task contingencies promoting processing biases expected to be more or less adaptive in the given circumstance might be used to examine the role of selective information processing biases during and following stress experimentally. For example, we would expect an increase in ability to recover from stress if a participant is shown happy and determined faces during the stressful episode, but impaired recovery if the participant is exposed to angry and despairing faces.

The degree of control that one has over exposure to adversity is an important factor in exhibiting adaptive responses, and with respect to our model, the associated resilient pattern of information-processing. For example, the degree of control an individual has over aversive experiences has been shown to modulate the expression of learned fear (Hartley, Gorun, Reddan, Ramirez, & Phelps, 2014). Participants who were able to control (escape) stressors showed improved fear extinction and reductions in retrieval of conditioned fear. Conversely, individuals who were unable to control stress exposure showed reduced fear extinction and increased fear expression at follow-up. In an early study, Brandtstädter, Voss, & Rothermund (2004) hypothesized that the degree to which attentional biases towards threat is expressed would depend upon the degree of control that an individual believed they had over the

impending danger or threat. Using a visual search task, they found evidence for this view by showing that when people can avoid the aversive consequences of a danger cue (by completing a secondary task) the sensitivity of the perceptual system to danger cues was enhanced whereas sensitivity actually decreased when there was no possibility of control. Using a somewhat similar methodology, biases in the prioritisation of stimuli conditioned to be pain-related have also been shown to be influenced by individuals' (perceived) control over pain experiences (Notebaert et al., 2011). Those participants who were told that performance speed on a secondary task would influence the likelihood of receiving an electro-cutaneous shock prioritized attention towards a conditioned pain stimulus, whereas participants who were not told about this contingency did not. Taken together, these studies highlight the importance of perceived control over adverse parts of the environment in guiding cognitive resources, suggesting that situational control is an important influencing factor in the development of resilience. These findings support the model of assimilative and accommodative coping (Brandtstadter & Rothermund, 2002) mentioned earlier, in which negative features of the environment should be suppressed when there is no possibility of escape or avoidance, but should be enhanced when there is a chance to actively change or escape from the problem. To further test the role of situation controllability, researchers might follow Notebaert et al. (2011) and expand upon the basic stress recovery study described above by manipulating the perceived control that participants have over threat exposure during the stress induction phase. If stressor controllability proves to be a valuable contributor to the mapping of appropriate processing styles, then this would support the view that perceived control over a situation helps to promote resilient responses.

Researchers must be mindful that the experience of dealing with adversity is an essential component in the study of resilience and this needs to be taken into account in both longitudinal and in cross-sectional (trait) designs. This is especially important given our

proposal that the mapping system develops over time through the monitoring of the cognitive processing associated with appropriate responses in different situations and integrating this with prior experience. Therefore, in order to discern the cause and effect of resilient responses to adversity, prospective longitudinal designs are necessary. Field and Lester (2010) have argued that longitudinal research is necessary in order to examine the causal relationships between processing biases and anxiety in childhood. We also suggest that prospective research is needed to examine the development of the proposed mapping system with respect to experienced adversity – and adaptive responses to that adversity. This research would help to examine how adaptations in the mapping system might support the development of resilience over the lifetime. Our model can be used to investigate the direction of causality between the proposed mapping system, and patterns of cognitive processing in promoting resilient outcomes. Experimental designs are essential in this endeavour. These designs have the potential to experimentally manipulate the environment and/or cognitive processing styles, which greatly enhance statistical power relative to correlational and longitudinal designs (Bakermans-kranenburg & van Ijzedoorn, 2015). For example, it is possible to experimentally induce a positive change in environment, for example with cognitive behavioural therapy, and examine how this positive environmental change influences resilience to stressors. Individual differences in cognitive processing in response to these positive environments (for example, the appropriate mapping of processing strategy) would be expected to predict the degree to which individuals derive benefit from these experiences (also see Pluess, 2015; Pluess & Belsky, 2012). Such designs enable a more direct examination of the respective roles of processing styles, and the mapping system in resilience. An increased understanding of the causal mechanisms by which resilience is demonstrated and developed in response to adversity, may offer important insights into how resilience might be boosted and drive future empirically based resilience interventions.

Applying a Cognitive Approach to Resilience

In the prior sections we have outlined the key aspects of our cognitive model of resilience. In terms of the personal attributes component of resilience, we have argued that the role of information processing biases and how they interact with executive control processes and active cognitions have not been well established in terms of resilience. We presented research from cognitive approaches to emotion vulnerability, such as CBM, in order to highlight how these experimental interventions might be applied to resilience research. Further, we have argued that the situationally-appropriate application of flexibility or rigidity in these cognitive systems is a key element in promoting resilient responses. We proposed that this mapping of cognitive processing can be conceptualised as being undertaken by an overarching mapping system, which serves to integrate information from the current situation, prior experience, as well as more conscious and goal-driven processes. A well-functioning mapping system is proposed therefore to be an integral part of the cognitive basis for resilience to adversity.

Our preliminary model is intended to provide an initial theoretical framework to guide research on the development of personal attributes, especially cognitive functions that are considered to be important in the resilience process. We have highlighted different perspectives in resilience science where many researchers focus on the development of resilience as a process in reaction to adversity in both children and adolescents (e.g., Garmezy, Masten, & Tellegen, 1984) and in adults (Bonanno, 2004), while others focus on the personality trait aspects of resilience (Block & Block, 1980). The latter approach leads to research designs in which those scoring low or high on a standardized personality trait scale are compared in terms of an aspect of their cognitive functioning (e.g., Schäfer et al., 2015). The former calls for longitudinal designs in which the unfolding of resilience can be observed

over time in response to different adversities. Our model of resilience centres on the dynamic process of applying appropriate cognitive processing styles, given the situational demands. This focus on the cognitive aspects underlying resilience necessitates treating resilience as a process, in particular with longitudinal designs.

However, it is worth noting that trait approaches to resilience also have their place. For example, individuals that generally apply appropriate cognitive processing strategies would be expected to exhibit resilient responses across a wider variety of situations, than those who are less resilient. Just as with trait notions of anxiety, we consider that high trait-resilience people will have resilient outcomes in a wider range of situations (than those low in trait-resilience) but not necessarily be resilient in all situations. Further, if we approach resilience research solely from a process perspective, we are likely to neglect the wealth of resilience literature exploring trait-approaches. We therefore argue that both approaches have a place in building a comprehensive science of resilience. We contend, that researchers must be careful to clearly define and operationalise resilience, including specifying whether resilience is being treated as an outcome, a trait, or a process (see Southwick, Bonanno, Masten, Panter-Brick, & Yehuda, 2014 for a discussion on this issue). These steps would allow empirical data to guide resilience research and help to avoid some of the definitional and conceptual issues that surround resilience research. We hope that our preliminary cognitive model offers a first step towards developing a solid theoretical framework that draws together the emerging fields of research on positive mental health and resilience within an information-processing framework.

Chapter 7

7

Alignment of Attentional Bias to Threat: A Proof-of-Principle

Attentional bias for threatening stimuli is widely considered a maladaptive process, largely due to its established association with anxiety vulnerability. However, allocating attentional resources to respond to threatening cues that signal a danger that can be avoided or mitigated should promote effective responses. In order to test the hypothesis that individuals align attentional biases towards threat depending on whether such a bias is adaptive or maladaptive, a novel attentional bias alignment assessment task was developed and tested. We manipulated the control that 160 participants had in avoiding exposure to a danger (loss of money), which was signalled by a "threat" cue. In high control blocks, the adaptive strategy was to attend to threat, as this would facilitate the avoidance of danger. In contrast, in low control blocks it was maladaptive to attend to threat as the danger could not be avoided. In support of our hypothesis, participants demonstrated greater attentional bias to threat in the high control condition and reduced attention bias under conditions of low controllability. Participants therefore showed greater attention bias when it was adaptive, and reduced bias when it was maladaptive to do so. The results provide proof-of-principle for the alignment hypothesis, demonstrating that individuals are capable of aligning their attentional bias depending on its adaptiveness in the current context.

Introduction

Attention bias to stimuli that signal the prospect of a future negative event, is considered to be a contributing factor to heightened trait anxiety (Notebaert, Tilbrook, Clarke, & MacLeod, 2017). Given this relationship, it is perhaps unsurprising that attentional bias for threatening stimuli is typically seen as a maladaptive process (e.g., Bar-haim et al., 2007; Mathews & MacLeod, 2002). It is also the case, of course, that attention bias for threat is an important cognitive function that facilitates survival (e.g., Dolan, 2002; Notebaert, Clarke, & MacLeod, 2016; Ohman & Mineka, 2001). In other words, attention biases for threat may serve an adaptive function, under some contexts. One such context is when individuals have some control over the impending danger by reacting to the threatening stimuli. In these contexts, attending to cues which predict danger, will allow an individual to react efficiently to engage in appropriate danger mitigation behaviours (Dolan, 2002; Notebaert et al., 2011; Ohman & Mineka, 2001; Wald et al., 2015). In contrast, when the individual has little or no control over the danger, then allocating attention to the threat cue does not contribute to the mitigation of danger and may indeed serve to increase state anxiety and the perception of danger (Gutiérrez-García & Contreras, 2016). Attentional bias for threatening stimuli therefore has potential to serve either an adaptive or maladaptive function depending on the context, and the degree of adaptiveness will depend on the degree to which the danger signalled by the threat can be controlled.

The cognitive model of resilience put forward in Chapter 6 proposes that in order for an individual to function well in an ever changing environment, the processing of environmental information must be calibrated to current demands, such as, the controllability of the danger. Despite this and other cognitive models suggesting that attention bias may have an adaptive function (e.g. Dolan, 2002; Notebaert et al., 2011; Ohman & Mineka, 2001; Wald et al.,

2015), prior research has focussed almost exclusively on the maladaptive role of attention bias. This is because attentional processing of threat has been investigated to a large extent in the context of pathological anxiety (e.g., MacLeod & Mathews, 2005). Importantly, most previous research has examined attentional bias for threat cues without any manipulation of the controllability of the dangers signalled by the cue. In this Chapter, the alignment of attentional bias is examined, as an attention specific process of mapping cognitive processing to the environment, in order to promote more adaptive responses. The alignment of attentional processes to current contextual demands is a critical process to optimise the efficacy of the behavioural and cognitive resources that could be dedicated to that threat (Blanchard, Griebel, Pobbe, & Blanchard, 2011; O'Donovan, Slavich, Epel, & Neylan, 2013; Rothermund, Voss, & Wentura, 2008). Proper alignment would consist of greater attentional bias to threat cues in contexts where an individual has more control of the danger signalled by these cues, and reduced attention to threat cues in contexts where the individual has less control of this signalled danger. This alignment of attentional bias is expected to be adaptive in that it restricts the state anxiety elevations that accompany attentional bias to threat to those situations in which such vigilance for threat facilitates effective danger mitigation.

The flexible altering of attentional processing in line with changing situational demands requires efficient executive functioning and a degree of cognitive flexibility (Kashdan & Rottenberg, 2010). Executive functions are cognitive control capabilities that enable individuals to process information, plan and behave in ways that facilitate attainment of their goals (Diamond, 2013). Aligning selective attention to threat cues with variation in the controllability of the danger signalled by such cues is therefore likely to require efficient executive functioning. It is plausible that individuals with poor executive functioning may be less likely to show adaptive alignment of attentional bias.

Assessing attentional bias alignment

To test the hypothesis that individuals align their attentional bias towards threat when they have a degree of control over that that threat, a novel Attentional Bias Alignment Assessment Task (ABAAT) was developed. In this task, a central grey circle is presented, sometimes accompanied by a peripheral ring of coloured circles. Each circle contains a unique digit. The correct identification of the digit in the central grey circle results in a gain of 3 cents per trial. In order to assess attentional bias alignment, several critical features were implemented. A threat cue was employed (e.g., a red circle) that signalled a genuine negative event or danger (the loss of 10 cents) which participants had a chance to avoid by correctly identifying the digit within the threat circle cue. The degree to which responding to the threat probe controlled the exposure to danger was manipulated between blocks (Notebaert et al., 2011). Thus, in half of the blocks (high control blocks), entering the digit that appeared in the threat cue (red circle) resulted in a high probability of avoiding the danger, while in the low control blocks entering the digit presented in the red circle resulted in a low probability of avoiding the danger. The task was configured such that it was adaptive to respond to the threat cue in high control blocks, and maladaptive to respond to the threat cue in low control blocks. Specifically, in high control blocks, attending to the threat cue facilitated avoidance of loss to a greater extent than the gains from attending only to the central task. In the high control blocks, an attentional bias to threat was therefore adaptive. In contrast, in low control blocks, attending to the threat cue meant that participants would lose more money than could have been gained by attending to the central grey circle. In the low control blocks, an attentional bias to threat was therefore maladaptive. Measures of attentional alignment were derived from comparing patterns of attentional bias to the threat cue observed on these two block types. The hypothesis of the present study is that participants will demonstrate

alignment of attentional bias. Alignment would be demonstrated by greater attentional bias to threat in the high control blocks, compared to the low control blocks.

