I, Obi Thompson Sargoni, confirm that the work presented in this thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.
Abstract

Sustainable transport planning highlights the importance of walking to low-carbon and healthy urban transport systems. Studies have identified multiple ways in which vehicle traffic can negatively impact pedestrians and inhibit walking intentions. However, pedestrian-vehicle interactions are underrepresented in models of pedestrian mobility. This omission limits the ability of transport simulations to support pedestrian-centric street design. Pedestrian navigation decisions take place simultaneously at multiple spatial scales. Yet most models of pedestrian behaviour focus either on local physical interactions or optimisation of routes across a road network. This thesis presents a novel hierarchical pedestrian route choice framework that integrates dynamic, perceptual decisions at the street level with abstract, network based decisions at the neighbourhood level. The framework is based on Construal Level Theory which states that decision makers construe decisions based on their psychological distance from the object of the decision. The route choice framework is implemented in a spatial agent-based simulation in which pedestrian and vehicle agents complete trips in an urban environment. Global sensitivity analysis is used to explore the behaviour produced by the multi-scale pedestrian route choice model. Finally, simulation experiments are used to explore the impacts of restrictions to pedestrian movement. The results demonstrate the potential insights that can be gained by linking street scale movement and interactions with neighbourhood level mobility patterns.
Impact Statement

The interdisciplinary research presented in this thesis is expected to be impactful across multiple academic domains. The development of a multi-scale model of pedestrian movement has involved synthesising research in the fields of psychology, spatial cognition, transport geography and transport planning, and science and technology studies. The methods employed and developed in this research are prominent in the spatial data science and quantitative geography fields; namely agent-based modelling, geocomputation, sensitivity analysis, and statistical hypothesis testing. This synthesis of fields creates opportunities for impact by identifying and exploiting the knowledge produced within each domain to better understand human behaviour in cities.

Specifically, this work proposes a novel method for simulating pedestrian movement in cities, based on a multi-scale route choice model. This method is directly relevant to transport planning and urban design. More granular and accurate models of pedestrian movement can help anticipate and predict the effects of interventions to urban traffic systems. The model presented in this work focuses on pedestrian road crossing behaviour and is therefore directly relevant designing road crossing infrastructure. Both academia and industry address issues around pedestrian safety, accessibility, and pedestrian-vehicle interactions and so this work can be expected to have impact across both sectors. One key motivation for this work is the development of autonomous vehicles. This technology has motivated much research into street level pedestrian behaviour, which this thesis contributes to. Detecting and anticipating pedestrian behaviour is considered by some to be a crucial challenge in the development of this technology. The granularity and scale of the
simulation of pedestrian movement presented in this thesis could be impactful in this area by improving the representation of pedestrian behaviour in simulations used to develop and test autonomous vehicles.

Pedestrian movement is simulated in three road network environments representing an unplanned European city (London) and grid based planned cities (characteristic of North American planning). Additionally, the related research discussed through the thesis is predominantly western European or North American in its origin and framing. As such the impact of this work is likely to be most direct in these geographies. However, by attempting to model human decision making, the work could have relevance in other regions.

These impacts will be achieved through the dissemination of this research as a thesis and in conference and journal publications. One conference publication and one journal publication based on the work presented here are already available.
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   Chapter 3: Modelling framework
This publication includes Figure 3.1 presented in this chapter and an abridged discussion of the framework.

Chapter 4: Upper level route choice

This paper presents the same upper-level route choice model presented in Chapter 5. The supplementary material for the paper includes figures presented in this chapter.

Chapter 5: Lower-level route choice

This paper presented the integration between upper and lower level route choice presented in this chapter.

Chapter 6: Verifying multi-scale pedestrian route choice

The experimental design used in this chapter is the same as the design used in the paper. However, the thesis uses a different parameter range for the vehicle number parameter $N_V$, which produces different results.

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   Obi Thompson Sargoni collected the data, performed the analysis, produced the figures

4. In which chapter(s) of your thesis can this material be found?

   Chapter 4: Upper level route choice

   The analysis and figures showing the coverage of OSM footways data were originally produced for a poster at the GISRUK 2021 conference

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Chapter 1

Introduction

The movement of people and vehicles on urban roads is coordinated though an intricate mix of factors spanning physical infrastructure, laws, social norms, and communication. The resulting behaviour of road users is diverse and multi-faceted. It is also subject to change. The history of the automobile provides a rich case study of the potential for new technologies to motivate broader societal change. As well as these changes being evident in post-war suburban development and out-of-town shopping centres, they are evident in the behaviour of road users. In the UK and elsewhere new infrastructure such as traffic lights and road crossings were developed to help coordinate pedestrians’ and vehicles’ shared use of the carriageway. Public information campaigns taught children how to cross the road and established new norms regarding safety and responsibility.

Two concurrent trends are motivating continued research into these detailed aspects of pedestrian and vehicle behaviour. First, the transition to a sustainable transport system. Walking is a notable component of sustainable transport plans, promising reduced vehicle emissions as well as significant improvements to public health. A wide range of negative impacts of vehicle centric urban design and transport planning on pedestrians are motivating alternative approaches to the design and management of city streets. Second, the development and anticipation of autonomous vehicles. Sitting within a broader trend of ‘mobility innovation’, autonomous vehicles promise to introduce a novel component to urban roads: an expansion of robotic automation into an uncontrolled, social environment. Improved
safety and efficiency are in the offering, but, a thoughtful examination of urban roads reveals these are just two among many, value laden, functions these spaces provide.

The numerous influences on pedestrian behaviour give rise to a variety of approaches to quantifying and modelling pedestrian movement and pedestrian-vehicle interactions on urban roads. A critical assessment of these methods identifies different behaviours that are included and excluded when making the simplifying assumptions quantitative models require. Similarly, in representing the road environment models necessarily make abstractions and define the spatial bounds of the system. The types of assumptions made differ depending on the spatial scale of analysis leading to distinct approaches to modelling pedestrian behaviour, broadly grouped by academic fields.

1.1 Thesis objectives

The central question this thesis addresses is whether by integrating different approaches to modelling pedestrian behaviour a more robust assessment of pedestrian-vehicle interactions can be made. By addressing this question this thesis aims to make a contribution to pedestrian modelling that is relevant to the transport planning challenges posed by decarbonisation and vehicle automation. This objective is expanded upon with the more detailed objectives below.

1. Critically review research into the determinants of pedestrian behaviour on urban roads and the representation of this behaviour in models.

2. Identify a suitable theoretical approach to modelling pedestrian navigation and movement at multiple spatial scales.

3. Develop a model of pedestrian movement in urban areas based on the outcomes of objectives 1 and 2.

4. Explore the behaviour produced by the pedestrian model and apply it to an assessment of the impacts of street infrastructure on pedestrian-vehicle interactions.
1.2 Thesis organisation

These objectives are addressed in the following chapters.

Chapter 2, Literature review, addresses objectives 1 and 2. This chapter expands on the themes introduced above, starting with a discussion of the transition to sustainable urban transport and the role of transport technology in achieving this. Following this a wide range of determinants of pedestrian behaviour and experience related to street level movement are reviewed. Finally, models of pedestrian decision making urban areas are critically reviewed with a focus on distinguishing between the representation of pedestrian decision making and the relevant spatial scales of both the decision and movement. Based on this review a research gap is identified in the lack of modelling approaches that integrate pedestrian decision making across spatial scales, specifically, linking street level decisions related to pedestrian-vehicle interaction with navigation over wider urban areas.

Chapter 3, Modelling framework, proposes a set of research questions to address this gap and presents a suitable modelling framework, further addressing objective 2 by drawing on the literature discussed in the Literature Review. This framework defines the modelling purpose, justifies the use of an agent-based modelling methodology, and presents the theoretical framework used to integrate models of pedestrian decision making across spatial scales.

Having established this framework, Chapters 4, Upper-level route choice, and 5, Lower-level route choice, address objective 3 by developing models of pedestrian movement at two spatial scales. Chapter 4 presents a model of pedestrians route choices across an urban neighbourhood, where pedestrians must travel along multiple road links to reach their destination. Chapter 5 presents a model of street level pedestrian route choice and movement and its integration with upper-level route choice presented in Chapter 4. Central to both chapters is the representation of road crossing behaviour and pedestrian heterogeneity.

Chapter 6, Verifying multi-scale pedestrian route choice, and Chapter 7, Incorporating multi-scale pedestrian movement into street infrastructure appraisal, both address objective 4. In Chapter 6 the behaviour produced by the multi-scale
pedestrian modelled is verified by running thousands of simulations of pedestrian movement in three different environments. The sensitivity of metrics of pedestrian behaviour to model parameters is assessed and the routes of pedestrian agents compared to an alternative route choice model. The results from these analyses demonstrate the breadth of pedestrian agent behaviour produced by the route choice model.

Building on this, Chapter 7, leverages this source of heterogeneous pedestrian behaviour to explore the impacts of restrictions to pedestrian road crossing. These restrictions are designed to represent laws or infrastructure that prevents, to varying degrees, pedestrians crossing outside of designated crossing infrastructure. By performing simulation experiments in three environments the effects of the policies on pedestrian accessibility and pedestrian-vehicle interactions are assessed. Differences in the effects between environments demonstrate the potential benefit of integrating pedestrian navigation and movement across spatial scales. While the policies relate only to street-level pedestrian behaviour, their effects depend on larger scale qualities such as road network morphology.

Chapter 8 concludes this thesis by summarising it contributions, limitations, and directions for future work.
Chapter 2

Literature review

2.1 Introduction

This chapter draws together a wide range of research related to the study of pedestrian behaviour in cities and its relevance to sustainable transport systems. The review begins, in Section 2.2, with the sustainable transport objectives of the United Kingdom (UK) government and specifically the targets related to increasing walking and cycling and decreasing car use in urban areas. The targets set by the UK government represent a significant break from historic trends. The challenge this poses for traditional decision making is discussed in Section 2.2.2.

Section 2.2 also discussed how new technology features heavily in transport decarbonisation plans, for example in the reliance on new types of vehicle such as electric vehicles (EVs), electric scooters (eScooters), and autonomous vehicles (AVs) to name just a few. In this context of transport innovation, the objective to achieve mode shift towards walking stands out as a move away from using vehicles rather than being reliant upon the proliferation of new ones (notwithstanding the complexities of multi-model transport systems). Sustainable transport planning paradigms provide the necessary perspectives and tools to achieve this target but these do not always align with the representation of urban mobility in transport simulations.

Having established the sustainable transport context for this work, the review progresses to discuss specific barriers to improving pedestrian experience in urban
areas in Section 2.3. Across safety (World Health Organisation, 2018), mobility (Anciaes and Jones, 2020), health (Hoffmann, 2019; Retting et al., 2003) and well-being (Bornioli et al., 2018), vehicles have been found to have negative impacts on pedestrians. These impacts are produced through the behaviours of individual road users and are experienced by pedestrians across spatial scales - from immediate interactions with road users on a street to aggregate impacts across a whole journey. Theory and evidence from a range of academic disciplines can be usefully applied to understand and model such behaviour, and in particular the behaviour of pedestrian.

Section 2.4 reviews how pedestrian behaviour is modelled, grouping studies by the spatial scale of pedestrian decision making and movement. Methods for modelling pedestrian mobility tend to focus on a particular level of granularity and spatial scale despite established theories explicitly detailing the way that multi-scale decisions are structured. Multi-scale approaches to pedestrian models are reviewed in Section 2.4.3 but notable gaps in the representation of pedestrian behaviour directly relevant to the negative outcomes listed above are found.

2.2 Transitioning to sustainable urban transport

Transport technology is potentially critical in assisting and obstructing the creating of cities that better support sustainable transport modes such as walking and cycling. Dealing with such uncertainties requires decision making processes that are capable of acknowledging a wide range of uncertainties, testing decisions against these unknowns.

2.2.1 Identifying sustainable transport futures

In the UK, emissions from domestic transport are greater than from any other sector at 23% of total emissions (UK Government, 2021). Passenger cars accounted for 55% of transportation emissions in 2019 with road transportation overall accounting for 90% (ibid). Accordingly, reducing emissions due to passenger cars features heavily in the government’s transport decarbonisation plan (Department for Transport, 2021) and carbon budget (Climate Change Committee, 2020). These decarbonisation plans contain widespread technological and social changes to how
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Among the many targets those related to modal shift from driving to walking and cycling are notable. The UK’s Sixth Carbon Budget assumes a model shift from driving to walking and cycling of 5-7% nationally by 2030 (Climate Change Committee, 2020) and the transport decarbonisation plan sets a target of half of all journeys in towns and cities walked or cycled by the same date (Department for Transport, 2021). Achieving this modal shift is not reliant on new technologies and instead on changing travel behaviour. Such changes would embed physical activity within urban travel with potential benefits to health and to the quality of urban areas, as will be set out below. Given this breadth of differences between vehicular and active transportation modes it follows that planning for each of these constitutes different paradigms, with different views on what a city should be.

Jones et al. (2018) identify three approaches to city transport planning that have been broadly adopted over time in Western European cities, referred to as the car based city, the sustainable mobility city, and the city of places. Jones et al argue that transport planning in western European cities has evolved through these approaches, being predominantly car-centric in the mid 20th Century before transitioning to sustainable, public transport focused mobility and now shifting again to a place-making approach. These transitions, particularly from the car-based city to the sustainable mobility city, are evident in an overview of the career of UK transport planner Professor Sir Peter Hall (Chen, 2016). At the same time these high-level trends obscure pockets of experimentation and stagnation. Pedestrian centric planning has been prominent in some areas from the 1980s through the establishment of the woonerf (Gill, 2006) and liveable streets (Appleyard, 1980). Jones et al (ibid) highlight that the transition between paradigms is never complete; these three approaches co-exist within cities and have their own geographies with the centre of cities being more place based and the periphery more car based. But the categorisation makes clear the choices available to city transport planners. Encouraging a shift from driving to walking and cycling corresponds to shifting planning approaches to those of the sustainable mobility city and city of places.
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The *city of places* approach importantly identifies a broader set of objectives for a transport system than those in either the car orientated or sustainable city approaches. Building on low emissions objectives, the *city of places* broadens this to consider the role of transport planning in producing places to visit and spend time at as well as the means to travel between them. The *link and place* categorisation of streets further articulates this distinction (Jones and Boujenko, 2009) by acknowledging that city streets are places in themselves as well as links to other places. This is a specific example of the greater integration between land use and transport planning identified in Banister’s ‘sustainable mobility paradigm’ (Banister, 2008).

A *city of places* has a specific relevance to pedestrian mobility and therefore the objective of increasing the share of walking trips. This is demonstrated by Jan Ghel’s evaluation of city places based on ‘street activity’ (Ghel, 2011; Gehl and Svarre, 2013). The quality of places is measured in terms of the numbers of people occupying them and the variety of activities being performed (for example sitting, chatting, watching). Jones and Anciaes (2018) also distinguish between metrics used to evaluate a *city of places* (e.g. intensity of street activities, social interaction) from those used for a car-orientated or *sustainable mobility city* (e.g. average network speeds and public transit frequency). Pedestrian mobility is least distinguishable from these activities compared to other forms of mobility. Without the need to disembark from a vehicle pedestrians can seamlessly transition between using the place and link function of urban roads. The *city of places* approach can therefore help achieve mode shifts from driving to walking.

The role of technology in transport decarbonisation cuts across planning approaches and paradigms. Vehicle electrification enables reductions in transport emissions while maintaining or increasing levels of car ownership and use (Langbroek et al., 2017; Holtsmark and Skonhoft, 2014). But without changes in travel behaviour these reductions are unlikely to be sufficient to reach sustainability targets (Brand et al., 2019; Barrett et al., 2021). Electrification is also producing a plurality of new mobility options, grouped under the banner of micromobility (Abduljabbar et al., 2021). These can be accessed by users through mobility-as-a-service
platforms, themselves a transport technology, which integrate payment and routing across transport modes (Lyons et al., 2019; Kamargianni et al., 2016) potentially encouraging changes in travel behaviour (Matyas and Kamargianni, 2019). Vehicle automation is similarly touted as a technology that will facilitate the transition to more efficient, shared modes of transport (Martinez, 2015; Gurumurthy et al., 2019), but could also entrench the auto-mobility systems and threaten sustainability goals (Cavoli et al., 2017; Cohen and Cavoli, 2019; Wadud et al., 2016).

These innovations demonstrate that technology can disrupt as well as reinforce existing mobility paradigms. A shared characteristic of these transport innovations is that they continue to perpetrate a mobility-centric view of transport planning. While the potential sustainability benefits ought to improve public spaces, for example through reducing noise and air pollution, by focusing on mobility these technologies overlook the integration between land use and place-making called for under the city of places approach and sustainable mobility paradigm. Greater consideration of pedestrian mobility within these transport technologies could help account for place making. Lyon’s walking-as-a-service concept identifies a potentially virtuous circle whereby assisting pedestrian navigation increases footfall for businesses (Lyons, 2020). The concept makes the connection between technologies that support walking and the quality of places, in this case high streets. Another example are appraisals of street design that simultaneously seek to improve the urban realm and pedestrian mobility Anciaes and Jones (2016a).

The tendency for transport technology to marginalise pedestrians is exemplified by the automobile. Through the twentieth century the car reshaped cities and the behaviour of their inhabitants. The early history of this process is well documented in Peter Norton’s Fighting Traffic (Norton, 2011). The safety and congestion problems that accompanied increasing car ownership through the 1920s and 1930s were re-framed as the problems of cities designed for the pre-car era. Fixing these problems involved the co-evolution of infrastructure and the formal and informal ‘rules of the road’ to create space for vehicles and make pedestrians responsible for their safety. New York’s ‘Expressways’ (Caro, 2015) and London’s ‘Westway’
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(Moran, 2010) were designed to facilitate automobility through and out of the city. Alongside these grand schemes were the creation of new laws and social norms regarding the use of street space, notably the invention of ‘jaywalking’, that redefined the rights of pedestrians to street space (Norton, 2011). Similarly in Britain, new laws, codes, and norms were established to facilitate the coordination of pedestrians and vehicles (Moran, 2006), influenced strongly by Colin Buchanan’s Traffic in Towns report (Buchanan, 1963). New road crossing infrastructure was created with public information campaigns to educate pedestrians on how to safely cross the road. As will be discussed further in Section 2.3, these interventions ultimately prioritised personal vehicle mobility in urban areas at the expense of pedestrian mobility and place-making.

Drawing comparisons with other technologies, scholars have identified the integration of automobiles into cities as an archetypal technological transition (Geels, 2002). Geel’s theory of technological transitions views technologies as sociotechnical configurations and makes explicit that technologies not only change the social systems they operate in but require social change to endure. The stability of the automobility system results from linkages between “road infrastructures and car regulations”, “cultural and symbolic meanings of cars” and “user practices and mobility patterns” (ibid). Detailed analysis of these linkages (to use Geel’s phrase) reveal points of weakness and strength (Urry, 2004; Cohen, 2012). From this perspective, autonomous vehicles (AVs) stand out among other novel transport technologies as particularly well positioned to entrench rather than disrupt the automobility system. Indeed, this potential is at the heart of studies that anticipate the impacts of AV mobility systems (Cohen and Cavoli, 2019; Wadud et al., 2016) whereby AVs are expected to increase demand for vehicular travel in the absence of regulation.

As well as entrenching existing linkages, automating the driving task could create new ones. In interviews with AV developers Tennant and Stilgoe (2021) uncover the ‘attachments’ AVs may require to operate successfully. Echoing the reconstruction of street space in the early twentieth century, some developers acknowledged the potential need to change urban environments to facilitate the tech-
nology by reducing the occurrence of ‘edge cases’. The challenges of automating interactions with pedestrians (Rasouli and Tsotsos, 2019; Markkula et al., 2020) threaten to problematise ‘edge case’ pedestrian behaviour. For example, authors have highlighted the possibility of pedestrians gaming AVs (Adams, 2015; Lin, 2013; Millard-Ball, 2018). This results from the inherently social nature of road user interactions, based on communication and mutual understanding (this point is discussed further in Section 2.4.1).

