

Investigating what makes people walk or cycle using a socio-ecological approach in seven European cities

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Abstract

Large efforts and investments have been made into public transport, walking, and cycling in cities around Europe. Yet, cars remain the most ubiquitous mode of travel in urban areas. Often, research into the barriers facing active travel evaluates only one part of the problem, such as a person's surrounding environment (the macro level), socially embedded practices that define the activity (meso level), or a person's own beliefs and sense of identity (micro level). However, barriers and enablers to active travel exist on multiple levels, and interventions to increase walking and/or cycling are less likely to work when implemented in isolation. Hence, a multilevel socio-ecological model is developed to demonstrate and test the importance of assessing these barriers together, and identify interrelationships among them. Using the Physical Activity Through Sustainable Transportation Approaches (PASTA) dataset on the travel behaviour of people in seven different European cities, this paper identifies the constructs that correlate with active travel most. Within PASTA, psychosocial constructs influence the decision to take a trip by bicycle or walk more than built environment variables. In addition, trip purpose and the meso level influence the importance of built environment and attitudinal variables in explaining active travel. These relationships do not vary significantly between cities. This research further supports the use of multi-faceted interventions to increase walking and cycling, rather than focussing on a single policy.

Keywords: Transport mode choice; socio-ecological model; built environment; attitudes; active travel

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1 Introduction

Walking and cycling for travel have long been recognised as practical means of reaching daily exercise targets, improving mental wellbeing and decreasing overall mortality (Gibson-Moore, 2019), as well as being environmentally beneficial, congestion-reducing and non-polluting modes of transport (Banister, 2008). 50-57% of all trips in the EU are shorter than 5km, and up to 75% are shorter than 10km (Dekoster and Schollaert, 1999; Aher et al., 2013), making car trips, particularly in well-connected urban areas, replaceable by public transport, walking, or cycling. Although significant efforts have already been employed to reduce car use in Europe, cars remain the most widely used transport mode in most European cities, and the transport sector is dominated by symbolic efforts to manage travel demand rather than observable mitigation (Bache et al., 2015).

Travel mode choice is determined by many factors. A review by De Witte et al. (2013) identified:

- 7 sociodemographic factors (age, gender, education, employment, income, household size and composition, and car availability);
- 5 socio-psychological factors (attitudes and experiences, familiarity, habits, lifestyle);
- 9 journey characteristic indicators (purpose, distance, time, cost, departure time, trip chaining, weather, information, interchanges on public transport);
- and 5 spatial indicators (density, diversity, proximity to infrastructure, public transit frequency, and parking).

While researchers agree that each of these factors contributes to the decision whether to travel by active mode, there is a lack of consensus regarding which factors are most important in determining trip mode, and how these factors interact. While earlier study reviews established a reliable relationship between socio-demographic variables, the built environment, and mode choice/trip length/frequency (Ewing and Cervero, 2001), more recent reviews stress the

importance of psychosocial determinants of travel (Lanzini and Khan, 2017). Furthermore, while certain environmental variables have been found to predict car use reliably, the same level of confidence has not been established for active travel (Zijlema et al., 2018; Christiansen et al., 2016).

Apart from several exceptions (Gascon et al., 2019; Ogilvie et al., 2011; Panter and Jones, 2010) research remains limited to evaluating one specific part of the system or topical perspective (Götschi et al., 2017). Götschi et al. (2017) synthesise this literature and construct a comprehensive socio-ecological framework that this study builds on.

Even when they do exist, studies that evaluate the relative importance of both the built environment and personal attitudes on walking and cycling often use survey and subjective data only (Cao et al., 2007), or a single location, such as the built environment at home (Dill et al., 2014; Van Acker et al., 2014), examine commuting trips only (Keyes and Crawford-Brown, 2018), or fail to assess the interactions between personal attributes and the built environment (Taube et al., 2018). Additionally, as Winters et al. (2017) point out, research is often spatially focussed within one neighbourhood or city, and assumes a homogenous collection of attitudes in the respondents, potentially limiting the applicability of research to other contexts. Meanwhile, price and car ownership fees, low emissions zones, and the planning context are all but excluded from the literature on attitudes and built environment with respect to mode choice, even though they have been shown to influence general patterns of travel behaviour significantly (Buehler et al., 2017; Duranton and Turner, 2018; Brand et al., 2013).

Many recent studies have reported significant levels of success in terms of increases in active travel following comprehensive and integrated policy interventions over multiple years (e.g. Chapman et al. (2018) and Aittasalo et al. (2019)). Evaluations of single infrastructure or information-based interventions report more mixed success (Song et al., 2017; Cairns et al., 2008). This evidence suggests that mixed policy interventions may provide higher value for money by inducing a larger shift in behaviour, but that active travel research often does not

integrate insights from different fields, or provide guidance on how these different levels of influence interact. There is a need for a greater understanding of the multi-level influences on active travel behaviour, so that these insights can be incorporated into policy more effectively.

The aim of this paper is therefore to help identify where policy efforts should focus most in order to promote active travel. It tests the hypothesis that each domain of active travel (the built environment, the individual, the trip itself) are equally important in determining which mode of transport is used, with a specific focus on the relative importance of the built environment compared to the other domains. This study uses logistic regressions for the analysis, a common method in research examining the strength of built environment and attitudinal factors in determining mode choice.

First, a conceptual framework was developed based on the socio-ecological models of Sallis et al. (2006) and Sallis et al. (2015) and Götschi et al. (2017). Based on the literature, this framework identifies the main domains that influence active travel behaviour. As health behaviour is complex, and changing it requires actions at multiple levels, with many different possible interventions. Due to the multi-level nature of a socio-ecological framework, it is capable of incorporating different theories at different levels, from different research fields. A key feature of the framework is that it combines both the social and environmental factors that influence travel behaviour is needed.

Second, the relationships formalised in the conceptual framework were tested using data from the multi-centre Physical Activity Through Sustainable Transportation Approaches (PASTA) study, and open-source spatial data. The PASTA study consists of transport and health behaviour surveys, trip-diaries, GPS and accessibility data from seven cities in Europe, Antwerp, Barcelona, London, Örebro, Rome, Vienna, and Zürich. Multivariate logistic regressions were conducted in order to test the relative importance of the built and social environments as opposed to psychosocial and individual characteristics. Separate analyses were carried out for different trip purposes (work/study, home-related responsibilities, and leisure), and built environment characteristics for both home and work/study locations of

the respondents.

The built environment, while explaining a small degree of variance in the PASTA dataset, provided less explanatory power than individual sociodemographic attributes, attitudes, and social environment. For individual psychological constructs, perceived behavioural control had the greatest explanatory power of whether a trip was taken by active mode. Still, habit was the single most influential variable in determining mode choice. Intent to travel by active mode and whether a trip was actually taken by active mode are correlated with different eTPB constructs. Finally, the influence of psychosocial and built environment variables did not differ significantly between the seven PASTA cities.

This paper provides an assessment of the varying degree to which the built environment and psychosocial factors affect daily travel behaviour, and may provide useful evidence for why a holistic and flexible policy approach is needed to encourage active travel in urban areas in Europe. The remainder of this paper is structured as follows: Section 2 describes the conceptual framework and the literature used to develop it, while Section 3 outlines both the PASTA study and the open-access datasets used and how different variables map onto the constructs developed for the socio-ecological framework. Section 4 then presents the results of the analysis, grouped by micro/meso/macro-level influences, which Section 5 then summarises and compares to previous research. Finally, Section 6 concludes the paper.

2 Theory and background

Socio-ecological models incorporate the environmental and policy context of a behaviour, as well as the psychological and social influences on it. There are several grounding principles of socio-ecological frameworks, namely that there are multiple levels of influence on a specific behaviour, these may interact with each other, and that such a framework should be behaviour-specific (Sallis et al., 2015). Taking unifying principles from the active living framework by Sallis et al. (2006), the conceptual framework for active travel by Götschi

et al. (2017) and the macro-meso-micro structure identified by Mattioli et al. (2016) for car-dependent behaviours, this paper develops a simpler tool to conceptualise active travel behaviour and feedback effects specifically, while retaining what we consider the core parts of these three frameworks. Mattioli et al. (2016) identify:

- the built and policy environment (macro),
- the individual and their agency (micro),
- individual and social practices and trip-activity related behaviour (meso),

as the three core levels of car-dependence. In addition, both Sallis et al. (2006) and Götschi et al. (2017) roughly follow a socio-spatial structure covering the Individual/Intrapersonal (micro), the Physical Environment, Policy (macro), and the Community/Social/Cultural Environment (meso).

Three distinct levels of influence were identified: the macro, meso, and micro. Within each of these levels, several factors that observable variables map onto were identified. The conceptual framework was designed specifically for a European setting. The socio-ecological framework in this paper, Figure 1, aims to balance conscious determinants of decisions - those often found in socio-cognitive models, which accentuate conscious individual decision-making - with unreasoned determinants of behaviour, such as self-identity and habit, while also incorporating the social and environmental context.

The planning context, the built environment, and the social environment are assigned to the macro level. The main identified sources of built environment influences of travel behaviour are the *density* of population or building floor area, *diversity* of service provision, the *design* of the urban street network and environment, *distance* to transit, and *destination accessibility measured as ease of reaching desired locations*, identified as the 5Ds by Cervero and Kockelman (1997) and Ewing and Cervero (2010). The natural environment in our framework is defined by greenness and pollution levels, whose importance was evidenced by, among others, Christiansen et al. (2016) and Koohsari et al. (2015).

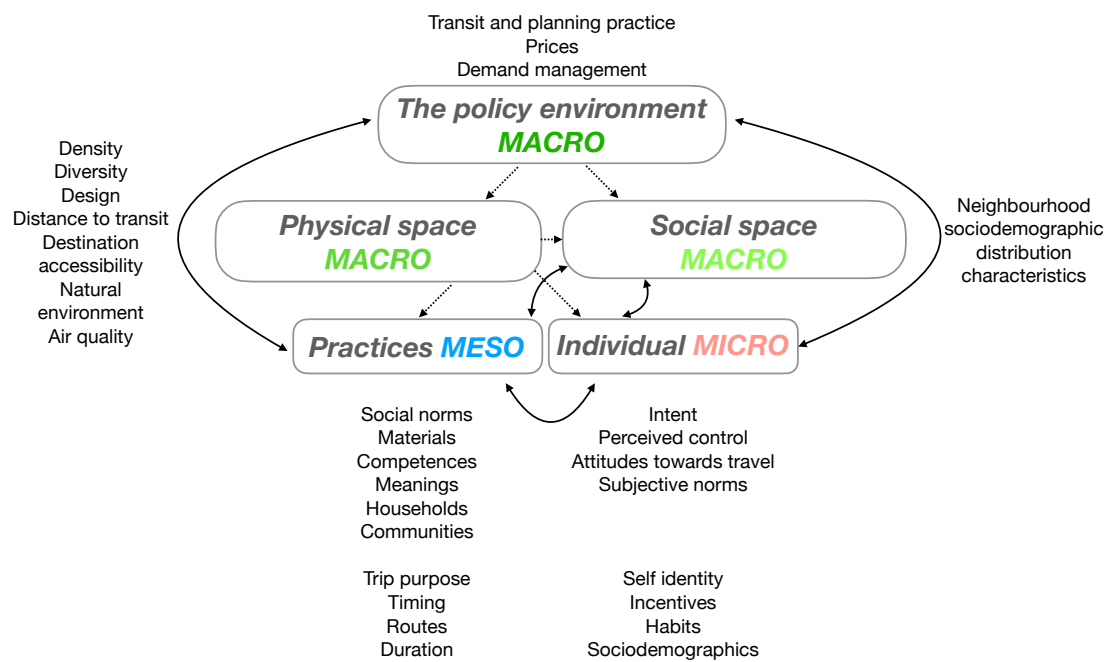


Figure 1: The conceptual framework. The colours represent the three levels of analysis: micro, meso, and macro. Next to each bubble is a list of constructs that comprise that level. Full, bi-directional arrows denote possible feedback effects, and single-headed dashed arrows denote a one-way effect.

2.1 The macro level

Ewing and Cervero (2010) conduct a systematic review of the built environment literature and evidence supporting the existence of the 5Ds, finding that vehicle miles travelled are most closely linked to accessibility at destination, followed by street design (e.g. intersections at regular intervals, visibility of the next turning for pedestrians) and connectivity. In a longitudinal study, Beenackers et al. (2012) found evidence that higher density, availability of desired destinations (shops, restaurants, workplaces/school), and connectivity were all significant predictors of increases in active travel. Christiansen et al. (2016) and Kerr et al. (2016) also found that greater land use mix and higher residential density are associated with higher walking levels. However, destination accessibility may be the most influential built environment determinant of travel mode choice (Ewing and Cervero, 2010), and more consistently significant than many other correlates of active transport (Christiansen et al., 2016).

Daramy-Williams et al. (2019) also stress the importance of active travel infrastructure and the provision of attractive alternatives to car use to determining modal choice, and Abdulrazzaq et al. (2020) suggest that improving time efficiency and reliability of public transport may help reduce car use. Therefore, this paper includes additional accessibility statistics not usually included in analyses of modal choice with respect to the built environment. In their systematic review of the effect of the built environment on travel, Fraser and Lock (2011) find that higher perceived safety, shorter trips, and proximity to green paths increase cycling. Perceptions of a walking-friendly environment also increase walking rates in some studies (Adams et al., 2016). Pucher and Buehler (2006) argue that, absent of a difference in culture, higher urban densities and land-use mix increase cycling rates, while Winters et al. (2011) argue that cycling routes, and separation from traffic, are essential. However, the estimates of the influence of the built environment on active travel still vary significantly - from up to 86% of the walking frequency in Northern California (Cao, 2010), to only 3% of car driving in Belgium, France, Hungary, the Netherlands, and the UK (den Braver et al.,

2020).