Capture and Scanning attentional biases

A distinction has been made between two manifestations of attentional bias towards threat (Richards, Benson, Donnelly, & Hadwin, 2014). One manifestation, *capture by threat*, reflects the degree to which attention is narrowed to prioritise the processing of threatening stimuli. Attentional capture by threat can be inferred when performance on a central task is impaired in the presence of threat, relative to when the threat cue is not present (e.g. Schmidt, Belopolsky, & Theeuwes, 2015). The other manifestation, *scanning for threat* involves excessive monitoring for potential threats to determine whether threat cues are present, serving to facilitate the cognitive systems alertness and readiness to detect threatening stimuli (Richards et al., 2014). Both manifestations of attentional bias may contribute to the effectiveness of threatening messages concerning more or less controllable dangers. Indeed, individuals may scan the environment for danger cues that they have the capacity to control, which, when presented may capture attention. On the other hand, when individuals have little control over the danger, they may inhibit scanning the environment for threatening cues and when it is presented it may be less likely to capture attention. As both attentional processes may contribute to the differential effectiveness of threat messages when the danger is more and less controllable, it is important to examine whether threat messages concerning more controllable dangers lead to both increased attentional monitoring and increased attentional capture, compared to threat messages concerning less controllable dangers.

Drawing and holding of attention

In addition, it is important to distinguish between the degree to which threatening information draws attention and the degree to which it holds attention (Fox, Russo, Bowles,

& Dutton, 2001). Some research has shown that, for subclinical levels of anxiety, threatening information may not rapidly draw attention, but may capture attention more than neutral information with a marked delay in disengagement from threat cues (Fox et al., 2001). One way in which these processes can be distinguished is by observing patterns of attentional bias at short and long stimulus exposure durations. Threatening information can rapidly draw attention, and therefore attentional bias to threat cues can be observed at relatively short exposure durations (Schmidt, Belopolsky, & Theeuwes, 2014). However, this rapid drawing of attention does not necessarily lead to sustained engagement with the threatening stimuli, meaning that the attentional bias to threat may no longer be apparent at longer exposure durations (Mogg, Bradley, Miles, & Dixon, 2004). Though, in a study with patients with Generalized Anxiety Disorder, it has been shown that disengagement from threat is more rapid (Yiend et al., 2015). Therefore, in the current study two stimulus exposure durations were used (250ms and 1000ms; otherwise referred to as short and long exposure durations), allowing us to examine whether threat cues signalling controllable danger will draw or hold attention to a greater extent than threat cues signalling less controllable danger.

The present study

In this study, we aimed to conduct a proof-of-principle examination of the alignment hypothesis. This research goes beyond single, static assessments of attentional bias for threat to examine the degree to which attention bias changes as a function of context, in this case the controllability of danger exposure. It was hypothesised that a normative sample of student participants would demonstrate alignment of attentional bias. Specifically, we expected that in high control blocks participants would demonstrate greater attentional bias to threat, indexed by impairments in accuracy on the central task, in comparison to the low control blocks, in which it was expected that participants would demonstrate a reduced attentional bias to threat.

Methods

Participants

One hundred and sixty undergraduate students of the University of Western Australia completed the study in partial fulfilment of course credit. Participants also received up to AU$ 5 based on task performance. All had normal or corrected-to-normal vision, and reported not to be colour-blind. All participants gave informed consent, and were advised that they could terminate their involvement in the study at any time. None made use of this option. The study was approved by the ethics committee of the School of Psychology at the University of Western Australia (Reference: RA/4/1/5295, project title: Attentional bias to controllable and uncontrollable threat).

Materials

The task was programmed in E-Prime 2 (Schneider, Eschman, & Zuccolotto, 2002). Tasks were presented on 21.5cm LG Flatron E2211 Monitors. Participants were seated approximately 60cm from the computer monitor.

Stimuli

The circle stimuli presented in the novel visual search task were generated with Microsoft Windows 10 PAINT. Circles appeared in 9 locations; the centre of the screen, and eight points equally spaced around the centre of the screen with approximately a 5cm radius. The central circle was grey. When present, peripheral circles appeared in a light, medium, or dark shade of one of five colours; blue, aqua, green, yellow, or red. For each participant, one of these five colours was designated as the threat cue (counterbalanced across participants). When presented, this colour predicted a loss of money, thus representing a threat cue signalling a danger. Circles presented in the threat colour always appeared in the medium shade, whereas the other peripheral circles each appeared in the light or dark shade of the

remaining four colours. The peripheral stimuli were created in this way to ensure that the colour of the threat cue could be counterbalanced, while safeguarding that for every participant, it differed from the non-threat cues along the same perceptual dimensions. In addition, this process also ensured that the non-threat cues differed from each other in a consistent manner for each participant. Each circle had a radius of approximately 7.5mm, and a colour band (5mm) with a transparent centre, allowing for a digit to be presented in the centre of the circle that could be equally easily discriminated across colours (Notebaert, Crombez, Van Damme, De Houwer, & Theeuwes, 2011).

Attentional Bias Alignment Assessment Task

The Attentional Bias Alignment Assessment Task (ABAAT; also see Notebaert, Georgiades, Herbert, Grafton, Parsons, Fox, & MacLeod, 2017) was developed to examine the alignment of attentional bias to threat. The adaptive value of exhibiting an attentional bias to threat was manipulated by varying the degree of control that participants had on avoiding the threat. Alignment in this task is indicated by the presence of a greater attentional bias towards the threat cue when the bias is adaptive (i.e. the threat exposure is more controllable), and reduced attentional bias to the threat cue when the bias is maladaptive (i.e. when the threat exposure is less controllable).

Central task – money gain. In the ABAAT participants could gain money by attending to a central task. Therefore, attending to a peripheral threat cue would reduce participants' ability to gain money. Every trial contained a central grey circle in which a digit probe (digits between 1 and 9) was presented (see Figure 7.1). In each trial in which participants pressed the corresponding key on the keyboard to the central probe, they gained 3 cents. Importantly, the digit probe was presented very briefly (100ms) in order that distractions from the central task would impair the opportunity to gain money.

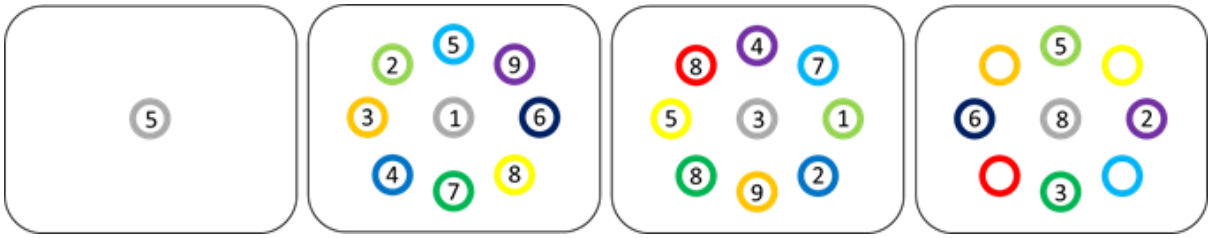


Figure 7.1. Representation of trial types. From left to right; *CentralOnly*, *RingNoThreat*, *RingThreatProbe*, *RingThreatNoProbe*. In this example, the red circle indicates threat of money loss.

Assessment of attentional bias to threat cues. An array of eight peripheral stimuli was sometimes presented surrounding the central cue. The peripheral ring of circles sometimes included the threat stimuli, allowing for the assessment of attentional bias. Attentional allocation away from the central task towards the peripheral stimuli is reflected in reduced accuracy to identify the central digit. Two indices of attentional bias were calculated to examine different aspects of attentional bias; scanning and capture.

Scanning. The degree to which participants monitor the visual display for the threatening cue, even in its absence, is reflected in reduced accuracy on the central task when peripheral cues are present, compared to when they are not present. Therefore, to calculate the attentional scanning index, performance was compared on two of the trial types; *CentralOnly* (Figure 7.1, Panel A), and *RingNoThreat* (Figure 7.1, Panel B). *CentralOnly* trials were comprised only of the central grey stimulus and the central digit probe. *CentralOnly* trials therefore provided a baseline measure of participants' accuracy on the central task, in the absence of distractors. *RingNoThreat* trials consisted of the central grey stimulus and its digit, and a ring of eight peripheral non-threat circle stimuli each with a digit probe presented within them. The scanning bias index was calculated by subtracting accuracy on the central task in *RingNoThreat* trials from accuracy on the central task in *CentralOnly* trials. Reductions in accuracy for the central task in the *RingNoThreat* trials relative to the

CentralOnly trials suggests that attention was allocated to the peripheral stimuli in search of the threat cue. Thus, higher values in the scanning bias index indicate greater scanning for threat.

Capture / engagement. The extent to which participants' attention is captured by the threat cue is indicated by impairments in performance on the central task on trials in which the peripheral ring contained the threat cue, compared to trials in which the peripheral ring does not contain the threat cue. As such, two trial types were constructed in which the peripheral ring of stimuli contained the threat cue. In *RingThreatProbe* trials (Figure 7.1, Panel C) the central grey circle was presented with a peripheral ring of coloured circles, one of which was in the threat colour. The presence of the threat colour indicated that there was a 50% chance of a money loss at the end of the trial. Participants were instructed that sometimes, the danger could be avoided by entering the digit displayed in the centre of the threat cue. Thus, if participants entered the digit presented in the threat cue rather than the digit presented in the central circle, they could avoid losing ten cents, at the cost of sacrificing their ability to gain three cents. This means however, that in the event participants were able to identify both the digit in the central circle and digit in the threat cue, they may strategically chose to enter one of these digits rather than the other. To avoid this confounding effect on the measure of attentional capture, a fourth trial type was created, in which only four of the eight peripheral circle stimuli contained digit probes, and critically the threat cue did not contain a digit probe. These trials were labelled *RingThreatNoProbe* trials (Figure 7.1, Panel D). Capture Bias scores were calculated by subtracting accuracy to identify the central digit on *RingThreatNoProbe* trials from central digit accuracy on *RingNoThreat* trials. Reductions in accuracy in the central task on the *RingThreatNoProbe* trials, relative to *RingNoThreat* trials, suggest that attention was captured by the presence of the threat stimuli. As such,

higher scores on the capture bias index are indicative greater attentional capture by the threat cue.

Manipulation of danger controllability. Critically, to examine individual differences in the alignment of attentional bias to variation in the controllability of danger exposure, the level of control participants had to avoid the money loss was manipulated across blocks. In High Control blocks, a correct response to the threat related probe is likely to avoid the loss of money (87.5%, corresponding to a successful avoidance on 7 out of 8 trials). In Low Control blocks, a correct response to the threat related probe is unlikely to avoid the loss of money (12.5%, corresponding to successful avoidance on only 1 out of 8 trials). As such, the task was configured such that in the high control blocks it was adaptive overall to attend to the threat cue at the expense of attending to the central task, as the total money loss that could be avoided outweighed the money to be gained by entering the digit presented centrally. In contrast, in low control blocks it was maladaptive to attend to the threat cue and forfeit the gain to be made from entering the central digit, as the total money that could be successfully avoided was less than the money to be gained from the central task.

Manipulation of presentation duration. To examine the drawing and holding of attention, the duration that circle stimuli were presented before the digit probes were presented was manipulated. Participants were therefore counterbalanced between a 250ms and 1000ms condition. The 250ms exposure duration condition was selected to provide sufficient time for attention to be drawn by the peripheral stimuli, resulting in a reduced capability to complete the central task. The 1000ms exposure duration condition was selected to provide sufficient time for the allocation of attention, followed by the holding of said attention. As such, reductions in accuracy on the central task under the 1000ms condition reflected how difficulty in disengaging from the peripheral stimuli (and threatening stimuli).

Task implementation. The task consisted of 8 blocks consisting of 48 trials. The blocks alternated between high control and low control blocks, with the starting block counterbalanced across participants. At the beginning of each block, participants were informed that there was a "high chance" (for high control blocks) of avoiding the danger by entering the threat cue, or a "low chance" (for low control blocks). The block order was counter-balanced between participants. Each block contained 16 *CentralOnly*, 16 *RingNoThreat*, 8 *RingThreatNoProbe*, and 8 *RingThreatProbe*. In each block, the threat cue was presented twice in each peripheral location, once containing the digit probe (*RingThreatProbe* trials) and once without (*RingThreatNoProbe* trials).

At the onset of the trial the circle stimuli were presented on screen, without the digit probes. Following a 250ms or 1000ms delay (depending on condition), the digits were presented for 100ms, with the circles remaining present. The screen was then wiped until participants responded by pressing a digit on the numerical part of the keyboard. At the end of the trial, participants were given a 500ms feedback indicating the gain (e.g. "+3"), loss of money (e.g. "-10"), or avoided the loss (e.g. "+0") for that trial. The inter trial interval was 1000ms.

Executive control assessment

The single N-back task was used to assess executive control (Jaeggi, Buschkuehl, Jonides, & Perrig, 2008). In the task, participants were presented with a sequence of irregular shapes, and are tasked to press the spacebar when the currently presented shape is either one (N = 1), two (N = 2), or three (N = 3) trials before. Participants first practised each N level in a 10-trial block, after which they were tested on 1-, 2-, and 3-back levels in that order, with each level presented for 3 consecutive blocks. The dependent measure was the number of hits (pressing the spacebar when there was indeed a match) minus false alarms (pressing the

spacebar when there was no match) averaged over all n-back levels, with a higher score representing better executive functioning (Jaeggi et al., 2008).

Questionnaire measures

Participants completed the state and trait measures of the State-Trait Anxiety Index (STAI; Spielberger, Gorsuch, Lushene, Vagg, & Jacobs, 1983), the attention control scale (ATC; Derryberry & Reed, 2002), the Behavioural inhibition system and behavioural activation system scale (BIS/BAS; Carver & White, 1994), and a four item scale developed by the Centre for the Advancement of Research in Emotion (CARE) lab to explore functional anxiety. These data are not reported in this Chapter.