Sidewalk Labs, an Alphabet company, has proposed ‘Street Design Principles’ that aim to harmonise pedestrian and AV use of street space (Sidewalk Labs, 2019) but whether such proposals are consistent with the place-making envisaged in a city of places remains to be seen. Even without changes to infrastructure, tensions may arise from the technology’s solidification of the laws, codes and norms currently governing driver behaviour (Tennant et al., 2021). Seemingly subtle differences in rule interpretations could be magnified by a homogeneous and ubiquitous fleet of AVs (Himmelreich, 2018).

At the same time AVs may improve pedestrian safety (Fagnant and Kockelman, 2015; Anderson et al., 2014). However, such assessments focus narrowly on collisions between pedestrians and vehicles. What sustainable transport paradigms highlight, as well as authors critiquing this narrow focus of AV impacts (Cohen and Cavoli, 2019; Legacy et al., 2019), are that the impacts of automobility encompass more than the direct threat to pedestrian safety through collisions, as tragic as such incidents are. These impacts are discussed further in Section 2.3.2.

Transformative visions of urban transport decarbonisation comprise sociotechnical changes. The task of switching travel behaviour from driving to walking surfaces the complicated and at times antagonistic relationship between social and technological components of change. Approaches to transport planning that incorporate place-making and land use considerations are considered helpful, if not necessary, for achieving this mode shift. At the same time, emergent technologies promise to assist this transition by disrupting the incumbent mobility system. However, the mobility-centric perspective of some of these technologies may be in
conflict with place-centric perspectives. Among these technologies AVs stand out as having potential to disrupt and entrench aspects of urban transport to the detriment of pedestrians. This highlights the importance of studying pedestrian behaviour for planning sustainable urban transport systems in the context of autonomous mobility transitions.

2.2.2 Decision making for a sustainable transport future

Navigating the context outlined above is a challenge for decision makers. This section discusses methods for making decisions in highly uncertain contexts in connection to the objective of sustainable transport planning and specifically planning for pedestrian travel in cities.

2.2.2.1 Dealing with uncertainty

The sociotechnical changes outlined above present decision makers with challenges. The UK’s Transport Decarbonisation Plan (Department for Transport, 2021) gives a high level vision of how decarbonisation will be achieved. Beyond this, decisions must be made regarding how to implement and regulate new transport technologies as well as how to encourage more people to walk and cycle. These decisions are complicated by the novelty of the technologies and the need to either accelerate or alter historic transport trends. The introduction of new transport modes and deviation from historic trends reduces the utility of historic trends for informing decisions about future investment and infrastructure (Lyons and Marsden, 2021). Lyons and Marsden argue this amounts to a wicked problem - problems characterised by their uniqueness, complexity and lack of a definitive formulation (different stakeholders will have different perspectives on exactly what the problem is) (Rittel and Webber, 1973). Transport planning decisions may also be classed as exhibiting ‘deep uncertainty’ (Lempert et al., 2003), a more quantitative formulation of the same basic tenants of wicked problems. Deep uncertainty occurs where

analysts do not know, or the parties to a decision cannot agree on,
(1) the appropriate conceptual models that describe the relationships among the key driving forces that will shape the long-term future, (2)
the probability distributions used to represent uncertainty about key variables and parameters in the mathematical representations of these conceptual models, and/or (3) how to value the desirability of alternative outcomes.

Wicked problems can also be defined by what they are not. Rittel and Webber (1973) use the phrase ‘tame problems’ to refer to a class of problems which are well defined and can be solved. For Kay and King (2020) these are small world problems, common in the natural sciences or in idealised circumstances but not in real societies.

Decision making in the context of ‘wicked problems’ or ‘deep uncertainty’ requires a distinct set of methods designed to account for these intractable uncertainties. Whilst tame problems can be solved by optimising well defined objectives this approach does not translate to wicked problems for which a precise objective cannot be agreed or defined. Scenario based planning methods, which evaluate policies against a range of plausible future scenarios, can better account for the uncertainties produced by sociotechnical change (Cohen and Jones, 2018; Lyons and Marsden, 2021). This “opening up” of future possibilities must also be accompanied with strategies for “closing down” possibilities without biasing particular paths of action (Lyons and Marsden, 2021). Kay and King (2020) emphasise the importance of establishing and challenging narratives in order to make sense of such problems. Narratives play an important role in scenario based planning whereby plans of action are examined under distinct future scenarios, described in both qualitative and quantitative terms.

Robust Decision Making (RDM) takes a computational approach to scenario-based planning (Lempert et al., 2020; Popper, 2019). Global sensitivity analysis techniques are used to explore the parameter space of high dimensional models of the system (opening up) and dimensionality reduction techniques to identify regions of parameters space that produce distinct outputs (closing down).

Across these methods there are some high-level similarities. The uncertainties in the system are treated as unavoidable and accordingly predictions of future
states of the system, to any degree of accuracy, are not entertained. Scenarios are identified through a process that considers a wide range of future states of system components and their interactions, typically producing a wider set of futures than those produced through forecasts. Approaching decision making in this way aligns with some aspects of Stilgoe et al. (2013)’s framework for responsible innovation. The framework is designed to help guide new technologies towards beneficial outcomes. This, in part, involves anticipation, asking “what if...?” questions, to consider contingency, what is known, what is likely, what is plausible and what is possible”. The process of “opening up” future possibilities in scenario-based planning methods supports responsible innovation by anticipating different impacts of the technology.

Once again, the emergence of AVs stands out as particular challenge for decision makers attempting to achieve a mode shift from vehicles to walking in terms of the uncertainties surrounding this technology. It also provides an opportunity to develop and apply suitable decision making methodologies. Lyons (2022) argues the uncertainties surrounding AVs amounts to a wicked problem in-of-itself due to both the transport systems AVs would operate in and their status as a nascent technology. Stilgoe (2020) argues the genuine capabilities of nascent technologies can be difficult to distinguish from the hype surrounding them. Regulators may be hesitant to place any restrictions on the development of nascent technologies for fear of losing out potential benefits.

Within the literature a range of methods have been used to help inform decision making around AVs. These account for different aspects of transport systems and different sources of uncertainty. The breadth of future scenarios within studies varies, with quantitative model based studies tending to produce a narrower set of scenarios due to the limitations of the models.

2.2.2.2 Modelling future mobility scenarios

Transport models have been widely used to study the potential impacts of AVs. Simulations of autonomous taxi services in cities explore potential efficiencies that could arise from increased sharing of vehicles (Fagnant and Kockelman, 2014;
Bischoff and Maciejewski, 2016; Boesch et al., 2016; Spieser et al., 2014) and rides (Zhang et al., 2015; Brownell and Kornhauser, 2014; Martinez, 2015). However these studies are highly contingent on their assumptions of travel behaviour. The limited exploration of alternative assumptions means the models do not sufficiently account for intractable uncertainty surrounding future travel behaviour and technology, which transport emissions are sensitive to (Wadud et al., 2016). For example, Bischoff and Maciejewski (2016) assume all inner city car journeys are made by AV taxis and Brownell and Kornhauser (2014) assume all synthesised trips are serviced by AV taxi rather than considering a wide range of adoption values. Similarly, Fagnant and Kockelman (2014) assume 3.5% of trips are made by AV taxi, Zhang et al. (2015) assume 2% of trips and Spieser et al. (2014) include all trips made by all modes of personal transportation as reported in a household travel survey. These assumptions preclude other travel behaviour that could plausibly emerge. The results are therefore useful as hypothetical examinations of a narrowly defined mobility scenario and not an attempt to open up and close down the space of possible AV mobility futures.

Other modelling exercises have attempted to account for potential changes in travel demand that could result from the introduction of AV transport modes. May et al. (2020) use an integrated land use and transport system dynamics model to explore the effects of AVs in Leeds, UK. Unlike the studies above, this model assumes a constant travel time budget which allows changes in accessibility to have knock-on effects for travel behaviour. In all scenarios which assume reduced travel costs due to AVs an increase in vehicle travel distance is observed. Enforcing shared ownership produces a shift to more dense city centre residences. Azevedo et al. (2016) also consider changes in travel demand in their agent-based simulation of future AV mobility scenarios. The location of activities without a fixed location (such as work or school) is allowed to change in response to the presence of a shared AV mobility service. The model also includes multiple transport modes, with agents choosing between these each day, providing an assessment of how the introduction of a new transport mode could change the use of other modes. In a simulation of an
AV transport option in Switzerland, Meyer et al. (2017) considered three scenarios defined by varying AV performance. This addressed the assumption that AVs are capable of operating in all road environments by considering a scenario in which AVs operate only in extra-urban roads such as highways. In the model, average accessibility was found to increase, however the geographical distribution of accessibility change is uneven, with reductions in accessibility for denser urban area and increases for suburban and rural areas.

By representing changing travel behaviours, these models can consider a broader range of outcomes resulting from the introduction of hypothetical AV mobility services. The scope of these studies is constrained by modelling methodologies which in turn limit the breadth of scenarios that can be considered. Qualitative methods for scenario development are not constrained in the same way. Lyons (2022) use a participatory methodology to develop and critique AV mobility scenarios through in person workshops. Cohen et al. (2018) used discursive workshops in which a broad set of narrative scenarios were used as probes for discussion.

At the same time, computational models offer the potential for a more detailed analysis of specific policies related to the design and management of mobility services such as AV taxis. Quantitative and simulation based models are embedded within the transport planning process and are likely to continue to inform decision making. Improving the representation of travel behaviour within these models can enable the consideration of a wider set of scenarios and impacts in transport planning decisions. This can help avoid modelling exercises that close off plausible scenarios of the kind identified in the qualitative studies discussed above.

The potential disruption posed by AVs introduces significant uncertainties. Sustainable transport planning emphasises the importance of pedestrian movement and place-making to developing sustainable urban transport systems. But these components of urban transport systems are missing from models seeking to explore the possible impacts of AV mobility systems. The transition to a car-dominant mobility system through the twentieth century changed how pedestrians used street space. Without incorporating pedestrians, transport models will preclude such im-
pacts in the development of future mobility scenarios. Where scenario development is not limited by models and instead qualitative and narrative methods are employed such impacts are raised as pertinent to the development of future scenarios.

Incorporating pedestrian movement into models of future mobility systems can help facilitate representation of a wider set of travel behaviours. In turn this enables a broader set of future scenarios to be produced in modelling exercises. Existing models of AV mobility systems do not include granular pedestrian movement. Having identified this gap in the literature we proceed to discuss how pedestrian are currently impacted by vehicular traffic as a guide to understanding what behaviour should be incorporated into models that seek to anticipate the impacts of AVs on pedestrians.

2.3 Pedestrian behaviour and experience

Planning for walking trips is central to the sustainable transport paradigm. Understanding how features of the urban environment affect pedestrian behaviour and experience can help inform how to design transport systems that improve pedestrian journeys.

This section distinguishes between two broad determinants of pedestrian behaviour and experience - the built environment and vehicle traffic - each broadly related to separate academic fields, providing complementary perspectives on the same phenomena.

2.3.1 The built environment effects

The role of the built environment in influencing behaviour is a prominent theme within the planning and architecture literature. Jan Ghel’s ‘Life Between Buildings’ (Ghel, 2011) exemplifies a design philosophy that centres the role of the built environment in shaping human behaviour. Ghel argues that human psychology and cognition can be usefully applied to the design of spaces between buildings (streets, plazas, courtyards, etc) to achieve certain behavioural outcomes, principally social interactions.

Space Syntax is a well established methodology used “to describe and anal-
2.3. Pedestrian behaviour and experience

yse patterns of architectural space - both at the building and urban level.” (Hillier et al., 1983) These patterns take the form of axial maps (Hillier and Hanson, 1984; Turner et al., 2005) which link spaces to one another based on uninterrupted lines of sight. The resulting network of spaces has properties which predict patterns of movement within cities (Hillier et al., 1993; Penn et al., 1998). Specifically, flows of pedestrians and vehicles are better predicted by geometric (meaning the angle between axial lines) and topographic properties of these networks than metric distances (Hillier and Iida, 2005). This conclusion identifies the configuration of urban spaces as the principle determinant of pedestrian and vehicle movement.

Criticisms of this view highlight its apparent inconsistency with the decision making of individual pedestrians (Ratti, 2004). Ratti argues that while aggregate patterns of movement may appear to be governed by geometric and topographic properties of urban space, the notion that individuals are insensitive to metric distance is inconsistent with multiple intuitive influences on people’s behaviour. This criticism is partly addressed through Dalton (2003)’s integration of the aggregate view of spatial behaviour provided by space syntax with a disaggregate analysis of individual decision making, revealing a more nuanced picture in which both the local configuration of space at intersections and the relative direction of a pedestrian to their destination inform route choice decisions. Developments of the theory have moved away from the pure ‘axial line’ representation of the environment to road networks and metrics such as cumulative angular distance (Simons, 2021).

The connection Dalton (2003) makes between individual decision making and aggregate patterns of behaviour (see also Conroy-Dalton (2001)) forms part of a rich synthesis between Space Syntax and spatial cognition (Hillier, 2012). The spatial cognition literature also identifies environmental influences on behaviour, though the perspective in this case is that behaviour is influenced through the cognitive representation of space through its influence on wayfinding decisions.

Cognitive maps (Tolman, 1948) are a foundational concept in the spatial cognition literature, defined as “the internal representation of experienced external environments, including the spatial relations among features and objects” (Golledge
et al., 2000). It is through the encoding and retrieval of spatial information in cognitive maps that wayfinding decisions are made. Information is organised hierarchically in cognitive maps (Mark et al., 1999; Hirtle and Jonides, 1985; Chase, 1983; Maki, 1981) with larger spatial scales corresponding to higher levels of the hierarchy than smaller spatial scales. Chase (1983) identified global environmental features such as rivers as belonging to the top level hierarchy whilst locations within neighbourhoods belonged to lower levels. Hirtle and Jonides (1985) and Stevens and Coupe (1978) find that spatial locations are grouped within high level hierarchies representing larger spatial areas such as urban neighbourhood and states.

The cognitive map model of spatial cognition is supported by observations of brain activity in animals and humans. O’Keefe and Nadel (1978)’s discovery of ‘place cells’ in the rodent hippocampus that are triggered by specific spatial locations has been followed by the discovery of head direction cells and grid cells (which encode metric distances between locations) in animal brains, “collectively form[ing] the neural basis of a cognitive map” (Grieves and Jeffery, 2017). Epstein et al. (2017) review a significant body of evidence that the human hippocampus similarly encodes spatial information and that this information is used when navigating urban areas.

An important distinction in spatial cognition is between egocentric and allocentric spatial representation (Nadel and Hardt, 2004). Under egocentric representation spatial knowledge is represented relative to the self whereas under allocentric representation spatial knowledge is represented without a particular vantage point. Byrne et al. (2007) present a model of spatial cognition that represents the encoding and retrieval of spatial information as requiring the “integration of egocentric and allocentric representations”, with multiple studies of the hippocampus and its neighbouring regions supporting this model (Wang et al., 2020). This model suggests allocentric spatial representations (i.e. map like representations) develop through repeated, egocentric exposure to the environment. These exposures shape the formation of the allocentric ‘cognitive map’.

Cognitive maps in turn shape future egocentric experience through spatial de-
cision making and behaviour (Golledge et al., 2000; Kitchin, 1994). For example, Passini (1984) analysed the decision making process of participants as they navigated commercial complexes. The verbalised decision processes revealed wayfinding decisions were hierarchically structured, with participants addressing decisions pertaining to larger spatial scales first and then making decisions pertaining to smaller, more immediate spatial scales. Wiener and Mallot (2003) present the results of two virtual reality navigation experiments that demonstrate the effect of cognitive spatial hierarchies on wayfinding. These results support the hypothesis that “route planning takes into account region-connectivity and is not based on place-connectivity alone”.

Human spatial cognition also directly affects perceptions of distances, which in turn can affect behaviour. Distances between within region locations tend to be underestimated while distances between locations in different regions tend to be over estimated (Newcombe and Liben, 1982; Sherman et al., 1979; Kosslyn et al., 1974), although this effect is moderated by experience of moving through the environment as well (Sherman et al., 1979). Manley et al. (2021) identify features of the urban environment that affect people’s estimation of distance. The authors combine metrics of landmarks and features, turns, network density and order, boundaries, travel speed, topography, and euclidean distance to form a measure of cognitive distance that reflect the way that each of these features augments human perception of distance in the built environment.

Recent research has investigated whether non-physical ‘spaces’ - particularly temporal and social - are encoded in the same way as physical spaces in the hippocampus (Epstein et al., 2017). Tavares et al. (2015) find that hippocampal “activity predicted changes in subjective affiliation and power between people and fictional characters”, suggesting information about social relationships may be encoded in a similar way to relationships between physical locations. Nielson et al. (2015) find that hippocampal activity predicted both the spatial and temporal location of life events. Tavares et al. (2015) argue their results support the declarative memory view (also termed the relational memory view) of the hippocampus
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(Eichenbaum and Cohen, 2014) which posits the hippocampus provides “a general relational processing mechanism” (ibid) rather than the narrower function of a cognitive map of the current physical space. Attempts to bridge these perspectives frame the hippocampus as “encoding events as a relational mapping of objects and actions within spatial contexts” (Eichenbaum and Cohen, 2014) and as using “space and time as a primary scaffold for defining contexts” (Ekstrom and Ranganath, 2018), organising other information around these central dimensions.

Within the psychology literature, the construal level theory (CLT) (Trope and Liberman, 2011) considers how spatial, temporal, and social dimensions influence decision making. According to CLT, choice construal (meaning how a decision is framed by the decision maker) depends on the psychological distance the decision maker associates with that decision (Trope and Liberman, 2010). Psychological distance is defined by Trope and colleagues as the “extent of divergence from direct experience of me, here and now along the dimensions of time, space, social perspective, or hypotheticality” and is considered to be a “base psychological dimension that represents how spatial, temporal and social distances are perceived.” Psychological distance is an egocentric distance metric.

Bar-Anan et al. (2007) present evidence for the congruence between spatial, temporal, social and hypothetical dimensions supporting the argument that these present an equivalence in terms of psychological distance. This congruence is also supported by evidence, discussed above, of the similarities between the hippocampal activity related to spatial relationships and social and temporal relationships (Epstein et al., 2017; Eichenbaum and Cohen, 2014); Tavares et al. (2015) argue their results support the proposition in CLT of an egocentric social dimension to psychological distance.

CLT states that choices are construed at either a high-level, where the object of the decision is psychologically distant from the decision maker, or at a low-level, where the object is psychologically proximate (a two-level hierarchy). To give an example, Fujita et al. (2006) found that participants’ stated preference between a ‘high-level’ and ‘low-level’ description of a task depended on the spatial
distance between the participant and the task location. Participants preferred to describe the task “locking a door” as “putting a key in the lock” (low-level description) when the house was located in the same city as the participant but as “securing the house” (high-level description) when located in a different city. Similar results have been observed for temporally proximate and distance actions (Liberman and Trope, 1998).

According to CLT, decisions pertaining to greater psychological distances are made by decision makers in terms of ‘high-level’ construals that are abstract and goal-orientated. Conversely, decisions pertaining to lesser psychological distances are made in terms of ‘low-level’ construals that are less abstract and feasibility orientated. CLT also argues that, in addition to ‘high-level’ construals, decisions are evaluated more in terms of desirability criteria at greater psychological distances versus feasibility criteria at lesser psychological distances. This follows from ‘high-level’ construals being more abstract and goal orientated than ‘low-level’ construals (Liberman and Trope, 1998; Trope and Liberman, 2003). This relationship between psychological distance and desirability/feasibility trade-off suggests that people may initially make choices based on desirability criteria but then revise these choices as they become more proximate.

To explain the connection between psychological distance and ‘high-level’ construal, Trope and Liberman (2010) argue that more abstract ‘high-level’ construals enable people to “traverse psychological distance” (and also that traversing psychological distance prompts abstraction). Abstractions afford distance traversal because they are more invariant than their component elements and therefore remain constant across psychological distances. This explanation is supported by experiments which identify differences in how visual and verbal stimuli are identified. Amit et al. (2009) find that verbal stimuli are better classified at distal psychological distances. Conversely, visual stimuli are better classified at proximate psychological distances. This relationship is explained as visual stimuli corresponding to less abstract representations than verbal stimuli and therefore being congruent with lesser psychological distance. The connection between visual processing mode and psy-
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Psychological construal is further developed by Yan et al. (2016) though a collection of experiments that demonstrate that activating visual processing mode (through a visual problem solving exercise) causes participants to adopt low level construals, even in psychologically distant contexts. These findings suggest a connection between visual information processing and psychologically proximal experience resulting in low level construal of visual stimuli.