Structural barriers to driving through prices, such as average parking prices and supply, costs of public transport, and whether an area is covered by a low emissions zone or congestion charge were added as part of a policy and planning context factor (Duranton and Turner, 2018) as Demand management, or the sixth D (also proposed by den Braver et al. (2020)). For example, difficulty parking has been associated with higher levels of active commuting (Bopp et al., 2012; Panter et al., 2013). Pucher et al. (2010) review case study cities that have managed to reduce car dependency, and identify parking restrictions as one of the most important policies. Ease of parking exists in the frameworks by Götschi et al. (2017) and Sallis et al. (2006), but is excluded in the review by Mattioli et al. (2016). As most studies that evaluate psychosocial and environmental reasons for behaviour are very context-specific, few consider city-wide planning context, and so it is often excluded. The present study examines the correlates of active travel in seven different cities, allowing us to control for city-level planning as well.

This study also includes objective measures of the social environment in an individual's home and work locations, called Social Distribution, the seventh D. This reflects the propensity of like-minded people to self-select into neighbourhoods with similar incomes, cultures and backgrounds, even where those neighbourhoods may be nearly identical in terms of their built environment. Similar variables were found to influence cycling and walking for work vs. leisure in the Netherlands (Rietveld and Daniel, 2004; van Lenthe et al., 2005). For Finland (Harms et al., 2014) and the Netherlands (Götschi et al., 2015), immigrant populations were significantly less likely to drive. However, these findings have not been consistently significant throughout the literature (Van Acker et al., 2010). Although these papers are country-specific, they point to cultural differences in active transport use, and potential shifts to or away from cars (Klein and Smart, 2017; McDonald, 2015; Hopkins and Stephenson, 2014). The proportion of foreign-born nationals in the respondents' neighbourhoods, car ownership, education levels, and incomes are therefore incorporated in this analysis.

However, den Braver et al. (2020) found that built environment and individual sociodemographic attributes explained only 2% and 3% of variance in car travel patterns in their study of five different urban areas in Europe, respectively. This finding supports the motivation to include psychosocial and trip-specific variables into the analysis in this study, in order to increase understanding of what drives mode choice.

2.2 The meso level

The importance of the meso level of trip-specific practices and the purpose of the trip itself is stressed by Mattioli et al. (2016), and much of the literature on social practice theory (e.g. Sarrica et al. (2019) and Schwanen et al. (2012)). Specific activities people carry out, such as shopping, going for walks in the park, or commuting, all have their specific needs and create new mobility patterns and practices (Watson, 2012). Different meanings associated with transport (e.g. public transport use being associated with bad parenting, or cycling being considered a low-income mode of transport (Aldred and Jungnickel, 2014)), the support of the social environment (Carlson et al., 2012), or “image” (Haustein and Nielsen, 2016; Anable, 2005), may influence mode choice. Walking is often conducted for more ad hoc, discretionary trips, while cycling is more common for repetitive, obligatory trips such as commuting (Song et al., 2013; Zhao et al., 2018).

Chan et al. (2019), for example, distinguish three trip purpose categories, and find that walking for work/study and household responsibilities is associated less strongly with the (perceived) built environment than leisure trips are. However, many studies focus on repetitive commuting trips only (e.g. Keyes and Crawford-Brown (2018) and Yang et al. (2017)). The timing (e.g. flexible working hours vs. morning rush hour trips (Shove, 2002) may influence mode choice from a reliability perspective, and daytime/nighttime travel and lighting also has an impact on accident rates, which may in turn influence the psychosocial attitudes towards the safety of a mode (Ramiani and Shirazian, 2020; Uttley et al., 2020). Depending on location, warmer weather may increase active travel (Børrestad et al., 2011), or conversely,

decrease it (Wang et al., 2020), although adverse conditions tend to decrease active travel in general. In addition, route-specific factors such as hilliness, weather, and cost will affect the mode choice decision. Alternatively, these can be classified as part of the macro domain - destination accessibility, and demand management.

2.3 The micro level

The micro level defines an individual through their sociodemographic profile, and proxy measures of reasoned and unreasoned justifications for action. The influences of age, income, employment, and household composition on mode choice have been explored extensively in the past (Dawson et al., 2007; Filion et al., 2006), and are now routinely being incorporated into policy (DfT, 2018).

Widely used socio-cognitive models of behaviour include the theory of planned behaviour (TPB) (Ajzen et al., 1991), the theory of interpersonal behaviour (Triandis and Values, 1979; Anable, 2005), the transtheoretical model of behaviour change, the self-determination theory (Buchan et al., 2012), among others. TPB has been used extensively in transport behaviour (Armitage, 2015).

Within the conceptual framework presented in this study, the reasoned action factors are therefore based on TPB, in which *attitudes* (an individual’s evaluative reaction to the behaviour), *perceived behavioural control* (beliefs about having the skills, ability and control to carry out a behaviour) and *subjective norms* (perception that others think the behaviour should or should not be performed) all impact the intention to carry out a behaviour, and Intention is seen as the main predictor of the behaviour itself. At its core is the belief that an individual makes conscious decisions about their actions. Empirical evidence suggests that the predominant predictors of behaviour in TPB are either attitudes (Lee and Shepley, 2012), perceived behavioural control (Beenackers et al., 2013), or a combination of the two (Dill et al., 2014; Bird et al., 2018). In the study by Bird et al. (2018), subjective norms, and visibility of the activity (proposed extensions to TPB), did not predict travel behaviour

change in their study. Lanzini and Khan (2017) conducted a meta-analysis of 58 primary studies, and found that intentions, habits and past use were the most relevant predictor of travel mode, followed by constructs consistent with the theory of planned behaviour and pro-environmental behaviour (consistent with the New Ecological Paradigm).

Attitudes have repeatedly been found to have a significant role in determining cycling, most significantly the perception that a trip-based distance benefit (cost and time savings) exists, and the perception of safety (Useche et al., 2019; Damant-Sirois and El-Geneidy, 2015; Heinen et al., 2011). The understanding that active travel yields the health benefits of exercise is also often the most significant and common reason people cite for cycling, as Useche et al. (2019) and Heinen et al. (2011) find in their study of cyclists' attitudes in 20 countries. In addition, the environmental and mental relaxation benefits (Fernández-Heredia et al., 2014), or the activity being perceived as fun (Fu and Farber, 2017), are also attitudes that help increase walking and cycling, though to a lesser extent. Conversely, crash risk, lack of safety and weather are the most commonly reported discouraging factors affecting active travel (Useche et al., 2019). This study includes many more attitudinal questions than direct attitudes about the travel mode of interest, because attitudes may have an effect on travel directly, but also manifest themselves through residential self-selection, and may mediate the effect of the built environment, or the built environment may mediate the effect attitudes would have had (Kroesen et al., 2017).

With a rise in literature criticising TPB (e.g. Sniehotta et al. (2014)) and increasing interest in heuristics-based decision-making, several measures indicating unreasoned action were also added. Based on social practice theory, we extend TPB measures to include *habit*, *visibility* of travel behaviours, and *self-identity* as potential determinants of travel behaviour. As travel, e.g. commuting to work or school, and going shopping, is considered highly repetitive, almost unintentional activity that is embedded in the habits of others, habit as a measure of past and automatic behaviour is likely to be a significant predictor of mode choice (Lanzini and Khan, 2017; de Bruijn et al., 2009; Bamberg et al., 2003). Visibility may

be an overlooked aspect of subjective norm (Bird et al., 2018), as perceived outside pressure to perform a behaviour may not only be injunctive and come from significant others, but may be descriptive in the form of visibility in the neighbourhood or local culture (Ball et al., 2010). Self-identity, such as a pro-environmental worldview or being a sports-car admirer, may also influence travel choices and styles in ways not encompassed by other attitudes. Developed extensively by Potoglou et al. (2020) and Whitmarsh and O'Neill (2010), it has been used in TPB-based studies, finding for example that self-enhancement or openness to change (Hunecke et al., 2010; Pojani et al., 2018) influence mode choice.

2.4 Interactions between the levels

Research on the strength of built environment vs. psychosocial variables does exist (e.g. Dill et al. (2014), Lemieux and Godin (2009) and Carlson et al. (2012)). These studies often found that attitudes have a slightly stronger influence on travel behaviour, in particular with regards to driving, than the built environment (Cao et al., 2007; Hunecke et al., 2010; Dill et al., 2014). For example, interactions between the physical and social environments were found to lead to significant increases in physical activity when encouraging conditions in both levels existed, but were far smaller when only the physical environment was activity-friendly (Carlson et al., 2012; Josey and Moore, 2018). Local destination accessibility was found to influence walking levels for people with positive attitudes towards walking, whereas higher connectivity was found to influence people with less positive attitudes (Joh et al., 2012). Giles-Corti (2006) argued that both are needed for substantial levels of active travel to be achieved.

Though a number of studies exist on the importance of psychological, or psychological and environmental variables in determining active travel, they typically involve a smaller sample size (130, Lemieux and Godin (2009); 404, Arroyo et al. (2020), 1698, Bird et al. (2018), 1159, Dill et al. (2014) compared to 4270 in this study), only one set of travel diary data or phone survey responses (Bird et al. (2018) being an exception), or look at land-use and key socio-

demographic characteristics, but do not evaluate further reasoned and non-reasoned action motivators for mode choice (Convery and Williams, 2019). Conversely, Dill et al. (2014) focus on the built environment and attitudes only, and overlook the importance of accessibility and public transport, while confirming that attitudes are often more important than the built environment. In their meta-analysis of studies evaluating attitudes towards transport using the theory of planned behaviour, habits, and value-belief-norm theory, Lanzini and Khan (2017) found 58 studies, but only seven looked solely at cycling, and none looked specifically at walking. **It is therefore relevant to evaluate the influences and interactions between determinants of active travel using a large sample, and detailed accessibility and attitudinal data, among other things.**

2.5 Proposed socio-ecological framework extensions

Four primary additions to the framework distinguish it from other such frameworks present in the literature. Self-identity was added to micro level influences, as a proxy for cross-situational, intrinsic motivation (Whitmarsh and O'Neill, 2010), for example strong environmental attitudes. This factor was not included in other studies evaluating behaviour using variations of the eTPB that included habit and visibility (e.g. Bird et al. (2018) and Neto et al. (2020)). Adding the visibility and habit factors at the micro level, and the social distribution factors at the meso level, allows us to incorporate insights from social practice theory made by Schwanen et al. (2012) and Spotswood et al. (2015). These variables go beyond the idea that travel patterns can change through the provision of information and reasoned action only (also criticised extensively by Kelly and Barker (2016)), and act as proxy measures for the mental environment of an individual and their surrounding society. Visibility and descriptive subjective norm also act as proxies for social capital and social network membership, which have been found to increase overall levels of physical activity (Legh-Jones and Moore, 2012; Josey and Moore, 2018). The next two additions - the two D's Demand management and social Distribution - reflect the car-dependent nature of modern

society, the social and mobility obligations that arise from participating in society in Western Europe, and recognise that emphasising individual attitudes and choice may obscure other, structural, reasons for choosing not to travel actively. Finally, although this study does not test for causality, feedback loops and causal links between levels identified elsewhere in the literature are also included in the conceptual framework. **By drawing explicit feedback loops, the socio-ecological framework highlights the need for policies and research at all levels of the framework to work with each other, rather than in a piecemeal fashion.** For example, Vienna, one of the PASTA case study cities, invested heavily into increasing public transit frequency, number of stops, reducing the cost of public transit and introducing parking demand management. At the macro level, this influenced the Policy environment, and improved destination accessibility and distance to transit in the Physical space. The change in accessibility and cost of parking can have a long-term effect on the Social space, reducing car ownership rates in an area, and these two factors can then change practices at the meso level through changes in routes, trip chaining or the skills required for travel. As the surroundings and behaviours of others around a person change, so can their attitudes, their habits, their beliefs of subjective norms, etc. This may, in turn, lead to more demand for further improvements in public transit, or alternatively pressures for changes in transportation provision, creating a feedback loop back to the macro level.

Overall, the framework combines the main psychological and environmental constructs common to most socio-ecological frameworks in the micro and macro level, while the meso level aims to emphasise aspects of urban transport that are harder to objectively observe - the cultures and sociology of everyday transport practices.

3 Materials and Methods

3.1 Study design and population

The Physical Activity Through Sustainable Transportation Approaches (PASTA) study¹ is a multi-centre longitudinal study of people’s physical activity patterns and travel behaviours in seven different cities in Europe (Antwerp, Barcelona, London, Örebro, Rome, Vienna, and Zürich), covering different geographical regions, city size, travel culture, density. Details of the study design and protocol have been provided elsewhere (Dons et al., 2015; Gerike et al., 2016; Gaupp-Berghausen et al., 2019), and a map of the study locations and table of city-specific characteristics were included in Appendix A. A standardised opportunistic sampling approach was used to recruit respondents in all seven cities. The respondents were representative of their city populations in terms of gender, but were over-educated and younger. In addition, due to the low prevalence of cycling in cities like Barcelona and Rome (2% and 1%, respectively, Mueller et al. (2018)), oversampling of cyclists was carried out on purpose. Respondents were asked to answer a web-based survey on a bi-weekly basis between November 2014 and October 2017². The baseline questionnaire included questions about sociodemographic, individual, and household characteristics, and respondents’ attitudes towards travel; physical activity, health, and mobility were gathered using the Global Physical Activity Questionnaire (GPAQ), in addition to a travel diary on a typical day. Attitudinal questions were developed in line with TPB (Ajzen et al., 1991) and the Transtheoretical model of behaviour change (Prochaska et al., 1998). 10,691 people answered the baseline questionnaire (Gaupp-Berghausen et al., 2019), but only 4503 included a valid trip diary and home address in the baseline. A further 254 participants were excluded because of missing sociodemographic data.

Baseline characteristics are shown in Table 1, incidence rate ratios (IRRs) are based on

¹The original study and data collection were funded by the EC under FP7-HEALTH-2013-INNOVATION-1.