Procedure

Participants were tested in groups in a quiet laboratory setting, seated approximately 60cm from the computer screen. First, participants provided demographic information and completed the self-report measures and N-Back task. Next, participants were given written instructions on-screen regarding the ABAAT. The task started with a staged practice component, first requiring participants to complete 10 trials (5 *CentralOnly* and 5 *RingNoThreat*), which allowed them to rehearse entering the digit presented in the central circle and gaining money. Next, participants were instructed that one of the presented colours signalled the danger of losing 10 cents at the end of the trial. Participants then completed another 16 practice trials, in which the threat cue was present on eight trials, four of which were followed by the money loss. Following these practice trials, participants were instructed about the possibility of avoiding the danger by entering the digit presented in the threat cue, and how the probability of successful avoidance would be varied across blocks. Participants were not informed of the specific statistical likelihood of avoiding danger in high and low control blocks (87.5% and 12.5% respectively), but rather were informed that “for this block,

there is a high/low chance that entering the number in the threat cue will prevent money loss". Next, participants completed the 8 blocks. Participants were informed prior to block commencement whether it was a high control or low control block. At the completion of each block, participants were informed how much money they had earned overall onscreen. At task completion, they were informed of the total amount they would receive. The experimenter then provided this amount in AUD, and debriefed the participant as to the nature of the experiment.

Results

Table 7.1 presents the means and standard deviations of accuracy on the central task for each of the three trial types used in the following analyses, separate for each controllability and exposure duration condition.

Table 7.1. Central trial accuracy rates for target trial types, separately for low and high controllability, and short and long exposure

	Low Controllability		**High Controllability**	
	Short exposure	Long exposure	Short exposure	Long exposure
	M (SD)	M (SD)	M (SD)	M (SD)
Central only	.99 (.04)	.99 (.02)	.99 (.04)	.99 (.03)
RingNoThreat	.98 (.04)	.99 (.03)	.97 (.03)	.99 (.03)
RingThreatNoProbe	.86 (.12)	.82 (.13)	.78 (.15)	.66 (.17)

Attentional Scanning

We first sought to examine whether participants showed differential attentional scanning for distractor cues, depending on the controllability of dangers signalled by the threat cues. Additionally, we sought to examine whether participants' attention was drawn to, and/or held, by these distractor cues. As such, accuracy scores for identifying the central digit were subjected to a 2x2x2 mixed design ANOVA that included Block type (high and low control)

and Trial type (*CentralOnly* and *RingNoThreat*) as within-subjects factors, and Exposure duration (long and short) as a between-subjects factor. Figure 7.2 presents this analysis visually.

There were non-significant main effects of exposure duration ($F(1,158) = 3.31$, $p = .071$, $\eta_p^2 = .020$), and controllability ($F(1,158) = 2.98$, $p = .086$, $\eta_p^2 = .019$). There was a significant main effect of trial type ($F(1,158) = 16.30$, $p < .001$, $\eta_p^2 = .093$). There were non-significant interaction between exposure duration and controllability ($F(1,158) = 1.73$, $p = .190$, $\eta_p^2 = .011$). There were significant interactions between exposure duration and trial type ($F(1,158) = 10.14$, $p = .002$, $\eta_p^2 = .060$), and between trial type and controllability ($F(1,158) = 5.14$, $p = .025$, $\eta_p^2 = .031$). The three way interaction between exposure duration, trial type, and controllability was not significant ($F(1,158) = 3.17$, $p = .077$, $\eta_p^2 = .020$).

To further investigate the significant interactions, we performed two paired t-tests on the central task accuracy scores between high and low controllability conditions. Figure 7.4 (Panel A) presents the scanning bias indices between controllability and exposure duration conditions. There was no significant difference between high and low controllability conditions in the *CentralOnly* trials ($M_d = 0.00$, 95% CI [0.00, 0.00], $t(159) = -0.18$, $p = .859$, d = -.01). In the *RingNoThreat* trials, the high control blocks (M = .98, SD = .03) had a significantly lower accuracy than the low control blocks (M = .99, SD = .03), $M_d = 0.01$, 95% CI [0.00, 0.01], $t(159) = 2.35$, $p = .020$, d = .19.

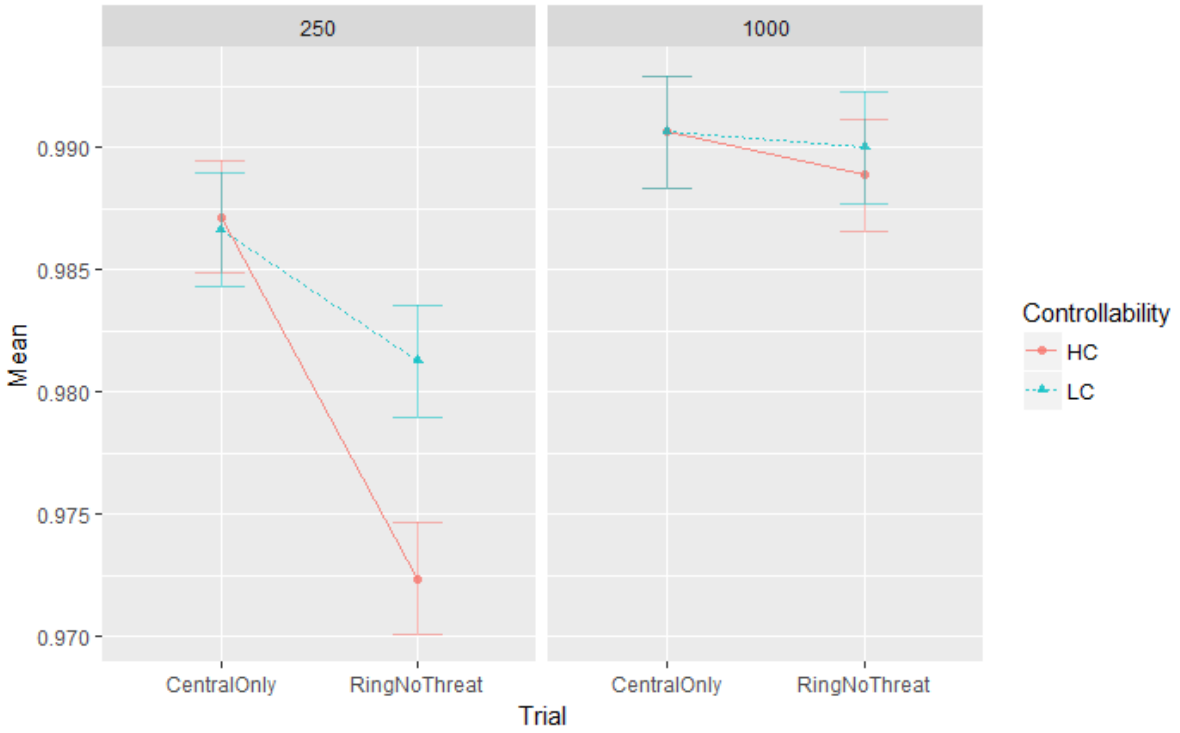


Figure 7.2. Mean accuracy on the central task in high and low control conditions, for *CentralOnly* and *RingThreatNoProbe* conditions, separately for short and long exposure durations.

Attentional Capture

We next examined whether participants showed differential attentional capture by threat cues, depending on the controllability of dangers signalled by these threat cues. In addition, we examined whether participants' attention was drawn to, and/or held, by these threat cues. As such, accuracy scores for identifying the central digit were subjected to a 2x2x2 mixed design ANOVA that included Block type (high and low control) and Trial type (*RingThreatNoProbe* and *RingNoThreat*) as within-subjects factors, and Exposure duration (long and short) as a between-subjects factor. Figure 7.3 presents this analysis visually.

There were significant main effects of exposure duration ($F(1,158) = 12.06$, $p = .001$, $\eta_p^2 = .071$), trial type ($F(1,158) = 437.08$, $p < .001$, $\eta_p^2 = .734$), and controllability ($F(1,158) = 116.23$, $p < .001$, $\eta_p^2 = .424$). There were significant interactions between exposure duration and trial type ($F(1,158) = 26.05$, $p < .001$, $\eta_p^2 = .142$), exposure

duration and controllability ($F(1,158) = 8.52,\ p = .004,\ \eta_p^2 = .051$), and trial type and controllability ($F(1,158) = 114.68,\ p < .001,\ \eta_p^2 = .421$). These interactions were subsumed in a three way interaction between exposure duration, trial type, and controllability ($F(1,158) = 14.87, p < .001, \eta_p^2 = .086$).

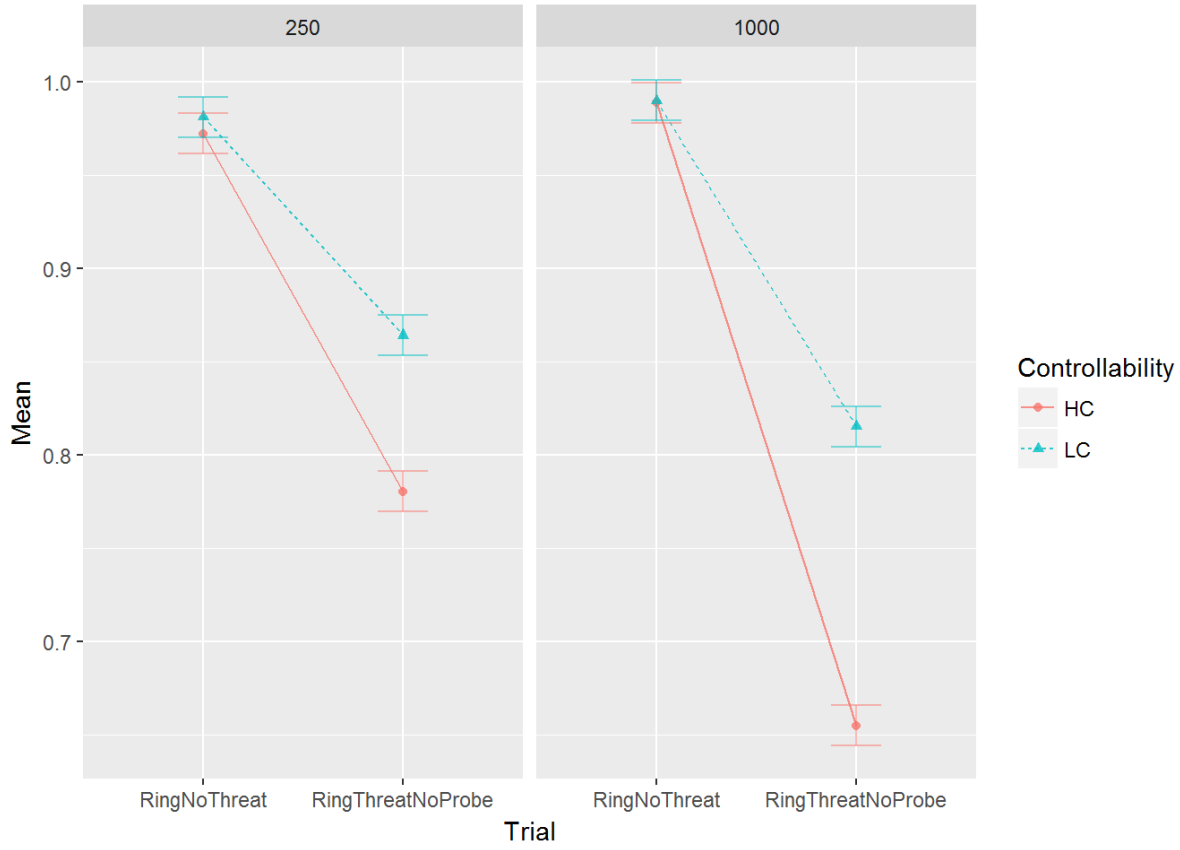


Figure 7.3. Mean accuracy on the central task in high and low control conditions, for *RingNoThreat* and *RingThreatNoProbe* conditions, separately for short and long exposure durations.

To further investigate these interactions, a capture bias index was computed by subtracting accuracy on the central task for *RingThreatNoProbe* trials from accuracy on the central task for *RingNoThreat* trials. Higher scores therefore indicate greater attentional capture by the threatening cue. Figure 7.4 (Panel B) presents the capture bias indices between controllability and exposure duration conditions. Paired samples t-tests showed that the Capture Bias Index scores in the high control condition were significantly larger than in the

low control condition, for both the short exposure duration condition ($M_d = -0.07$, 95% CI $[-0.10, -0.05]$, $t(79) = -5.96$, $p < .001$, d = -.67), and long exposure condition ($M_d = -0.16$, 95% CI $[-0.19, -0.12]$, $t(79) = -8.90$, $p < .001$, d = -.99).

An additional difference score was created by subtracting low control Capture Bias Index scores from high control Capture Bias Index scores. This Capture Bias Difference Index reflects the degree to which threat cues captured attention more in high control than in low control blocks. An independent samples t-test showed that this Capture Bias Difference Index was greater in the 1000ms exposure duration condition (M = .16, SD = .16), than in the 250ms exposure duration condition (M = .07, SD = .11), $M_d = 0.08$, 95% CI $[-0.13, -0.04]$, $t(141.64) = -3.86$, $p < .001$, d = -.61. This suggests that while threat cues both drew and held attention more in high control blocks than in low control blocks, the effect on attentional holding was greater than the effect on attentional drawing.