CLT has not been applied to the study of wayfinding behaviour but we can identify commonalities with spatial cognition theory that suggest it may have relevance in this field. The role of hierarchies in structuring decision making is central to CLT, with high-level and low-level choice construal distinguished by their level of abstraction and feasibility criteria. Cognitive spatial hierarchies affect route choices, with people choosing coarser (i.e. more abstract) routes between larger scale spatial hierarchies (Wiener and Mallot, 2003). Anchor points refer to spatial features which features prominently in the hierarchical organisation of spatial information (Gärling and Golledge, 2018). An analysis of vehicle trajectories in London shows that routes tend to go via anchor points more than predicted by a distance minimising wayfinding strategy, suggesting these high-level features of the environment affect wayfinding behaviour (Manley et al., 2015a).

CLT also explicitly discusses the low-level re-construal of decisions made initially under high-level construal. Wayfinding decisions are also made at varying levels of detail, with the spatial scale affecting the level of detail. For example the distinction between ‘fine’ and ‘coarse’ plans in Wiener and Mallot (2003)’s model. Passini (1984) state the “execution [of wayfinding decisions] has to happen at specific points in space” and Golledge et al. (2000) argue their results comparing the wayfinding ability of sighted and blind participants showed the groups did not differ in their ability to form cognitive maps but that the blind participants’ “lack of visual perception ... restricted their ability to recognize location cues along the route as they traversed it”. This shows that visual information processing is integrated with the use of cognitive maps, with each used in relation to different spatial scales.

At the same time CLT exhibits some differences to spatial cognition theory.
First, CLT differs by identifying different decision making processes - in terms of how goal oriented vs feasibility oriented the choice is - between the high and low hierarchies. Second, CLT states that decision hierarchies are based on egocentric psychological distance whereas the hierarchies of cognitive maps are based on a spatial, allocentric representation of the environment. CLT may therefore complement spatial cognition theory by identifying non-spatial and egocentric aspects of the environment that influence decision making, through high and low-level choice construal. For example, role of dynamic components of the environment in shaping decision making is not well integrated into the cognitive map framework. Authors do acknowledge that cognitive maps are dynamic (Kitchin, 1994; Mark et al., 1999) (owing to changes to the environments and to people’s relationship with the environment), however, by defining choice construal in terms of the base dimension of psychological distance, CLT provides a more general theory of decision making that may be relevant to explaining and predicting some environmental influences on pedestrian behaviour.

### 2.3.2 Vehicle traffic effects

In the studies discussed above the urban environment is reduced to static forms representing buildings, roads, rivers, and other prominent structures. This provides only a partial representation of pedestrian behaviour and experience. Interactions between road users, and particularly interactions between pedestrians and vehicles, are also known to be an important determinant of pedestrian behaviour and experience in urban areas. Building on the discussion of how the presence of road users at a particular location in the city owes something to the structure of the built environment, this section discusses studies which ask how, given the co-location of these road users, they interact and affect one another. From this perspective, behaviour is shaped through the combined decision making of pedestrians and drivers.

#### 2.3.2.1 Safety

Research has identified multiple ways that cars and car-centric planning negatively impact pedestrian walking experiences. Perhaps the most salient are collisions with
vehicles which are responsible for around 474 deaths per year in the UK, out of a total 2000 deaths caused by road traffic accidents (globally the impact is greater with traffic incidents being the leading cause of death for those aged 5-29) (World Health Organisation, 2018). Accordingly, a significant body of research investigates the contributing factors to this threat. These studies consider both the granular movement and behaviour of pedestrians and vehicles at the street scale as well as the characteristics of the wider urban area that contribute to the occurrence of pedestrian-vehicle collisions.

**Safety on individual roads**

Research into pedestrian behaviour at the street level considers how conflicts and collisions result from the road crossing and yielding actions of individual pedestrians and vehicles. Pedestrian road crossing behaviour is frequently analysed in terms of gap acceptance - the time gap between vehicles that a pedestrian ‘accepts’ in order to cross the road. Gap acceptance studies identify local street environment and traffic conditions that influence when pedestrians cross the road. Alternatively, driver yielding studies consider factors that influence when drivers yield to pedestrians.

Whilst traffic rules and codes attempt to ensure safety by clearly stating which users have right-of-way at any given time, observations of road crossing and yielding find that significant proportions of road users violate these. Sucha et al. (2017) found that in 36% of interaction events drivers did not yield to pedestrians in situations where the official rules obliged them to. Suh et al. (2013) found that a high proportion of pedestrians exhibited gap seeking behaviour, choosing to cross the road during a suitable gap in traffic rather than wait for a traffic signal. Várhelyi (1998) observations at a single unsignalised mid-block zebra crossing suggested drivers increased their speed in order to avoid stopping for pedestrians at the zebra crossing. Pedestrian crossing behaviour also differs between locations with and without crossing infrastructure (Dey and Terken, 2017). Identifying these non-compliant behaviours provides a better understanding of how collisions between road users arise.
Pedestrian crossing and driver yielding behaviour are both dependent on the behaviour of other road users. Drivers’ yielding decisions are affected by the assertiveness (Schroeder and Rouphail, 2011) or apparent distraction (Sucha et al., 2017) of pedestrians. Pedestrian gap acceptance depends on the speed of the approaching vehicle (Rasouli et al., 2018), the presence of other pedestrians (Sun et al., 2003). Camara et al. (2018b)’s analysis of sequences of road crossing events that frequently occur suggests that pedestrians seek clues from vehicle movement, rather than direct communication with drivers, to anticipate the driver’s actions. Similarly, Domeyer et al. (2020) better predicted aspects of pedestrian-vehicle encounters such as wait time with a model that included the joint state of both road users than with models based on only either one of the road users. Tennant et al. (2022)’s report into public attitudes towards AVs highlights the value placed on role of social interaction in coordinating roads users, with a majority of participants feeling that that eye contact and communication were important when using zebra crossings. Together, these results provide strong evidence that conflicts and collisions between road users result from and are mediated by the actions of each road user in response to one another, a form of social interaction.

The Theory of Planned Behaviour (TPB, Ajzen (1991)) has been used study why pedestrians choose to behave in ways that increase the risk of collisions, helping to explain differences between pedestrians’ behaviour. Studies explain the tendency for certain people to perform more risky road crossings in terms of them having a more positive attitude towards committing violations (Moyano Díaz, 2002) as well as perceiving themselves to have a high level of control over their road crossing behaviour (Evans and Norman, 1998; Evans, 2003).

Research has also found connections between pedestrian attitudes and crossing behaviour. Cantillo et al. (2015) found latent variables representing crossing option attractiveness (measuring the convenience and comfort of a crossing) and security/safety were significant predictors of the utility of informal mid-block crossing options. Similarly, Papadimitriou et al. (2016) surveyed 75 pedestrians before observing their road crossing behaviour. Principal component analysis (PCA) of the
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Survey results identified three groups distinguished by attitudes to risk and journey purpose. Including the principal components as latent variables in a crossing location choice model revealed only the “risk taking and optimisation” principal component was significant, suggesting that in terms of observed crossing behaviour, the pedestrian sample consisted of two groups only - optimising risk takers and risk averse.

Pedestrian safety can be more directly measured by the frequency and severity of conflicts between road users. The road crossing behaviour discussed above may be considered risky due to its violation of laws, rules or norms but without knowing whether the behaviour caused a conflict between road users it is difficult to ascertain the real risk posed by the behaviour. Svensson (1998) propose a 'severity hierarchy', where interactions between road users are assigned an objective severity, with collisions having the highest severity and 'near misses’ having a lower but nearby severity. Laureshyn et al. (2010) propose a comprehensive set of conflict indicators. Svensson and Hydén (2006) applied conflict severity metrics to pedestrian-vehicle interactions, producing severity hierarchies for encounters at two junctions used to argue the metrics provide information road user behaviour not provided collision statistics alone. The junction with a lower number of collisions had a higher mean conflict severity and narrower distribution, suggesting the presence of conflicts does not necessarily imply a risk to pedestrian safety. Domeyer et al. (2020) use conflict indices extracted from a naturalistic driving dataset to model pedestrian-vehicle interactions, and therefore distinguish between safe and unsafe conflicts and the pedestrian and driver actions that produce them.

Analysis of conflicts has also been used to study the impact of changes to street infrastructure and design. Ismail et al. (2010) compared conflicts at an intersection before and after the introduction of a pedestrian scramble phase, finding clear differences between the distributions of conflict indicators observed in the before and after cases. Conflict severity has also been used to study the impact of changing a road to a ‘shared space’ design which makes less of a distinction between vehicle and pedestrian space (Kaparias et al., 2015). In each of these studies the collection
and analysis of conflict metrics between pedestrians and vehicles is argued to be important for the investigation of pedestrian safety. However, there remains a lack of clarity regarding how to draw conclusions on pedestrian safety based on conflict severity - whilst Svensson and Hydén (2006) found fewer collisions in high conflict severity environments, studies of vehicle-vehicle conflicts have found high conflict severity is correlated with collisions (Xie et al., 2018; Dijkstra et al., 2010).

Finally, research also identifies specific features of urban environments around which conflicts and collisions tend to occur. Zheng et al. (2015) find that certain urban locations host a greater frequency of non-compliant crossing behaviour (where pedestrian cross the road outside of established infrastructure) which suggests these areas could be conflict hot spots. In an analysis of natural driving recordings Du et al. (2013) found that areas such as car parks, community spaces and schools hosted nearly double the rate of conflicts between pedestrians and the vehicle than other urban areas. Similarly, in a big data analysis of pedestrian collisions Xie et al. (2017) find crash hot spots tended to be located around the entrances and exits to tunnels and bridges as well as in areas with high bus stop density.

These studies analyse pedestrian safety at the scale of a pedestrian’s immediate road environment. The factors identified as affecting safety are limited to the behaviour of road users involved in the (potential) conflicts and the street infrastructure that mediates these interactions. Road crossing can concentrate in certain areas of a city and the risk of collision is greater in locations where pedestrian and vehicles are likely to be brought into conflict. Once pedestrians and vehicles are required to coordinate use of the same space (i.e. the carriageway) safety is strongly shaped by pedestrian road crossing and vehicle yielding behaviour.

Safety across an urban area

Moving beyond this scale of analysis research has identified other factors affecting pedestrian safety as well as replicating some of the findings discussed above. In a detailed and comprehensive review of the built environment’s impact on road safety, Ewing and Dumbaugh (2009) identify ways that safety is influenced by characteristics of urban areas. They conclude that urban areas are safer than rural areas...
due to the lower vehicle miles travelled (VMT) per person in urban areas, identifying a different kind of behaviour - travel mode choice - as being central to pedestrian safety. The role of road user behaviour and interactions at the street level is also identified as an important determinant of safety but the focus of the analysis is identifying patterns of street design that encourage safer driving practices. The ‘4Ds’ - density, diversity, design, and destination accessibility - encapsulate this view, framing pedestrian safety as a property of the wider mobility system and not only the result of individual road user characteristics and street infrastructure.

Similarly, ‘urban sprawl’ has been identified as a contributing factor to the risk of pedestrian collisions, investigated through the production of a ‘sprawl index’ that combines indicators of residential density, land-use mix, centredness (measures of concentration of population and economy in centre of metropolitan area), and street accessibility (Ewing et al., 2003). The results found areas of increased density, land-use mix and centredness (i.e. low-sprawl areas) had significantly fewer road accident fatalities.

Analogous to the ‘sprawl index’, walkability indices have been used to measure the suitability of an area for walking as a transport mode. Southworth (2005) defined walkability in terms of six attributes: connectivity of the street network, linkage with other transport modes, fine grained and varied land use patterns, safety from traffic and social crime, quality of path, path context (street design, visual interest of the built environment, etc). Whilst walkability indices are composed differently across the literature, indicators of street connectivity, land use mix and residential density are common to most, with high connectivity, land use mix and residential density giving higher walkability scores. Walkability indices have been found to correlate well with walking activity in multiple locations and at varying scales (Owen et al., 2004; Saelens et al., 2003; Stockton et al., 2016; Dhanani and Vaughan, 2016) and therefore relate to pedestrian safety by identifying urban areas that facilitate walking, rather than driving, as a mode of transport.

Research also identifies safety differences between types of road, as well as types of built environment. Analysis of pedestrian deaths and injuries resulting
from collisions with motor vehicles shows that vehicles pose a greater risk per mile travelled on minor roads than major roads (Aldred, 2019). The author suggests potential mechanisms for this influence: different pedestrian and driver behaviours between major and minor roads, poorer visibility and greater pedestrian flows on minor roads. Whilst the reason for the difference is uncertain, the finding supports a perspective on road safety that sees collision risks as shaped by higher level categorisations of roads and urban areas.

These studies identify important, compounding ways in which the safety of pedestrians is affected by qualities of the built environment. Land use which creates large distances between residential areas and locations for out of home activities makes driving the most suitable mode of transport. Similarly, designing roads for high vehicle speed and throughput make environments more suited to driving. These environmental factors increase the risk pedestrians are exposed to. This perspective on pedestrian safety complements more granular assessments that focus on the behaviour and movement of pedestrians and vehicles when approaching and crossing the road.

Pedestrians’ experiences of safety are therefore determined in part by the behaviour of drivers, their own behaviour, as well the built environment. This compliments the discussion of environmental determinants of pedestrian behaviour in Section 2.3.1 by linking the environment to interactions between pedestrians and vehicles - not just the behaviour of individual road users. This is an additional causal pathway, from the environment to pedestrian behaviour and experience via pedestrian-vehicle interactions, that is also apparent in the following sections.

2.3.2.2 Barrier effect

Researchers have also investigated the impacts of vehicle traffic and vehicle-centric road designs on pedestrian mobility, termed the barrier effect or community severance (the term community severance has connotations of impacts to social relationships as well so the term barrier effect is preferred when focusing on mobility impacts) Anciaes (2015). The barrier effects is defined by Anciaes et al. (2016) as “effects of transport infrastructure or motorised traffic as a physical or psychologi-
cal barrier separating one built-up area from another built-up area or open space”.

Whilst Anciaes et al. (2016)’s focus is on larger forms of transport infrastructure such as “railways, motorways, and dual carriageways” studies also identify more subtle ways roads can act as a barrier to pedestrian movement. At the scale of individual roads the barrier effect manifests as pedestrian’s choice of road crossing location and whether this imposes additional journey time or distance costs that could be alleviated through changes to crossing infrastructure or vehicle flow. Beyond this, research considers both the cumulative costs of barriers across whole pedestrian trips and cases where barriers cause pedestrians to avoid certain destinations altogether. As with pedestrian safety, this phenomena is produced at multiple spatial scales, through both pedestrians’ experience of the immediate street environment and the larger urban geographies they move through.

Studies into pedestrian crossing location choice identify factors related to traffic, road design, infrastructure, and pedestrian attitudes that influence this choice. Many of these are integrated in Anciaes et al. (2018)’s stated preference model assigning monetary values to improvements to road crossing infrastructure. The study’s survey includes a wide range of possible interventions including reducing the number of lanes, reducing vehicle traffic, adding a median strip and reducing vehicle speed, all of which had positive value to pedestrians. The following paragraphs focus on three well-established factors: vehicle traffic, types of crossing infrastructure, and crossing location.

The traffic level along a link is found be be a significant predictor of crossing location choice in multiple studies, with higher traffic levels reducing the likelihood of a pedestrian choosing to cross at an informal location (one without markings or infrastructure) (Papadimitriou, 2012, 2016; Cantillo et al., 2015; Anciaes and Jones, 2016b). The effect of traffic levels on crossing choice has also been observed to vary between different road types. In Papadimitriou (2016) crossing choice is compared between principle arterial (highest vehicle flow), minor arterial (medium vehicle flow), and collector (lowest vehicle flow) road types in high and low traffic conditions. On minor arterials and collectors, mid-block (informal) crossing prob-
ability was observed to decrease and junction crossing probability increase with an increase in traffic. On principle arterials there was no such change in crossing probability. This suggests that pedestrian road crossing locations are influenced both by the current traffic level but also qualities that distinguish different road types such as long-term average levels of flow or road design.

The types of crossing alternatives available to a pedestrian have also been reported as influencing pedestrian crossing choice. Papadimitriou (2012) found the presence of a traffic signal at a junction increased the likelihood of choosing to cross at the junction. In Sisiopiku and Akin (2003) 87% of survey respondents said the presence of a marked mid-block crossing (dedicated crossing infrastructure) affected their decision to cross at a specific location and 74% said the presence of a traffic signal affected this decision.

By surveying pedestrians’ stated preference of crossing location, Cantillo et al. (2015) find that the location of a crossing alternative influences a pedestrian’s choice, with greater distances associated with a reduced likelihood of choosing that crossing option. Similarly, Chu et al. (2004) find that the likelihood of choosing to cross at an intersection either end of a road was sensitive to the distance to the intersection. The probability of choosing either a marked or informal mid-block crossing option was far less sensitive, suggesting that on longer roads pedestrians will typically choose to cross at mid-block locations. Sisiopiku and Akin (2003) report 90% of survey respondents stated that the distance of a crossing to their destination influenced their decision to use the crossing, with crossings further from their destination being less desirable. Whilst the majority of pedestrians are influenced by the availability and location of multiple crossing alternatives, the presence of a group of pedestrians for whom these are not influential factors reveals important heterogeneity between pedestrians.

The findings discussed so far consider how features of roads and crossing infrastructure affect where pedestrians cross the road. These crossing choices shape pedestrian behaviour and experience by determining how a pedestrian traverses each section of the road network. In turn, this impacts patterns of pedestrian movement
over larger areas. Papadimitriou (2012) consider pedestrian choice of crossing location along a journey of multiple road links, identifying that pedestrians choose to delay road crossings on longer journeys but take crossings early on shorter journeys. The authors also find a sequential choice model best explains the crossing choices of the pedestrians. The authors argue these results suggest pedestrians make crossing decisions sequentially with a limited planning horizon, incorporating both their immediate environment and their position relative to their destination into the decision.

Barriers also cause people to avoid walking trips due to both the objective costs imposed on pedestrian movement such as additional journey distance and time as well as subjective perceptions of inaccessibility. Anciaes et al. (2019) find that people that perceived traffic volumes and speeds as high on certain roads were more likely to avoid walking to those roads altogether. These perceptions were also associated with reporting that traffic conditions impeded their ability to walk to local places. This work builds on Appleyard and Lintel’s foundational study comparing behaviour on three streets (Appleyard and Lintell, 1972). The study considered three adjacent streets in San Francisco with light, moderate, and heavy levels of traffic flow respectively finding that residents spent more time on low traffic streets. Similarly, Biddulph (2012) studied the effect of differences in street design on street activity on two residential streets in Cardiff. Unlike Appleyard and Lintel’s study, the streets differed significantly in design as well as traffic flow; one street permitted through traffic and had traffic calming measures and the other did not permit vehicle through traffic. A higher frequency of longer stays in the street without through traffic was observed.

The importance of subjective perceptions of the street environment is highlighted in these studies. In Appleyard and Lintell (1972)’s and Biddulph (2012)’s studies the travel distances and times of partaking in the activities observed differed little between streets with different levels of traffic flow. Similarly in Anciaes et al. (2019)’s study, perceptions of traffic were found to impact walking intention independently of the distance to the busy road. This suggests that the presence of vehicle
traffic changed residents’ perceptions of the street environment which in turn inhibited the trips they made. This explanation is supported by two studies by Bornioli et al. that evidence the negative impact of traffic on walking experience and the role of negative experiences in inhibiting pedestrian trips. Bornioli et al. (2018) considers “specific micro-qualities related to traffic and architectural style that could influence affective experiences.” By measuring affective experiences the psychological well-being conferred by different environments was evaluated. The results identified self-reported psychological benefits of walking in different built environments, with perceived restorativeness rated more highly in non-traffic urban environments than in those with traffic. Pedestrian well-being was found to be affected by the immediate street environment pedestrians walk through. Crucially, a related study found that negative affective experience reduces walking intention (Bornioli et al., 2019).