²http://pastaproject.eu/fileadmin/editor-upload/sitecontent/City_survey/PASTA-questionnaires.pdf

Variable	Level	Value (%)	IRR (95 % CI)
City	Antwerp	618 (15%)	1
	Barcelona	719 (17%)	0.55 (0.49-0.61)
	London	520 (12%)	0.54 (0.47-0.62)
	Örebro	456 (11%)	0.57 (0.50-0.65)
	Rome	763 (18%)	0.30 (0.26-0.33)
	Vienna	593 (14%)	0.43 (0.38-0.49)
	Zürich	(14%)	0.41 (0.36-0.47)
Age	(range) in years	38 (17-91)	1.00 (0.99-1.00)
Gender	Male	2064 (49%)	1
	Female	2185 (51%)	0.99 (0.93-1.06)
Household composition	Without children under 17	2875 (68%)	1
	With children under 17	1374 (32%)	1.07 (0.99-1.14)
Education level	Primary or other	48 (1%)	1
	Secondary school	1008 (24%)	1.42 (1.01-2.03)
	Tertiary or equivalent	3193 (75%)	2.01 (1.44-2.85)
Employment status	Employed	3374 (79%)	1
	Student	621 (15%)	0.85 (0.78-0.94)
	Retired or other	254 (6%)	1.11 (0.96-1.28)
Access to a vehicle	Never	960 (23%)	1
	Sometimes	1197 (28%)	0.93 (0.85-1.02)
	Always	2092 (49%)	0.64 (0.59-0.70)
Access to a bicycle	No	740 (17%)	
	Yes	3509 (83%)	3.09 (2.81-3.41)
Self-rated health	Excellent/good	2084 (49%)	1
	Fair/poor	2165 (51%)	0.78 (0.70-0.86)
Self-rated frequency of walking	Daily or almost daily	4091 (73%)	1
	1-3 days per week	698 (16%)	1.25 (1.15-1.37)
	1-3 days a month	272 (6%)	0.99 (0.87-1.13)
	Less than once a month	188 (4%)	0.54 (0.46-0.65)
Self-rated frequency of cycling	Daily or almost daily	1676 (39%)	1
	1-3 days per week	677 (16%)	0.30 (0.27-0.33)
	1-3 days a month	424 (10%)	0.14 (0.12-0.16)
	Less than once a month	1472 (35%)	0.14 (0.13-0.15)

Table 1: Descriptive statistics for the 4249 respondents and odds ratios showing relationship with an actively travelled trip.

univariate analysis, the outcome variable is whether a trip was taken by an active mode. The reference group has an IRR of 1, the comparison group is either more likely to travel actively (a value higher than 1) or less likely (a value less than 1) than the reference group, based solely on the variable in question. The univariate analysis most strongly demonstrates the unique (highly active) travel patterns of respondents in Antwerp as opposed to the other cities. This is true even when compared with Örebro, though average rates of cycling are very similar in the two cities. Walking and cycling are the least common modes of transport in Rome. Zürich and Vienna are second and third lowest in terms of active travel trips. In these two cities, public transport use is very high relative to the other cities.

Higher education levels, lack of access to a car and good health are all associated with higher likelihood of active travel. Conversely, on its own, having children does not affect active travel patterns significantly. The relationship between employment and actively travelled trips was variable. As the outcome variable is whether a trip was taken actively, respondents who walk several times a week (but not daily) may be more likely to cycle as well as walk. This leads to a higher IRR for an active trip relative to the daily walkers. This relationship does not appear to exist for cycling, however - lower frequency of cycling is associated with a significantly lower likelihood of a trip being travelled actively. The univariate analysis was used to identify potential confounding variables. As a result, a set of control variables were selected, to be included in every regression. These are described further in Section 3.3.

Comprehensive built environment characteristics were collected for the respondents' home and work locations using geographic information system (GIS) analysis (using Navteq (2012), Open Street Map (OSM), local layers (2015–2020), and census/neighborhood data (2011–2016)). Additional accessibility-based measures³ were calculated using the statistical software R 3.6.2 and packages *osmdata*, *openrouteservice*, *stplanr* and *tidytransit*. Map data from OpenStreetMap, General Transit Feed Specification (GTFS) data from city authorities, and routing services from GraphHopper, OpenRouteService and Google Maps APIs were used. Kujala

³These included distance and time to nearest shop, school, the city centre by all four modes of travel, for both work/study and home address.

et al. (2018) describe the necessary steps to extract and validate GTFS public transport feeds, which were followed in this study.

For each city, permission to collect, store, and process data was obtained from local ethics committees. On enrollment, participants registered on the PASTA website and gave informed consent.⁴

3.2 Outcome assessment

The primary outcome variable of interest was whether a trip was taken by active mode (Yes/No). This was obtained from the survey travel diary, for each trip stage, and included walking, cycling, or e-bike.

3.3 Correlates of active travel

To characterise respondents who chose to walk or cycle, individual (sociodemographic, attitudinal) indicators, social characteristics at the neighbourhood level, the built environment, and the larger policy context were considered. All the variables used, and the way they map onto the socio-ecological framework, are described in Appendix B. **Following the univariate analysis presented in Table 1, a set of sociodemographic attributes was included in every regression as control variables. This takes into account that sociodemographic attributes, and where a person lives, may significantly influence trip preferences and behaviour.** These variables are sex, age, level of education, employment status, access to a car or van, and city as random effect. Income was excluded because respondents typically under- or over-report income, or do not supply the information (e.g. Bound and Krueger (1991)). Instead, employment status and car access were used as proxies for income levels. **Car access was chosen over access to a bicycle, as walking does not require access to a bike but is still active.** Finally, city membership was included to account for city-specific cycling and walking cultures and

⁴Available at http://pastaproject.eu/fileadmin/editor-upload/sitecontent/City_survey/PASTA-questionnaires.pdf

infrastructure. The following subsections explain which variables map onto which construct and level of the socio-ecological framework in the analysis, and the statistical approach.

3.3.1 The micro level: individual attributes

Following the eTPB, attitudes, perceived behavioural control, subjective norm, and extended TPB constructs were included in the analysis. Attitudes were defined by an individual's view of walking and cycling with respect to: air pollution, safety with respect to crime, contribution to overall health, comfort experienced during the activity, travel time, predictability, privacy, and flexibility. In most cases, the attitudinal variables were averages of two questions asking respondents to rank the importance of a specific attribute of the activity, one with regards to walking, and one to cycling, ranked from "not important" to "very important" on a 5-point Likert scale. Categorical variables can be treated as continuous without severe bias if there are at least 5 levels on the Likert Scale (Finney and DiStefano, 2006), and there is no severe kurtosis in the observations. Perceived behavioural control was measured by an individual's self-rated ability to control the process or outcome of the behaviour, namely whether a person finds it impossible to travel by foot or bicycle, is obliged to travel a lot due to work, cannot change travel habits due to work (similarly to Bird et al. (2018) and Neto et al. (2020)), and is not fit enough to travel by foot or bicycle. Following Bird et al. (2018), subjective norms were measured in two ways: injunctive ("I believe people around me think it is important I do X for travel") and descriptive ("People around me use mode X travel").

Habit was measured using some of the key components of Verplanken and Orbell's (2003) self-reported habit strength index, measuring automaticity of behaviour, and subjectively measured history of repetition ("daily or almost daily" to "less than once per month"). Visibility was measured as the perception of how common it is to walk and cycle in one's neighbourhood. Self-identity measured one's sense of moral responsibility to carry out environmentally-friendly behaviours, and own beliefs ("Regardless of what other people do, my own values and principles oblige me to walk 'for travel' whenever possible."), in line with definitions

used by Whitmarsh and O'Neill (2010). These were also all measured on a 5-point Likert scale ("very much disagree" to "very much agree"). The results were also compared when the actual trip mode was the outcome variable of interest, and when intent to travel actively was the outcome variable of interest.

3.3.2 The meso level: trip attributes

We include trip purpose, time of trip, and trip distance as meso-scale determinants of active travel in our models. Our trip diary data classified trip purposes into ten categories, which we collapsed into three: commuting, including work/study and business trips, shopping and other household responsibilities, and leisure trips. This recognised that grocery and other shopping trips, and escort trips for other members of the family may have to be carried out using a car due to its cargo-carrying capacities. Some of the original 10 sub-categories, e.g. fitness, were too small to determine statistical significance of the explanatory variables with confidence.

3.3.3 The macro level: neighbourhood, social, and planning context

Variables measuring environmental characteristics have a number and a D before their name to denote what construct they belong to. Density, 1D, was measured by population, residential, and building density (in the number of inhabitants and metres squared per km sq., respectively). Diversity, 2D, was measured by the density and the richness of facilities (number of facilities and number of facility types per km sq.). Street design, 3D, was measured by the connectivity of streets (number of intersections per km sq.), street density and bike lane density (both in metres per km sq.). Distance to transit, 4D, consisted of a measure of public transport route density (number of stations per km sq.), and distance to the nearest public transport stop (in metres). Destination accessibility, 5D, was measured by the number of routes stopping at the nearest transit stop, average waiting time at the transit stop, distance and time (in metres and minutes) to city centre, nearest secondary school, and gro-

cery store, by all four modes of transport, as well as the Euclidian distance between home and work/study address. The demand management construct, 6D, consisted of city-specific variables, and included a dummy variable for having a low emissions zone, average spending on public transport as a proportion of average income, and average price of on-street parking in the city. The social distribution variables, 7D, were car ownership, mean income, the proportion of foreign born nationals, and the proportion of people with higher education in a 500m² area. Based on Pearson’s chi squared test and bivariate logistic regressions, a subset of the available measures and buffer area size was chosen. All area-based measures used were for a 500m² area within the home/work/study location, apart from diversity, for which only data for a 300m² area was available. This distance is also easily walkable in less than 8 minutes, the time used in many public transport accessibility evaluations (TfL, 2016).

3.4 Statistical Analysis

In order to test the relative importance of each of the levels (micro, meso, and the three macro sub-levels) and obtain odds ratios for the correlates of active travel with trip-level mode choice, a logistic regression set-up was used. Multinomial logistic regressions have been used by Panter et al. (2013), Bird et al. (2018) and Keyes and Crawford-Brown (2018) and others in order to analyse the relationships between psychosocial constructs, the built environment, and travel mode choice in the past. The following levels of influence on mode choice were tested:

- demographic variables (minimally adjusted model)
- the micro level, or agency (the influence of each construct of eTPB tested separately, and together)
- the meso level, or practices (trip-specific attributes)
- the macro level: (the influence of each of the seven D environments at home and at work, city-level influences to identify policy and cultural context)

City was included as a random effect to account for the influence of city-level clustering, as city membership explained about 3.7% of the variance in the PASTA sample. Stepwise regressions were carried out in order to select the most parsimonious model, which included only the most influential variables in each level. The variables were interacted with city membership to estimate any city-specific and universal relationships. Finally, the separate models were combined into a global model, and the paper presents parsimonious models derived using backwards step-wise elimination.

The built environment characteristics were standardised with standard deviation as the contrast. As attitudes, travel behaviours, and habits influence each other (Kroesen et al., 2017), the variance inflation factor (VIF) was calculated in order to estimate collinearity between variables in the base model, built environment characteristics, social norms, and transport habits. Logistic regression results are presented in the form of odds ratios; linear regression results for the Intent model are presented as standardised coefficients. Subtracting 1 from the odds ratio and multiplying by 100 provides the percentage change in the odds of choosing to take a trip by bicycle or walk for a one unit change in the independent variable. All analysis was conducted in the statistical software R v3.6.2.

4 Results

4.1 Study population characteristics

Summary statistics for the PASTA dataset are shown in Table 1. The final sample included 4249 respondents who reported 16 018 trips. The sample was balanced in terms of gender, and more than three-quarters of the study population had attained a university degree.⁵ The average age was 38.3 years (17-91), 34% had at least one child in the household, and 81% were economically active. The trip diary data revealed an average of 3.40 ± 1.74 trips

⁵This is partly due to the opportunistic sampling method, partly due to advertisement on social media, and partly due to the purposeful oversampling of cyclists.

per person per day, with a total of 101 ± 57 minutes of travel per day. On average, people walked between 15 minutes (Antwerp) and 19 minutes (Barcelona) per trip; cycled between 16 minutes (Örebro) and 30 minutes (London) per trip; drove for between 25 minutes (Örebro) to 32 minutes (London); and were on public transport for between 13 minutes (Örebro) to 20 minutes (Antwerp) per trip.

4.2 Micro level: individual characteristics

The parsimonious eTPB-based logistic regression results for trip-level decisions are presented in Figure 2. This model measures the strength of correlation between certain attitudes, perceived control over the behaviour, subjective norms, habits and whether a trip was walked or cycled, while accounting for sociodemographic variables that may confound the results. The Intent model shows the independent variable correlates with a person’s stated intention to walk or cycle, “My intention to walk/cycle for travel is [weak-strong]”, measured on a 5-point Likert-like scale. The Behaviour model shows the independent variable correlates with whether or not a trip the respondent took was actually made by active mode, i.e. their decision in reality. As Intent is a continuous variable but Behaviour is a binary variable, Figure 2 presents results as standardised coefficients, where for every standard deviation increase in the independent variable, the outcome variable increases by a proportion β of a standard deviation. The benefit of using standardised coefficients is that they are unit-free, and so can be used to compare values in different metrics (Menard, 2011). However, as the Intent and Behaviour models are not the same models (they have different dependent variables, and the Intent model includes trip cost as a variable), coefficient sizes are not directly comparable. In-text and in other figures, we present outcome likelihoods of logistic regression models as odds ratios.