Associations between executive control and attention bias alignment

Finally, we were interested in exploring whether executive control, indexed with the N-Back task (M = -.09, SD = 04), was associated with attention biases in the ABAAT, and examining the associations between the attention biases observed in the ABAAT. We calculated a scanning bias difference index by subtracting low control Scanning Bias Index scores from high control Scanning Bias Index scores. Higher scores therefore represented greater alignment of scanning attention bias between high and low control conditions. There was no significant correlation between N-Back scores and scanning bias index scores (r = -.07, p = .318, 95% CI [-.23, .08], t(158) = -1.00). There was a negative correlation between N-Back scores and Capture Bias Index scores that almost reached significance (r = -.15, p = .052, 95% CI [-.30, .00], t(158) = -1.96).

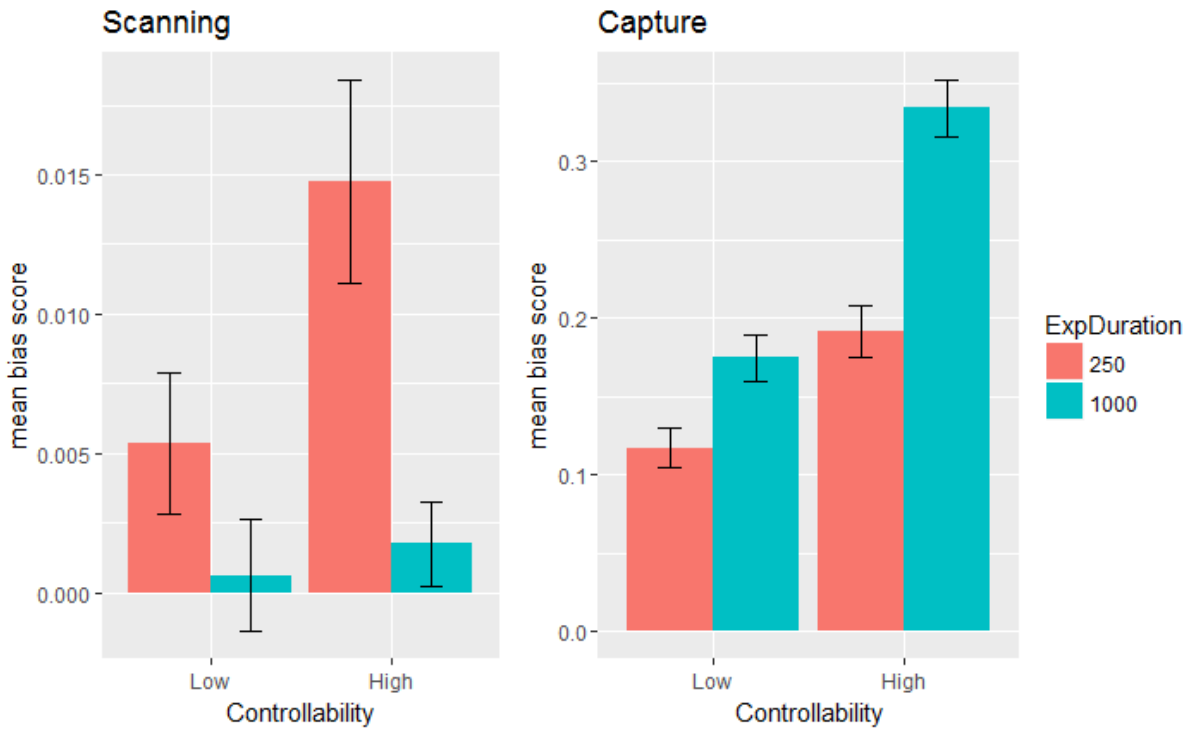


Figure 7.4. Panel A: Scanning attentional bias indices for high and low control conditions, in each of the short and long exposure duration conditions. *Panel B:* Capture attentional bias indices for high and low control conditions, in each of the short and long exposure duration conditions.

Discussion

The aim of the current study was to test the attention bias alignment hypothesis as a proof-of-principle examination. The alignment hypothesis predicts that attentional bias for threat is modified as a function of the controllability of danger exposure afforded by responding directly to the threat. Specifically, we expected that participants would show greater attentional bias for threat when it is more adaptive (high control blocks) to do so, compared to when it is less/mal adaptive (low control blocks) to attend to threat. Two manifestations of attentional bias to threat were examined, *scanning* (an increased vigilance for threatening stimuli in the absence of such cues) and *capture* (an increased engagement with threatening stimuli, giving them processing priority). In addition, short and long stimuli exposure durations were used to examine whether threat cues (in the case of capture) or non-

threat cues (in the case of scanning) were more likely to draw or hold attention when presented in a context in which danger is more controllable, compared to a context in which danger is less controllable.

The results suggest that scanning for threat is subject to alignment between high and low control conditions, in so far as accuracy on the central task when the distractor circles were present (*RingNoThreat* trials) was lower in high control compared to low control blocks. This effect appears to be specific to the short stimuli exposure duration condition, suggesting that the degree of control that participants are afforded to avoid the danger influences immediate scanning for threat. It is important to note that in the long duration condition, it is highly likely that participants would have enough time to scan the peripheral cues to discover that there is no threat present, and re-attend to the central cue. As such, the scanning bias may only be accessible in the short stimuli duration condition.

The results suggest that attentional capture by threat is also subject to alignment between high and low control conditions. The capture bias index, which reflects the degree to which attention is captured by the threatening cue, was significantly larger in the high control condition, compared to the low control condition. This pattern was significant for both the short and long exposure duration conditions. Additionally, there was a stronger alignment of capture in the long duration condition compared to the short duration condition, indicating that this effect was more pronounced in the holding of attention than the drawing of attention. This suggests that when danger is controllable, and individuals have more time to prepare a response when the threat cue is present, it becomes harder to disengage from the threat cue.

These findings support the attentional alignment hypothesis in that participants were capable of modifying their attentional biases to threatening information based on whether demonstrating such a bias would currently be adaptive or maladaptive. This also supports the

hypothesis proposed by the parallel processing model (Witte, 1992; Witte & Allen, 2000), which proposes that threat exposure drives action, but only under conditions in which the individual believes that the action will effectively reduce the danger. While this attentional hypothesis has been used to explain why some threat messages relating to health behaviours (e.g. fear appeals in the media) capture attention, previous research has not evaluated whether threats signalling a highly controllable danger capture attention more than threats signalling a less controllable danger. The present study provides empirical support for this hypothesis with a novel laboratory-based computerised attention bias assessment task. This laboratory-based cognitive-experimental approach confers several benefits. While self-report measures considering participant responses to threat messages have the potential to be biased or influenced by external factors, a laboratory-based task such as this provides a snapshot of cognitive response to threat through behavioural responses. Further, the capability to modify the degree of control that participants have over exposure to danger provides the opportunity to investigate differential attentional allocation between contexts characterized by these differing levels of danger controllability, i.e. the alignment hypothesis. The task goes further than other tasks, such as the emotional dot-probe task (MacLeod et al., 1986), which provide a snapshot of attention bias, by manipulating controllability of danger exposure to dynamically assess differences in attentional bias between situations in which such a bias is adaptive or maladaptive.

We also explored plausible relationships between executive control, indexed by the N-Back task, and alignment, indexed by scanning and capture difference bias indices. There was no strong evidence for a relationship between executive control and alignment of attention bias. Although, the near-significant correlation with alignment in capture suggests that future research examining the attentional bias alignment hypothesis should further investigate the role of executive control in attentional alignment. As the N-back primarily taxes working

memory, it may not overlap with the attention control processing that is likely to mediate proper alignment of attention bias. Future research may benefit from using an anti-saccade task for example, to examine attention control directly.

The cognitive model of resilience described in Chapter Six posits that cognitive processes are more or less adaptive as a function of contextual demands. Further, it was proposed that more resilient individuals are more capable of shifting their biases as circumstances dictate relative to less resilient people. In this Chapter, alignment of attentional bias to threat was examined as a specific instance of adaptive mapping of cognitive processing. This proof-of-principle research demonstrates that individuals are capable of increasing and decreasing attentional bias to threat under conditions in which such a bias is adaptive or maladaptive, respectively. This is an essential and promising first step in testing the cognitive model of resilience proposed in the previous Chapter. Future research can test the hypothesis that individual differences in attentional alignment will predict mental health. In addition, to more fully test the cognitive model of resilience, future research will be needed to examine whether other cognitive biases are as malleable in response to changing situations.

It is worth considering the results of the present study in light of some limitations. First, participants were explicitly instructed prior to each block as to the degree of control they would have in controlling exposure to the danger. These instructions were not so specific as to describe the precise likelihood of controlling the danger in each block, with the intention to be comparable to real-world danger exposure. To illustrate, it is common to be given some information about whether one has more or less control over a particular danger, than it is to be given a statistical likelihood of danger controllability. However, it is possible that participants may have varied interpretations of what constituted high and low control.

Individual differences in these conceptualisations of controllability may have influenced patterns of attentional bias and attentional alignment. Future research would benefit from collecting self-reported ratings of danger controllability in high and low blocks, to statistically control for these individual differences. Second, the danger used in the present study was a loss of money, which could be considered less related to danger mitigation and rather an avoidance of loss or seeking of maximal reward. The purpose of this was to ensure tight experimental control and to provide a quantifiable response to danger. These dangers are not as ecologically valid to emotional states (for example) as more socially related threats or other more pressing dangers, such as aversive noise bursts or electroshocks (e.g. Notebaert et al., 2011). Future research would benefit from extending these findings to test the attentional bias alignment hypothesis with more ecologically valid threat cues and dangers that more closely resemble the types of dangers individuals commonly experience.

In conclusion, this study is the first to address the attentional bias alignment hypothesis in a general sample. The results supported the alignment hypothesis, participants were able to modify their attentional biases such that they demonstrated greater biases when it was adaptive, i.e. when they had a high level of control over mitigating the danger exposure, and further modifying their attentional biases such that they demonstrated reduced biases when such a bias was maladaptive, i.e. when they had little control over mitigating the danger exposure. Though the full hypothesis proposes that individuals high in trait anxiety will show impaired alignment, compared to individuals low in trait anxiety, the propose of this study was to provide proof-of-principle evidence for alignment of attentional bias contingent on the controllability of danger exposure. Research is needed to build on the results of the present study to further examine the role that alignment of attentional bias plays in anxiety, and as a specific application of the mapping system proposed in Chapter 6 as part of the cognitive model of psychological resilience driving adaptive outcomes.

Chapter 8

8

Discussion

The research presented in this thesis concern the role of information-processing biases in mental health and resilience. The empirical studies and theoretical Chapter address three related research questions:

Research Question 1. Are there specific cognitive biases, and specific patterns of relationships amongst cognitive biases that are associated with positive mental health?

Research Question 2. Is attention bias malleability (the capacity to shift attention bias due to contextual demands) associated with positive mental health and wellbeing?

Research Question 3. Are cognitive biases more or less adaptive in certain situational contexts, and are individuals able to shift their bias to be more adaptive?

This final Chapter briefly summarises each Chapter and integrates the data concerning each research question. The findings are then discussed with respect to future directions in research investigating the cognitive-affective processes in mental health and resilience, relevant to each research question. Finally, several broader considerations and recommendations are discussed to build on the work presented in this thesis.

Summary of Results

Chapter Two examined cognitive biases in; attention, emotion recognition, and memory, in relation to positive mental health, psychological flexibility, and resilience in a cross-sectional sample. Attention bias was measured using an emotional dot-probe task presenting pairs of positive, negative, and neutral stimuli. Three indices of attention bias were calculated, indexing relative speeded responses of one category of stimuli to another; positive (relative-to neutral), negative (relative-to neutral), and positive relative-to negative. Emotion recognition bias was measured using a forced-choice emotion recognition bias in which participants indicated which emotion (angry, disgust, fear, happy, sad, and surprise) they believed a face presented on-screen was expressing. Each face stimuli was generated from composite images such that they were more emotional or more ambiguous along a linear morph sequence. Participants' accuracy in recognising the emotional expressions was the key outcome measure. Memory bias was measured using a self-referential encoding task in which participants imagined themselves in a scene described by a series of positive or negative words and, following a two minute distraction task, were asked to recall as many items as possible. The self-reported ability to imagine the scenes and total number of words recalled were used as the outcome measures, for positive and negative items separately. Attention biases to both positive and positive relative-to negative stimuli were predicted by an interaction between anxiety and psychological flexibility. This pattern was not observed for negative attention bias. Positive mental health was associated with subtle differences in the recognition of facial expressions of emotion. An interaction was observed suggesting that higher mental health associated with greater benefits in emotion recognition accuracy with increasing emotional intensity. In particular, this effect appeared to be driven by responses to emotional expressions of sadness and fear. Though it is also important to note that the interaction effect, while significant, was extremely small. No associations between memory

bias for positive or negative items, and self-reported measures of mental health or illness. Self-reported ability to imagine a scene described by the positive words was found to associate strongly with positive mental health and resilience.