Together these studies identify ways that the barrier effect influences pedestrian movement. At small spatial scales the level of traffic and available crossing infrastructure on a road shape pedestrian movement by influencing the choice of crossing location. Conditions of the immediate road environment shape people’s perceptions and these perceptions determine travel behaviour and movement over larger spatial scales including suppressing trips altogether and avoiding busy roads when walking places. Vehicle traffic therefore affects pedestrian behaviour and experience across multiple spatial scales through the barrier effect.

2.3.2.3 Health, well-being, and social interaction

Moving beyond safety and the barrier effect a broader range of influences on pedestrian experience can be identified, encompassing health (beyond the threat of collisions with vehicles), well-being, and social interactions. As before these impacts are produced through (in this cases indirect) interaction between pedestrians and vehicles. These impacts are shaped both by the immediate environment and the characteristics of larger urban geographies, with sprawling and vehicle-centric urban environments playing a role in producing the vehicle traffic that pedestrians interact with.
Health and well-being

Air pollution is one of the most impactful pathways, with fossil fuel burning vehicles being the dominant source of air pollutants in urban areas (Holman, 1999; Hoffmann, 2019). Globally, “air pollution was ranked fourth as risk factor for premature mortality, only exceeded by hypertension, smoking and dietary risks” (Hoffmann, 2019). Air pollution increases the risk of both cardiovascular and respiratory disease with a review across studies finding “an approximate 20% increase in cardiovascular disease mortality risk per 10 $\mu g/m^3$ increase in PM2.5 and an approximate 2.5% increase in respiratory disease risk per 10 $\mu g/m^3$ increase in PM10” (Stevenson et al., 2016). High resolution models and sensing of air pollution in cities reveal variation in pollution at the street level (Santiago et al., 2022; Hasenfratz et al., 2014). Increasing the spatial and temporal resolution of measurements of air pollution exposure of road users reveals larger variations between populations as well as higher mean exposure than reported in coarser analyses (Gurram et al., 2019). Variations in exposure were due, in part, to variations in pollution concentrations between road links and differences between people’s routes through a city. Repeated measurements of air pollution at 1Hz for each 30m of road in Oakland, California further revealed spatial variation at the sub road link scale, with concentrations of $NO_2$ twice as high around intersections that at mid block locations in some cases (Apte et al., 2017). A complete representation of pedestrian exposure to air pollution would therefore account for ambient back ground pollution levels, variations between road links and potentially even sub road link variations (with intersections in particular being high exposure environment). Exposure and its related health impacts are therefore partially determined by pedestrian movement at multiple spatial scales.

Traffic noise is hypothesised to impact mental health and quality of life, however results are mixed and causality difficult to establish. Some studies do find significant associations between traffic noise and measures of health related Quality of Life (HRQOL) when controlling for socioeconomic and environmental factors (Héririer et al., 2014; Dratva et al., 2010). However, in studies with larger sam-
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ple sizes and meta analysis this relationship is hard to establish. Roswall et al. (2015)’s analysis of a sample of 38,964 people over three years found modelled traffic noise exposure to be significantly associated with the mental health component of HRQOL after controlling for socioeconomic factors, but the association was greatly attenuated by the inclusion of lifestyle control variables. A meta analysis similarly concluded that there is “is evidence of ‘very low’ quality that increasing exposure to road traffic noise may be associated with depression and anxiety”, citing the complex pathways through which noise can impact mental health as making causality difficult to establish (Dzhambov and Lercher, 2019). Furthermore, these studies focus on residential noise exposure and not that experienced by pedestrians. Botteldooren et al. (2011) estimated noise exposure experienced over the course of a trip and found it correlated significantly with reported quality of life but without controlling for socioeconomic or lifestyle variables (which were found to attenuate this relationship elsewhere (Roswall et al., 2015)) causality remains elusive. So whilst there is some evidence that traffic impacts well-being, a strong association or causal effect remains to be established.

The research reviewed in this section considers indirect forms of interaction between pedestrians and vehicles and the resulting impacts. These interactions necessarily take place where pedestrians can perceive vehicle traffic and in this sense are related to the immediate street environment. Research is accordingly conducted at this scale, simulating and observing the experience of walking in these environments as well as modelling the air and noise pollution of a street segment. But, as with safety, larger geographies are also relevant. Traffic is a product of the wider urban and transport system, as shown by sprawl indices, and so any interaction with vehicle traffic is to some extent a product of this wider system. More specifically though, a pedestrian’s experience is also the result of continuous and varied exposure to traffic across the journey which shapes their perceptions of the environment. This is acknowledged through the use of virtual walks that present a trip through a reasonably homogeneous environment, the road network analysis that similarly models walking trips or the modelled effects of air and noise pollution across the
whole of a pedestrian’s trip. In each case traffic is only ever experienced in the immediate environment but the effect is attributed to the whole journey or area. A pedestrian’s experience of vehicle traffic is therefore multi-scale, comprising of a series of exposures to immediate traffic conditions that accumulate in some way to a trip level experience that spans a larger geography.

Social interaction

As well as recording the impact of vehicle traffic on residents’ trips and street activity, Appleyard and Lintel (1972) also measured the social ties between neighbours on each street, finding that residents on the heavy traffic street had a higher average number of friends and acquaintances on the street than on the light traffic street. Residents’ statements explained this difference in social contacts was due to the presence of traffic in part, but also a range of other factors including the number of children living on the street and the number of years residents had lived there. Similar findings were observed in a recent replication of Appleyard and Lintel’s study in Bristol (Hart and Parkhurst, 2011). The residents on the light traffic street had significantly more friends and acquaintances on the street than those on moderate or heavy street, citing the traffic on the street as a barrier to forming friendships. Biddulph (2012) also observed a higher frequency of social activity on a street with greater traffic calming compared to one without traffic calming.

Identifying that vehicle traffic appears to inhibit social interactions between residents prompts consideration of whether this phenomena can be identified across larger geographic areas. Attempts to measure this ‘community severance’ tend to consider larger spatial scales than the individual street comparisons discussed above, creating opportunities to establish more general relationships between the built environment and social connections. However, establishing the effects at these scales proves elusive owing to the many factors that mediate social interaction.

Leyden (2003) investigated the connection between walkability and social capital by surveying residents in Galway, Ireland. By asking how many destinations they were able to access by walking and how well the residents knew their neighbours (amongst other questions assessing social capital) the authors identified a
significant association between the walkability of a neighbourhood and the social capital of its residents (controlling for variables such as age, years spent living in the neighbourhood, whether the resident had dependent children at home, and how much television the resident watches).

Other studies have not been able to identify a significant association between social capital and the built environment. (Hanibuchi et al., 2012) found that walkability was not significantly associated with any measures of social capital once measures of community history (the build period of the buildings and the length of residents’ stay) and urbanisation were included. In a similar study of social capital and the built environment in Perth, Australia Wood et al. (2008) found that the number of destinations within an 800m radius was negatively correlated with their measure of social capital, also contradicting the link between walkability and social capital. These inconsistent findings have been compared with other studies in a systematic review of the relationship between the built environment and social capital (Mazumdar et al., 2018). The majority of significant findings conclude that components of design (how the road network is laid out) and destination (the proximity of a range of destinations) are associated with social capital - with areas of greater accessibility to destinations by walking and more traditional road network layouts (greater connectivity) having greater social capital. Another review, Boniface et al. (2015), concludes that “Walkable environments can promote social capital and social cohesion. Traffic and severance have important consequences for social networks.” Though they also acknowledge that the direction of causality is difficult to establish.

The findings presented in (Leyden, 2003) are explained in terms of more walkable neighbourhoods having a higher proportion pedestrian trips which results in more opportunities for neighbours to interact. These explanations are in part supported residents’ claims that the presence of traffic inhibited street activity (Appleyard and Lintell, 1972; Biddulph, 2012; Hart and Parkhurst, 2011). It’s important to note criticisms of this perspective. Schwanen et al. (2015) critiques the benign construction of social capital presented in studies such as those discussed above,
arguing that “analysts should not *a priori* assume that the local area or neighbour-
hood is the most relevant spatial scale for the formation of social capital among
such individuals.” and that social capital can also lead to the exclusion of those not
in the group. Potentially, a balance exists between facilitating local social interac-
tions through suppressing traffic, and facilitating travel to other destinations where
people also socially interact.

This section highlights how a class of interactions, those between pedestrians
and vehicles, affect pedestrian behaviour and experience in urban areas. These ef-
facts are related to but distinct from the affect of the built environment on pedestrian
behaviour. The spatial arrangement of buildings and roads in cities determines, in
part, where people colocate. But the details of this colocahion, how people behave
and experience one another, are determined through the interaction of different road
users. These interactions are also connected to the environment, but it is funda-
mentally the presence of different kinds of road user, in this case pedestrians and
vehicles, that introduces a different set of determinants of pedestrian behaviour and
experience. As a result pedestrians’ health, well-being, and social interaction are
affected, with these effects identified through the direct interaction of pedestrians
and vehicles on individual streets as well as analyses of whole neighbourhoods and
cities.

### 2.4 Modelling pedestrian movement in urban areas

Section 2.3 identified a wide range of influences on pedestrian behaviour and ex-
perience, broadly grouped into effects of the built environment and effects of in-
teraction with vehicle traffic. Modelling pedestrian behaviour can help to account
for these influences when designing urban environments and appraising transport
proposals. This section reviews methods that are useful for representing the aspects
of pedestrian behaviour and experience discussed in Section 2.3. These existing
studies do not represent many of the behaviours discussed above and the specific
gap this research aims to address is discussed at the end of this section.

An important distinction in this discussion is between the spatial scale of the
determinants of pedestrian behaviour. Conflicts with vehicles, road crossing decisions, and social interactions result from dynamic interactions between pedestrians and vehicles. These are small-scale influences in the sense that the information pedestrians appear to be responding to in these situations is local to the pedestrian. These are categorised as ‘small-scale decisions’. Section 2.3 also discussed non-local determinants of pedestrian behaviour, predominantly through wayfinding decisions based on of the environment. These are categorised as ‘large-scale decisions’.

The importance of dynamic interactions to small scale pedestrian decisions makes agent-based modelling well suited to representing these decisions (Batty, 2001). Whilst the various crossing choice models discussed in the section above do model small-scale decisions the process of a pedestrian moving through space is not represented. Without connecting decision making to movement models cannot represent the complex interactions that characterise road environments. Accordingly, the discussion of small-scale models is dominated by agent-based approaches to modelling pedestrian decision making and movement at the street level.

At larger scales dynamic interactions become obscured by the wider urban context; accordingly, different methods tend to be used. These studies model decisions as being made based on spatial (and non-spatial) information across a wide geographic area. Where ABM have been used to model such large-scale decision making, this is achieved by providing agents with knowledge of the wider environment (such as road networks and activity locations) to base their decisions on.

2.4.1 Small-scale decisions
A foundational group of model of pedestrian movement are those based on social forces (Helbing and Molnár, 1995; Helbing et al., 2001) and heuristics (Moussaid et al., 2011). In these models agents’ movement decisions are based on the immediate environment, defined in terms of a field of vision. Agents respond to other agents and environmental features (such as walls and other barriers) within the field of vision. These models demonstrate that realistic patterns of movement and coordination can be produced through simple rules and limited knowledge of the envi-
2.4. Modelling pedestrian movement in urban areas

Environment, although agents are assigned a destination to move towards which may be outside the field of vision. It’s through the continuous dynamic interaction among pedestrian agents and between agents and the environment that these simple rules give rise to realistic movement behaviour.

Tangential to these agent-based models are the ‘isovist agents’ used to model natural movement (also called configurational movement) (Hillier et al., 1993; Penn et al., 1998) through decisions based on an exosomatic visual architecture (Turner and Penn, 2002; Turner, 2007b). Natural movement is the flows of people in buildings and cities predicted by an axial map (see the discussion of Space Syntax in Section 2.3.1 above) representation of the space. The movement is ‘natural’ in the sense that it arises purely from the spatial configuration of the environment. Turner and Penn (2002) develop this by producing natural movement through an agent-based model. In the model, each step agents choose their direction of movement based on their isovist (the non-occluded region of the space), also referred to as an exosomatic visual architecture, moving in the direction which affords the most space. The resulting movement patterns match those predicted by the axial map representation (Turner, 2007b) and are well correlated with observed flows in buildings (Turner and Penn, 2002) but are produced through the small-scale decision making of individual agents. Interactions between these isovist agents are limited and so these models do not produce the kinds of emergent behaviour (lane formation, stop and go traffic) produced by Helbing’s social force agents (Helbing et al., 2001). Instead they demonstrate that realistic flows through buildings and streets can be produced through only small-scale decision making. However, both groups of models consider only pedestrian movement, restricting their application to pedestrian-only spaces such as transit stations or galleries. When applied to pedestrian movement in street environments interactions between road users are neglected (Penn and Turner, 2002).

Beyond pedestrian only spaces these simple rules are insufficient and must be replaced or supplemented by additional decision making on behalf of the pedestrian agents. In urban street environments road crossing behaviour is an important aspect
of pedestrian movement to represent due to its connection to pedestrian safety and the barrier effect. As discussed above, pedestrians exhibit a range of road crossing behaviours that, to different extents, adhere to the laws, codes and norms defining right of way for road users. Incorporating road crossing and driving yielding behaviour into models of pedestrian movement at the street scale is therefore relevant to representing these aspects of pedestrian experience. In this vein, many studies develop agent-based models and micro simulations of pedestrian road crossing using a variety of decision making frameworks and models. Additionally, the development of autonomous vehicles is motivating increasingly high-fidelity models of pedestrian decision making and road user interaction.

Non-compliant pedestrian road crossing behaviour (road crossing that deviates from right-of-way guidance or laws) has been produced in several pedestrian movement models using rule based decision making. Suh et al. (2013) develop pedestrian agents that used simple rules to decide when to cross the road. Implementing these in VISSIM, a commercial transport micro-simulation software, produced road crossing behaviour that did not comply with pedestrian traffic controls and instead crossed through gaps in vehicles. By comparing with observations, authors demonstrated the effect of pedestrian behaviour on wait times, evaluating the connection between traffic, pedestrian behaviour and pedestrian mobility. Chao et al. (2015) modelled pedestrian jaywalking using a rule based gap acceptance model, modifications to a social force model of pedestrian movement, and a model of vehicle movement. However, the model was not validated and the focus of the study is producing realistic looking movement for animation purposes. Feliciani et al. (2017) present a cellular automata model of pedestrian road crossing for a single zebra crossing. In the model vehicles are either compliant or non-compliant, with non-compliant vehicles never yielding to pedestrians at the crossing. Pedestrians perceive a vehicle’s speed, whether it is compliant or not, and the time gap the pedestrian requires to cross to decide when it is safe to cross the road. Pedestrian agents are initialised with heterogeneous time gap requirements, reflecting differences in perceptions of safety and walking speed within the population.
The representation of decision making and interaction in these models is limited to the use of simple rules. These simplifications potentially exclude plausible and observable pedestrian behaviours from the model. Wang (2012)’s method improves on this by developing a micro-simulation of pedestrian road crossing behaviour at signalised crossings, zebra (unsignalised) crossings, and mid-block crossings (jaywalking). Pedestrian crossing location and time was modelled through the iterative application of a binary logit choice model of gap acceptance (when to cross the road). The logit model was calibrated and validated against observations of pedestrians crossing the road in different environments and reproduced the observed behaviour of pedestrians continuing to walk along the pavement until a suitable gap becomes available to cross the road. This micro-simulation represents detailed pedestrian decision making and diverse road crossing behaviour in the presence of different crossing infrastructure.

More recently, and motivated in part by the development of autonomous vehicles, studies have sought more granular and psychologically realistic models of pedestrian crossing and movement along urban streets. Markkula et al. (2018) model a pedestrian’s decision of when to cross a zebra crossing as a network of binary ‘drift-diffusion’ decision nodes. Each node gradually accumulates information from the environment varying the node ‘activations’ in the process. When a threshold activation value is reached one of the binary options is chosen. This model explicitly represents the cognitive process of retrieving information from the environment and because this process happens over time the choice model naturally incorporates the dynamic nature of the road environment. The model reproduces the bimodal characteristic of the distribution of observed pedestrian zebra crossing decisions - with greater proportions of pedestrians crossing either without waiting for the car to slow down or once the car has fully stopped compared to those that cross as the car is slowing down. Initial attempts have been made to estimate model parameters (Giles et al., 2019). Tian et al. (2022) model road crossing decisions with a logit based gap acceptance model. Rather than using the time gap between vehicles as the gap indicator the authors use visual looming which measures the
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changing size of the vehicle’s image in the retina of the pedestrian. Visual looming provides a connection between real world objects and perception of those objects, producing a choice model that is more reflective of human cognition. Wang et al. (2021) present a drift-diffusion based model, applied to a similar scenario to that in Wang (2012). Pedestrian agents move along one side of the road tasked with choosing a crossing location (either at a marked crossing or some other location on the road) and crossing time. By using decision field theory to model this choice the authors similarly represent the decision as a gradual process that intrinsically accounts for the dynamic nature of the environment. By representing the connection between perception, cognition and decision making these choice models are able to incorporate different sources of heterogeneity between pedestrians such as ‘noisy perception’ or biases towards certain features of the environments. This is not possible with standard logit or regression based choices models, where parameters are set for the whole population and variances between agents are due to the uncertainty in the parameter estimates rather than real psychological differences among the population.

Models of pedestrian movement in ‘shared space’ environments consider a different form of more fluid road user interaction due to the lack of formal rules governing the right-of-way of different road users (Hamilton-Baillie, 2008). In some cases this more informal movement is modelled by including additional terms in a social force model, such as for pedestrian-vehicle interaction (Pascucci et al., 2015; Anvari et al., 2015). Anvari et al do also impose additional rules on vehicle movement to resolve conflicts that persist. Prédhumeau et al. (2022) similarly uses a mixture of adjustments to social force models and rules to produce shared space pedestrian movement, however, in this case additional rules are also imposed on pedestrians to produce yielding and non-yielding movements in the presence of vehicles. The need to add additional rules to handle the variety of pedestrian behaviour in shared-space scenarios connects to the open questions surrounding how AVs could motivate restrictions to pedestrian behaviour discussed in Section 2.2.1. What happens if AV developers do not account for all the ways pedestrians and ve-
vehicles coordinate themselves currently? This may restrict the scenarios AVs operate in but also, as Norton (2011) argues occurred with the introduction of cars to city streets, pedestrians may be required to adapt their behaviour.

These models provide tools for assessing the mobility impacts of pedestrian road crossing behaviour. By producing conflicts between pedestrian and vehicle agents both at formal and informal crossing locations the models can be used to evaluate the safety of street designs in the presence of different pedestrian behaviours. The interactions between pedestrians agents, street infrastructure and vehicle agents also determine the journey time and distance of the pedestrian agents, enabling assessments of pedestrian accessibility and the barrier effect. However, interactions between road users are treated as obstacle avoidance problems, reduced to the mechanics of moving objects. This overlooks the role communication and negotiation play in coordinating road users’ movements (Straub and Schaefer, 2019; Markkula et al., 2020; Tennant et al., 2022).

Game theory has been proposed as a potentially suitable model of road user interaction in multiple road scenarios that explicitly represents social interaction between road users. Schönauer et al. (2012) used a mixture of the social force model and game theory to simulate the interactions between agents in a shared space. Fox et al. (2018) propose a sequential game theoretic model of two road users coordinating their movement as they pass through an unsignalised intersection from orthogonal directions. Initial attempts have been made to estimate the model’s pay off values for pedestrians from movements of pedestrians in a laboratory setting (Camara et al., 2018a). One complication of game theoretic models is specifying which agents are involved in the game. The social force and drift-diffusion methods discussed do not created a binary distinction between agents included and excluded from the game and instead allow many agents to influence decision making to different degrees. Drift-diffusion models are also more cognitively plausible since they assume people only make simple calculations rather than the more complex identification of nash equilibria required by game theory.