Overall, perceived behavioural control variables had the strongest correlation with actual trip mode (Figure 2, right-hand side). Finding it impossible to travel actively or being obliged to travel a lot both significantly reduce the likelihood of using an active mode. Conversely,

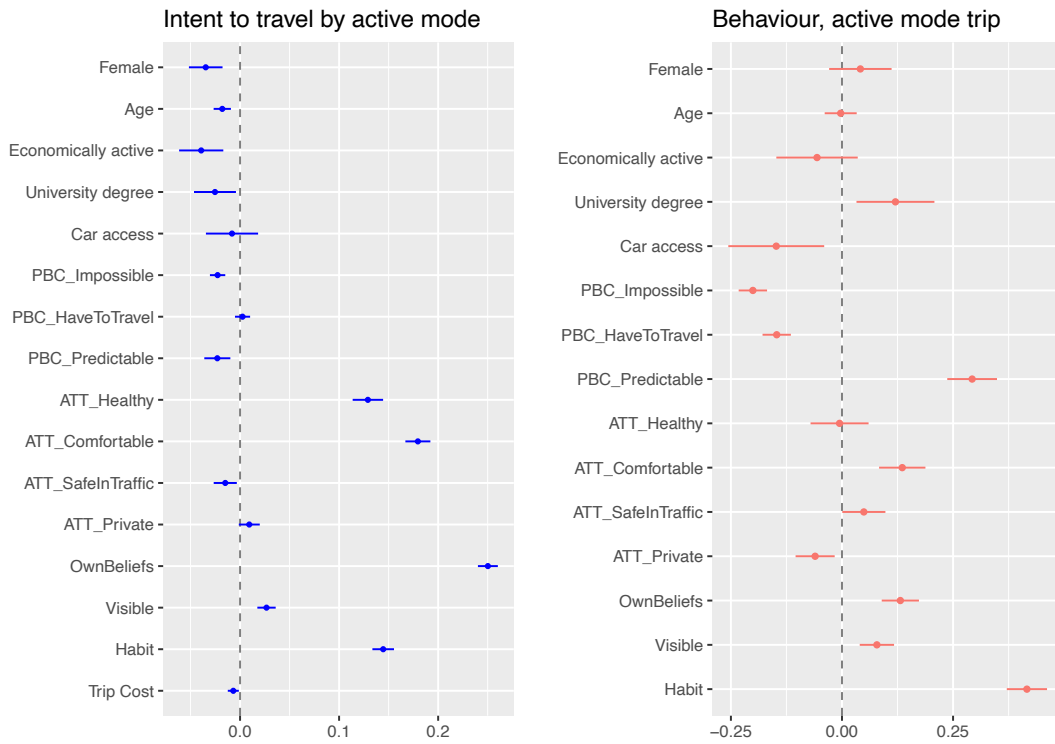


Figure 2: Micro level model determinants of active travel behaviour. A positive value indicates a higher likelihood of walking or cycling a trip. Note that for comparability, estimates in this Figure are presented as standardised coefficient estimates, not odds ratios. The first five variables are sociodemographic control variables; PBC_ variables belong to the TPB construct of perceived behavioural control, ATT_ variables belong to the attitudes construct; OwnBeliefs, Visible, and Habit are part of eTPB.

believing that walking and cycling is highly predictable increases likelihood of active travel. Within attitudes, believing walking and cycling are comfortable was the best predictor of active travel mode choice. As a result of backwards elimination, no variables describing subjective norms were selected for the parsimonious model, as none improved the model fit. This confirms findings from previous studies (Bird et al., 2018), and so was not changed. Within the extended TPB, having own beliefs that incentivised people to walk or cycle more (whether environmental or health related) had a significant influence on active mode choice. Finally, habit, measured as average past travel behaviour, was the strongest predictor of mode choice, again confirming previous studies (Lanzini and Khan, 2017).

Variables that have effects in the same direction for both Intention and Behaviour models are employment status (“Economically active”); from PBC constructs whether a person considers it impossible to walk or cycle (“PBC_Impossible”); from Attitudes constructs the extent to which a person considers active modes comfortable (“ATT_Comfortable”); from the extended TPB the strength of own beliefs motivating active travel regardless of what others do or think (“OwnBeliefs”), the visibility of active modes (“Visible”), and habit (“Habit”). However, attitudes towards the comfort levels of active modes, as well as own beliefs, mattered more for Intent than Behaviour, while habit was more strongly associated with Behaviour than Intent. Interestingly, car access was not associated with Intent, but did reduce the likelihood of taking a trip by active mode in reality (0.86, 95% CI 0.77-0.96).

It is notable that certain variables have opposite influences in the Intent and in the Behaviour models. Higher predictability of active modes (“PBC_Predictable”) lowered Intent to walk or cycle, but increased the likelihood of carrying out the behaviour of walking or cycling (1.34, 95%CI 1.27-1.42). Conversely, positive attitudes about the healthiness of active travel (“ATT_Healthy”) were associated with higher Intent to walk/cycle (for every standard deviation increase in strength of belief of how healthy active travel is, the Intent to travel actively increased by 12.9%), but this association did not exist when actual travel patterns were the outcome variable (0.99, 95% CI 0.93-1.06). Hence, while the health aspect of active

travel may contribute to the overall motivation to walk or cycle, it does not influence day-to-day trip decisions as much.

In other words, in this dataset, the intention to do something does not mean a person will carry out that action. This suggests that using a stated preference (the desire or intention to carry out a behaviour) or self-reporting surveys rather than revealed preference (whether or not the activity was carried out) may be misleading and lead to inaccurate conclusions about what drives that behaviour.

Table results of both the full eTPB and the parsimonious models are presented in Appendix C.1.

4.3 The macro level

The macro level consists of the built and social environments, and the planning context. The importance of the built and social environments at home and work neighbourhood locations was compared, shown in Figure 3, with a set of sociodemographic variables acting as controls for confounding effects. Overall, McFadden’s pseudo- R^2 was slightly higher for the model with work location built environment (0.13), than home environment (0.10).⁶ There is a slightly greater freedom of choice over home location than work location, which implies that the residential self-selection effect may reduce the importance of the home built environment to mode choice on a day-to-day basis (Mokhtarian and Cao, 2008). Figure 3 shows the results for the parsimonious models with city as random effect. Appendix C.2 contains the results for these two models in table format.

Built environment indicators at both home and work locations have a very similar influence on active travel. The most significant correlate of whether a trip was taken by active mode were the distance from home to work (“5D_DistanceHW”), and hilliness of the route (“5D_HillinessHW”), widely accepted as the most significant determinants of mode choice (Ewing and Cervero, 2001).

⁶Typically, values for McFadden’s pseudo- R^2 are much lower than those of OLS R^2 .

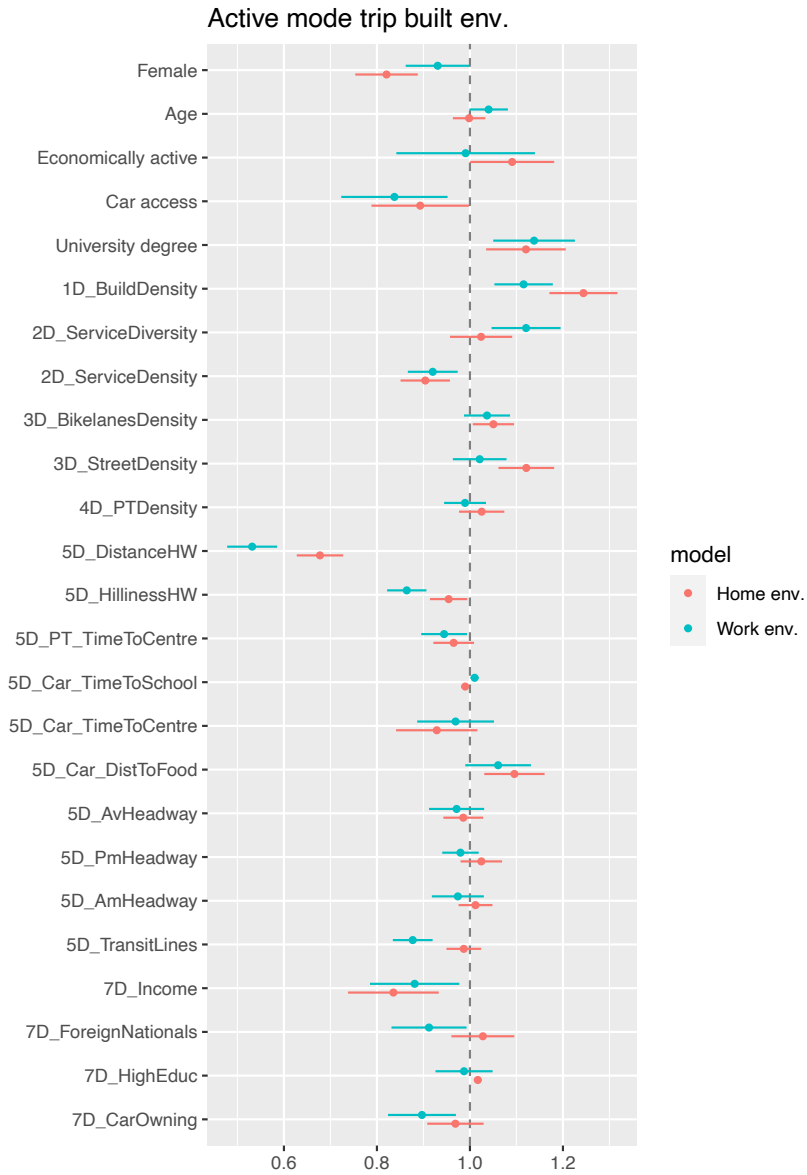


Figure 3: Correlates of an actively travelled trip, both at home and work locations. Coefficients presented as odds ratios. Distances or Time to a location are taken to be from the respondent's home or work location to the nearest point of interest identified in OpenStreet-Map. HW refers to Home to Work. The first five variables are sociodemographic control variables; 1D refers to measures of density, 2D measures of diversity, 3D measures of design, 4D measures of distance to transit, 5D measures of destination accessibility, 7D to measures of social distribution.

Other indicators of accessibility, the 5th D, also affected mode choice. Longer distance from the home to the nearest grocery store (1.09, 95% CI 1.02-1.16) (“5D_Car_DistToFood”) increases likelihood of active travel, but this relationship does not hold for the work environment. It is likely that grocery stores are far away in more rural areas, which encourages car trips for some purposes, but also walking and cycling for others (such as greater road safety, or more pleasant surroundings). Contradictory effects such as this one require a more detailed analysis of possible interaction effects, and will be explored in more detail in Section 4.4. The time taken by public transit to reach the city centre (0.91, 95% CI 0.85-0.97) (“5D_PT_TimeToCentre”) from the work location was significant as well. Worse connectivity between points of interest reduce the use of active transport modes, and encourage the use of inactive travel modes.

A higher number of service lines from the nearest transit stop decrease likelihood of walking or cycling at work location (0.88, 95% CI 0.84-0.92) (“5D_TransitLines”) but not home location, which is likely due to the greater odds of using public transportation for commuting to and from work and other highly repetitive trips. Other accessibility measures, denoted with “5D_” in Figure 3, were not strongly associated with active travel.

Within the original 3Ds of built environment (density, diversity, design, Cervero and Kockelman (1997)), density and diversity were most influential. Higher building density (“1D_BuildDensity”) increases the likelihood of active travel (1.12, 95% CI 1.05-1.19 for work and 1.24, 95% CI 1.15-1.3 for home locations). This is in line with expectations and past research, as higher density of possible origin and destination points for trips makes walking and/or cycling more convenient relative to the time and financial cost of public transport or car driving. Conversely, higher provision of similar services/shops (service density, “2D_ServiceDensity”), an indicator of an area that is economically more specialised (e.g. shopping malls, industrial parks), reduces the likelihood of active travel. Within the 3rd D, design, bike lane density had a small but significant effect on increasing active travel. This might be due a general underprovision of cycle lanes, their inaccessibility when they

do exist, as well as the fact that cycle lanes do not directly help increase walking. Higher street density, which implies a higher number of intersections and therefore faster access to a destination, also significantly increased the chance of an active mode trip, more so for the home location (1.12, 95% CI 1.06-1.19) than the work location (1.02, 95% CI 0.96-1.08).

In the social distribution construct, the 7th D, only average income levels in the area (“7D.Income”) are significant for both locations. For both work and home locations, a standard deviation increase in the income levels decreases the odds of a trip being taken by active mode (0.88, 95% CI 0.80-0.97 and 0.84, 95% CI 0.76-0.92, respectively). The “6D_” demand management variables did not include enough variation to offer a realistic insight into their effects, and were dropped for the parsimonious models.

4.4 The meso level

The macro and micro level models were combined, and a backwards stepwise regression was conducted to eliminate the least influential variables. The model was then stratified by trip purpose, in order to elicit whether different built environment and psychosocial variables impact decisions to travel differently depending on the reason for the trip. The most influential variables are presented in Figure 4, and full results can be found in Appendix C.3.