Chapter Three investigated the role of interrelationships amongst biases in attention, interpretation, and memory in samples of adolescents scoring high and low in mental health. Attention bias was assessed with an emotional dot-probe task using happy, angry, and pained emotional faces. Interpretation bias was assessed with the Adolescent Interpretation and Belief Questionnaire (AIBQ; Miers, Blöte, Bögels, & Westenberg, 2008). The AIBQ asks participants to gauge how likely it was that positive and negative interpretations of ambiguous points within social and non-social scenarios would pop into their mind. Memory bias was assessed similarly to Chapter 1, with the exception that participants did not imagine a scene described by the word, but instead, rated whether the word describes them to make the items self-referential. A psychological network approach was used that models the direct relationships amongst the cognitive biases. These relationships were visualised as a network of interconnected nodes in order to make inferences about the differences between the interrelationships amongst cognitive biases in high and low mental health. The high mental health group had much more connected networks compared to the low mental health group. In particular, we observed that in the high mental health group the relationships between negative interpretation biases of social scenarios was only weakly connected with negative memory bias, whereas in the low mental health group this relationship was much stronger. Similarly, in the high mental health group we observed no relationship between positive interpretation biases for social scenarios and positive memory biases, whereas in the low mental health group this relationship was strong. In addition, the connections between positive and negative biases were absent in the high mental health group, compared to there being a number of connections in the low mental health group.

Chapter Four investigated attention bias malleability, that is, individual differences in changes in attention bias in response to contextual demands, i.e. attention bias modification (Clarke et al., 2012, 2008). Specifically, we examined the prospective relationship between training-induced shifts in attention bias (the difference between attention bias before and after attention bias modification training), and positive emotions and happiness twelve weeks later. An emotional dot-probe based attention bias modification procure was used in which the probe appeared almost always in the location of the positive stimuli (approximately 92% trials) in order to implicitly train participants to attend to the positive stimuli and avoid the negative stimuli. Training-induced shifts in attentional bias were indexed as the difference between a pre-training bias assessment and a post-training bias assessment. Training-induced shifts in attention bias predicted; self-reported positive emotions and happiness as well as attention bias in the follow-up session. These prospective associations were found to be driven by the post-training bias and not the pre-training bias. In addition to the primary analyses, we estimated the internal consistency of the attention bias measures. The reliability estimates were higher than typical estimates of reliability of dot-probe bias indices (e.g. Schmukle, 2005; Staugaard, 2009), with a sizable increase following training.

Chapter Five was a replication and extension of Chapter Four. In addition to an ABM condition following the protocol in Chapter Four, a control training and a no training condition was included. In the control training condition, participants completed the same number of trials as the ABM group, however the probe was as likely to appear in the location of the positive or the negative stimuli. In the no-training group, participants only completed the pre-training and post-training attention bias assessments. The ABM training was successful in producing a group level change in attention bias and no such change was observed in the other groups. However, the results from Chapter Four were not replicated; in the ABM group post-training bias was not significantly associated with future happiness or

positive emotions. In contrast, in the control group, post-training bias was associated with positive emotions at follow-up. Similarly, the post-training attention bias was only associated with attention bias at follow up in the control training group. In addition, estimates of internal consistency were low in this study, compared to Chapter Four.

Chapter Six introduces a cognitive model of psychological resilience which was designed to integrate the information-processing approach to emotional vulnerability with a resilience framework. Cognitive biases may be adaptive or maladaptive under certain contexts, and as such a fixed bias is unlikely to promote resilience and mental health. However, flexibility without direction is equally unlikely to promote adaptive responses. Therefore, a hypothetical mapping system was proposed that is intimately tied to cognitive-affective processing and acts to direct cognitive biases and executive control towards adaptive responses to contextual demands. In particular, the argument is that the situationally appropriate application of flexibility or rigidity in affective-cognitive systems is a key element in promoting resilient responses.

Chapter Seven built upon the cognitive model presented in Chapter Six, and examined the attentional bias alignment hypothesis. A novel attention bias alignment assessment task was used to test the hypothesis that individuals align attentional biases towards threat depending on whether such a bias is adaptive or maladaptive. In the task, participants could respond to a central cue, which was rewarded with a small monetary gain. In some trials, a threat cue signalling a larger loss of money was presented peripherally. By responding to the threat cue, participants had a chance to mitigate this loss. The control participants had of mitigating this loss was manipulated such that in high control blocks it was adaptive to attend to threat, as participants were highly likely to control avoidance of danger, whereas, in low control blocks it was maladaptive to attend to threat, as the danger was unlikely to

successfully be avoided. Participants were found to shift attention bias to the threat cue as a function of the control they had of mitigating the danger. Specifically, participants showed greater attention bias when the bias was adaptive, and a reduced bias when it was not adaptive. The results demonstrated that individuals are capable of aligning their attentional bias depending on its adaptiveness in the current context.

Cross sectional approaches to cognitive-affective processes in mental health and resilience

Chapter One emphasised that very little previous research has examined biased cognitive processing in relation to positive mental health and resilience. A singular focus on emotional dysfunction is unlikely to result in an understanding of mentally healthy, or flourishing, individuals (e.g. Csikszentmihalyi, 2014; Keyes, 2007; Seligman & Csikszentmihalyi, 2000). Similarly, targeting emotional vulnerability does not equate to building psychological resilience (e.g. Carver, 1998; Luthar, Cicchetti, & Becker, 2000; Schoon, 2006). By focusing almost exclusively on emotional vulnerability and failing to investigate the cognitive processes that underpin positive mental health and successful adaptation to adversity, current cognitive-experimental approaches are providing an incomplete understanding of human mental health.

Data reported in Chapters Two and Three addresses Research Question One: *Are there specific cognitive biases, and specific patterns of relationships amongst cognitive biases that are associated with positive mental health?*

Some prior research has been conducted in this area, for example positive biases have been associated with positive mood and reward-seeking (Tamir & Robinson, 2007), as well as positive attention biases associating with trait happiness and life satisfaction (Raila et al.,

2015). However, as little previous research has been conducted examining positive mental health specifically, these two studies sought to explore the plausible role of cognitive bias in mental health in cross-sectional samples. Together, these data have two plausible implications for the cognitive-affective approach to mental health. First, cognitive biases in attention may play a role in psychological flexibility and the accurate recognition of emotional expressions may play a role in mental health. Second, that the relationships amongst interpretation and memory biases may play a role in distinguishing between high and low levels of mental health. The results are encouraging for future investigations of cognitive-affective processes in mental health. However, as these two studies were cross-sectional and exploratory, Chapter Two was exploratory and Chapter Three was data driven, these studies should be considered as hypothesis generating for future research. As such, further directed research is needed to investigate the mechanisms of biased cognitive processing, establish testable cognitive models, and evaluate the causal role of cognitive biases in positive mental health.

Future directions

A number of research questions remain to be addressed regarding the role of cognitive biases in mental health and resilience. Here two main points are considered on the future directions of this work.

First, in Chapter Two we observed a small interaction between the intensity of an emotional expression and positive mental health to predict the accurate recognition of that emotion. Early changes in emotion recognition have been argued to precipitate positive clinical outcomes from pharmaceutical interventions (Harmer, 2010; Harmer & Cowen, 2013). For example, a single dose of an antidepressant drug has been shown to produce more positive emotional processing in the recognition of happy emotions (Harmer et al., 2003).

These early positive emotion recognition effects may lead to the beneficial clinical effects because the shift in bias has facilitated a virtuous cycle of positive social interactions and subsequent embedding of the positive emotion recognition bias (Penton-Voak et al., 2012). Emotion recognition was only assessed in Chapter Two, however the results warrant further investigation of the role of accurate emotion recognition in positive mental health. In particular, this investigation would benefit from attempts to replicate and further exploring the significant interaction between mental health and emotional intensity. The interaction suggests that improved emotion recognition at higher intensities, but not at low intensities, is associated with mental health. Similar has been observed in social anxiety, with higher levels associated with poorer emotion recognition accuracy (Button et al., 2013). The implication is therefore that perceiving almost completely ambiguous emotional expressions as emotional may, in itself, be a maladaptive cognitive bias.

Second, Chapters Two and Three do not address the causal role of emotional information-processing in mental health, nor do they provide an indication of the role of these processes in the development of mental health. Cognitive bias modification procedures offer a powerful tool to address the issue of causality. By experimentally shifting a cognitive bias and observing the impact on outcomes, such as mental health or more transient positive emotional experiences, provides an indication of causality that cannot be obtained from cross-sectional studies alone (Hertel & Mathews, 2011). For example, in line with the previous point, training emotion recognition biases (Penton-Voak et al., 2013) may be a promising intervention to improve interpersonal relations, which in itself may improve social aspects of wellbeing and further promote positive mental health. Relative to adult populations, less research is conducted to investigate cognitive bias in adolescence. As such, the development of cognitive bias throughout development itself is not understood (Field & Lester, 2010). In order to understand the development of mental health in relation to

cognitive biases, first an understanding of the development of cognitive biases themselves is needed. Chapter Three presented data from the first wave of data collection in the CogBIAS project (Booth et al., 2017) when the secondary school students were around 12 years old. Although cross-sectional, the project is due to be completed in 2018 and will include three waves of testing approximately one year apart each. These data provide an opportunity to investigate the development of cognitive bias throughout adolescence, and to further examine the role of cognitive biases in the development of positive mental health.

Cognitive Bias Modification approaches to cognitive-affective processes in mental health and resilience.

Data reported in Chapters Four and Five addresses Research Question Two: Is attention bias malleability (the capacity to shift attention bias due to contextual demands) associated with positive mental health and wellbeing?

Together, these Chapters sought to further the attention bias malleability account forwarded by Clarke and colleagues (Clarke et al., 2012, 2008), in which the individual differences in the capacity to shift attention bias to threatening information in response to contextual demands is important in the degree to which individuals shift in trait anxiety in response to more positive or negative life experiences. Research investigating attention bias malleability towards positive information has also found an association with reductions in anxiety to a lab stressor (Taylor et al., 2011). The research presented in Chapters Four and Five aimed to examine an attention bias malleability account in positive mental health. Although no associations were found for trait-level mental health factors, Chapter Four found some evidence for a prospective association in which attention bias malleability (training-induced shifts in attention bias) predicted the state-level factors of positive emotions, happiness, and attention bias at follow-up twelve weeks later. Chapter Five was conducted as

an internet-administered replication and extension intended to further investigate the results of Chapter Four. The key results from Chapter Four were not found to replicate. It is therefore difficult to draw strong conclusions from either study.

Future Directions

A number of research questions remain to be addressed on Cognitive Bias Modification approaches to cognitive-affective processes in mental health and resilience. Here two main points are considered on the future directions of this work.

First, a limitation of both Chapters Four and Five was that detailed measures of emotional experiences were not administered in the twelve week period between the two testing sessions. Whereas prior research examined responses in trait anxiety in response to an extended acutely stressful period (Clarke et al., 2008) or a more positive period including cognitive behavioural therapy (Clarke et al., 2012), Chapters Four and Five used a non-specified period between testing sessions. Therefore, it is difficult to discern whether changes in bias or self-reported measures over time is a result of emotional experiences during that time. It is worth noting however, that although researchers characterise a period of time as being more or less positive due to a particular intervention, or indeed any other prior expectation, we cannot assume a great deal of experimental control over the experiences of each individual participating in the research. The human experience contains multitudes and a prolonged period of 12 weeks during any period of the year has the capacity to contain impactful life events, regardless of the researchers' desire for experimental control. Instead of assuming that our participants' experiences are even approximately similar, researchers can embrace this heterogeneity by making use of experiential sampling methodologies (e.g. Csikszentmihalyi & Larson, 1987; Larson & Csikszentmihalyi, 2014). Typically these methods involve contacting participants several times throughout the day to record a current

or recent emotional experience and provide a range of self-reported indices, including; the activity, emotions experienced, people the experience was with, and so on (for a daily diary measure also see Catalino & Fredrickson, 2011). This provides an extremely rich account of an individual's emotional experience across a period of time and would benefit many longitudinal research designs. Importantly, this would allow researchers to draw better inferences on the role of emotional experiences on cognitive bias and mental health, without a reliance on assumptions on expected emotional experiences over time.

Second, a heated debate continues regarding the efficacy of cognitive bias modification procedures, both to produce a clinical effect and even to reliably produce a change in bias in the first place. It is important to note that attention bias modification was originally designed to be an experimental tool to invoke an attention bias, in order to examine subsequent effects on anxiety, for example in the form of stress responsivity (as in MacLeod et al., 2002). A recent meta-analysis was particularly scathing of the clinical utility of cognitive bias modification, arguing that; the myriad of task variations, poorly powered studies, and publication bias pose substantial issues for the field (Cristea et al., 2015). In response, MacLeod and Grafton (2016) have argued that it is important to distinguish attention bias modification as a tool to investigate the causal mechanisms of attention bias in anxiety and attention bias as a clinical intervention aimed at reducing anxiety. The crux of the argument counter to Cristea et al. (2015) is that; in order to state that attention bias modification has an impact on emotional vulnerability, it must first be demonstrated that the bias modification resulted in a change in attention bias (Grafton et al., 2017). Only then can it be stated that the mechanism of attention bias was or was not implicated in changes in emotional vulnerability. In a reanalysis of studies, Grafton et al. concluded that successfully modifying cognitive biases indeed significantly reduced emotional vulnerability. However, continuing the debate, an invited commentary criticised the methods used to reanalyse the original meta-analysis

(Cristea, Kok, & Cuijpers, 2017), in particular the strategies for concluding that biases had or had not been modified; ultimately arguing that serious problems in the cognitive bias modification field raised by Cristea et al. (2015) were glossed over and major issues remain to be overcome. Summarily, the ongoing cognitive bias modification debates reflect issues with the robustness of bias modification procedures and stress the need for the development of reliable tasks and procedures for evaluating them.