The agent-based and micro-simulation models reviewed here use a variety
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of methods to model pedestrian decision making and produce realistic pedestrian movement at the street level. This necessarily involves road crossing behaviour which is shaped both by street design, infrastructure and the presence of other road users (generally other pedestrians and vehicles). These are important aspects of pedestrian experience in urban areas with direct relevance to safety and the barrier effect. They are also directly relevant to AVs, which will be required to anticipate and respond to these behaviours - though the extent to which they will replicate current pedestrian-vehicle interactions remains to be seen. However, these models are detached from location and trip purpose. While the natural movement produced by isovist agents does, in aggregate, correspond to flows over whole urban areas, the decision making of the individual agents lacks purpose and awareness of the non-immediate environment.

2.4.2 Large-scale decisions

Counter to models of small-scale pedestrian decision making are models that incorporate knowledge of the wider urban area into decisions. These larger-scale decision models better account for trip purposes and land use and model pedestrian movement over larger spatial scales.

While natural movement models of pedestrian flows are based only on network configuration, the varying correlations with observed flows for different radii over which closeness and betweenness centrality measures (measures that predict pedestrian flows) are calculated implies a role for large-scale components of the environment in influencing pedestrian movement (Omer et al., 2015; Dhanani et al., 2017). Additionally, incorporating land use components into a Space Syntax based model of pedestrian movement improves the correspondence to observed flows (Omer and Kaplan, 2017). In this study pedestrian movement is modelled with pedestrian agents whose trip destinations are based on the relative weight of different land uses and whose route choices were based on the network analyses used in space syntax (minimising angular distance, topographic distance, and metric distance). Dhanani et al. (2017) also incorporate land use into their model of pedestrian demand.

The inclusion of land use metrics in models of pedestrian behaviour deviates
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from the pure configurational perspective and represents movement as being based on large-scale spatial decisions. Hoogendoorn and Bovy (2004) helpfully articulate this view, separating out strategic, tactical and operational components of pedestrian decision making that together produce flows on city streets. Routing and navigation decisions are categorised as tactical level decisions, within which small-scale isovist agents and larger-scale network optimal shortest paths each fall. In reality, it appears that, along, neither of these two approaches satisfactorily align with either human cognition or observed route choices. This is addressed in recent work that use novel route choice and navigation methods that incorporate multiple aspects of cognition to more accurately model flows of people in cities, discussed in Section 2.4.3 below.

However, before discussing multi-scale models of pedestrian decision making, there is another aspects of large-scale models to address: network representations. Small-scale models generally adopt a high-fidelity representation of the environment, for example, by using continuous spaces and distinguishing between the carriageway and pavement. But, when modelling larger-scale decisions more abstract road centre line (RCL) representations of the environment are generally used. Where pedestrian dedicated space is allocated at either side of the carriageway (e.g. pavement and sidewalks) this simplification obscures movements across the carriageway, precluding investigations related to the safety, the barrier effect and well-being impacts of vehicle traffic discussed above. Addressing this, authors have created pedestrian networks based on a pavement centre line representation (PCL) (Ballester et al., 2011; Andreev et al., 2015; Timms, 1992; Rhoads et al., 2020). Rhoads et al. (2020) provide the most comprehensive example, creating PCL networks for 10 cities across three continents and using these to compare the availability of pedestrian infrastructure and the effects of road closures on pedestrian mobility. Pedestrian movement was modelled using shortest path algorithms. Palominos and Smith (2019) use a different approach to incorporating pedestrian infrastructure into network representations of cities by measuring pavement and carriageway widths of road links in London. Although not directly related to modelling pedestrian movement their use of network centrality measures aligns with
Space Syntax models of movement.

The small and large-scale pedestrian decisions modelled in these studies can be contrasted in their representation of the environment. While small scale models use continuous or grid based representations large scale models use network representations derived from road geometries or building polygons. There are also differences in the ways pedestrian decisions are represented. Social force based methods are the basis of pedestrian movement in small scale models, with pedestrian agents deciding how to move based on the agents within their assigned field of vision. Beyond these simple collision avoidance decisions are those related to road crossing and vehicle interaction which for which a variety of methods are used (examples discussed include rule based, logit and drift-diffusion models). Unlike the well defined field of vision, these use different rationales to justify which features of are included in the decision making process. The more structured network representations used in large-scale models result in a shared basis for decision making of edges and nodes. Finally, the two scales lend themselves to analysis of different aspects of pedestrian behaviour. The detailed representation of pedestrian-vehicle interactions in small-scale models enable granular and dynamic assessments of safety and the barrier effect. The large scale models incorporate the role of location and connect pedestrian movements to trip purposes. Integrating these scales could enable a more comprehensive assessment of pedestrian experience. Doing so requires developing methods to integrate the different ways the environment and decision making are represented at these scales. To this end, multi-scale models and theories related to movement in cities are reviewed in the following section.

2.4.3 Multi-scale decisions

As mentioned in the previous section, accurately modelling flows of people in cities requires accounting for spatial decisions made with respect to multiple spatial scales. Recent approaches to modelling route choice distinguish between these different scales by leveraging the flexibility afforded by agent-based modelling. Wiener and Mallot (2003) propose a ‘fine-to-course’ wayfinding model in which a route is comprised of fine scale information within a region and coarse space infor-
2.4. Modelling pedestrian movement in urban areas

Information for locations in another region. Manley et al. (2015b) model the navigation decisions of taxi drivers in London, developing a novel route choice model based on the hierarchical cognitive map representation of human spatial cognition discussed in Section 2.3.1. Their model distinguishes between decisions made with respect to different spatial scales comprising region based, node based, and route based choices, with the spatial information available to agents at each of these scales differing. The resulting routes were found to correlate better with the observed routes of taxi drivers compared to an optimal choice model. Filomena et al. (2020) present a model of pedestrian navigation based on urban subdivisions. This agent-based model also represents multiple scales of decisions making, distinguishing between global regions and barriers and locally bounded knowledge of the road network. These models base the decision making of the agents on spatial cognition and cognitive map theory, generating more realistic behaviour by applying different choice mechanisms to different spatial scales.

Other examples of route choice models blending different heuristics and spatial information to more accurately model pedestrian flows can be found. Bongiorno et al. (2021) find that pedestrians deviate increasingly from shortest paths as the distance between origin and destination is increased. This is incorporated into a route choice model that uses both the direction to the destination as well as the road network to choose a route, improving the correspondence with observed routes. Kielar et al. (2018) integrate multiple route choice strategies, each based on different cognitive principles related to both small-scale and large-scale spatial information. These studies highlight the importance of integrating different aspects of spatial decision making to model pedestrian paths. Such multi-scale approaches are discussed further in the following section.

While several of these models consider pedestrian movement they exclude interactions between road users. Papadimitriou (2012) models road crossing choices across an urban area. This work integrates road crossing decisions with route choice decisions by using a nested logit discrete choice model. The nesting of choices treats route choice as a sequential process which is multi-scale in the sense that
the immediate road environment is distinguished from the rest of the environment. However, the logit choice modelling methodology lacks the granularity and potential for interaction afforded by the small-scale agent-based models discussed above. Tong and Bode (2021) present a novel model of pedestrian route choice in which agents sequentially update their routes in response to new information perceived in the environment. This study identifies how the sensitivity of route choices to novel environmental information changes as people progress and is an example of multi-scale route choice applied to pedestrian route choice decisions within buildings rather than in cities.

The small-scale models discussed in this section incorporate aspects of pedestrian behaviour that result in non-compliant road crossing, with pedestrians seeking to cross the road at locations and times that require coordination with vehicles. There is variation in the types of pedestrian road crossing decisions that are modelled, with some studies allowing greater flexibility over the choice of crossing location and others modelling only decisions of when to cross given a specific crossing location. Different models of pedestrian decision making are employed including heuristics, discrete choice models, game theoretic models, and cognitive perception models. Moving beyond a single street enables pedestrian movement to be connected to locations and trip purposes. Models at this scale represent urban areas using networks and model movement as resulting from decisions on these networks. Agent-based models of multi-scale urban movement have demonstrated the increased realism of modelled behaviour achieved by integrating decisions made pertaining to different spatial scales. However, a gap remains in the integration of decisions at the street level which account for movement across the carriageway (and the associated pedestrian-vehicle interactions) with movement decisions across multiple streets.

2.5 Conclusion

Taking the UK government’s objective of achieving a modal shift from driving to walking as a starting point, this review began by discussing the transport planning
approaches that support active travel. The importance of place making was identified as particularly relevant to encouraging walking trips. Considering the emergence of new transport technologies and their potential to support sustainable mobility transitions highlighted potential tensions between the integration of land use and transport planning required for place making and the mobility-centric nature of transport technologies. AVs exemplify this tension since, more than any other transport technology, they have the potential to entrench a vehicle-centric land use system.

Navigating these tensions requires high-quality assessments of the choices available to decision makers that better account for the uncertainties attached to future travel behaviour. One way to improve such assessments is by improving the representation of behaviour in models of urban mobility. Doing so can broaden the range of impacts considered by such models and improve the utility of their forecasts.

Models of future AV mobility services exclude pedestrians. Given the wide ranging impacts on pedestrians of vehicle traffic this omission significantly limits the ability of such models to produce a wide range of plausible future scenarios and their impacts across different populations. Incorporating relevant pedestrian behaviours into such models requires modelling street level pedestrian movement and road crossing at whole neighbourhood or city spatial scales.

Existing models of pedestrian movement do not consider this range of spatial scales and set of behaviours. Whilst models of some aspects of pedestrian road crossing behaviour and pedestrian-vehicle/AV interaction have been developed, these are limited in their representation of urban geography and disconnected from models of urban pedestrian flows. The following chapter sets out a multi-scale decision making framework that can be used to model multi-scale pedestrian decisions that addresses this gap.
Chapter 3

Modelling framework

3.1 Introduction

This thesis concerns the development of a novel model of pedestrian movement in urban areas. Modelling involves formalising hypotheses and assumptions in ways that can be “tested and refined through confronting their predictions with new data” (Batty and Torrens, 2005). According to Epstein (2008), the choice “is not whether to build models; it’s whether to build explicit ones”; models are fundamental to studying real systems. It follows that modelling is a broad term encompassing many different ways of explicitly stating hypotheses and assumptions about the world. This plurality requires modellers to specify and justify the approach they have taken to building an explicit representation of a real system. This is especially important where multiple disciplines and perspectives can be brought to bear on a system (complex urban systems being a prime example), leading to debates about what kind of models are useful or necessary, such as that between data driven methods (Anderson, 2008) and other epistemologies (Kitchin, 2014; Duarte and deSouza, 2020).

The chapter provides clarifications to these points and others. The framework below sets out the system of interest and the approach that will be taken to model it. The intention is to make explicit, at an early stage, the foundations of the model so that later chapters can focus on modelling details and results. To begin, the modelling objective is defined with reference to a research gap identified in the lit-
3.2. Research gaps in models of pedestrian movement

Chapter 2 revealed a disconnect between models of pedestrian movement at the street scale and at the neighbourhood or urban scale. At the street scale pedestrian movement has been represented with sufficient detail to differentiate between road crossing movements that do or do not comply with traffic regulations and social norms. Dynamic interactions between pedestrians and vehicles have been modelled in ways that account for the gradual nature of decision making and the role of communication and negotiation in this context. And yet these behaviours have not been integrated with larger scale models of pedestrian movement in which location and urban form are paramount.

As outlined in Chapter 2.3, there are numerous negative contributions to pedestrian safety, mobility, and health from aspects of vehicle mobility. These negative impacts have been studied in terms of the detailed movements of road users at the street scale as well as patterns of mobility that are connected to larger urban geographies. Small scale models are suitable for representing road user behaviours such as driver non-yielding and pedestrian jaywalking that impact safety and mobility. But their limited scale means these behaviours are disconnected from a particular place or location. Conversely, larger scale studies highlight the significance of different urban forms and land uses in understanding mobility behaviour.

Bridging these two scales of pedestrian movement could support sustainable transport planning by better representing how pedestrian experiences are shaped by
both the behaviour of individual road users and by wider urban geographies. For example, pedestrian movement is absent from many simulations of future autonomous mobility systems. And yet, interacting with other road users in complex urban road environments may be one of the hardest aspects of the driving task to automate (Markkula et al., 2022). Without incorporating street level pedestrian movement into city wide simulations of AVs, researchers are limited in the ways they can explore how this new mobility service could alleviate or exacerbate the negative impacts of vehicle mobility on pedestrians. Regardless of the development of new mobility technologies, existing pedestrian movement models are unable to represent how both small and large scale phenomena interact to produce the impacts on pedestrians reviewed in Chapter 2.3. A multi-scale pedestrian model could anticipate the impacts of changes to street infrastructure in ways that account for both the behaviours of road users at the location of the infrastructure but also the significance of its location within the wider urban area.

3.3 Modelling methodology and purpose

Our overarching research objective is to address this research gap by developing a model of street-level pedestrian movement in urban areas in a way that represents road crossing behaviour and dynamic interactions between road users through individual level decision making.

Agent-based modelling is a suitable modelling methodology for addressing this objective. A defining characteristic of agent-based modelling is the ability to represent dynamic interactions between autonomous agents (Crooks et al., 2018). Because of this, agent-based modelling is a well established methodology for modelling granular pedestrian movement (Batty, 2001), as illustrated by the many agent-based models and simulations of pedestrian movement discussed in Chapter 2. The suitability of agent-based modelling stems, in part, from its inherent flexibility (Heppenstall et al., 2016); the modeller is constrained by software rather than analytical mathematics. In our case this flexibility allows the decision making of pedestrian agents, street level movement, road crossing, and road user interaction to
all be represented in a single modelling framework.

This brings its own challenges in the form of a plurality of modelling approaches which can obfuscate comparisons between models. To combat this authors have proposed approaches to model development, reporting, and evaluation that introduce some standardisation to the process. Grimm et al. (2005) propose Pattern Oriented Modelling (POM) as an approach to designing and evaluating agent-based models. Edmonds et al. (2019) argue that making the purpose of the model explicit helps ensure suitable model design as well as establishing the criteria the model should be judged against. This section proceeds by outlining the modelling purpose and how pedestrian agent behaviour will be designed in line with POM.

The purpose of the model developed in this project is to provide a description of pedestrian movement that is granular (individual pedestrian trajectories through streets) and has a wide geographical coverage (a neighbourhood). A descriptive model, as opposed to descriptive text or images, has value “where the essence of what is being described is how several mechanisms might relate over time” (Edmonds et al., 2019).

In our case the objective is to develop a model that describes how path finding decisions made in relation to different sections of the urban environment (i.e. different spatial scales) and in relation to dynamic components of the environment combine to produce pedestrian trajectories.

The reason for developing a descriptive model, rather than an explanatory or predictive one, is to contribute to the development of novel approaches for appraising changes to street infrastructure in light of new transport technologies. Anticipating possible impacts of new transport technologies and associated changes to street infrastructure requires considering the possibility that future behaviour differs from past behaviour. Focusing only on reproducing past observations of pedestrian trajectories may therefore be insufficient for anticipating possible future impacts. Pedestrian use of street space has changed in response to the development of the automobile and may continue to change as cities transition to sustainable transport paradigms. Given these intractable uncertainties, there is value in developing a
3.3. Modelling methodology and purpose

modelling approach that can generate pedestrian behaviour that deviates from historic norms.

Modelling how pedestrians make decisions and how these decisions determine their trajectories can better anticipate changes in future behaviour. By producing trajectories ‘from the bottom up’ through a model of pedestrian perception and decision making, the model will produce outputs across multiple scales - ranging from individual cognitive processes to route choices and trajectories. This provides opportunities to validate model outputs against a broad range of evidence from multiple domains and avoid over fitting to pedestrian behaviour observed at a specific place or time.

Edmonds and Moss (2005) make this point when setting out the advantages of a descriptive modelling approach. Descriptive agent-based modelling, they argue, “allows and facilitates a more direct correspondence between what is observed and what is modelled” which makes a larger swathe of evidence available for model validation. Grimm et al. (2005) argue that models designed to reproduce multiple patterns are likely to be “structurally realistic”, meaning that “model components correspond directly to observed objects and variables, and processes correspond to the internal organization of the real system”. Polhill and Salt (2017) talk about the “ontological structure” of a model, meaning the correspondence of the model structure to the real system it is modelling, and also argue that the extent of this correspondence is an important criteria for comparing and selecting models. Due to the intractable uncertainties discussed above (which are often inherent to complex systems) model structure becomes an important criteria itself.

However, a potential downside of this modelling approach is a loss of clarity regarding the intended applications of the model. The outputs of different components of the model may correspond to very different processes and contexts, potentially requiring different validation data and methodologies. This is a common complication of agent-based and microsimulation methodologies; by producing higher-level behaviour from the actions and interactions of individual components such models often integrate theories spanning multiple domains and settings.
In this thesis, the model’s primary intended use is ultimately to predict pedestrian trajectories. However, to produce pedestrian trajectories the model also makes predictions about pedestrian perception and cognition and, therefore, has potential supplementary use as a model of these phenomena in urban environments. These different uses require different validation data and methodologies, and this point will be expanded upon in subsequent sections and chapters (specifically Section 6.5.5 and Section 7.4.3).

If explanation or prediction are not the modelling objectives, how will the model developed in this thesis be refined and evaluated? To answer this it is useful to first clarify the differences between model verification, calibration, and validation. Verification is the process of ensuring that the model correctly implements the mathematical expression of a theory (Thacker et al., 2004). This is achieved by comparing model outputs under different parameter settings to ensure the parameters are affecting model outputs in the intended way. Calibration is the process of tuning model parameters such that the model produces outputs - in this case pedestrian trajectories - that most closely correspond with empirical data. Once the model has been calibrated, its outputs can be viewed as predictions of pedestrian behaviour in the calibration scenario. Validating the model then involves comparing these predictions to a separate sample of empirical observations of the same pedestrian behaviour to provide an estimate of how accurate the model is (Trucano et al., 2006). It’s important that the validation data set is ‘out of sample’ of the calibration data set. A permissive reading of this requirement is that the validation data should not include observations included the calibration data. A stricter view is that validation data should be drawn from a different source entirely.

The POM (Grimm et al., 2005) framework for designing and evaluating agent-based models provides guidance on model evaluation that is relevant to the descriptive pedestrian agent-based model presented in this thesis. According to POM, “[p]atterns are defining characteristics of a system and often, therefore, indicators of essential underlying processes and structures.” Patterns of real pedestrian behaviour at multiple scales should be used to design model structure. The multi-scale pedes-
3.3. Modelling methodology and purpose

The pedestrian navigation model should then be evaluated by comparing patterns produced by the model to the system across these multiple scales and not just at one scale. The description of pedestrian movement sought in this thesis comprises trajectories across an urban neighbourhood at street level granularity produced by pedestrian decision making. Patterns of pedestrian movement should be produced at both the street and neighbourhood level to facilitate multi-scale comparisons to observed patterns of pedestrian movement. Model evaluation is further discussed below in Section 3.5 and in later chapters.

These modelling objectives can now be articulated as research questions that this thesis will address. The question of how pedestrian decisions should be represented to achieve good correspondence with the decision making of real pedestrians is articulated in research question 1, listed below. Building on this, research question 2 concerns the development of a computational model of pedestrian movement at the street level. The final research question concerns the application of this multi-scale pedestrian navigation model to appraisals of street infrastructure.

1. How should pedestrian decision making be structured when modelling street level movement across urban neighbourhoods?

2. How should pedestrian movement on urban streets be modelled to incorporate road crossing behaviour?

3. How does modelling pedestrian movement at these spatial scales inform the appraisal of street infrastructure?

The remainder of this chapter addresses research question 1 by proposing a framework for modelling street level pedestrian movement across an urban neighbourhood. This framework is developed into a multi-scale pedestrian model in Chapters 4 and 5 with the resulting behaviour verified using simulation experiments in Chapter 6, together addressing research question 2. Finally, simulation experiments are used to explore the impacts of restricting pedestrian road crossing in Chapter 7 which addresses research question 3.
3.4 Multi-scale pedestrian navigation framework

In developing this framework I attempt to provide a theoretical basis for pedestrian agent decision making from which an agent-based simulation of multi-scale pedestrian movement can be developed. The framework considers the decision making of individual able-bodied pedestrians walking from predefined trip origins to destinations located within a fixed neighbourhood. To begin, I argue that Construal Level Theory provides a suitable theory of decision making for the context of integrating street-level and neighbourhood level pedestrian navigation. Using this as the theoretical basis of pedestrian agent decision making, the framework defines the relevant spatial scales of decision making and which components of the real decision making process will be translated into the perception, decision making, and action processes of a pedestrian agent.