Figure 4 shows the most important influences on active travel mode choice when all three levels - the macro, meso, and micro - are considered together. Macro level influences vary by trip purpose, as each type of trip has distinct qualities. Work trips are highly repetitive, easily automated, and often timing-specific. Service trips, on the other hand, are often more flexible in terms of timing, but also require more flexibility, something a car may offer. In line with this hypothesis, car access slightly lowers the likelihood of using a car for service trips in this study. Leisure trips are even more flexible, and are likely to occur at different times of the day/week relative to the other trips. Being older is associated with higher odds of travelling actively for leisure (1.10, 95% CI 1.01-1.19 within the home environment model). This may be due to a sorting effect that occurs with age, as travelling further for recreation

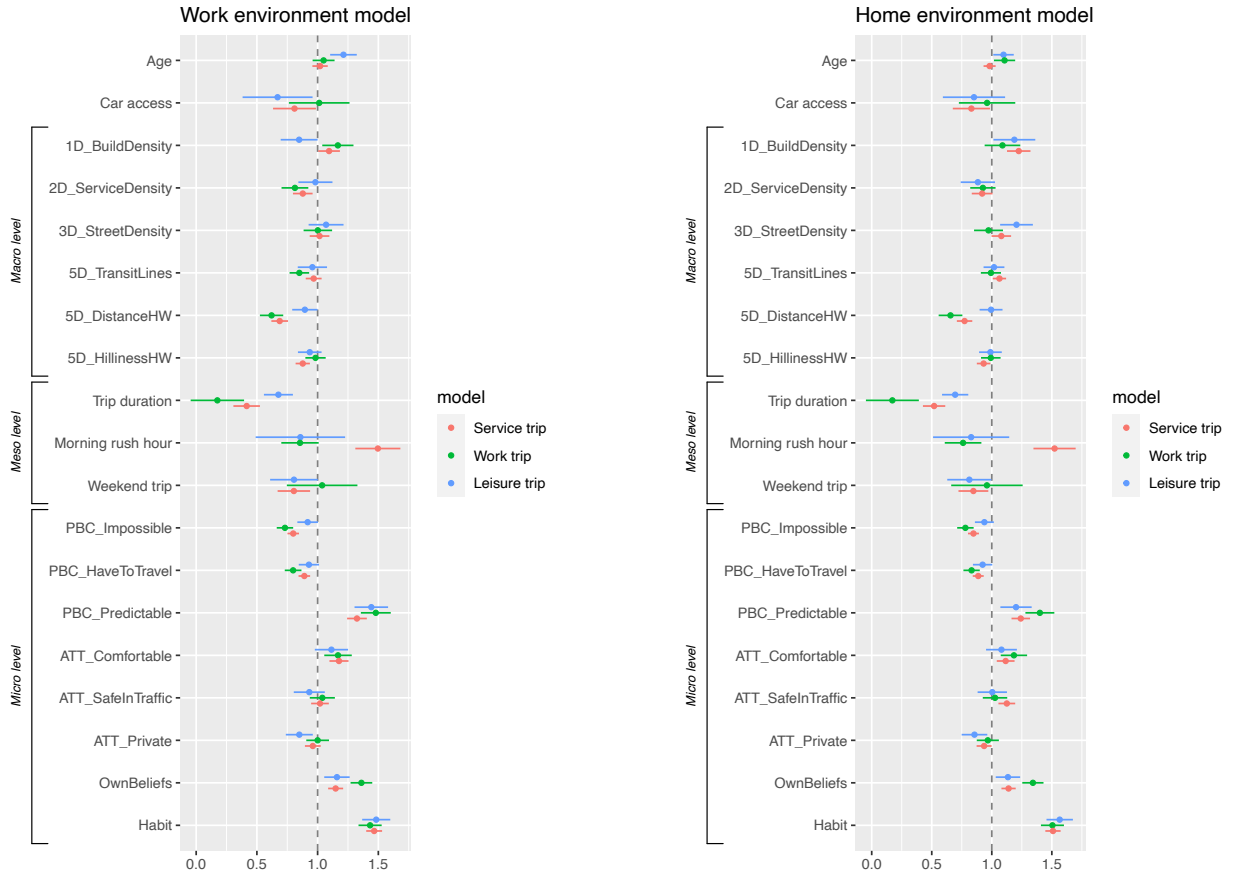


Figure 4: Correlates of an actively travelled trip by trip purpose, both at home and work locations and trip attributes. Coefficients presented as odds ratios. Distances or Time to a location are taken to be from the respondent's home or work location to the nearest point of interest identified in OpenStreetMap. HW refers to Home to Work. 1D refers to measures of density, 2D measures of diversity, 3D measures of design, 4D measures of distance to transit, 5D measures of destination accessibility, 7D to measures of social distribution; PBC refers to the perceived behavioural construct within TPB; ATT refers to the attitudes construct within TPB; the final two variables are measures within the eTPB.

becomes less attractive.

When separated out by trip purpose, no built environment variable influenced mode choice significantly for all three trip purpose categories. As expected, longer trip duration reduced the likelihood of walking and cycling for all trip purposes. The distance between home and work locations (“5D.DistanceHW”) remains highly significant for work and service trips. Leisure trips, trips conducted for fun or recreation, are far less influenced by the work built environment. This is likely because leisure trips start at home, not at work. Most other accessibility indicators within the 5th D do not remain significant once trip purpose is accounted for, apart from the number of different public transport lines that service the immediate area, which is a proxy indicator for access to a diverse set of destinations. When meso and micro level attributes are taken into account, the importance of accessibility to specific destinations diminishes.

Meso level trip-specific attributes and trip purpose have a larger influence on the decision to walk or cycle than the macro-level built and social environments do. Taking a trip during the morning rush hour, between 7am and 10am (“Morning rush hour”), does not consistently influence the mode choice for work or leisure trips, but it does significantly increase the likelihood of walking and cycling if the purpose of the trip is service - for personal business, errands, or dropping off or picking up someone (1.52, 95% CI 1.28-1.82 for the home environment model). This is likely done to avoid sitting in congestion for a trip whose timing is flexible. However, if a service trip was made during a weekend, e.g. for a large weekly shop, it was less likely to be taken by active mode (0.85, 95% CI 0.75-0.96 for the home environment model).

Unlike the macro and meso level influences, micro level influences, specifically attitudes and perceived behavioural control, influenced all trips in a similar way. The influence of psychosocial variables is thus more consistent than that of the built environment or trip attributes, whose importance varies by trip purpose. the micro level were habit (“Habit”), the strength of own beliefs that oblige people to walk to cycle (“OwnBeliefs”), and the degree

to which walking or cycling for travel was considered predictable (“PBC_Predictable”). The strongest predictor that increased the likelihood of walking and cycling was habit (1.57, 95% CI 1.41-1.76 for the home environment model for leisure trips).

4.5 Variations by city

Finally, this study estimates whether the influence of each of these factors varies significantly by city. This was done in order to determine whether each of the seven cities has a unique culture and built environment, or whether certain attributes and preferences are common to all seven of the cities. It also takes into account the correlation of responses from the same city, and that this was an incomplete selection of cities out of all possible cities. Visual results are available in Appendix C.4. This analysis largely confirmed the results in previous sections, thereby providing evidence that these results are generalisable to other urban areas in Europe. Antwerp had the highest prevalence of active travel of the sample (23% of the modal share is walking, 20% cycling), so it was chosen as the reference city. Overall, micro level constructs do not vary significantly by city. Being female resulted in slightly less active travel than in Antwerp in all cities but Zürich. Habit was a slightly stronger predictor of active travel in all cities but Vienna, when compared to the influence habit had in Antwerp. Compared to people in Antwerp, those in other cities who expressed a strong sense of conviction that it is impossible for them to walk or cycle more, were nonetheless more likely to cycle or walk than people in Antwerp. These results imply that in most cities with moderate levels of walking and cycling, attitudes and self-identity influence active travel in similar ways. In a city such as Antwerp, where active travel is better established, the ability of eTPB constructs to determine (active) travel mode choice might be lower, as mode choice starts to be determined by perceived control and trip purpose, rather than attitudes and beliefs.

5 Discussion

5.1 Summary of results

The PASTA study collected information on respondents' sociodemographics, attitudes, travel habits and activity data, and the built environment they are most exposed to at home and work locations. The aim of this paper was to identify the most significant correlates of active travel behaviour in the seven PASTA cities, helping identify policy levers in transport. Using a socio-ecological framework that combined the extended theory of planned behaviour at the micro level, the concept of 7Ds at the macro level, and specific trip attributes at the meso level, the following order of influence on mode choice of the different levels of the socio-ecological framework was identified.

This study found that psychosocial constructs influence mode choice most significantly within the PASTA study dataset, relative to the built environment, and variations due to trip purpose. Within the micro level and the theory of planned behaviour, habit and past behaviour, followed by the construct of perceived behaviour control have the strongest influence on whether or not a trip will be taken by active mode. Attitudes and constructs from the extended TPB also matter, but subjective norm constructs are not significantly associated with daily travel. Interestingly, the intent to carry out a behaviour and the action itself are associated with different variables; for example, whether a mode is perceived as being predictable does not influence the intention to travel actively by a large amount, but it does significantly increase the likelihood of actually travelling actively.

Within the meso level, the morning rush hour mostly affects the decision to take service (personal business, visiting friends) trips by active travel mode. This is followed by whether the trip is done on a weekday or weekend, which reduces time constraints and improves predictability of all private modes of transport.

Within the macro level, the built environment influences active travel only marginally, and the distance travelled is the greatest determinant of transport mode choice. This does

not vary significantly by work or home location, or city. Accessibility, measured as the time/distance to the nearest amenity, was the second most important, followed by building density. Diversity, and street network design, did not have a consistent effect on mode choice. The socio-demographic distribution of an individual's neighbourhood is relevant to mode choice, and higher income in the area was significantly associated with active travel. Practices, the natural environment, and the policy environment were not included in the statistical analyses, though they all may play a significant role in active travel mode choice.

5.2 Comparison with previous studies

In their meta-analysis of 58 studies, Lanzini and Khan (2017) find that psychological variables, particularly habits and intentions, consistently predict mode choice. They also find that although environmental variables predict intention, they do not predict actual mode choice, forming a “deep intention behaviour gap”. The findings in this study support those of the meta-analysis, with habits having the strongest association with choosing to cycle or walk, followed by most of the psychosocial variables, and the built environment having a smaller role to play in travel mode choice.

This study also finds strong support for the relevance of using theory of planned behaviour constructs in determining travel attitudes and behaviour, and the relevance of the micro level in general. Bird et al. (2018) evaluated the relevance of using extended TPB constructs as predictors of behaviour change (walking) in the iConnect study, finding that habits, attitudes and perceived behavioural control do predict time spent walking for travel. Similarly, this study found that perceived control over a behaviour explained (marginally) more of the variation in trip mode choice than attitudes (McFadden's pseudo- R^2 0.11 vs 0.09), and almost double the variance that subjective norms did (McFadden's pseudo- R^2 0.05). This contrasts the findings of Lois et al. (2015), who find that attitudes and subjective norms explain far more of the variation in bicycle commuting than self-efficacy did (their name for perceived control).

Similarly to Heinen et al. (2011) and De Souza et al. (2014), this study finds that higher perceived safety in traffic is positively associated with the decision to travel by active mode. Health benefits of exercise are commonly cited as the main reasons for active travel, in particular cycling (Useche et al., 2019; Börjesson and Eliasson, 2012). Results in this study suggest that this benefit is the motivation why people decide to travel more actively in general (intention), but does not determine day-to-day mode choice decisions (actual behaviour). Whitmarsh and O'Neill (2010) and Fekadu and Kraft (2001) find that self-identity is more important than other TPB factors in determining carbon off-setting behaviours, and this study also finds that self-identity was consistently a strong predictor of active travel. However, this could also be due to the self-selection of people interested in active travel, health, and the environment into the PASTA study, and so should not be extrapolated to the general population.

As Lanzini and Khan (2017) have identified, what often changes the findings of studies about the psychological and environmental influences of mode choice are recruitment methods and the year of study. The benefit of using PASTA data is that the project recruited respondents in a unified manner across all seven cities, over the same time period (2014-2016), ensuring that results between cities are comparable. Indeed, what this study finds is that psychosocial variables have a slightly different influence between cities, but that most influences are all in the same direction, a finding also reported in the meta-analysis by Lanzini and Khan (2017).

This study also found that psychosocial variables were differently correlated with Intention to carry out the behaviour than with actual behaviour, confirming the existence of the intention behaviour gap. This supports arguments made elsewhere (e.g. Schwanen et al. (2012), de Bruijn et al. (2009) and Verplanken et al. (1998)) about the strength of habit and practices, as opposed to conscious choices, in everyday travel behaviour. The outcome measure of interest does have a significant impact on the results of any study, and should be a topic of discussion in any policy intervention plan, as well.

Finally, at the macro level, this study tested the seven Ds: the relative importance of the work and home built environments, and social distribution. These were all measured by objectively measured variables, not subjective perceptions, as is sometimes done (Schneider, 2013; Panter et al., 2013; Adams et al., 2013). The meta-analysis of 42 studies conducted by Cerin et al. (2017) found that density and diversity of facilities, and street connectivity at small scales, have a significant effect on walking. However, consistent evidence does not exist for the effects on cycling, or total active travel. Using data from 14 cities and over 12 000 people, Christiansen et al. (2016) found highly curvi-linear effects of the built environment on cycling, with higher density, diversity and design (connectedness) being most strongly associated with active travel. Gascon et al. (2019) also identified that high-density areas with many facilities increase walking.

In line with much of previous research (e.g. in the review of studies done by Ewing and Cervero (2001)), in this study trip distance was the most significant determinant of mode choice among environmental variables. This study confirms the findings that high density increases active travel. As both lower trip distance (a proxy for trip cost) and the attitude that active travel is comfortable, increase active travel, there is an incentive for policy to work on reducing cost and increasing convenience of active mode use. This was also the conclusion of the survey of commuters in Montreal, Canada, conducted by Damant-Sirois and El-Geneidy (2015).

Ewing and Cervero (2010) also emphasised that the accessibility of destinations influences mode choice, and this study therefore included time and distance to the city centre, school, and shops from home and from work, as well as public transit frequency data. Similar to Ding and Cao (2019), here the frequency, and number of different services operating the nearest public transport stop to work, decrease the likelihood of active travel (probably through increasing public transport use), but most of the other accessibility indicators do not have a consistent and significant effect on active travel.

However, this study did not find a consistent effect for facility diversity or density, though

the meta-analysis of 62 studies conducted by Ewing and Cervero (2010) also found a strong effect of diversity on walking. Instead, this study finds a positive correlation between higher diversity of services provided around the work/study location of a respondent only when trip purpose was not taken into account. Once trip purpose is accounted for, the effect of diversity decreases.

Confirming the findings of Marquet and Miralles-Guasch (2015), this study also finds that neighbourhood income and socio-economic variables influence the decision to travel actively. In this study, the built environment played a secondary role in determining active travel.

In order to examine the meso level, the dataset was stratified by trip purpose (for work, home-related responsibilities, and leisure). Work-related trips were consistently more strongly associated with attitudes and built environment factors than home- and leisure-based trips, likely due to the repetitive nature of commuting trips. From trip attributes, trip duration is the strongest deterrent of walking or cycling, confirming findings from Yang et al. (2018) and Handy et al. (2014) and Bopp et al. (2012), among others. Perceived behavioural control constructs were most strongly associated with mode choice for work trips, exemplifying the inflexible nature of most work.⁷

Overall, this study finds support for previous research findings suggesting that attitudes matter more than the built environment (Handy et al., 2005; Cao et al., 2007; Dill et al., 2014), and that out of built environment characteristics, accessibility matters most (Ding and Cao, 2019; Keyes and Crawford-Brown, 2018).