Psychological flexibility and resilience

Chapters Six and Seven addresses Research Question Three: Are cognitive biases more or less adaptive in certain situational contexts, and are individuals able to shift their bias to be more adaptive?

Chapter Six provides a rationale and framework for examining the role of cognitive biases in resilience, described as positive adaptation and proposed to be characterised by the appropriate mapping of cognitive processes to situational demands to produce beneficial outcomes. Although this Chapter does not answer Research Question Three, it is intended to provide a framework for future investigations of the contextual adaptiveness of cognitive-affective processes and suggests a mechanism by which directed flexibility of cognitive biases helps to promote psychological resilience. Chapter Seven sought to examine a specific hypothesis that can be drawn from the cognitive model of resilience in Chapter Six. Namely, the hypothesis that individuals are capable of shifting attention bias as a function of whether the bias is adaptive or maladaptive in the current context. The data provided proof of principle support for this hypothesis; participants were able to shift attention bias to be more adaptive in the current context. Specifically, a greater attentional bias towards threatening cues was demonstrated when such a bias was more adaptive, i.e. participants had a high-level of control over the mitigation of the money loss.

Future Directions

A number of research questions remain to be addressed on the role of flexibility in applying cognitive biases adaptively under different contexts. Here three main points are raised on the future directions of this work.

First, more work is needed to further test the attentional alignment hypothesis. One study (Notebaert et al., 2017) used the same task as described in Chapter Seven, with the addition of short bursts of white noise to the monetary loss. In this study, the effects observed in Chapter Seven were replicated, further supporting the alignment hypothesis in a generalised sense. In addition, this study found that, relative to low trait anxious participants, high trait anxious participants were less able to shift attention bias between contexts in which such a bias was more or less adaptive (high or low control over the threat exposure). This relative inability to shift bias when it is adaptive to do so suggests that anxiety may be characterised not specifically by an increased attentional bias to threatening information, but rather an inability to shift away from such a bias, even when it is more adaptive to do so. However, the attentional alignment hypothesis has only been tested in Chapter Seven and Notebaert et al. In particular, the anxiety linked effect was small and based on limited variance as the two accuracy variables used to calculate it were near ceiling. Separate replication attempts and work to build on these findings will be necessary to support the validity of this anxiety linked effect. Moving forward from examining the anxiety linked effects and to test the cognitive model of resilience in Chapter Six, the role of attentional alignment in resilience could be examined with a similar paradigm including varying levels of control over exposure to danger, and perhaps also reward.

Second, in future research testing the alignment hypothesis, one of the next steps to be taken is to attempt to train the process of attention bias alignment. Above, the perspective

was raised that examining the causal role of a process in a particular outcome can be achieved by changing that process. In a similar vein to early attention bias modification research (Mathews & MacLeod, 2002; also see Hakamata et al., 2010) the purpose of training attention bias alignment would be to investigate its causal relationship with emotional vulnerability and mental health. This kind of design might follow the early attention bias modification work in which attention alignment could be trained under laboratory conditions and followed by a social stressor task to examine if improvements in alignment result in reductions in stress reactivity.

Third, Chapter Seven sought to test a specific hypothesis that can be drawn from the cognitive model of resilience in Chapter Six as a proof-of-principle study. The results demonstrate that individuals are capable of shifting attention bias when it is adaptive to do so, and further research has found that this ability is associated with trait anxiety (Notebaert et al., 2017). These results provide initial support for Chapter Six's model of resilience. However, future work is needed to go beyond the attention alignment hypothesis and to directly examine the role of mapping cognitive biases across different contexts in resilience to stressors. A promising route would be to expand beyond attentional bias and examine the mapping of interpretation biases or emotion regulation biases under contextual demands that make these biases more or less adaptive. First, it will be necessary to demonstrate that these biases are malleable under different contexts. Second, to examine the role of mapping these biases in relation to resilient responses, stress induction procedures or longitudinal designs over periods of prolonged stress or recuperation will be necessary.

General Future directions

In addition to the future directions discussed above, there are also several considerations to be made for future research that are relevant to the fledgling cognitive-affective

approaches to mental health and resilience, as well as the broader work on emotional vulnerability.

What about executive control?

The empirical work presented in this thesis has concentrated on the role of emotional information-processing biases in mental health. The focus of this thesis has been on emotional information processing biases in mental health and resilience, and not executive control. However, executive control may be important to positive mental health, particularly given that executive control has been implicated in emotional vulnerability (for example see Eysenck & Derakshan, 2011; Eysenck et al., 2007; Mathews & MacLeod, 2005). For example, difficulties in switching between self-generated thoughts to environmental information has been found to mediate the relationship between dysphoria and the frequency of rumination, self-blame, and catastrophizing (Rochat, Billieux, & Van der Linden, 2012). Rumination has also been associated with impaired filtering of currently irrelevant task instruction information and reduced flexibility to adapt behaviour to task demands (Owens & Derakshan, 2013). Importantly, both studies utilised non-valenced stimuli in the cognitive tasks and therefore, these results cannot be explained in terms of emotional bias. The results are be better explained as cognitive inflexibility, characterised by active maintenance and tendency to perform a dominant task (or emotion regulation strategy, for example) regardless of whether the behaviour is adaptive. Although the role of executive control in the flexible mapping of cognitive biases to current contextual demands was discussed in Chapter Six, the only study to assess executive control was Chapter Seven. The N-Back task included in this study was included solely to examine the correlation between executive control and the attention bias alignment measures. As such, the role of executive control in mental health remains a question to be addressed in future research.

Chapter Six argues that that appropriate mapping of information processing biases, as a result of a flexible cognitive style and/or well-functioning cognitive control, is important in psychological resilience. The selection and allocation of an appropriate processing bias for the circumstance by cognitive control processes was hypothesised to be directed by a theoretical mapping system. The distinction between executive control and the mapping system was made for conceptual clarity in order to propose that appropriately mapping cognitive biases and allocating executive control resources to the current circumstances is adaptive and promotes resilience. However, whether the mapping of cognitive bias is a separate process to executive control remains an open question. Studies examining the interplay between executive control and cognitive biases under varying contexts will be useful in addressing this question.

Building robust measures and dealing with the issue of reliability

The ongoing doubts raised about the robustness of cognitive bias modification procedures to produce both changes in cognitive bias and subsequent clinical effects have been discussed above (amongst others; Cristea, Kok, & Cuijpers, 2015; Cristea, Kok, & Cuijpers, 2017; Grafton et al., 2017). However, a pervasive problem exists in assessing cognitive biases before even considering the modification of bias. Namely, the internal consistency or reliability of cognitive bias measures and understanding of the impact of this on our analyses is woefully under reported. In Chapters Four and Five, the role of the internal consistency of dot-probe based attention bias indices is considered briefly, which was made possible by work undertaken in parallel to this thesis, in particular the development of the *splithalf* R package (Parsons, 2017). The greatest barrier in this area is not necessarily that measures of cognitive bias are unreliable, but that as a field we fail to estimate and report the internal consistency of our tasks in the first place. Without this reporting, we cannot know if the measures are unreliable in the first place. It is generally understood that greater amounts

of measurement error reduce the precision of the measurement score and ultimately reduces the precision with which we can estimate effect sizes in an analysis. Therefore, calculating and reporting the reliability of our tasks enables us to make more informed judgments about the implications of our analysis. As others have argued, "researchers should calibrate their confidence in their experimental results as a function of the amount of random measurement error contaminating the scores of the dependent variable." (LeBel & Paunonen, 2011, p. 578). Cognitive bias research stands to benefit greatly from adopting a standard practice of routinely calculating and reporting the reliability of cognitive tasks. Unfortunately at present, it is the exception rather than the rule to report task reliability for cognitive measures (Gawronski et al., 2011).

To illustrate the importance of estimating the reliability of cognitive tasks, the emotional dot-probe task may be used as an example. In four decades of use of the dot-probe task in the emotion vulnerability literature many variations of the dot-probe task have been used, utilizing a wide range of stimuli sets and stimuli presentation durations. Despite two early papers reporting on reliability problems with the dot probe (Schmukle, 2005; Staugaard, 2009), the use of the dot probe methodology has grown exponentially over the last decade (see Kruijt, Field, & Fox, 2016, supplemental figure 1). From 2014 onwards, there has been a renewed concern about the reliability of the task with several papers addressing the psychometric properties of the dot probe (H. M. Brown et al., 2014; Kappenman, Farrens, Luck, & Proudfit, 2014; Price et al., 2015; Sigurjónsdóttir, Sigurardóttir, Björnsson, & Kristjánsson, 2015; Waechter, Nelson, Wright, Hyatt, & Oakman, 2014; Waechter & Stolz, 2015). Nevertheless, most reliability estimates available to date are found in these more methodological papers while papers assessing applied research questions using the dot probe methodology only very rarely report reliability estimates for their task version.

Importantly, without the routine reporting of task reliability, it is difficult to determine how common or widespread problems with task reliability are in cognitive assessment. Strictly speaking, the low task reliability reported in the methodological papers examining the psychometric properties of the dot-probe task may not generalize to the wider literature, given that they represent the reliability for only a single variation of the paradigm in the specific sample that it was assessed in. The internal reliability of a measure is not an inherent feature of the measure itself and is dependent on the sample being tested (Streiner, 2003). It is not possible to generalize coefficient alpha from one sample to another and Wilkinson and the APA Task Force on Statistical Inference have argued that "authors should provide reliability coefficients of the [questionnaire] scores for the data being analysed even when the focus of their research is not psychometric. Interpreting the size of observed effects requires an assessment of the reliability of the scores" (Wilkinson & APA Task Force on Statistical Inference, 1999, p. 596). Nevertheless, it is clear that the unacceptably low reliability estimates reported (as low as -.12 in Waechter et al. 2014) are cause for great worry and this is likely to be the case for many cognitive behavioural tasks. Yet it is also worth noting that a few applied dot probe task studies report widely ranging reliability estimates, occasionally getting close to the generally accepted lower threshold of .7 for acceptable internal consistency (Bar-Haim et al., 2010: r = .45; Enock, Hofmann, & McNally, 2014: r = -.25 – r = .70; Chapter Four in this thesis: r = .42 – r = .68; also see Waechter & Stolz, 2015 for an overview). In short, more information on the reliability of the cognitive tasks used to assess biased attention in psychopathology is required. Although the dot-probe task is used here as an example, it is worth stressing that these arguments stand for many cognitive tasks and assessment tools.

A reasonable approach therefore would be for researchers to routinely estimate and report task reliability for each study, especially when novel stimuli are used or the task is

adapted in some way. Routine reporting of reliability will enable researchers to assess whether cognitive tasks are more or less reliable in certain contexts and with certain populations allowing tailoring of the cognitive task to more accurately address the research question at hand. This will allow psychological scientists to develop more optimal cognitive assessment tools based on how well a specific cognitive task reflects the psychological construct or process that the task is designed to measure.

Conclusions

Mental health can be distinguished from emotional vulnerability as something positive, and something to strive towards. An almost exhaustive focus on the cognitive-affective processes in emotional vulnerability has left a missing piece in the understanding of the cognitive processes implicated in complete mental health and flourishing in life. The empirical work presented in this thesis provides some evidence that biases in the processing of emotional information and the flexibility of these biases may be associated with positive mental health. The theoretical position taken in this thesis has been that the integration of cognitive-experimental methodologies drawn from the emotional vulnerability literature can be applied to investigate positive mental health and resilience. Together, the research in this thesis contributes to the understanding of emotional information processing in mental health and resilience and stands to inform future work in the important, yet underserviced, field.