3.4.1 Construal level theory for multi-scale pedestrian navigation

Chapter 2.4 discussed several psychological and cognitive theories that explain spatial cognition and decision making as being structured hierarchically, with larger spatial scales corresponding to higher levels of the hierarchy than smaller spatial scales (Mark et al., 1999; Hirtle and Jonides, 1985; Chase, 1983; Maki, 1981). While these theories have informed models of pedestrian navigation, the relationship between spatial scale and decision hierarchy is not applicable to the scales of pedestrian movement considered in this thesis. Decision hierarchies are distinguished by larger spatial scales (for example between local neighbourhood locations and global features such as rivers (Chase, 1983)) than those spanning street and neighbourhood level pedestrian movement. Furthermore, cognitive maps are considered static, or only slowly changing with time, in contrast to the dynamic road environments pedestrians move in, where navigation decisions must be enacted at a particular point in time with consideration to the movements of other road users. Defining hierarchies in purely spatial terms fails to consider how the dynamic aspect of an environment could contribute the formation of decision hierarchies.
CLT proposes a two-level hierarchy with decisions construed at either a high- or low-level. CLT additionally explains how high- and low-level decisions are integrated. CLT can be distinguished by its use of ‘psychological distance’ - comprising spatial, temporal, social and certainty dimensions - in determining decision hierarchy (referred to as construal level) (Trope and Liberman, 2011) rather than the purely spatial distinction between hierarchies common to the theories discussed above. The role of visual information processing also contributes to decision construal, with visual information processing prompting low-level construal. Furthermore, CLT hierarchies are defined in relative terms through comparison of decision making between a psychologically proximate and distant setting. Similarly, evidence that visual information processing prompts low-level construal comes from comparison to verbal information processing rather than identifying an absolute level of visual information required to prompt low-level construal. This differs from the use of absolute spatial scales in defining decision hierarchies (such as identifying rivers as global environmental features compared to groups of locations that belong to a neighbourhood) in theories of spatial cognition. The multiple dimensions of psychological distance and the comparative nature of CLT hierarchy definition provides a more general description of multi-scale decision making.

CLT is a useful theory for describing decision making where a decision is made in two settings that differ in the psychological proximity of the object of the decision and the role of visual information processing in making the decision. It therefore provides a suitable theoretical basis for a modelling framework that integrates dynamic street level decisions with navigation to locations within an urban neighbourhood. Following Passini (1984)’s characterisation of wayfinding, pedestrian’s first make navigation decisions pertaining to larger spatial scales and then make decisions pertaining to smaller scales. However, pedestrians are able to revise earlier navigation decisions at the time these decisions must be enacted. According to CLT, this navigation decision will transition from being construed at a high-level to a low-level if the decision was initially made from a psychologically distant position and is then reconsidered at a psychologically more proximate position with
more significant visual perception. The modelling framework should therefore distinguish between high- and low-level decision construal where a decision is made initially from a psychologically distant perspective and can be revised from a psychologically proximate perspective.

The literature review identified dynamic and interactive aspects of road environments as important influences on pedestrians’ road crossing decisions. At the same time, people’s perceptions of walking accessibility are influenced by road crossings located beyond the immediate street environment. As such, CLT’s distinction between high- and low-level construal may be usefully applied to modelling road crossing decisions. When navigating to a location within the neighbourhood, CLT suggests pedestrians’ road crossing decisions are based on a high-level construal - one that is abstract and goal orientated. This is because the location is spatially distant, temporally distant (it will take the pedestrian some time to get there), more uncertain (the pedestrian cannot be sure what other road users will be doing) and visually occluded, requiring the pedestrian to “traverse psychological distance” to make decisions about navigating to this location. When navigating to locations in the immediate road environment road crossing decisions may be re-construed at a low-level - one that is less abstract and feasibility based. This is because road users and infrastructure within a pedestrian’s immediate environment can be visually perceived with ease and exhibit a higher degree of certainty owing to their spatial and temporal proximity. This aligns with previous research that finds pedestrians choose crossing locations sequentially, evaluating exactly how to progress along a road link only once the pedestrian reaches that road link (Papadimitriou, 2012). It differs by introducing multiple scales of decision making at which the same decision is construed in different ways, initially at a high-level and then at a low-level.

For other navigation decisions that are less influenced by dynamic and interactive aspects of road environments, such as which turn to take at intersections, it is harder to justify distinguishing between high- and low-level choice construal between the immediate street environment and wider neighbourhood. The lack of dynamic influences on such decisions limits the difference in psychological distance
3.4. Multi-scale pedestrian navigation framework

between street and neighbourhood settings; they differ in spatial distance but less so in the other dimensions of psychological distance. Therefore, within the framework, path finding decisions involving road crossing are integrated across spatial scales on the basis of CLT whilst other path finding and movement decisions are modelled at a single spatial scale only.

3.4.2 Representation of the urban environment

The components of real urban environments that are represented in the framework are now established. These environmental components are used to distinguish between psychologically distant and proximate environments and therefore between locations for which navigation decisions are construed at a high-level or low-level.

The psychologically proximate environment should be visible and the movements of road users in the environment should exhibit a relatively high degree of certainty. The road network provides a suitable way of distinguishing between psychological proximity and distance for the following reasons. Visibility can be measured by the angular distance between links in the network, with zero angular distance implying greater visibility due to a lack of building occlusions. The predictability of road users decreases as they move through successive intersections, due the potential for changes of direction and multifaceted interactions with other road users and traffic infrastructure. By defining road network links as straight, non-intersected sections of carriageway the current road link of a pedestrian can be defined as psychologically proximate. Locations on the current road link are visible, due to its straightness; locations are temporally proximate because the link can be traversed in a relatively short amount of time; and the movements of other road users relatively predictable, given the link does not contain any intersections. This distinction between proximate and distant locations is based on multiple components of psychological distance - spatial, temporal, and certainty - and provides a stronger distinction between decision hierarchies that one based only on seen and unseen environments.

The representation of the environment also informs the decision making of pedestrian agents. Decisions pertaining to psychologically distant locations are
construed at a high-level and, accordingly, the representation of the environment is abstract to afford “traversing psychological distance”. At a minimum, the abstract representation must contain components of the built environment that enable an agent to distinguish between desirable and undesirable paths. Additionally, because the behaviour of interest is interactions between pedestrians and vehicles through pedestrian road crossing, the abstract representation also needs to distinguish between crossing and non-crossing trajectories. This is provided by a road network in combination with a pavement network. The road network represents the geometry and connectivity of carriageways and therefore the available directions of travel at each intersection. The pavement network additionally represents the geometry and connectivity of pavements, and therefore distinguishes between sides of the road and crossing and non-crossing movements. The networks are static and coarse representations of the environment that permit agents to identify desirable paths in terms of the direction of travel the road crossings required to reach a destination.

When navigating the psychologically proximate environment decisions are construed at a low-level and therefore a more detailed representation of the environment is used. The detailed representation treats the space as continuous, representing the carriageway and pavements as polygons. The locations and velocities of road users can be perceived as well as the presence of infrastructure such as road crossings.

Figure 3.1 illustrates the distinction between the psychologically proximate and distant environments. The representation of the environment is more abstract beyond the current road link. Within the current road link a more detailed representation of the environment is available to the pedestrian; this includes the presence of other road users and road crossing infrastructure.

The precise implementation of the distinction between these hierarchies is covered in Chapter 4 where the process of producing the model environment is detailed. The following section proposes how decisions made based on high- and low-level construals should be integrated.
3.4.3 Decision making process

Having established the structure of pedestrian decision making and the related representation of the urban environment the pedestrian route choice model can be designed. Two levels of route choice decisions are defined, upper-level route choice and lower-level route choice. Upper-level route choice identifies a path to psychologically distant locations, those beyond the current road link, based on high-level construal. Lower-level route choice identifies a path to psychologically proximate locations, those within the current road link, based on low-level construal. Full details of route choice models are given in Chapter 4 (upper-level route choice) and Chapter 5 (lower-level route choice). In this section the requirements of these route choice models are put forward.

It’s helpful here to reiterate model objectives and purpose: to provide a granular description of pedestrian movement across an urban neighbourhood. This descriptive model should enable exploration of how pedestrian movement and road crossing behaviour is produced through pedestrian decision making in street envir-

Figure 3.1: a) Diagram illustrating the CLT route choice framework. Red pillars indicate an origin and destination. Within the psychologically proximate environment road users and crossing infrastructure can be perceived. The psychologically distant environment is perceived as more abstract. b) Summary of upper-level and lower-level route choice. Grey arrows indicate interaction between levels.
3.4. *Multi-scale pedestrian navigation framework*

Environments. To provide a rich description of pedestrian movement the route choice models should relate “as strongly to the target domain as possible” (Edmonds and Moss, 2005). This is achieved by representing multiple aspects of heterogeneity between pedestrians from which a diverse set of trajectories may be produced.

Two sources of pedestrian agent heterogeneity are accounted for in this framework: spatial knowledge and reasoning, and route choice preferences. Whilst the modelling framework defines two levels of decision making, each related to a different spatial scale, each level in this hierarchy contains its own range of spatial scales which may continue to affect pedestrian decision making. Pedestrians may also differ in the extent of rational optimisation they apply to route choices, as mentioned in the discussion of human navigation in Chapter 2. Variation is also produced through different pedestrian agent preferences. Following the framework’s focus on road crossing decisions, route choice preferences are expressed in terms of road crossing preferences. While pedestrian route preferences will differ in other aspects, road crossing choices have been identified as suitable to CLT’s distinction between high and low-level construal and this continues to be the focus of pedestrian route choice decisions. To summarise, the route choice model employed at each level of the framework should:

- represent differences in spatial knowledge and reasoning
- represent different perceptions of the costs of crossing roads
- integrate with decisions made at the other level

Having established these universal requirements, the specific ways in which *upper-level* and *lower-level* route choice achieve this can be set out. These requirements will be met in different ways owning to different scale and associated construal of route choices at each level.

*Upper-level* route choices are made based on the abstract representation of the environment given by the road network and the pavement network. *Upper-level* route choice chooses a path on the road network and the pavement network. Paths on the road network correspond to choices of which turns to take at intersections.
The pavement network additionally distinguishes between sides of the road by accounting for the availability of pedestrian designated space (the pavement) typically available either side of carriageways. Paths on the pavement network therefore identify which, if any, road links to cross. Differences in spatial knowledge and reasoning are represented at this level by varying knowledge of the spatial networks across the pedestrian population. Different preferences are represented through different criteria for selecting between multiple candidate paths on this bounded section of the pavement network.

Integration of upper-level paths with lower-level route choice is achieved through low-level choice reconstrual. When a pedestrian agent enters and moves along a road link their upper-level route choices must be enacted. The section of the upper-level path that lies within the current road link becomes psychologically proximate and so these route choices are reconstrued as lower-level route choices - a set of way points the pedestrian agent moves between to reach the end of the road link. The upper-level choice of which intersection turns to make remains unchanged by low-level construal because there is no aspect of the psychologically proximate environment that would alter this choice. Similarly, upper-level paths along one side of the road are unaffected by low-level construal because is it assumed movement along the pavement is not greatly impacted by the presence of other road users or pavement geometry. (Future work could extend this to consider how low-level construal could affect non-crossing upper-level choices.) However, low-level construal of road crossing decisions does differ to high-level construal because of the increased detail the pedestrian agent now perceives for their current road link. Practically, this means the pavement nodes of the upper-level path are retained as way points and lower-level route choice additionally identified a crossing location that is added to the set of way points.

As with the upper-level, lower-level route choice also incorporates differences in spatial knowledge and reasoning and road crossing perceptions. Pedestrian agents choose a specific road crossing location based on their perception of crossing infrastructure and vehicle traffic, which they perceive for their current road link (the
psychologically proximate environment). These perceptions are varied to produce choices that optimise for the pedestrian agent’s preferences to a greater or lesser degree. As outlined in Chapter 2, coordination between road users at the street level is aided by infrastructure and social norms which regulate the flows of different road users. As such, lower-level road crossing decisions incorporate different pedestrian agent preferences regarding the road crossing infrastructure that are based on the road conditions at the time of crossing.

Lower-level route choice additionally integrates with pedestrian movement by pedestrian agents moving between the chosen lower-level way points. Representation of pedestrian movement is required to produce the dynamics of the psychologically proximate environment, dynamics which influence route choice decisions and ensure pedestrian trajectories are shaped by both ‘top down’ and ‘bottom-up’ processes. The level of detail of pedestrian movement should suit the modelling context. Pedestrian movement may need to account for interactions with other road users, the environment, or the target way point but could also simply assume pedestrians move at a constant rate in a straight line between way points. For this study a simple social-force model of pedestrian movement is used to move pedestrian agents between way points, detailed further in Chapter 5.

Once the end of the road link is reached the next road link, previously categorised as psychologically distant, becomes psychologically proximate. This means both high- and low-level representations of the environment are updated due to the progression of the pedestrian towards their final destination. The upper-level path is re-chosen in light of the updated high-level representation and a new lower-level path is chosen for the newly perceived road link.

### 3.5 Simulating and verifying pedestrian agent movement

The multi-scale pedestrian navigation framework establishes how a model of pedestrian route choice should be structured. To simulate pedestrian movement a multi-scale route choice model will be developed and used to guide the movement of
3.5. Simulating and verifying pedestrian agent movement

pedestrian agents in an agent-based simulation (ABS) of urban mobility. The resulting behaviour of pedestrian agents will be studied by performing simulation experiments.

The multi-scale route choice model will be parameterised to produce the varied pedestrian behaviour discussed above. In addition to the route choice model parameters, the initial conditions of the simulation will be given as inputs. These initial conditions determine the origins, destinations, frequency, and volume of pedestrian trips. Route choice model parameters are varied to explore the behaviour produced by the model. Many simulation initial conditions are held constant to ensure the same set of pedestrian trips are modelled each run, however, pedestrian agent trip frequency and the volume of vehicle agents are varied to produce different traffic conditions. Pedestrian agents share the environment with vehicle agents that similarly complete trips in the study area according a vehicle route choice and movement model.

Broadly two kinds of simulation experiments will be conducted. Firstly, the multi-scale pedestrian route choice model will be verified by comparing patterns of pedestrian agent behaviour at the lower-level and upper-level to the patterns of decision making described by CLT and patterns of pedestrian behaviour (specifically road crossing behaviour) identified in the literature. These verification experiments establish ranges of route choice model parameter values that produce the desired pedestrian agent behaviour. These experiments also establish how, when implemented in a simulation, route choice model parameters affect pedestrian behaviour. Sensitivity analysis and meta-modelling are used to quantify the effect parameters have on pedestrian agent movement. This is used to develop a theoretical understanding of how different components of pedestrian path finding could impact journeys and whether these impacts differ between different environments. Together, this produces an understanding of how the decision making of individual pedestrian agents produces patterns of movement at lower and upper spatial scales. These simulation experiments are detailed in Chapters 5 and 6.

Building on this, a second set of simulation experiments seek to demonstrate
the utility of modelling multi-scale pedestrian movement for exploring the impact of interventions to street design and infrastructure. Simulations are performed under different policy scenarios representing different interventions to traffic management or street infrastructure. By performing many simulations under each policy scenario the role of route choice behaviour in mediating the impacts of policies, as well as the impacts of different urban environments and traffic flows, can be analysed. These simulation experiments are detailed in Chapter 7.

Across all experiments the simulation outputs will be metrics that quantify pedestrian agents’ routes and road crossing behaviour. These reveal how pedestrian agents’ routes are shaped by their route choice preferences, their environment, and interactions with other road users (i.e. vehicle agents). Additionally, metrics of vehicle trips are recorded and analysed to compare the effect of parameter setting on pedestrian and vehicle agent mobility.

Whilst these verification experiments will not validate the model, the work will still provide a valuable contribution towards modelling pedestrian behaviour by developing the theory of how route choice decisions at the spatial scales in question are conceived and integrated. The descriptive modelling approach will explore the implications of the mathematical representation of these decisions and their integration. This can be a useful precursor to developing a predictive model and is a valuable activity for developing theory regarding how a pedestrian’s route choice decisions are shaped by their own characteristics as well as by dynamic and static aspects of their environment. Exploring the full range of behaviour produced by the model will inform the relative importance of model components and suggest ways in which real pedestrian trips are shaped by their characteristics and environment. Additionally, exploratory modelling permits comparisons of model outputs between different idealised environments that, whilst not truly representative of any real city, and therefore unsuitable for validation, inform how pedestrian movement is shaped by the environment.
3.6 Conclusion

The modelling framework has two objectives. Firstly to establish the research gap to be addressed and the modelling approach that will be taken to address this gap. The representation of multi-scale pedestrian decision making and movement in models of urban mobility was identified as a gap. This gap will be addressed by developing a descriptive agent-based model of pedestrian movement. This modelling approach requires a theoretical basis to structure pedestrian agent decision making.

This motivates the second objective of the framework: establishing how pedestrian agent decision making will be structured in the model. A CLT based framework for modelling street level movement of pedestrian agents across an urban neighbourhood is presented for this purpose. This builds upon existing research by integrating decisions made regarding the immediate street environment and those made regarding the wider urban area, addressing research question 1 in doing so.

A core component of the pedestrian decision making framework is the treatment of road crossing decisions. These decisions are identified as an important component of street level pedestrian movement and require distinguishing between sections of pavement on either side of the carriageway (the two sides of the road). Pedestrian agents first choose a path in based on a more abstract but larger representation of the environment (high-level construal). They then choose a more detailed path but only for their current road link (low-level construal). Through this process the environment is represented in increasing detail; from a network of road intersections to a continuous space populated by road users and crossing infrastructure. CLT provides the theoretical basis for representing decision making and the environment in this way.

The following chapter develops this framework by presenting the decision models used to model pedestrian route choice. Simulation experiments are then developed which used the pedestrian route choice models to simulate pedestrian movement.
Chapter 4

Upper-level route choice

4.1 Introduction

Chapter 3 presented a hierarchical Construal Level Theory (CLT) framework for modelling street level pedestrian movement across urban neighbourhoods. The framework provides the theoretical basis for route choice decisions, distinguishing between two levels of decision making - upper and lower - when modelling street level pedestrian movement at the neighbourhood scale.

According to the framework, upper-level route choice should be made based on high-level decision construal that is abstract and desirability based. In this chapter we present method for modelling route choice in this way. The chapter begins by detailing how GIS data is used to build an abstract representation of the urban environment that is suitable for high-level decision making. The upper-level route choice model uses this abstract representation of the environment to choose a path to a destination within the study area, as detailed in Section 4.3.

4.2 Representing the neighbourhood level environment

In the hierarchical CLT framework, upper-level route choice is made based on an abstract representation consisting of a road network and a pavement network. The production of the road network and pavement network from GIS data follows from the requirements of these networks in the modelling framework. The road network
4.2. Representing the neighbourhood level environment

is required to represent turning choices at intersections. Additionally, road links must represent straight, non-intersected sections of carriageway in order to distinguish between psychologically proximate and distant environments. The pavement network represents the connectivity of designated pedestrian infrastructure. Assuming this is located beside carriageways, the pedestrian network therefore represented road crossing movement as well as movement alongside carriageways. The road network represents the geometry and connectivity of a study area’s carriageways and the pavement network expands on this by distinguishing between the two sides of a carriageway, and therefore crossing and non-crossing movement.

4.2.1 Identifying suitable data sources

The minimum requirement for producing these network representations are carriageway geometries. From these a road network based on carriageway centre lines could be produced and a pavement network produced based on the assumption that the edge of each carriageway boarders a pavement. However, additional geographic data sources can improve the representation of the environment whilst simplifying the data processing required to build the networks. Furthermore, additional information about a study area can help improve the realism of pedestrian and vehicle movements by representing right-of-way and the availability of pavement infrastructure in greater detail.