There are strong interactions between the built environment and psychosocial influences on behaviour. Dill et al. (2014) identify that the built environment impacts behaviour indirectly through influence on attitudes and behavioural control, but that attitudes themselves have stronger predictive power on mode choice. This supports the hypothesis (presented in e.g. Joh et al. (2012) that for people with positive attitudes towards active travel, improving the built environment enhances walking and cycling more than for people with negative at-

⁷In pre-Covid 19 pandemic times.

attitudes towards active travel. Attitudes and perceptions of important factors such as travel safety, the presence of facilities, or environmental benefits vary significantly between regular cyclists' and non-cyclists (De Geus et al., 2008). For policy within the built environment, improving factors seen as “external”, e.g. perceived safety, may help improve the attitudes of non-cyclists and non-walkers, thus encouraging them to adopt these modes (Giles-Corti, 2006; Fernández-Heredia et al., 2014). In this study, attitudes influence mode choice more strongly and consistently than the built environment, and policies targetting them may be less financially intensive. Hence, it is recommended that policies target the built environment as well as people's attitudes.

5.3 Limitations of this study

This study has several limitations. The opportunistic recruitment methods of the original sample mean that PASTA respondents are not representative of the general population; the sample is younger, better educated, and regular cyclists in particular were purposefully oversampled (Gaupp-Berghausen et al., 2019). This study finds that university education increases odds of travelling actively (1.13, 95% CI 1.03-1.23 for the micro-level regression), though not when stratified by purpose or location. This is complimentary to Gascon et al. (2019), who found that higher education has a significant effect on walking for travel. The trip data collected was self-reported, rather than measured objectively, which may lead to the under-reporting of very short trips (Kohla and Meschik, 2013). All trip diaries were for one day only, so it is possible that the data is not representative. However, the large sample size increases the likelihood that the responses are normally distributed.

This study is cross-sectional, making it difficult to control for residential self-selection and rule out reverse causality observed between correlations of the built environment and travel behaviour. It also do not include questions asking people to rank why they decided to live where they did, the way e.g. Knuiman et al. (2014) have, which may have helped control for self-selection. Nonetheless, their evidence, specifically on destination accessibility, supports

our findings.

The research only applies to the European context, and is geographically limited as a result. While many attitudinal factors may be universal, such as safety concerns on roads (Davis, 2018), others may not be. Smaller towns and villages will also exhibit different travel patterns, with less diversity in terms of density, service provision, or distance from green spaces. For example in the US, where infrastructure for cyclists and pedestrians is often severely limited, this relationship may even be reversed. In West African countries, gender norms prevent the majority of women from cycling at all (Porter, 2011).

The regressions in this analysis use different dependent variables (in the case of the micro level models) or different independent variables and parts of the trip diary dataset (in the case of the meso and macro level models), which means that the odds ratios and coefficients cannot be directly compared against each other between regressions. Instead, this paper provides evidence of what is significant in a particular context only.

Information on the proportion and proximity of green and blue spaces, and noise and air pollution levels in neighbourhood areas is excluded in this analysis, as this information was not available for many respondents in the PASTA dataset and would reduce the sample size significantly. As the debate on green spaces has not been settled yet (e.g. Christiansen et al. (2016)), and noise in particular is increasingly recognised as a significant public health exposure (Basner et al., 2014), the addition of these variables would have been useful. In the future, micro-built environment factors such as road lighting, graffiti, and pedestrian traffic control should also be explored more (Cerin et al., 2017; Uttley et al., 2020; Ferrer et al., 2015).

The importance of attitudes as opposed to the built environment may be overplayed if incorrect areas were used to determine the built environment variables. 500m buffers were used in most cases, but only 300m buffers were available for land use data, meaning different buffer areas were mixed. In high density and diverse cities such as Barcelona, the 500m buffer may be too large and may not capture the minutiae of surrounding neighbourhoods

accurately. However, when sensitivity analysis with 300m buffer areas was done, similar results to the ones reported were obtained. As PASTA respondents are also more likely to be active than the general population, it is also possible that the built environment plays less of a role for PASTA participants than the general population.

In addition, transport has an impact on mental well-being and levels of distress experienced on a daily basis (St-Louis et al. (2014) and De Vos and Witlox (2017)), but this is not included in the analysis. Evidence on the relationships between mental well-being and mode of transport using the PASTA study has, however, been published by Avila-Palencia et al. (2018). Cerin et al. (2017) also find that for different groups of people, different interactions between psychosocial, health and sociodemographic factors, as well as the built environment, matter. This implies that there are subgroups of people for whom different aspects of the socio-ecological model may be most relevant, but this type of analysis was not undertaken in this study.

6 Conclusion

Active travel is influenced by a complex set of factors from policy and organisation, the built and natural environments, community and interpersonal relationships, to intrapersonal motivations, as well as the interdependencies between them (Sallis et al., 2015). This study evaluated the hypothesis that each domain of active travel is equally important in determining which mode of transport is used, with a specific focus on the relative importance of the built environment compared to the other domains (psychosocial determinants and trip-specific attributes in particular). In order to achieve this, this paper presents a socio-ecological framework that considers the multiple levels, and their interactions, that influence active travel behaviour, and applies the framework to a European setting.

Using data for 4249 respondents and over 16,000 trips from seven different European cities, this study highlights the importance of psychosocial variables in determining active

travel relative to built environment influences. Habit and perceived control over an outcome influence mode choice most significantly, although accessibility of the destination and trip distance are also highly significant, even when interacted with habit and perceived control. This study also shows the importance of considering specific trip attributes and purposes when planning interventions to increase walking and cycling, such as whether routes are accessible and used mainly for commuting and rush-hour traffic, or to reach services and recreation. If the individual and trip-specific attributes are not considered, the importance of the built environment may be overstated in some European contexts.

Although the relationships demonstrated in this study appear to be common to the seven cities studied, local context is likely to influence which factors influence active travel the most. In this regard, the socio-ecological framework is meant to serve as a guiding tool, suggesting which relationships may exist. As a health behaviour, active travel is complex, and therefore future research should, where possible, adopt a multi-level perspective on the influences of active travel.

Author Statement

Simona Sulikova: Conceptualisation, Data curation, Software, Formal Analysis, Writing - Original Draft.

Christian Brand: Supervision, Data curation, Conceptualisation, Writing - Review Editing.

Research Data

Due to the sensitive nature of the questions asked in this study survey respondents were assured raw data would remain confidential and would not be shared.

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A Case study cities

Figure A.1 shows the location of the seven PASTA case study cities.

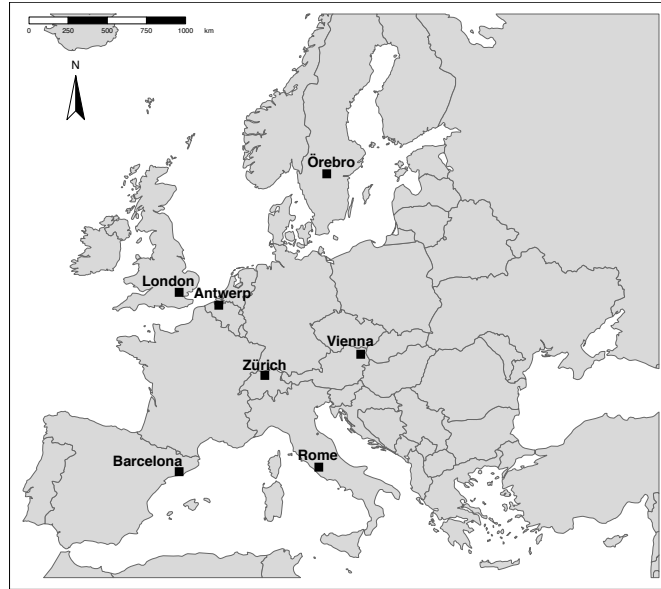


Figure A.1: Map of the seven case study cities in the PASTA study.

The cities vary by size, climate, and travel patterns. These are summarised in Table A.1.

Variable	Antwerp	Barcelona	Newnham (London)	Örebro	Rome	Vienna	Zürich
Description	Second largest city in Belgium	Second largest city in Spain	South-east London Borough, United Kingdom	Regional centre, 200km west of Stockholm, Sweden	Largest city in Italy	Largest city in Austria	Largest city in Switzer- land
Population*	510,610	1.6 million	265,688	140,000	2.9 million	1.8 million	400,000
Average monthly income per capita in EUR end 2019 ex- change rate**	3749	3117	4333	4100	2824	5120	5980
Weather							
Average annual temperature, C***	10.1	16.5	11.1	6.1	15.7	9.9	9.3
Annual rain- fall, mm***	778	612	621	633	798	623	1085
Koeppen- Geiger climate classifica- tion***	Temperate oceanic	Dry sum- mer	Temperate oceanic	Humid continental	Dry sum- mer	Humid continental	Humid continental
Mode share %							
Driving	41	26	38	55	54	27	30
Cycling	23	2	3	25	1	6	4
Public trans- port	16	40	29	9	29	39	39
Cycling net- work km (OSM)****	469.17	159.54	969.17	361.35	120.64	715.63	118.36

Table A.1: PASTA city characteristics

* From worldpopulationreview.com

** Various sources

*** from climate-data.org

**** from Mueller et al. (2018)

B Variable details

Table B.1 details how questions from the PASTA survey map onto eTPB constructs. Each statement was ranked by the respondents on a Likert-like scale with possible values from 1 to 5, the lowest value means lowest ranking or greatest disagreement. Where possible, responses from at least two different questions were averaged to create a TPB construct question. For each question on walking, a similar statement on cycling existed. Table B.2 details the macro level variables, and how they were measured. Table B.3 describes the meso level variables. Figure B.1 shows how each of the variables that appear in the main text map onto each level within the framework.

Construct	Item	Question code
Attitude		
Instrumental	“Walking for travel saves time.”	ATT_Time
	“Walking for travel is unpleasant due to high levels of air pollution.”	ATT_Airpol
	“Walking for travel is offers personal health benefits.”	ATT_Healthy
Experiential	“Walking for travel is comfortable.”	ATT_Comfortable
	“Walking for travel is safe with regards to road traffic.”	ATT_SafeInTraffic
	“Walking for travel is safe with regards to crime.”	ATT_SafeCrime
	“Walking for travel offers privacy.”	ATT_Private
Subjective norm		
Injunctive	“Most people who are important to me think that I should walk 'for travel'.”	SN_INJ
Descriptive	“In my neighbourhood walking is well regarded.”	SN_Descript
Perceived behavioural control		
Self-efficacy	“Personal circumstances make it impossible for me to walk more (e.g. family or work commitments, carrying luggage, escorting children).”	PBC_Impossible
	“I am fit enough to walk.”	PBC_Fit

Construct	Item	Question code
Controllability	“The organisation of my everyday life requires me to travel a lot.” “I have to travel all the time to meet my obligations.”	PBC_HaveToTravel
	“Walking for travel offers flexibility (e.g. with regards to departure time).”	PBC_Flexible
	“Walking for travel offers a predictable travel time.”	PBC_Predictable
	The cost of a trip by car or public transport in Euros	Trip_Cost
Extended TPB constructs		
Intention	“I intend to walk more ‘for travel’ in the future.” “My intention to walk ‘for travel’ is ... strong/weak”	Intent
Self-Identity	“I feel morally responsible to walk in order to decrease the negative effects on the environment that motorized methods of travel have.”	Morals
	“Regardless of what other people do, my own values and principles oblige me to walk ‘for travel’ whenever possible.”	OwnBeliefs
Habit	“Walking ‘for travel’ is something I do automatically without really thinking about it.”	Habit
	“I walk daily/almost daily; 1-3 days per week; 1-3 days per month; less than once per month; never.”	MettravWalk
Visibility	“In my neighbourhood it is common for people to walk ‘for travel’.”	Visible

Table B.1: PASTA survey questions and how they map onto the constructs of the extended theory of planned behaviour. The constructs follow the structure by Bird et al. (2018).

Measure	Variable
DENSITY	
Residential, 500m2	1D_ResDensity
Population, 500m2	1D_PopDensity
Building, 500m2	1D_BuildDensity
DIVERSITY	
Land use mix, 300m2	2D_ServiceDiversity
Service density, 300m2	2D_ServiceDensity
DESIGN	
Connectivity (intersection density) in 500m buffer, m/km ²	3D_Connectivity
Street density in 500m buffer, m/km ²	3D_StreetDensity
Bike lanes density in 500m buffer, m/km ²	3D_BikeLanesDensity
DISTANCE TO TRANSIT	
Distance to the nearest PT stop, in m	4D_pub_tr_dist
DESTINATION ACCESSIBILITY	
Euclidean distance from home to main work/study address	5D_DistanceHW
Height difference from home to work or study address.	5D_HillinessHW
Distance to school by car, km*	5D_Car_DistToSchool
Distance to city centre by car, km*	5D_Car_DistToCentre
Distance to nearest grocery store by car, km*	5D_Car_DistToFood
Time to school by car, km*	5D_Car_TimeToSchool
Time to city centre by car, km*	5D_Car_TimeToCentre
Time to nearest grocery store by car, km*	5D_Car_TimeToFood
Frequency of transit operation	5D_AvHeadway (also PM and AM)
Number of service lines of transit	5D_TransitLines
SOCIAL DISTRIBUTION	
Mean income in 500m buffer	7D_Income
Percentage of foreigners in 500m buffer	7D_ForeignNationals
Percentage of higher degree education in 500m buffer	7D_HighEduc
Car ownership in 500m buffer	7D_CarOwning

Table B.2: Macro level variables included in full model.

*Variables exist for car, public transport, walking, and cycling.