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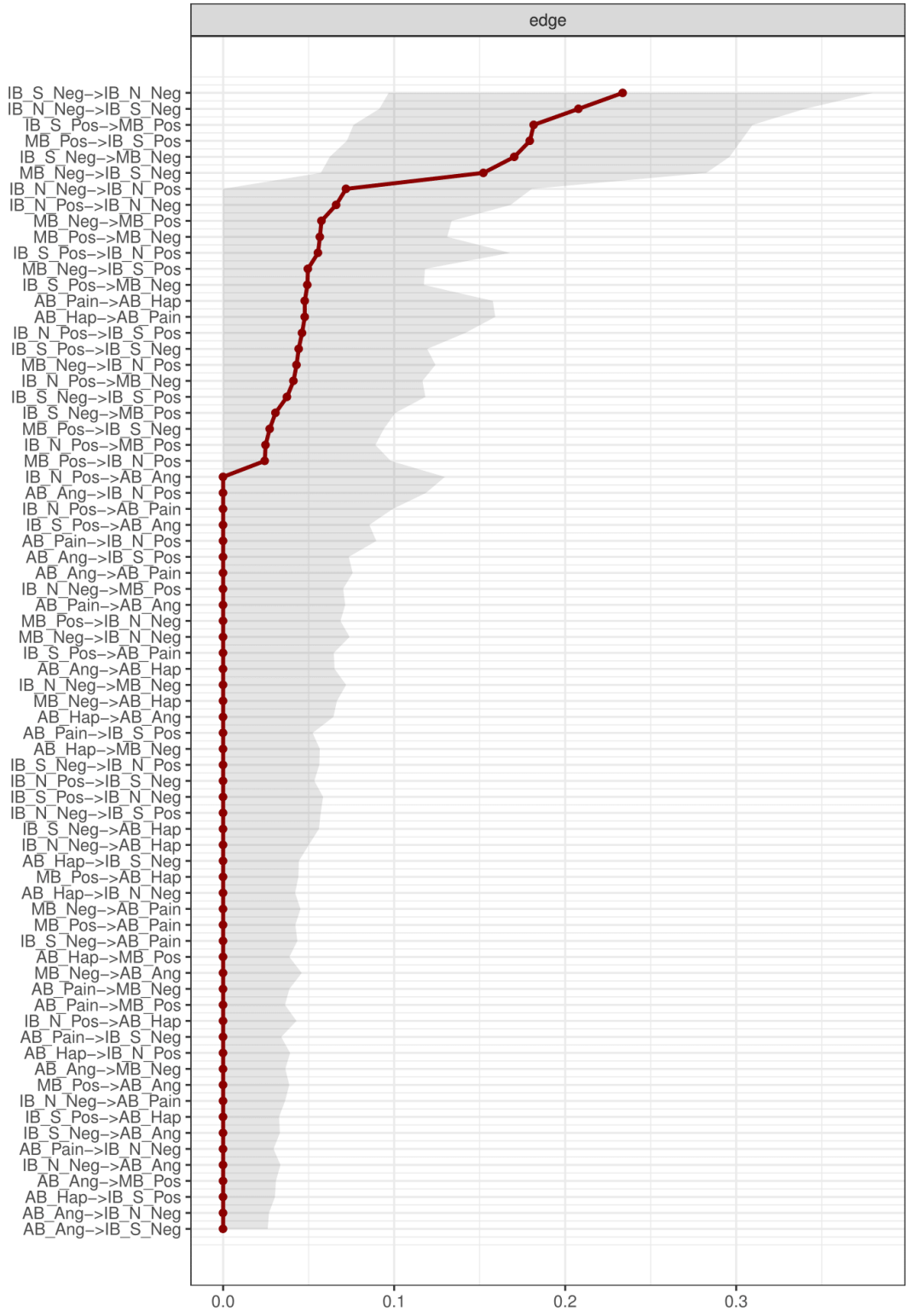
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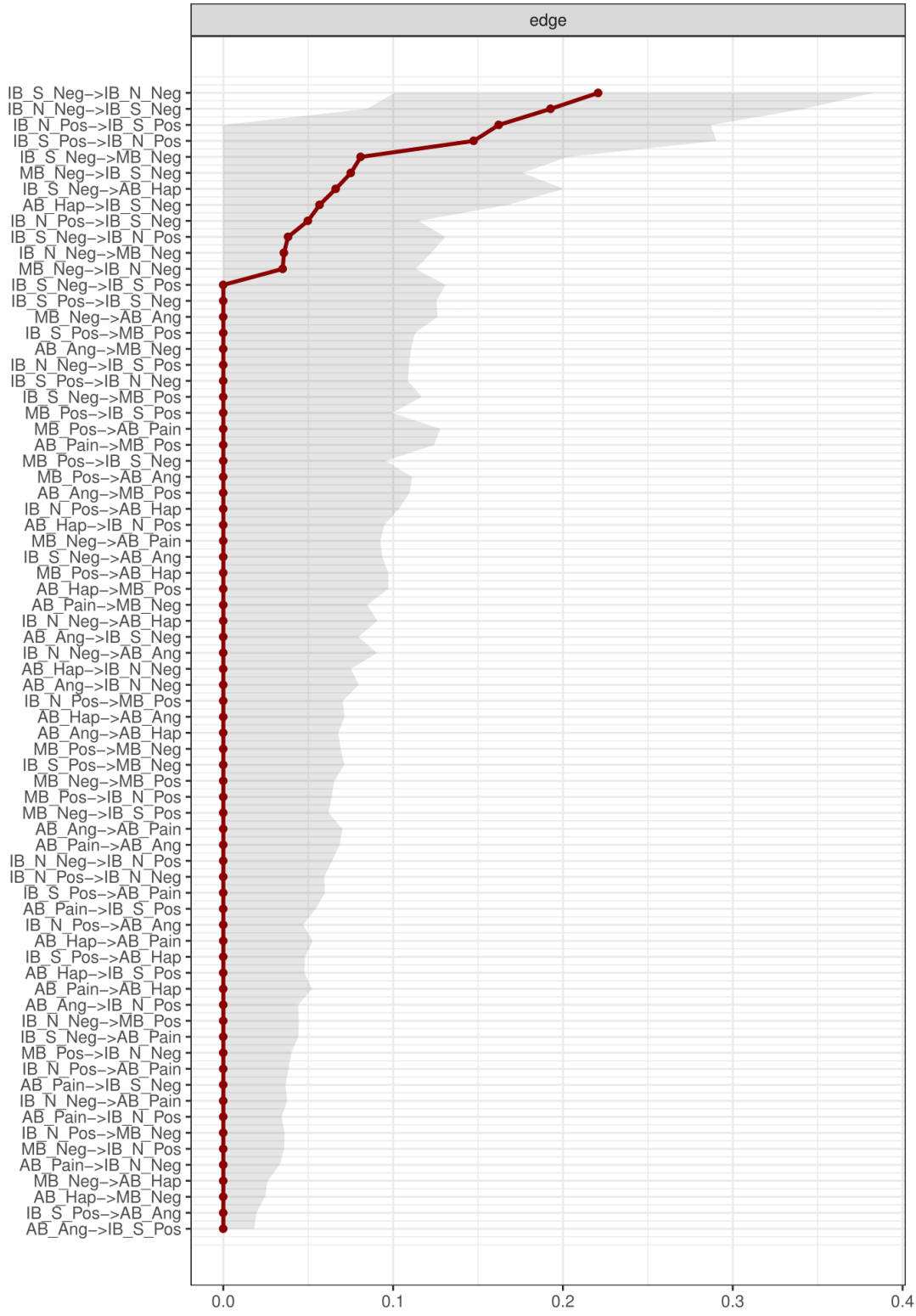
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Appendices

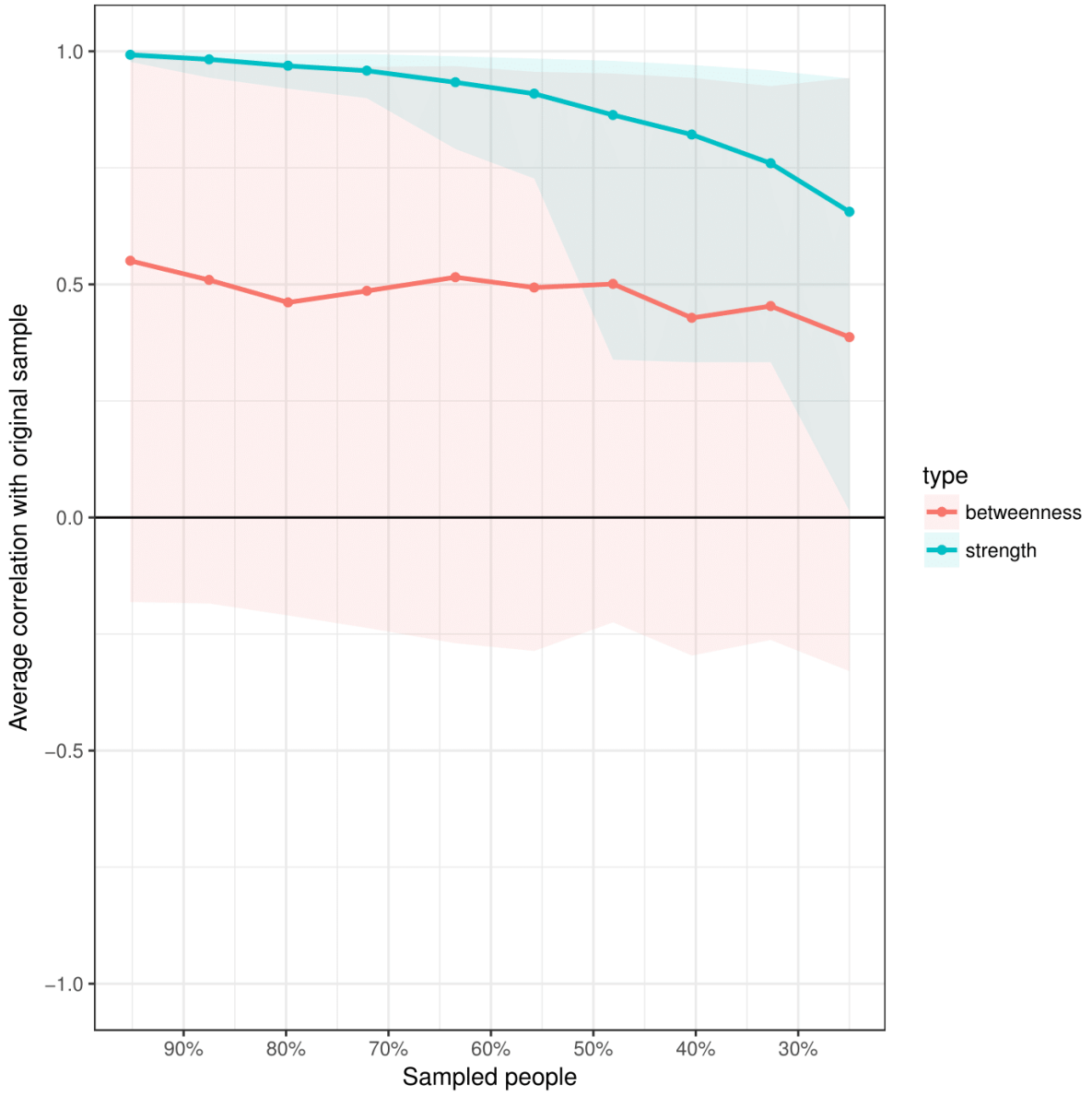
Appendix 1: *Figure A1.* Bootstrapped edge weight confidence intervals for the low-MH group relative importance network.



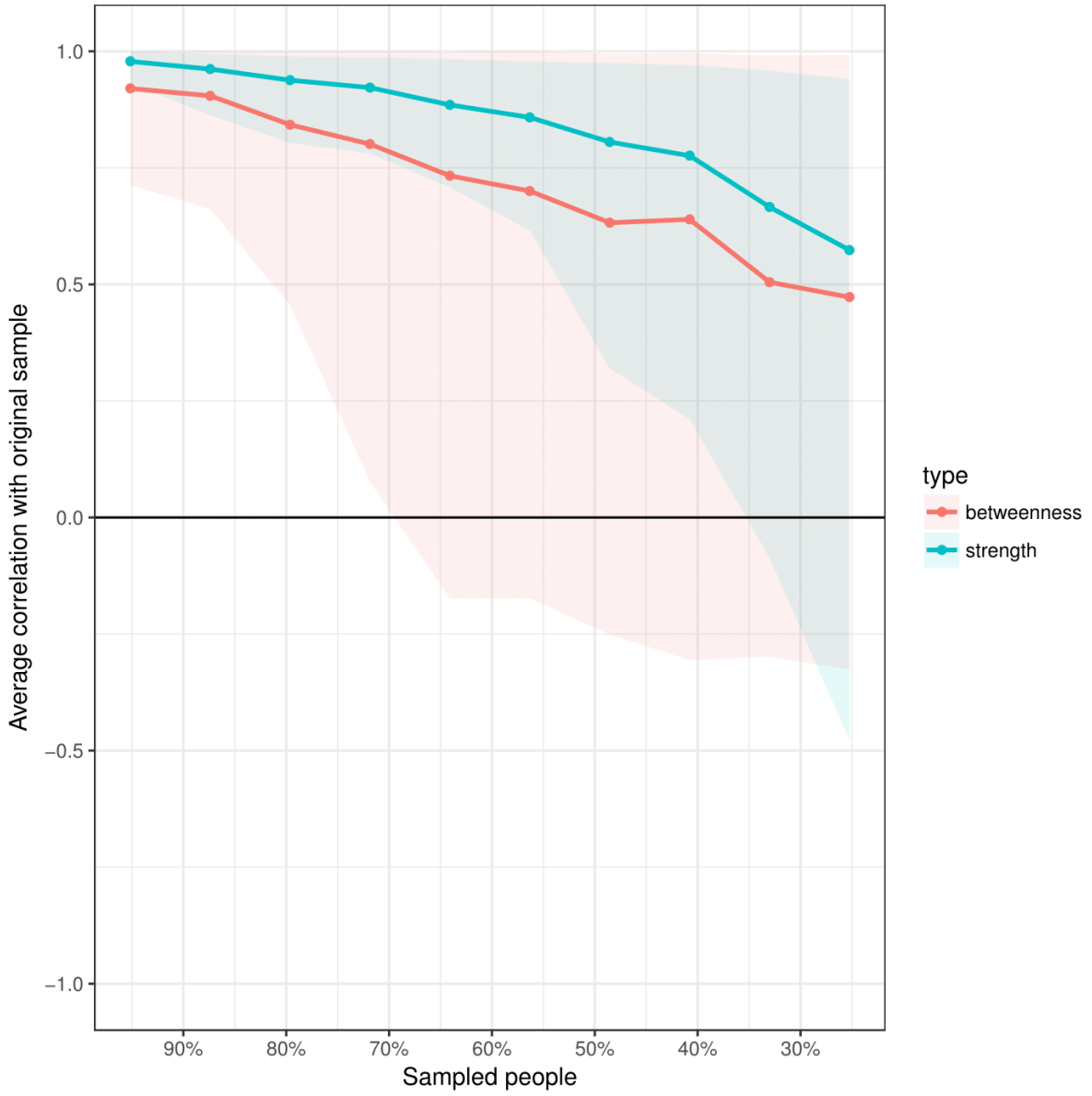
Appendix 2: *Figure A2.* Bootstrapped edge weight confidence intervals for the high-MH group relative importance network



Appendix 3: *Figure A3.* Stability of centrality indices of the relative importance network in the low-MH group. Note: Closeness centrality index is excluded by default due to omitted edges



Appendix 4: *Figure A4.* Stability of centrality indices of the relative importance network in the high-MH group. Note: Closeness centrality index is excluded by default due to omitted edges



Appendix 5: Rationale and Development of the R package *splithalf*

Here, I present the rationale for developing the *splithalf* package in R (Parsons, 2017), which was used to estimate the internal consistency of attention bias indices in Chapters 4 and 5.