Two sources of geographic data were investigated: OpenStreetMap (OSM) and Ordnance Survey (OS). OSM is the “world’s largest Volunteered Geographic Information (VGI) platform” (Anderson et al., 2019) and is a well-used and valuable source of free and open geographic data. OS “provides Great Britain’s national mapping services” (Ordnance Survey, 2022). While OS does offer some open data products these are limited. Many data sets, particularly the most detailed, are proprietary and have license fees attached (although these are waived for research and education purposes). Using open data sources with global coverage as the input to a model lowers barriers to sharing, replicating and extending the work. We audit and compare the availability of data in OSM and OS to inform a whether using exclusively open data is feasible given the modelling objectives.
4.2. Representing the neighbourhood level environment

Ordnance Survey Data Availability

The OS Mastermap Topographic (OS-MT) data set contains polygons mapping land use across Great Britain with a high level of granularity and accuracy. Polygons representing carriageways and pavements are identifiable through polygon metadata.

OS also provides several data sets related to navigation and routing. OS Integrated Transport Network (OS-ITN) provides a high resolution representation of the road network, with lines representing carriageways and detailed information related to right-of-way (e.g. one way streets and turning restrictions). OS Open Roads (OS-OR) is an open source road network data set which is less detailed but suitable for routing and navigation purposes. The simplified road network representation of the OS-OR data set is better suited to upper-level route choice than the OS-ITN. The OS-ITN provides a high level of detail, for example detailing different paths through junctions, that are not directly relevant to pedestrian movement. The OS-OR data set simplifies junctions, typically to a single node, providing a representation limited to coarse road link geometry and turning decisions. However, the OS-ITN data is suitable for modelling the movement of vehicle agents.

There is no OS data set that provides a network representing pedestrian dedicated street space and infrastructure. The OS ITN Urban Paths (OS-ITN-UP) data set consists of line geometries that indicate the locations and connectivity of pedestrian-only routes such as pedestrianised streets and paths through parks. These do not directly integrate with the road network and do not indicate the presence of road side pedestrian space such as pavements. As such, the OS-ITN-UP data set is not suited to distinguishing between pedestrian and vehicle dedicated street space, and therefore not well suited to the modelling objectives of this study. Instead, information about the presence and location of pavements must be extracted from the OS-MT data set. By connecting the OS-ITN-UP data to the road network the representation of pedestrian accessibility would be improved, however, this is outside the scope of this study.

To summarise, OS provides three data sets that can be used to build the required
representation of the built environment; OS-OR is a simplified road network that is suitable for representing pedestrian decision making at intersections; OS-MT provides detailed land use polygons from which a pavement network can be produced; and OS-ITN provides a more detailed road network suitable for modelling vehicle movement. These data are only available for Great Britain but provide consistent coverage and detail across this area because of the role of OS as Great Britain’s mapping agency.

**OpenStreetMap Data Availability**

Assessing the availability of OSM data is complicated by its nature as volunteered geographic information which results in varying detail and coverage across the world. The OSM data standard permits the recording of a vast array of geographic features but large discrepancies between the coverage of these features exist. The proposed model requires a high coverage of data describing the road network and the geometry of carriageways and pavements.

Barrington-Leigh and Millard-Ball (2017)’s study of the completeness of OSM suggests that over 80% of the world’s road have been mapped. For the UK they estimate the coverage of OSM’s roads to be between 99-100%. OSM can therefore be confidently relied upon for the road network component of the high-level environment representation.

It is less clear whether OSM can provide sufficient data to produce the pavement network representation. OSM conventions do not include the mapping of carriageway or pavement spaces as polygons. However, there are multiple OSM conventions for mapping pedestrian designated space. Provided sufficient detail and coverage, these could serve as suitable sources of data for the pavement network, as opposed to building a pavement network using carriageway and pavement polygons from OS-MT.

Pedestrian space and pedestrian accessible routes can be mapped in OSM in several ways. OSM features are assigned tags - key-value pairs of metadata that indicate what real-world object the feature represents. The ‘highway’ tag is assigned to line features to indicate that they represent any intentional route that connects one
place with another. Two dominant conventions are used to indicate the presence of
dedicated pedestrian space. Firstly, ‘highways’ can be assigned the ["sidewalk"="both\left|right\right|no"] keyword tags to indicate the presence of pedestrian designated
space beside carriageways. However, this convention does not provide any spatial
information regarding the dimensions or exact location of pavements. Secondly,
line segments which record the ‘pavement centre line’ (PCL) - the line passing
through the middle of pavement geometries - can be added to the map. These are
referred to as ‘footways’ in the OSM data model and are assigned the tags ["high-
way"="footway"] or ["footway"="sidewalk"]).

By indicating the location and geometry of dedicated pedestrian space, ‘foot-
way’ geometries could be used to produce a pavement network representation of an
urban environment, provided sufficient coverage of these features in OSM. Studies of the coverage of pedestrian designated space in OSM are ad-hoc and of lim-
ited relevance to the specific requirements of this research. Timaite et al. (2022)
present proof-of-concept results of a project intended to evaluate the suitability of
OSM transport network data for sustainable transport modes. The results cover four
metropolitan regions in England and suggest that the coverage of ‘footway’ links in
OSM is insufficient for the requirements of this research.

We undertook an additional survey of the coverage of pedestrian dedicated
space to more thoroughly evaluate the suitability of OSM data for the pedestrian
model pursued in this research. OSM data was downloaded for a sample of 112
urban areas in England and Wales, as defined by the boundaries in the Office for
National Statistics (ONS) ‘Major Towns and Cities (December 2015) Boundaries
V2’ data set, available from the Office for National Statistics’ ‘Major Towns and

For each city three groups of OSM geometries were downloaded: the walka-
ble road network, highway geometries with sidewalk tags, and footway geometries.
The OSM queries used to identify each of these groups are shown in Table 4.1. The
walkable road network provides the ‘ground truth’ of an urban area’s road network
against which the coverage of mapped pedestrian infrastructure can be measured.
This query was adapted from the OSMnx (Boeing, 2017) query used to download a walking network by omitting any geometries representing pedestrian only spaces. The total length of footway geometries and the total length of highway geometries with sidewalk tags (geometries tagged as having sidewalks on both sides of the road are counted twice) was calculated. This gives two measures of the amount of pedestrian designated space data for each urban area. To make comparisons between urban areas these lengths were divided by twice the total length of the walkable road network. This implicitly assumes that pavements are located on both sides of every walkable road. This is a coarse assumption but is suitable for the purposes of broadly assessing the coverage of pavement location data in OSM. High coverage ratio values indicate greater equivalence between the availability of pavement location data and the walkable road network.

Figure 4.1 shows that the coverage of footways and highway geometries with sidewalk tags is low across all major towns and cities in England and Wales. Comparing the coverage of footways geometries and road geometries with sidewalks tags shows that in general pedestrian space is mapped using separate footway geometries although a few places have greater coverage of sidewalk tags than footways. Grouping places into population quartiles shows footways coverage does not tend to increase or decrease with the population of an urban area. From this analysis it is clear the coverage of footways is insufficient for use as a pavement network. Similarly, the coverage of sidewalk tags is insufficient to use as a basis for approximating a pavement network.

Based on this assessment using only open data as input to the hierarchical CLT route choice model is currently infeasible. Instead a mixture of open and proprietary data from OS will be used.

### 4.2.2 Data processing

The OS-OR and OS-MT data sets provide the detail and coverage required by the hierarchical CLT route choice framework. Additional processing is required to ensure correspondence between the geometries in these data sets and the representation of the urban environment proposed by the modelling framework.
### 4.2. Representing the neighbourhood level environment

#### Walkable Road Geometries
```
["highway"="footway"]
["highway"="bus_guideway"]
["highway"="cycleway"]
["highway"="motorway"]
["highway"="planned"]
["highway"="proposed"]
["highway"="raceway"]
["highway"="pedestrian"]
["footway"="sidewalk"]
["foot"="no"]
["service"="private"]
```

#### Footway Geometries
```
["highway"="footway"]
["footway"="sidewalk"]
```

#### Road Geometries With Sidewalk Tags
```
["sidewalk"="both"]
["sidewalk"="left"]
["sidewalk"="right"]
```

**Table 4.1:** Queries used to select OSM ways that correspond to the walkable road network, footway geometries, and road geometries with sidewalk tags.

**Figure 4.1:** Footway and sidewalk tags coverage for 112 towns and cities in England and Wales. **a)** Comparing the coverage of sidewalk tags and footways geometries. **b)** Coverage of footway geometries grouped by population. The distribution across all towns and cities is shown by the shaded area in the background.
4.2. Representing the neighbourhood level environment

Figure 4.2: Data used to build model environment. a) OpenStreetMap data. shown for reference. b) Ordnance Survey Open Roads. c) Ordnance Survey Mastermap. Topographic data with pavement polygons in red, carriageways polygons in blue, and all other polygons, mostly building footprints, in grey.

Road network

From the full OS-OR data set, link and node geometries that lie within the study area are selected. The specific study area will depend on the application intended for the agent-based simulation; in Chapters 6 and 7 we use a catchment area from a metro station as the study area.

The OS-OR road network geometries are simplified, using the OSMnx python package (Boeing, 2017) in addition to our own software, by consolidating junctions represented by multiple nodes to a single node and retaining only intersection nodes. Road links are then simplified to single straight line geometries, with new nodes added where the road geometry bends by more than 10°. The resulting geometries correspond to straight and non-intersected section of carriageways connected by nodes representing either bends in the road or intersections at which pedestrians have a choice of which direction to travel in.

OS-ITN road network data is used to model vehicle agent routing and movement. OS-ITN data is similarly filtered to select only geometries within the study area. For the purposes of this study vehicle movement is modelled simply as the global shortest path. Because of this further processing of the OS-ITN network is not performed because the network does not need to correspond to a driver’s psychological representation of the environment.

Pavement network

The process of producing a pavement network from land use polygons is more involved; OS-MT polygons are used in combination with the simplified OS-OR
data to produce the pavement network. Carriageway polygons are identified by intersecting OS-MT polygons with road link geometries from the processed OS-OR and OS-ITN road networks. Polygons that do not intersect road link geometries but are surrounded by polygons that do are also categorised as carriageway polygons. Pavement polygons are identified as OS-MT polygons using the ‘descriptivegroup’ metadata field. Polygons with ‘descriptivegroup’ values shown in Table 4.2 are selected as pavement polygons. Some pavement polygons are also classified as carriageway polygons due to being intersected by a road link geometry and these are removed from the set of carriageway polygons. Traffic islands are also excluded from the set of pavement polygons and do not feature in the pavement network.

At this stage the pavement and carriageway polygons are mapped against the full OS-MT data set to inspect by eye the quality of the classification. A gap in the continuity of pavement polygons was observed and by cross referencing against Google Street View imagery it was confirmed that a topographic polygon had been incorrectly excluded from the set of pavement polygons. This polygon was manually included by noting its ID number and making an exception in the data processing script. This exception was applied to only one polygon and was caused by incorrect ‘descriptivegroup’ metadata.

Once the pavement and carriageway geometries have been identified the pavement network is produced. The starting point is the OS-OR network. Working on the assumption that pedestrians are able to walk along either side of every OS-OR network link, pavement network nodes are placed at either end and either side of each road link. This assumption could be later revised based on the availability of pavement polygons. However, in this study we assume that pedestrian are still able
4.2. Representing the neighbourhood level environment

To walk alongside a road link in the absence of a dedicated section of pavement. The carriageway and pavement polygons are used to locate the pavement nodes by casting 20m rays with an angular resolution of 10° in a 90° arc between pairs of OS-OR links connected to a road node, illustrated in Figure 4.3a. The nearest intersection between a ray and a pavement polygon is chosen as the pavement node location. Where pavement polygons are not present, the intersection between the ray and edge of the carriageway is used, based on the assumption that, in the absence of a pavement polygon, the edge of a carriageway corresponds to the edge of a building. 660 out of a total of 666 pavement nodes are located by following these rules. In the 6 remaining cases the edge of the carriageway is greater than 20m from the road node and additional rules are needed to locate the pavement nodes. First, the 90° arc constraint is removed and rays are cast across the whole space bordered by the two road links - this identifies a further 2 pavement nodes. Second, pavement island polygons are included as potential sites for pavement nodes - this also identifies a further 2 pavement nodes. The final 2 nodes are located by simply placing the pavement node 5m from the road node directly in between the two connecting links.

Pavement nodes provide a more detailed representation of the urban environment than the OS-OR network by distinguishing between sides of the road. Movement between pavement nodes can therefore represent road crossing movement that is perpendicular to the direction of movement implied by OS-OR road links. How pavement network nodes are connected reflects the set of possible movements a pedestrian can consider making when choosing an upper-level path. Given that high-level construal makes more desirability based decisions, the connections between pavement network nodes should represent all possible movements. This can be achieved by fully connecting the four pavement network nodes that correspond to a road link, meaning that pavement network links represent line of sight movement between nodes. This creates 6 pavement network links per OS-OR road link. These are classified as non-crossing links where the link connects two nodes on the same side of the road, direct crossing links where the link connects pavement nodes
4.2. Representing the neighbourhood level environment

Figure 4.3: a) The process for locating a pedestrian node, illustrated by the orange circle. b) The pavement nodes for a single road link. c) Pavement nodes belonging to the same road link are connected to each other.

at the same end of a road link, and diagonal crossing links when a link connects pavement node on different sides and different ends of a road link. These links are illustrated in Figure 4.3c.

Alternative pavement network construction methods are more detailed. Rhoads et al. (2020) build a comparable pavement network but use road crossing links to represent the locations of road crossing infrastructure. Additionally, network links follow the geometry of pavements more faithfully. This level of detail is reserved for lower-level route choice in this study.

Linking Data Layers

Creating look-ups between data layers improves the legibility of the GIS environment and aides the development of the simulation. There are four data layers in total: the OS-OR network, the OS-ITN network, the pavement network, and the pavement and carriageway geometries. The pavement and carriageway geometries are not directly used in upper-level route choice since the pavement network abstracts the key features of these geometries, however, they are used for the more detailed lower-level representation of the environment and so are also linked to the other data layers.

The OS-OR network is used as the based layer that other GIS layers are linked to. The pavement network is created based on the OS-OR network which makes the linking of these two layers straightforward. Pavement network links are nested within OS-OR links creating a 6:1 lookup from pavement to OS-OR links. Similarly
pavement network nodes are nested within OS-OR nodes, creating a d:1 lookup from pavement to OS-OR nodes, where d is the degree of the OS-OR node.

Creating a lookup from OS-MT pavement and carriageway geometries is more complicated because these geometries do not align with the OS-OR link geometries. To align these two layers, OS-OR road link voronoi regions are produced and intersected to the OS-MT pavement and carriageway geometries. Pavement and carriageway geometries are then dissolved to give two pavement polygons and one carriageway polygon for each OS-OR road link. Since each carriageway polygon maps the carriageway of a single OS-OR link these are used to link OS-ITN road links with OS-OR road links. A many:many lookup between OS-ITN and OS-OR links is produced by assigning OS-ITN links the OS-OR link IDs of the carriageway polygons they intersect.

4.3 Upper-level route choice model

The OS-OR road network and the pavement network comprise the abstract upper-level representation of the environment. Using these networks upper-level route choice ‘traverses psychological distance’ and chooses a path to locations that are psychologically distant. This section details upper-level route choice and it’s implementation. To reiterate, the requirements set out in the modelling framework are:

- represent differences in spatial knowledge and reasoning
- represent different perceptions of the costs of crossing roads
- integrate with decisions made at the other level (the lower-level)

Differences in spatial knowledge are produced by varying how much of the pavement network pedestrian agents perceive when choosing an upper-level path. Enforcing partial knowledge of the road network has been used to improve the realism of models of human navigation. In Filomena et al. (2020) pedestrian agents are only able to plan optimal routes within regions of a city’s road network. This builds on models of driver navigation which similarly limit perfect knowledge of the road
network to spatially bounded regions of the city (Manley et al., 2015b), and additionally varying knowledge of the nodes within the region across the driver agent population. The regions in these studies represent meaningful urban sub-divisions such as neighbourhoods. It is uncertain whether knowledge of the more detailed pavement network should similarly be delineated by these, or other fixed regions. Instead, partial knowledge of the pavement network is produced by assigning pedestrian agents a planning horizon, $PH$.

The planning horizon is a threshold distance, within which pedestrian agents can perceive the pavement network. Two prominent distance metrics on road networks are link length and turning angle (Simons, 2021); minimising link length produces ‘shortest paths’ while minimising cumulative turning angle produces ‘simplest paths’. Turning angle is widely used as a distance metric when modelling pedestrian movement (Turner, 2007a; Dalton, 2003) and so this is adopted as the metric to define agents’ planning horizons with. Angular distance also approximates the visibility of the road network. The planning horizon therefore implies reduced knowledge of visually occluded sections of the road network. Specifically, a pedestrian agent’s planning horizon, $PH$, is a threshold angular distance within which they can perceive the pavement network. Once a road link is traversed, the upper-level path is re-planned to account for the planning horizon potentially extending to a new section of the pavement network.

The planning horizon is restricted to included only road links in the shortest length road network path from pedestrian origin to destination, calculated using Dijkstra’s algorithm (Dijkstra et al., 1959) with link weight given by road link length. Links along this path that lie within the planning horizon are identified and only the section of the pavement network along these links is perceived by the pedestrian agent. Restricting the planning horizon to lie along the shortest road network path means that turning decisions are made based on the OS-OR road network alone. The upper-level pavement network path inherits these turning decisions and provides additional detail by distinguishing between sides of the road. An alternative approach would be to permit the planning horizon to extend in all directions. The
upper-level path would then represent both turning and road crossing decisions, with turning decisions being potentially influenced by the presence of road crossings. This extension is left as a future direction of work.

Where the destination node lies within the planning horizon upper-level route choice simply chooses a path to this. Otherwise the target pavement node is chosen from the two pavement nodes at the far end of the final road link in the planning horizon. Four pavement nodes are associated to this link, two at each end. Pavement network paths to both far end pavement nodes are computed and the most desirable path chosen.

Having established how variable spatial knowledge is represented through the use of a planning horizon parameter $PH$, the method for choosing between alternative upper-level paths can detailed. As mentioned, a common approach to modelling route choice in urban road networks is to use the shortest or simplest path. As well as these base characteristics route choices have been also found to correlate with components of the built environment (Salazar Miranda et al., 2021). Road crossing choices are also influenced by a range of factors related to infrastructure and traffic (Anciaes and Jones, 2020, 2017).

For the purposes of this study these detailed representations of pedestrian preferences are not accounted for. Rather than seek to represent a wide range of subtle pedestrian preferences, upper-level route choice is intended to represent, at a high-level, different perceptions of links costs related to road crossing behaviour. Accordingly, upper-level paths are chosen by either a distance minimising or crossing minimising heuristic, controlled by a Boolean parameter termed $MC$. These heuristics are chosen to represent an abstract, desirability based choice that represents carriageways as either a barrier or facilitator of pedestrian movement. Path distance is given by the sum of pavement network link lengths. The number of crossings is calculated by summing the number of pavement network links in the path that cross a road. When distance minimising ($MC = false$), paths are first ranked on distance then number of crossings and visa versa when minimising the number of crossings ($MC = true$). If a single shortest path is not identified by ranking a path is randomly
chosen from the tied candidates.

Varying parameters $MC$ and $PH$ changes the upper-level paths chosen by pedestrian agents. High $PH$ values means upper-level route choice will approximate optimal least cost paths and switching between $MC = true$ and $MC = false$ changes the cost metric to optimise.

Figures 4.4a, 4.4b and 4.4c illustrate how differences between agents’ planning horizons can result in different route choices. In both cases the agent chooses paths that minimise the number of crossings ($MC = true$) but having a lower planning horizon means that the agent in Figures 4.4a and 4.4b doesn’t account for the left-hand turn when choosing an upper-level path until they reach the turning intersection. Because of this their path includes an additional road crossing.

Figures 4.4d and 4.4e illustrate the differences between the upper-level paths produced by $MC = true$ and $MC = false$ path finding heuristics. The path in Figure 4.4d minimise route length by following successive diagonal crossing links. Choosing to minimise the number of crossings instead produces a path that doesn’t cross the road at all.