Measure	Variable
Duration of trip, minutes	Trip duration
Trip was taken between 7 and 10am	Morning rush hour
Whether a trip was taken on a Saturday or Sunday	Weekend trip
Trip purpose	Service /Work /Leisure

Table B.3: Meso level variables included in the full model

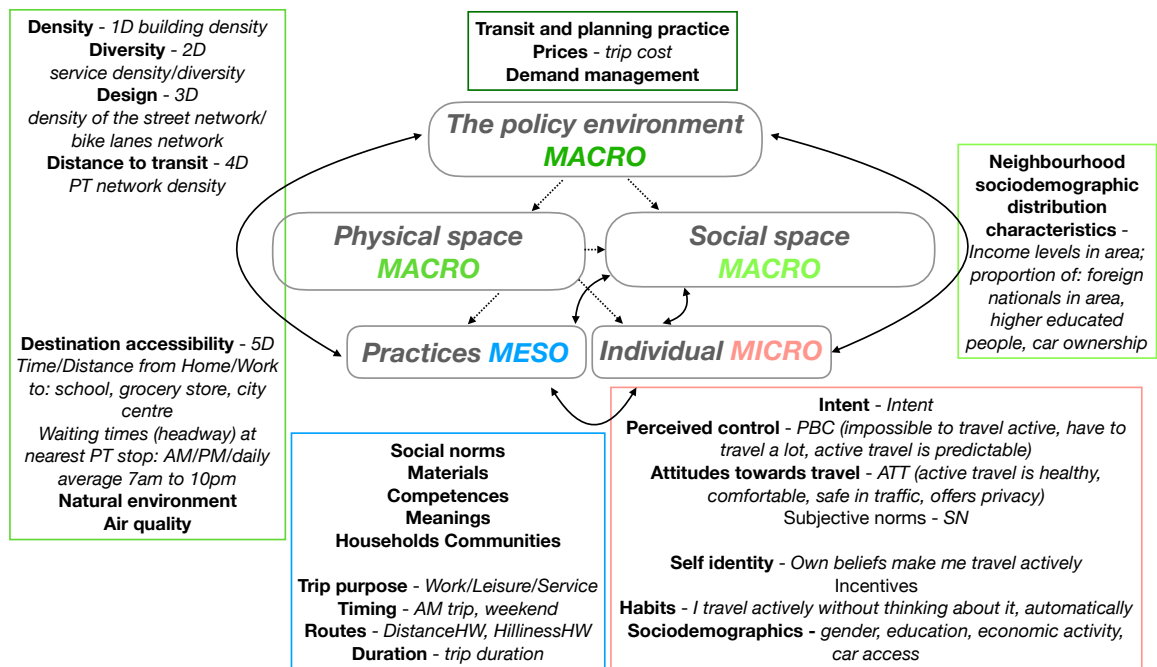


Figure B.1: Variables and how they map onto each part of the socio-ecological framework.

C Model details

This sections shows the regression results used as inputs for the graphs in the main text. Note that since they either use a different regression method (Table C.1), or different datasets (Table C.2 or C.3), so coefficients are not directly comparable.

C.1 Micro level model

Table C.1 shows the regression results for the micro level models. Model (1) is a generalised linear mixed effects negative binomial model, the dependent variable, Behaviour, a binary (0/1) variable for whether a trip was taken by active mode (1, walking or cycling) or not (0, driving or public transport). Model (2) is a linear mixed effects multiple regression model, the dependent variable, Intent, is a scalar with values from 1 to 5, 5 showing highest intention to walk or cycle in the present and future.

Table C.1: Micro level effects

	<i>Dependent variable:</i>	
	Behaviour	Intent
	(1)	(2)
Female	1.042 (0.972,1.118)	-0.035*** (-0.052,-0.018)
Age	0.997 (0.962,1.034)	-0.018*** (-0.027,-0.009)
Economically active	0.945 (0.863,1.036)	-0.039*** (-0.062,-0.017)
University degree	1.128*** (1.033,1.231)	-0.025** (-0.047,-0.004)
Car access	0.863*** (0.774,0.961)	-0.008 (-0.034,0.018)
PBC_Impossible	0.818*** (0.793,0.845)	-0.023*** (-0.030,-0.015)

Table C.1: Micro level effects

	<i>Dependent variable:</i>	
	Behaviour	Intent
	(1)	(2)
PBC_HaveToTravel	0.863*** (0.836,0.891)	0.003 (-0.005,0.010)
PBC_Predictable	1.340*** (1.267,1.418)	-0.023*** (-0.036,-0.010)
ATT_Healthy	0.995 (0.932,1.062)	0.129*** (0.114,0.144)
ATT_Comfortable	1.145*** (1.087,1.207)	0.180*** (0.167,0.192)
ATT_SafeInTraffic	1.050** (1.001,1.103)	-0.015** (-0.027,-0.003)
ATT_Private	0.941*** (0.901,0.984)	0.009* (-0.001,0.020)
OwnBeliefs	1.140*** (1.094,1.189)	0.250*** (0.240,0.260)
Visible	1.082*** (1.041,1.124)	0.027*** (0.017,0.036)
Habit	1.516*** (1.041,1.124)	0.145*** (0.134,0.155)
Trip Cost		-0.007** (-0.012,-0.001)

Table C.1: Micro level effects

	<i>Dependent variable:</i>	
	Behaviour	Intent
	(1)	(2)
Intercept	0.060*** (0.039,0.092)	1.042*** (0.872,1.212)
Akaike Inf. Crit.	19,610.740	25,112.170
Bayesian Inf. Crit.	19,741.320	25,258.120
N. of observations	16,018	16,018
<i>Note:</i>	*p<0.1; **p<0.05; ***p<0.01	

C.2 Macro level

Table C.2 shows the regression results for the macro level models. All models are generalised linear mixed effects negative binomial models, the dependent variable, Behaviour, a binary (0/1) variable for whether a trip was taken by active mode (1, walking or cycling) or not (0, driving or public transport). Model (1) uses work- or study-place built environment variables as independent variables, Model (2) uses home-address built environment variables as independent variables.

Table C.2: Macro level effects

	<i>Dependent variable:</i>	
	Work env.	Home env.
	(1)	(2)
Female	0.931** (0.869,0.997)	0.821*** (0.767,0.878)
Age	1.040* (0.997,1.084)	0.997 (0.963,1.033)
Economically active	1.008 (0.866,1.174)	1.092* (0.997,1.195)
Car access	0.837*** (0.747,0.938)	0.893** (0.804,0.992)
University degree	1.139*** (1.043,1.243)	1.119** (1.027,1.219)
1D Building density	1.115*** (1.047,1.187)	1.242*** (1.154,1.336)
2D Service diversity	1.118*** (1.038,1.204)	1.020 (0.954,1.091)
2D Service density	0.921*** (0.872,0.971)	0.904*** (0.857,0.953)

Table C.2: Macro level effects

	<i>Dependent variable:</i>	
	Work env.	Home env.
	(1)	(2)
3D Bikelane density	1.037 (0.987,1.090)	1.049** (1.004,1.097)
3D Street density	1.021 (0.963,1.081)	1.122*** (1.057,1.192)
4D PT density	0.989 (0.946,1.035)	1.024 (0.976,1.075)
5D Distance HW	0.531*** (0.504,0.561)	0.677*** (0.644,0.712)
5D Hilliness HW	0.864*** (0.828,0.901)	0.955** (0.917,0.994)
5D PT time to centre	0.912** (0.843,0.987)	0.908*** (0.851,0.968)
5D Car time to school	1.010** (1.001,1.018)	0.990*** (0.984,0.996)
5D PT distance to centre	1.046 (0.970,1.128)	1.077*** (1.021,1.136)
5D Car time to centre	0.966 (0.889,1.049)	0.930 (0.852,1.015)
5D Car distance to grocery store	1.052 (0.979,1.130)	1.085** (1.017,1.158)

Table C.2: Macro level effects

	<i>Dependent variable:</i>	
	Work env.	Home env.
	(1)	(2)
5D Average waiting time	0.974 (0.918,1.034)	0.979 (0.937,1.022)
5D Afternoon waiting time	0.979 (0.941,1.018)	1.029 (0.984,1.077)
5D Morning waiting time	0.973 (0.920,1.029)	1.013 (0.976,1.050)
5D No. of transit lines	0.877*** (0.840,0.915)	0.987 (0.951,1.025)
7D Income in area	0.882** (0.801,0.971)	0.837*** (0.759,0.922)
7D Foreign nat. in area	0.915** (0.844,0.992)	1.029 (0.961,1.101)
7D Higher education in area	0.987 (0.929,1.050)	1.017*** (1.012,1.022)
7D Car ownership in area	0.897*** (0.834,0.965)	0.970 (0.913,1.030)
Akaike Inf. Crit.	19,779.750	20,508.430
Bayesian Inf. Crit.	19,994.020	20,723.420
N. of observations	15,563	15,563

Note:

*p<0.1; **p<0.05; ***p<0.01

C.3 Meso level

C.3.1 Home environment

Table C.3 shows the regression results for the meso level model in the home environment. All models are generalised linear mixed effects negative binomial models, the dependent variable, Behaviour, a binary (0/1) variable for whether a trip was taken by active mode (1, walking or cycling) or not (0, driving or public transport). Model (1) uses independent variables for a subset of trip data whose purpose was travel to work or study, Model (2) uses independent variables for a subset of trip data whose purpose was travel for leisure, Model (3) uses independent variables for a subset of trip data whose purpose was travel for administrative purposes, shopping, or other service-type trips. All three models use only home-address built environment variables as independent variables.

Table C.3: Meso level effects

	<i>Home environment, trip type:</i>		
	Work	Leisure	Service
	(1)	(2)	(3)
Female	1.019 (0.877,1.184)	1.063 (0.896,1.262)	0.948 (0.858,1.048)
Age	1.103** (1.009,1.205)	1.096** (1.006,1.193)	0.980 (0.932,1.031)
Economically active	0.940 (0.743,1.19)	1.075 (0.873,1.325)	1.021 (0.899,1.159)
Car access	0.958 (0.758,1.212)	0.849 (0.655,1.1)	0.828** (0.709,0.966)
University degree	0.976 (0.81,1.176)	1.015 (0.813,1.268)	1.007 (0.89,1.14)
1D Building density	1.092 (0.942,1.267)	1.189* (0.999,1.415)	1.240*** (1.125,1.366)
2D Service density	0.926	0.884*	0.921*

Table C.3: Meso level effects

	<i>Home environment, trip type:</i>		
	Work	Leisure	Service
	(1)	(2)	(3)
	(0.834,1.029)	(0.766,1.02)	(0.844,1.004)
2D Service diversity	1.020 (0.885,1.175)	1.035 (0.879,1.219)	1.071 (0.971,1.181)
3D Street density	0.975 (0.864,1.1)	1.209*** (1.055,1.385)	1.084* (0.999,1.177)
5D No. of transit lines	0.994 (0.914,1.08)	1.019 (0.934,1.111)	1.063** (1.006,1.124)
5D Afternoon waiting time	1.003 (0.93,1.082)	1.090* (0.991,1.198)	0.996 (0.945,1.051)
5D Distance HW	0.652*** (0.59,0.719)	0.991 (0.901,1.09)	0.768*** (0.72,0.819)
5D PT distance to centre	1.046 (0.972,1.127)	1.029 (0.967,1.095)	0.985 (0.919,1.057)
5D Hilliness HW	0.990 (0.913,1.074)	0.986 (0.898,1.084)	0.928*** (0.877,0.982)
7D Income in area	0.968 (0.806,1.163)	1.002 (0.878,1.143)	0.934 (0.818,1.066)
7D Higher education in area	1.011** (1.002,1.021)	1.014*** (1.005,1.024)	1.013*** (1.006,1.019)
Trip duration	0.172*** (0.138,0.215)	0.695*** (0.623,0.776)	0.521*** (0.474,0.571)

Table C.3: Meso level effects

	<i>Home environment, trip type:</i>		
	Work	Leisure	Service
	(1)	(2)	(3)
Morning rush hour	0.764*** (0.656,0.89)	0.823 (0.6,1.13)	1.519*** (1.275,1.811)
Weekend trip	0.962 (0.715,1.296)	0.815** (0.678,0.979)	0.848*** (0.749,0.96)
PBC_Impossible	0.782*** (0.73,0.837)	0.939 (0.868,1.016)	0.845*** (0.808,0.884)
PBC_HaveToTravel	0.831*** (0.776,0.889)	0.923* (0.852,1.001)	0.887*** (0.848,0.929)
PBC_Predictable	1.405*** (1.245,1.585)	1.204*** (1.057,1.372)	1.241*** (1.148,1.34)
ATT_Comfortable	1.184*** (1.06,1.321)	1.082 (0.952,1.23)	1.116*** (1.036,1.202)
ATT_SafeInTraffic	1.025 (0.925,1.135)	1.001 (0.886,1.132)	1.124*** (1.048,1.205)
ATT_Private	0.968 (0.883,1.061)	0.856*** (0.77,0.953)	0.936** (0.879,0.996)
OwnBeliefs	1.337*** (1.224,1.46)	1.130** (1.021,1.25)	1.138*** (1.073,1.208)
Visible	0.978 (0.899,1.065)	1.076 (0.976,1.187)	0.982 (0.929,1.039)

Table C.3: Meso level effects

	<i>Home environment, trip type:</i>		
	Work	Leisure	Service
	(1)	(2)	(3)
Habit	1.513*** (1.375,1.666)	1.574*** (1.41,1.757)	1.510*** (1.417,1.609)
Intercept	0.031*** (0.013,0.076)	0.085*** (0.036,0.203)	0.073*** (0.042,0.128)
Akaike Inf. Crit.	4,689.499	3,338.618	10,020.550
Bayesian Inf. Crit.	4,882.526	3,515.448	10,232.620
N. of observations	4,602	2,682	8,684

Note:

*p<0.1; **p<0.05; ***p<0.01

C.3.2 Work environment

Table C.4 shows the regression results for the meso level model in the work environment. All models are generalised linear mixed effects negative binomial models, the dependent variable, Behaviour, a binary (0/1) variable for whether a trip was taken by active mode (1, walking or cycling) or not (0, driving or public transport). Model (1) uses independent variables for a subset of trip data whose purpose was travel to work or study, Model (2) uses independent variables for a subset of trip data whose purpose was travel for leisure, Model (3) uses independent variables for a subset of trip data whose purpose was travel for administrative purposes, shopping, or other service-type trips. All three models use only work- or study-place built environment variables as independent variables.