The importance of estimating and reporting internal consistency of our measures

In order to accurately interpret and develop psychological measurements, the routine estimation and reporting of measurement reliability is essential. As others have argued, "researchers should calibrate their confidence in their experimental results as a function of the amount of random measurement error contaminating the scores of the dependent variable." (LeBel & Paunonen, 2011, p. 578). In other words, we might be more confident in our results if our tasks show high reliability, and more cautious in interpreting our results if our tasks show low reliability. In extreme cases the measurement error contained within, for example, a cognitive bias measure may be so high as to cast doubt on the utility of such a measure in any instance. However, without a standard practice of reporting the reliability of these measures, it simply cannot be known how much confidence can be placed in our analyses. Here, I focus on the internal consistency of response time based measures, though it should be stressed that the internal consistency of a measure will influence different 'families' of statistical tests to varying degrees.

To illustrate the importance of estimating the reliability of cognitive tasks I will focus on research using the emotional dot-probe task. In a typical dot-probe or what is often called an "attentional probe" task (MacLeod et al., 1986) one threat stimulus and one neutral stimulus are presented simultaneously for about 500 milliseconds. Participants are then required to categorize a probe (e.g., : or ..) that is presented in the location of one of these stimuli by pressing either a right or a left-hand key. Speed of response (reaction time) is measured from

the onset of the initial stimuli pair (e.g., threat and neutral images) until response to the probe. A large body of literature has shown that participants reporting higher levels of anxiety and psychopathology demonstrate speeded responses to probes that appear in the location of threat or negative stimuli, compared to neutral stimuli and this is interpreted as a reflection of attentional bias towards threat (Bar-haim et al., 2007; Peckham et al., 2010; Yiend, 2010). However, in four decades of use of the dot-probe task in the emotion vulnerability literature many variations of the dot-probe task have been used, utilizing a wide range of stimuli sets and stimuli presentation durations. Despite two early papers reporting on reliability problems with the dot probe (Schmukle, 2005; Staugaard, 2009), the use of the dot probe methodology has grown exponentially over the last decade (see Kruijt, Field, & Fox, 2016, supplemental figure 1). From 2014 onwards, there has been a renewed concern about the reliability of the task with several papers addressing the psychometric properties of the dot probe (Brown et al., 2014; Kappenman, Farrens, Luck, & Proudfit, 2014; Price et al., 2015; Sigurjónsdóttir, Sigurardóttir, Björnsson, & Kristjánsson, 2015; Waechter, Nelson, Wright, Hyatt, & Oakman, 2014; Waechter & Stolz, 2015). Nevertheless, most reliability estimates available to date are found in these more methodological papers while papers assessing applied research questions using the dot probe methodology only very rarely report reliability estimates for their task version. A similar story will likely be found across a wide range of cognitive assessment tools.

Without the routine reporting of task reliability, it is difficult to determine how common or widespread problems with task reliability are in cognitive assessment. Strictly speaking, the low task reliability reported in the methodological papers examining the psychometric properties of the dot-probe task may not generalize to the wider literature, given that they represent the reliability for only a single variation of the paradigm in the specific sample that it was assessed in. Nevertheless, it is clear that the unacceptably low reliability estimates

reported (as low as -.12 in Waechter et al. 2014) are cause for great worry and this is likely to be the case for many cognitive behavioural tasks. Yet it is also worth noting that a few applied dot probe task studies report widely ranging reliability estimates, occasionally getting close to the generally accepted lower threshold of .7 for acceptable internal consistency (Bar-Haim et al., 2010: r = .45; Enock, Hofmann, & McNally, 2014: r = -.25 – r = .70; Chapter 4: r = .42 – r = .68; also see Waechter & Stolz, 2015 for an overview). In short, more information on the reliability of the cognitive tasks used to assess biased attention in psychopathology is required. A reasonable approach therefore would be for researchers to routinely estimate and report task reliability for each study, especially when novel stimuli are used or the task is adapted in some way. Although I have used the dot-probe task here as an example, I stress that these arguments stand for many cognitive tasks and assessment tools.

Estimating reliability with the split half methodology

A commonly used method of estimating the internal reliability of a task is the split half method (Spearman, 1910). In this procedure, a measurement is split into two halves, typically by odd and even numbered items or trials. The correlation between these halves is then calculated as an estimate of the internal reliability of a measure. The Spearman-Brown formula (Brown, 1910; Spearman, 1910) is often subsequently applied to this estimation. The Spearman-Brown formula is intended to account for the underestimation of reliability estimates resulting from splitting the number of observations in half to enable correlation. It is calculated as follows:

$$r_s = \frac{2r}{1 + r}$$

Where r_s is the Spearman-Brown corrected estimate, and r is the observed Pearson correlation between the two halves. The spearman-brown correction is commonly used in the

calculation of reliability estimates in the experimental psychopathology literature (e.g. Koster, De Lissnyder, & De Raedt, 2013; Waechter et al., 2014) and formed the basis of the **splithalf** package.

Robust methods of calculating split-half reliability

The **splithalf** functions return the raw Pearson, and Spearman-Brown corrected, with an added Monte Carlo option. It has been argued that standard split-half reliability estimates tend to be unstable. A common method, for example, is to split the data into odd and even numbered trials. However, these reliability estimates have the potential to vary greatly depending on which trials happen to be odd and even (Enock, Robinaugh, Reese, & Mcnally, 2011). Similarly, a single random split of the data can yield a wide range of estimates, depending on which trials are selected per half. A Monte Carlo simulation approach can be used to yield more precise estimates of internal consistency. This process involves splitting the data into two halves randomly and calculating the split-half estimate across a large number of permutations before averaging these estimates to provide a more stable estimate of reliability (Enock et al., 2011; Enock, personnal communication, November 21, 2016). To examine how many random splits are required to provide a precise estimate, a short simulation was performed including 20 estimates of the spearman-brown reliability estimate, for each of 1, 10, 50, 100, 1000, 2000, 5000, 10000, and 20000 random splits. This simulation was performed on data from one block of trials reported in Parsons et al. (submitted). Based on this simulation, I recommend 5000 random splits be used to calculate split-half reliability. This number of splits yielded a standard deviation of .002 and a total range of .008, indicating that the reliability estimates are highly stable to two decimal places with this number of random splits. Increasing the number of splits improved precision, however 20000 splits were required to reduce the standard deviation to .001. Our recommendation of 5000 splits is based on our estimation of what constitutes a sufficient

balance between precision of estimation and processing time (see the package vignette for information on processing time requirements). As the 5000 splits Monte-Carlo Spearman-Brown estimation differs in its calculation from other estimates of split-half reliability, I recommend that authors include this information when reporting estimates using this method. I recommend the nomenclature mc5000-Spearman-Brown, to indicate that the Spearman-Brown adjusted split-half reliability estimate was calculated with the Monte-Carlo procedure described here, using 5000 random splits. The functions in the **splithalf** package have been developed to enable this method with relative ease and minimal programming experience on the part of the researcher interested in the reliability of their outcome measure. I hope that the provision of an easy to use tool such as this will encourage researchers to estimate and report the reliability of their tasks as part of standard practice, in a similar manner to questionnaire measures.

The *splithalf* R package

The *splithalf* package is available from the Comprehensive R Archive Network (CRAN) at https://cran.r-project.org/package=splithalf. The package imports functions from *plyr* (Wickham, 2011), and *stats* (R Core Team, 2013). The latest development version of the package can also be found at https://github.com/sdparsons/splithalf and on Figshare at https://figshare.com/articles/splithalf/5559175. The *splithalf* package was developed to provide several tools that researchers can use to estimate the reliability of their cognitive tasks, preferably with the random simulation method described above. It is our hope that access to these relatively simple to use functions will enable researchers to add the calculation of reliability to their research workflow as standard practice. I encourage researchers to contact us regarding specific tasks that do not easily conform to any of the *splithalf* package functions. This will allow us to develop new functions tailored to those tasks, employing a similar underlying process to estimate reliability. On release, the *splithalf*

package contains three functions which contain similar underlying scripts; splithalf, DPsplithalf, and DPsplithalf.all. A vignette is provided which provides several examples of the use of the DPsplithalf function, with simulated data. The second example also includes useful information about restructuring datasets to be compatible with the functions.

Current development of the *splithalf* package

The *splithalf* package is currently undergoing significant overhaul in order to increase its applicability to a wider range of tasks. The procedures outlined above to estimate the internal consistency of dot-probe based attention bias indices is being expanded to be applicable to a wider range of response time based tasks. In particular, three functions will be developed. The first will estimate internal consistency of raw scores, for example in the case of the dot-probe this could be separate estimates for congruent and incongruent trials. The second will follow the procedure of the DPsplithalf function described above but with generalisability to measures calculated as a difference score between two conditions. The third will then expand this to estimate the internal consistency of measures calculated as a difference score of difference scores, for example the training-induced shifts in bias index used in Chapter 4. These functions will robustly estimate the splithalf reliability (both raw and Spearman-Brown corrected) along with 95% confidence intervals based on the percentiles of the total number of permutations performed. In addition to these changes, functionality to estimate the internal consistency of accuracy based tasks will be added. Finally, an R Shiny app is under development (development screenshot overleaf in Figure A5), which allows non-R users to estimate the internal consistency of their tasks easily over the internet.

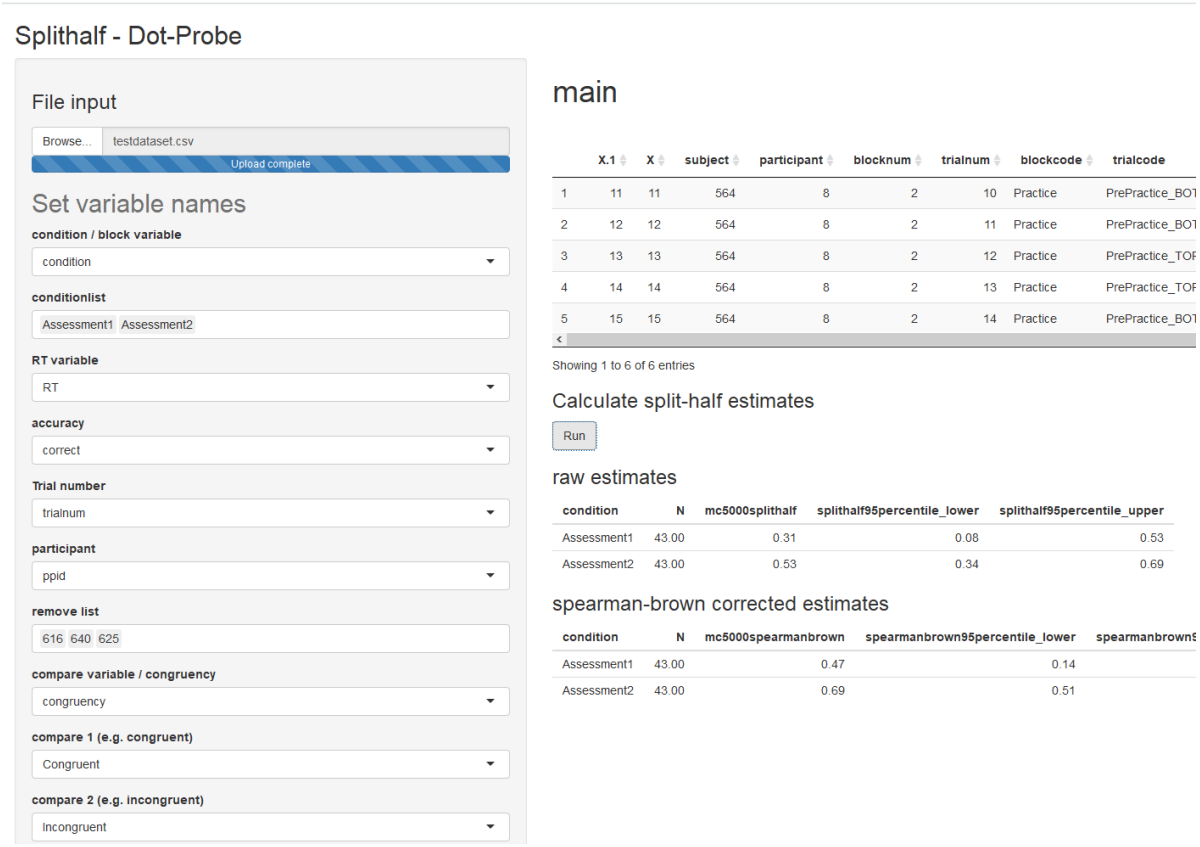


Figure A5: Current development screenshot of the *splithalf* package Shiny R app.