Table C.4: Meso level effects

	<i>Work environment, trip type:</i>		
	Work	Leisure	Service
	(1)	(2)	(3)
Female	1.061 (0.912,1.235)	1.141 (0.954,1.366)	0.991 (0.892,1.101)
Age	1.05 (0.959,1.149)	1.214*** (1.088,1.355)	1.019 (0.957,1.086)
Economically active	1.07 (0.82,1.396)	0.971 (0.717,1.313)	0.972 (0.814,1.161)
Car access	1.014 (0.79,1.302)	0.673*** (0.504,0.897)	0.81** (0.679,0.966)
University degree	0.869 (0.72,1.048)	0.919 (0.725,1.164)	0.979 (0.859,1.117)
1D Building density	1.166 (1.025,1.326)	0.851 (0.731,0.991)	1.098 (1.005,1.201)
2D Service density	0.814*** (0.729,0.909)	0.984 (0.855,1.132)	0.879*** (0.811,0.953)

Table C.4: Meso level effects

	<i>Work environment, trip type:</i>		
	Work	Leisure	Service
	(1)	(2)	(3)
2D Service diversity	1.094 (0.937,1.278)	1.089 (0.914,1.299)	1.076 (0.966,1.198)
3D Street density	1.004 (0.893,1.129)	1.08 (0.935,1.247)	1.021 (0.941,1.107)
5D No. of transit lines	0.851*** (0.785,0.923)	0.957 (0.848,1.08)	0.969 (0.907,1.034)
5D Afternoon waiting time	0.976 (0.908,1.05)	1.024 (0.908,1.156)	0.979 (0.926,1.035)
5D Distance HW	0.625*** (0.567,0.689)	0.877** (0.786,0.978)	0.683*** (0.637,0.732)
5D PT distance to centre	0.935 (0.849,1.029)	1.047 (0.944,1.161)	1.01 (0.948,1.076)
5D Hilliness HW	0.982 (0.903,1.068)	0.945 (0.856,1.043)	0.879*** (0.829,0.933)
7D Income in area	0.963 (0.798,1.161)	1.002 (0.869,1.155)	0.898* (0.791,1.02)
7D Higher education in area	0.961 (0.851,1.085)	1.017 (0.892,1.159)	0.986 (0.908,1.072)
Trip duration	0.174*** (0.14,0.217)	0.676*** (0.6,0.762)	0.416*** (0.373,0.464)

Table C.4: Meso level effects

	<i>Work environment, trip type:</i>		
	Work	Leisure	Service
	(1)	(2)	(3)
Morning rush hour	-0.158** (0.732,0.996)	-0.155 (0.593,1.238)	0.403*** (1.243,1.801)
Weekend trip	0.854 (0.779,1.393)	0.857** (0.661,0.979)	1.496*** (0.704,0.92)
PBC_Impossible	1.042*** (0.684,0.783)	0.805* (0.845,1.001)	0.804*** (0.763,0.839)
PBC_HaveToTravel	0.732*** (0.745,0.855)	0.92* (0.854,1.009)	0.8*** (0.849,0.934)
PBC_Predictable	1.478*** (1.307,1.672)	1.44*** (1.254,1.654)	1.324*** (1.221,1.436)
ATT_Comfortable	1.17*** (1.044,1.31)	1.109 (0.967,1.272)	1.176*** (1.087,1.272)
ATT_SafeInTraffic	1.04 (0.938,1.153)	0.933*** (0.821,1.06)	1.02 (0.949,1.097)
ATT_Private	0.998 (0.909,1.096)	0.849 (0.76,0.949)	0.959 (0.899,1.023)
OwnBeliefs	1.362*** (1.246,1.49)	1.159*** (1.043,1.286)	1.149*** (1.08,1.222)
Visible	0.948 (0.87,1.031)	1.234*** (1.115,1.365)	1.083*** (1.022,1.148)
Habit	1.432***	1.488***	1.466***

Table C.4: Meso level effects

	<i>Work environment, trip type:</i>		
	Work	Leisure	Service
	(1)	(2)	(3)
	(1.302,1.575)	(1.325,1.67)	(1.373,1.565)
Intercept	0.041*** (0.016,0.1)	0.067*** (0.026,0.173)	0.068*** (0.039,0.12)
Akaike Inf. Crit.	4,704.744	3,069.722	9,155.963
Bayesian Inf. Crit.	4,899.482	3,244.069	9,366.400
N. of observations	4,602	2,682	8,684
<i>Note:</i>		*p<0.1; **p<0.05; ***p<0.01	

C.4 City specific effects

This section shows variation in micro and macro level variables by city, in graphic form for easier understanding. Antwerp has the highest rates of active travel, and therefore may be slightly different to the other 6 cities.

C.4.1 Micro level effects

Micro level constructs do not vary significantly between the 6 cities.

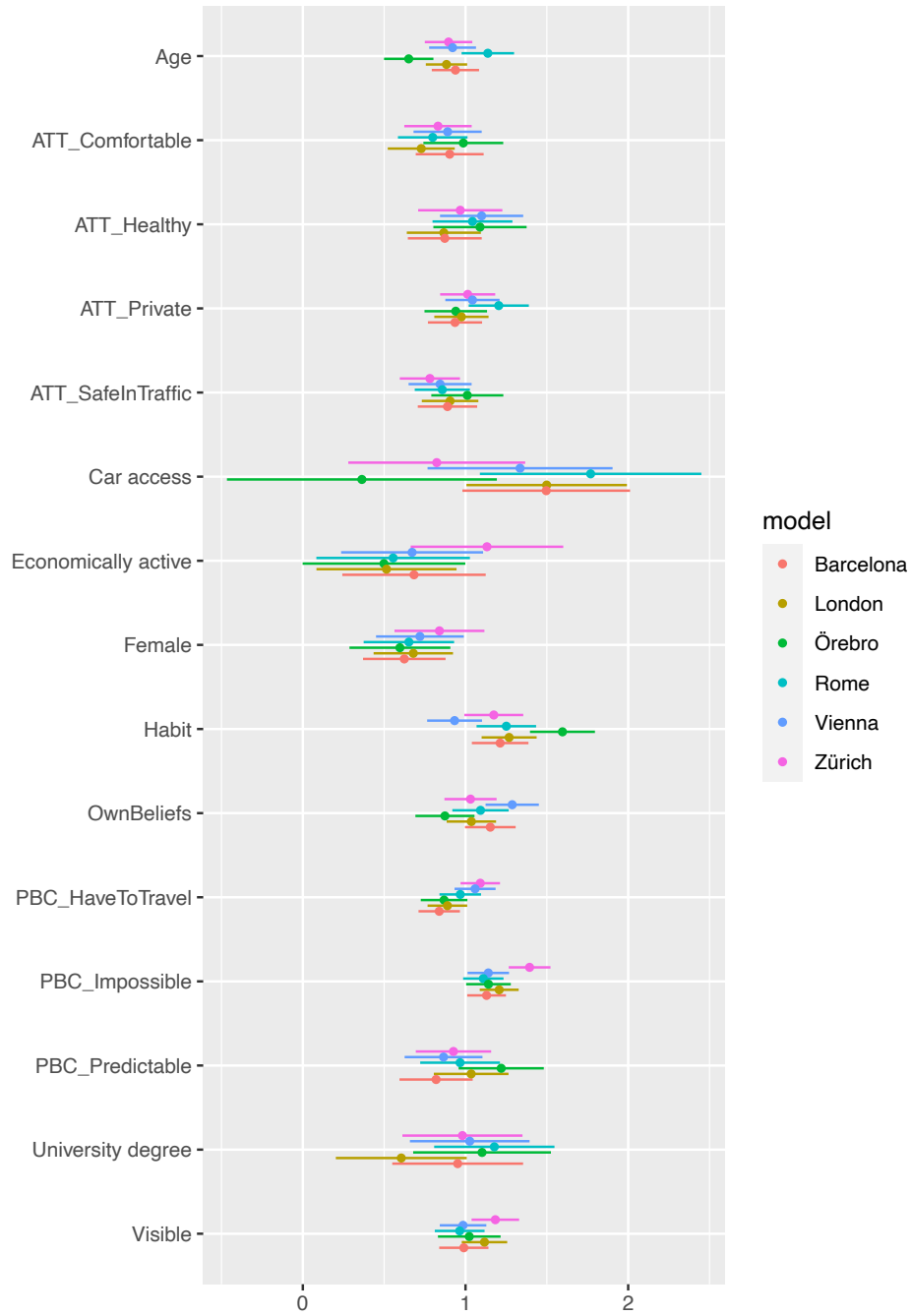


Figure C.1: City-level effects for micro level variables. Antwerp, with the highest active travel rates, is the reference city. Variations away from the average in Antwerp are shown in the graph. Age, being female, economically active, having a higher education and access to a car are sociodemographic control variables; PBC_ variables belong to the TPB construct of perceived behavioural control, ATT_ variables belong to the attitudes construct; OwnBeliefs, Visible, and Habit are part of eTPB.

C.4.2 Macro level effects

Largest variation between cities is within the destination accessibility construct of the macro level, in particular with regards to public transport accessibility and level of service. Although this study did not evaluate public transport use directly, research does exist suggesting that increased public transport access may increase both walking and cycling rates (e.g. Kager et al. (2016) and Dalton et al. (2013)), but this research is not conclusive.

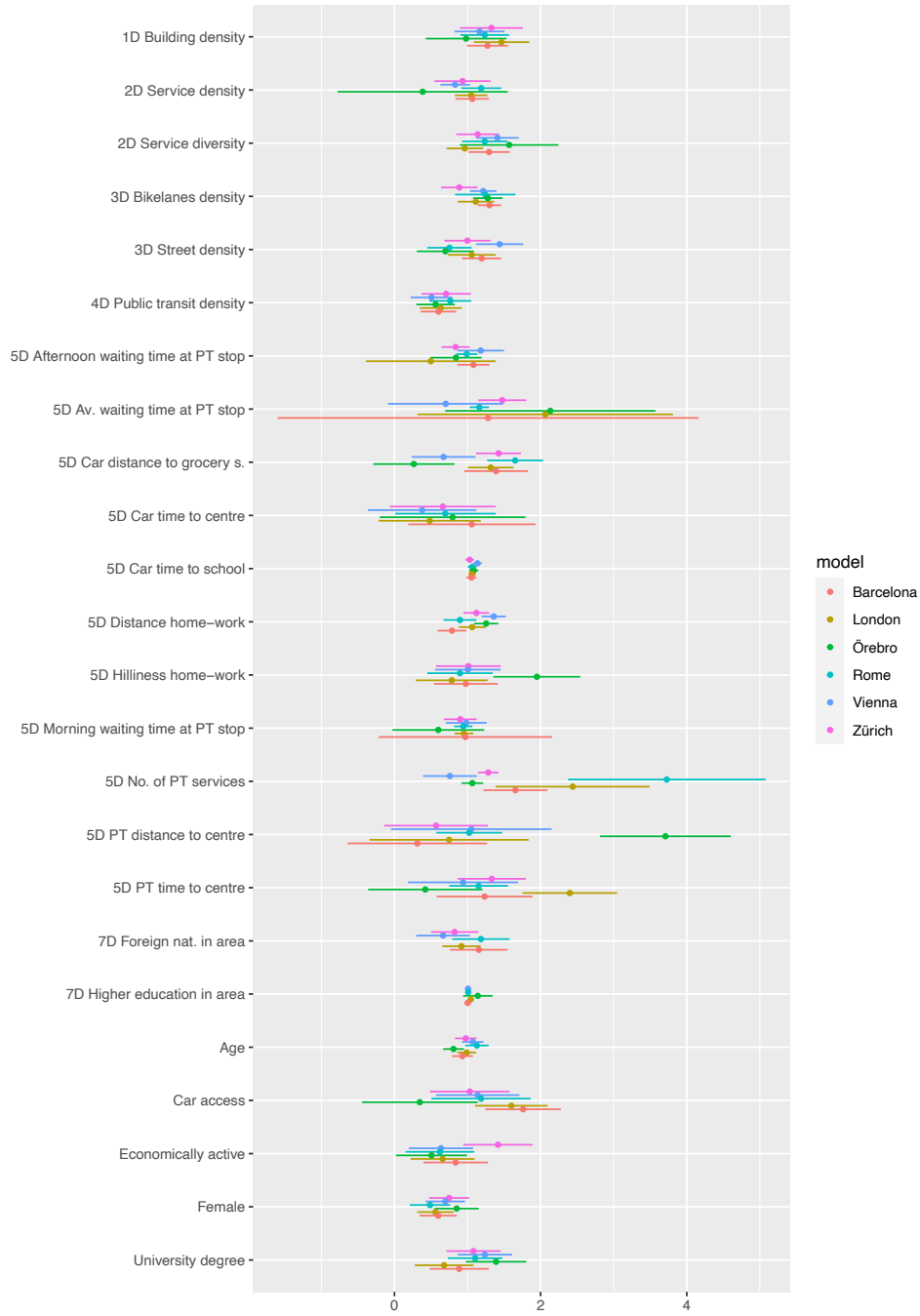


Figure C.2: City-level effects for macro level variables. Coefficients presented as odds ratios. Distances or Time to a location are taken to be from the respondent's home or work location to the nearest point of interest identified in OpenStreetMap. HW refers to Home to Work. The last five variables are sociodemographic control variables; 1D refers to measures of density, 2D measures of diversity, 3D measures of design, 4D measures of distance to transit, 5D measures of destination accessibility, 7D to measures of social distribution.