Upper-level route choice integrates with lower-level route choice through low-level choice reconstrual when a pedestrian enters and moves along a road link. This processes is detailed in Chapter 5 where the lower-level route choice model is presented. Under the CLT framework, road crossing decisions are reconstrued at the lower-level due to the influence of dynamic interactions with road users. This means an upper-level choice to traverse road crossing pavement network links must be reconstrued at the lower-level.

4.4 Conclusion

The data processing and route choice methodologies presented in this chapter are designed to represent high-level construal of pedestrian movement decisions, specifically road crossing decisions. Under high-level construal the environment is represented in an abstract way by a road network and a pavement network. Road network nodes represent turning decision points whilst pavement network nodes
4.4. Conclusion

(a) & (b) & (c) Two upper-level paths from origin O to destination D produced using $PH = 20^\circ$ (a) & (b)) and $PH = 100^\circ$ (c)). Road links within the planning horizon are shown with solid lines and those outside with dashed lines. d) & e) Upper-level paths where distance is minimised ($MC = \text{false}$) and the number of crossings is minimised ($MC = \text{true}$).

Additionally distinguish between sides of the road. The chosen pavement network paths correspond to desired line-of-sight movement along pavements and across roads. Through the use of a planning horizon to control spatial knowledge and heuristics to rank alternative paths, a wide variety of paths can be produced, ranging from globally optimal to myopic. Upper-level route choice therefore produces heterogeneous pedestrian route choices based on high-level construal. These choices are insufficiently detailed from the perspective of street level pedestrian movement - line-of-sight movement fails to account for interactions between road users and the presence of street infrastructure. These upper-level paths must be reconstrued at the lower-level where a specific road crossing location is chosen based on a continuous environment occupied by other agents and road crossing infrastructure. This is the subject of Chapter 5 where the lower-level route choice model is presented along with its integration with upper-level route choice and pedestrian movement.
Chapter 5

Lower-level route choice

5.1 Introduction

The modelling framework presented in Chapter 3 distinguished between two levels of decision making - upper and lower - and in this chapter the lower-level route choice model is presented. The upper-level path represents an abstract plan of how the pedestrian intends to travel towards its destination, but, this plan is enacted in relation to the pedestrian’s immediate street environment. Under the framework, this prompts low-level reconstrual of route choices initially made at the upper-level. Specifically, the framework identified road crossing decisions as being subject to reconstrual between upper and lower levels. This is because road crossing decisions are sensitive to environmental details, such as other road users and street infrastructure, which are only perceived within the psychologically proximate environment. Non-road crossing movement is less sensitive to other road users. These decisions are treated as invariant under high and low-construal and warrant less detailed consideration but should still be accounted for at the lower-level.

This chapter begins with Section 5.2 identifying primary factors affecting crossing choice reported in the literature and the ways these behaviours have been modelled using established and novel methodologies.

Section 5.3 outlines how the environment is represented under lower-level route choice. As set out in Chapter 3, lower-level route choice pertains to the psychologically proximate environment which is defined as the pedestrian’s current
5.2 Road crossing behaviour

Studies into pedestrian crossing location choice identify factors related to traffic, road design, infrastructure, and pedestrian attitudes that influence crossing location choice. By considering ‘informal’ crossing locations, where the pedestrian crosses at a location without crossing infrastructure, in addition to crossing locations with infrastructure, studies importantly account for pedestrians’ more heterogeneous compliance with normative or legal ‘rules of the road’ compared to other transport modes.

The traffic level along a link is a significant predictor of crossing location choice, with higher traffic levels reducing the likelihood of a pedestrian choosing an informal crossing option (Papadimitriou, 2012, 2016; Cantillo et al., 2015; Anciæes and Jones, 2016b). The effect of traffic levels on crossing choice has also been observed to vary between different road types. In Papadimitriou (2016) crossing choice is compared between principle arterial (highest vehicle flow), minor arterial (medium vehicle flow), and collector (lowest vehicle flow) road types in high and low traffic conditions. On minor arterials and collectors, mid-block (informal)
crossing probability was observed to decrease and junction crossing probability increase with an increase in traffic. On principle arterials there was no such change in crossing probability. Anciaes and Jones (2016b) find that the ratio of people crossing a road to the number walking on either side is lower on roads with high traffic volumes. This suggests that pedestrian crossing behaviour is conditional both on the current traffic level but also qualities that distinguish different road types such as long-term average levels of flow or road design.

The types of crossing alternatives available to a pedestrian have also been reported as influencing pedestrian crossing choice. Papadimitriou (2012) found the presence of a traffic signal at a junction increased the likelihood of choosing to cross at the junction. In Sisiopiku and Akin (2003) 87% of survey respondents said the presence of a marked mid-block crossing (dedicated crossing infrastructure) affected their decision to cross at a specific location and 74% said the presence of a traffic signal affected this decision.

Cantillo et al. (2015) find that the location of a crossing alternative influences a pedestrian’s choice. They surveyed pedestrians on location in urban areas and recorded their stated preference of crossing location between an informal mid-block crossing, a signalised crossing, and a pedestrian footbridge. Variables for the additional distance to the signalised crossing and to the foot bridge were significant in their discrete choice model and indicated that a greater distance was associated with a reduced likelihood of choosing that crossing option. Similarly, Chu et al. (2004) find that the likelihood of choosing to cross at an intersection either end of a road was sensitive to the distance to the intersection. The probability of choosing either a marked or informal mid-block crossing option was far less sensitive, suggesting that on longer roads pedestrians will typically choose to cross at mid-block locations, perhaps due to their likely proximity to either the pedestrian or destination. Sisiopiku and Akin (2003) report that 90% of survey respondents stated that the distance of a crossing to their destination influenced their decision to use the crossing, with crossings further from their destination less desirable. Whilst the majority of pedestrians are influenced by the availability and location of multiple crossing al-
ternatives the presence of a group of pedestrians for whom these are not influential factors suggests some interesting heterogeneity between pedestrians.

Research has also found connections between pedestrian attitudes and crossing behaviour. Cantillo et al. (2015) collected data on pedestrian attitudes towards crossing roads. Two latent variables representing crossing option attractiveness (measuring the convenience and comfort of a crossing) and security/safety were included in their discrete choice model to account for the effect of pedestrian attitudes. These latent variables were significant predictors of the utility of informal mid-block crossing options, suggesting that a pedestrian’s attitude towards security/safety and attractiveness influence their decision to cross the road at an informal location.

Similarly, Papadimitriou et al. (2016) surveyed 75 pedestrians before observing their road crossing behaviour as they walked through Athens. The survey was used to identify principal components of pedestrian attitudes towards walking and road crossing. Principal component analysis (PCA) identified three groups distinguished by attitudes to risk and journey purpose. Including the principal components as latent variables in a discrete choice model of crossing location choice improved the fit of the model, suggesting that pedestrian attributes played a small but significant role in crossing behaviour. Furthermore, only the “risk taking and optimisation” principal component was significant in the model suggesting that in terms of observed crossing behaviour, the pedestrian sample consisted of two groups only - optimising risk takers and risk averse. Interestingly, the PCA also grouped together survey respondents with low risk tolerance and low optimisation behaviour with those that reported more frequent pedestrian activity, suggesting that those pedestrians that walked more were less willing to take risks. However, the opposite trend was found in Sisiopiku and Akin (2003)’s study of pedestrian crossing choice where occasional walkers were less willing to take risks in their crossing decisions.

These studies demonstrate that pedestrians’ choice of crossing location is influenced by a combination of physical infrastructure (such as crossing availability and type, road type), traffic levels, and pedestrian attributes (predominantly risk tol-
5.2. Road crossing behaviour

erance and route optimisation characteristics). These crossing choices determine how pedestrians move along a road link. The resulting trajectories cut across the carriageway, breaking the segregation between transport modes which introduces the potential for conflicts. Modelling these choices can therefore help develop a better understanding of how street space is shared by multiple transport modes.

Random utility theory discrete choice models are perhaps the most common method used to model the choice of road crossing location and have been used effectively to identify pertinent choice factors. Typical methods are logit models (including nested and sequential logit) (Chu et al., 2004; Papadimitriou et al., 2016; Papadimitriou, 2012) and latent variable models (Cantillo et al., 2015). Crossing choice sets are identified and utility functions for each option defined using metrics of physical infrastructure, vehicle traffic, and pedestrian attitudes (accounted for using latent variable analysis). These methodologies are limited in certain respects. The representation of interactions between pedestrians and vehicles is limited to coarse space-time aggregations that do not capture short-term variations in traffic such as gaps in vehicle platoons or driver yielding behaviour. Crossing choices are similarly quantised into discrete locations which limits their ability to model the diversity of pedestrian trajectories at the street level.

Gap acceptance and driver yielding models have historically also adopted similar discrete choice methods to infer the contributing factors to pedestrian and driver decisions (Sun et al., 2003; Sucha et al., 2017; Schroeder and Routhail, 2011). In these studies crossing location is treated as fixed but pedestrian and driver movement are analysed at more granular scales that account for time gaps between vehicles and interactions between individual drivers and pedestrians. Fixing crossing location prevents the models from representing spatial heterogeneity in pedestrian trajectories. It also precludes any effects of granular variations in vehicle flows on pedestrian trajectories, such as informal crossings occurring during a break in traffic that wouldn’t have otherwise. These methods also assume choice sets are constant across the pedestrian population, further limiting representation of pedestrian heterogeneity.
By implementing rule based road crossing decision making models within micro-simulations authors have overcome some of the limitations highlighted above (Suh et al., 2013; Chao et al., 2015; Feliciani et al., 2017). In these studies, pedestrian road crossing decisions are modelled dynamically in response to the movements of vehicles. By assigning different decision making preferences or processes to pedestrians the simulations are also able to produce heterogeneous choices and therefore trajectories (ibid), despite crossing locations being fixed.

A broader critique of the models discussed above is that the pedestrian and driver choice models make implicit assumptions about the decision making capabilities of people that are unjustified. Random utility theory models assume the ability to accurately measure a wide range of quantities and perform weighted sum calculations to determine the ‘utility’ of a crossing option. Rule based approaches avoid this assumption but, if insufficiently complex, can be unable to represent a wide range of pedestrian behaviours.

Recent advances in modelling road user decision making suggest a more psychologically realistic modelling approach is possible. Sequential sampling models provide one such alternative approach to discrete choice modelling. Decision Field Theory (DFT, also referred to as drift-diffusion models) has been used to model perceptual decision making. DFT models explicitly represent a person’s gradual retrieval of information from their memory or environment when performing two-choice decision making tasks (Ratcliff, 1978; Ratcliff and Rouder, 2000). DFT models have also been used to explain human decision making behaviours that violate assumptions made in random utility theory (Busemeyer and Townsend, 1993). DFT has been generalised to consider choices involving more than two alternatives (Roe et al., 2001) and decisions involving comparisons between multiple attributes of alternatives (Diederich, 1997; Busemeyer and Diederich, 2002).

In DFT models, information is obtained from all alternatives within the choice set simultaneously, allowing direct comparison between alternatives at each time step. Golman et al. (2019) presents a sequential sampling model of decision making in two-player strategy games which takes a different approach. Rather than
5.2. Road crossing behaviour

sampling information from all choice alternatives and comparing at each time step, the agent samples information from a single alternative each time step. The sampling probability is based on the alternative’s salience, with more salient alternatives being sampled more frequently. Once sampled, the perceived utility of the strategy is calculated and used to accumulate ‘activation’ for that strategy. The level of activation indicates the agent’s preference for a strategy. Recently, sequential sampling models have been adapted to model road user interactions (Markkula et al., 2018) and pedestrian road crossing (Wang et al., 2021). In this chapter we describe a sequential sampling model of crossing location choice and implement it within an agent-based model (ABM) of pedestrian and vehicle movement.

ABMs of have a rich history in pedestrian modelling and have been used to model pedestrian movement in a variety of contexts, including museums (Turner and Penn, 2002), retail markets (Ward, 2006), evacuations (Johansson et al., 2007), carnivals (Batty et al., 2003), and shared street space (Anvari et al., 2015). Despite this, few studies attempt to model informal and formal movement across the carriageway, an important source of pedestrian-vehicle conflicts. The authors are aware of only two such studies (Wang, 2012; Wang et al., 2021).

Wang (2012) produce road crossing behaviour through the iterative application of a gap acceptance model in which the probability of ‘accepting’ a gap in traffic is modelled using a binary logistic regression model. This produces informal road crossing where the pedestrian agent accepts a gap before reaching crossing infrastructure. If the pedestrian agent reaches crossing infrastructure before accepting a gap they cross at the crossing infrastructure. Wang et al. (2021) use a DFT model to model a similar scenario: pedestrians choosing a crossing locations as they walk towards their destination on the other site of the road. In the model, preference for each crossing alternative (informal vs marked crossing) is chosen based on three attributes: efficiency, safety, and fairness in combination with time-varying weights pedestrian agents assign to each of these attributes.

This chapter’s contribution is a novel model of pedestrian road crossing that seeks to reproduce some of the road crossing behaviour discussed above whilst
addressing some of the limitations of existing studies. Specifically, the difference between our model and the two most similar studies discussed above is as follows. Primarily, our model integrates a choice of whether or not to cross on a particular road link with the choice of where along the road link to cross. This is achieved through bi-directional interaction between upper and lower-level route choice which is not represented in either of the above studies. An additional difference in our crossing location choice model is the dynamic and heterogeneous perceptions of crossing alternatives. This aspect of bounded rationality is not possible with the logistic choice model presented in Wang (2012), however, the decision field theory model in Wang et al. (2021) does permit similar dynamic variation in preferences.

### 5.3 Representing the street level environment

*Lower-level* route choice is made based on a continuous representation of the environment. The main components of the *lower-level* environment are the pavement network nodes located on the current road link and road crossing infrastructure.

Pavement network nodes form the way points of pedestrian agents’ *lower-level* routes. Crossing infrastructure is represented as a straight line geometry connecting coordinates on either side of the carriageway polygon, extracted from the OS-MT data set. The straight line runs perpendicular to the road network link geometry. The two coordinates represent the entrance and exit to the crossing and these are also used as way points in *lower-level* routes.

Polygons representing the carriageway, pavement, and buildings are also perceived by pedestrians at the *lower-level*. These influence pedestrian movement indirectly through obstacle avoidance with pedestrian agents avoiding collisions with walls. In practice, obstacle avoidance is simplified to reduce the computational cost of simulations given the focus of the research on route choice.

### 5.4 *Lower-level* route choice model

Using the representation of the road link environment set out above, *lower-level* route choice chooses way points to move between on the current road link. These choices must satisfy the requirements set out in the modelling framework:
• represent differences in spatial knowledge and reasoning

• represent different perceptions of the costs of crossing roads

• integrate with decisions made at the other level (the upper-level)

In the following subsections each of these requirements is addressed. Differences in spatial knowledge and perceptions of crossing cost are incorporated into lower-level road crossing decisions, detailed in Section 5.4.1. Then the integration of lower-level route choice with upper-level route choice is presented in Section 5.5 followed by integration with pedestrian movement in Section 5.6.

5.4.1 Road crossing decisions

Lower-level route choice reconstrues upper-level crossing decisions in greater detail, choosing between specific crossing locations termed crossing alternatives. The entrance and exit coordinates of the crossing alternative become the way points the pedestrian agent moves between to navigate the road link.

To model the choice of crossing location a sequential sampling discrete choice model is developed. This choice is modelled by repeatedly sampling choice alternatives from the set of options and accumulating the perceived utilities to give a preference score for each alternative, with an alternative chosen once its preference value reaches a certain threshold. The model is adapted from that presented in Golman et al. (2019) and has several features which makes it well suited to this application.

The decision making process is gradual which allows the dynamics of the model environment to affect decision making. In this case, crossing alternative utilities are defined as dependent on the movements of other road users, allowing road crossing decisions to be influenced by dynamic vehicle traffic. The review of pedestrian road crossing behaviour at the start of this chapter identified risk taking and optimisation as core characteristics of pedestrian road crossing behaviour. At the lower-level these preferences are represented in a detailed way through the calculation of crossing alternative utility. This reconstrues the upper-level representation of these characteristics where paths are chosen based on either distance or
crossing minimisation, with crossing minimisation corresponding to risk avoidance and distance minimisation to route optimisation.

In Golman et al. (2019)’s model the sampling probability of choice alternatives is interpreted as their salience, since higher probabilities lead to those alternatives being ‘considered’ (having their utility accumulated) more often. In this sequential sampling model, salience is used to represent differences in spatial knowledge at the lower-level, with more proximate crossing alternatives being more salient. This mirrors the use of a planning horizon at the upper-level. As pedestrian agents move, their position relative to crossing alternatives changes. This results in changing perception of the environment which affects decision making through the changing sampling probabilities of crossing alternatives.

This modelling approach has advantages over other discrete choice models. Unlike the iterative binary logit model approach used by Wang (2012) past perceptions of utility continue to influence the choice, through the accrued activation. Decisions can be interpreted as being made based time averaged perceived utility. With the iterative binary logit model only a single road crossing decision is required to determine the pedestrian’s future trajectory. In DFT, preference for choice alternatives is also accumulated gradually. The main difference with Wang et al. (2021)’s DFT model to the one presented here is that in Wang et al. (2021) all alternatives are compared each step of the model. Their model does not represent choice alternative salience and therefore the role of distance in limiting knowledge of choice alternatives. However, a DFT model such as the one presented in Wang et al. (2021) does confer many of the same advantages of this sequential sampling model and could be usefully applied in this context.

Below, the lower-level crossing choice model is defined mathematically and the behaviour of model components demonstrated for an abstract road environment illustrated in Figure 5.1. In this scenario, a pedestrian agent is added to the model with origin $O$ and destination $D$. The agent perceives two crossing alternatives - an informal crossing at its current location and a marked crossing at point $P$ - and uses the sequential sampling model to choose between these as it moves along the road.
5.4. Lower-level route choice model

Figure 5.1: A diagram of an abstract road environment in which a pedestrian moves from origin $O$ to destination $D$. The current position of the pedestrian is given by $x_p(t)$. If the pedestrian crosses the road at their current location they would move to point $x'_p(t)$. A marked crossing is located at $P$.

**Activation Accumulation**

At time $t = 0$ the activation of all crossing alternatives is set to zero as pedestrians are assumed not to have an initial crossing preference. At each time step each crossing alternative’s activation value is updated according to

$$A_j(t) = \begin{cases} 
\gamma A_j(t-1) + U_j(t), & \text{if } j \text{ is the sampled crossing alternative} \\
\gamma A_j(t-1), & \text{otherwise}
\end{cases}$$

(5.1)

where $A_j$ is the activation for crossing alternative $j$, $0 < \gamma \leq 1$ is a decay factor, and $U_j(t)$ is the utility of the sampled crossing alternative perceived by the pedestrian agent. Decaying activation values assumes the greater importance of more recent information gathered about a crossing alternative.

Throughout this thesis, crossing alternative activation is updated once per model time step. Higher and lower frequencies could be used to represent additional differences between pedestrian’s decision making, with higher frequencies implying greater deliberation between choice alternatives. For the objectives of this project this is an unnecessary detail as a sufficient range of road crossing behaviour can be produced with the current model definition.

**Crossing Alternative Sampling**

The sampling probability of crossing alternative $j$, $p_j(t)$, is given by

$$p_j(t) = \frac{e^{\lambda d_j(t)}}{\sum_j e^{\lambda d_j(t)}}$$

(5.2)
5.4. Lower-level route choice model

Figure 5.2: This figure shows how the distance metric, \( d_j(t) \) and sampling probability, \( p \), change for a pedestrian with location \( x_p(t) \) with a single marked crossing at one end of the road and \( \lambda = 0.5 \). The distance to the informal crossing is 0 throughout, giving a value of \( d_j(t) = 1 \). The distance to the marked crossing initially decreases and then increases. Initially, the informal crossing’s sampling probability is much greater, reflecting its greater proximity to the pedestrian. As the pedestrian approaches the marked crossing the sampling probabilities converge, before diverging again.

where \( d_j(t) \) is the proximity distance metric and \( \lambda \) is a pedestrian agent attribute that controls the sensitivity of salience to the distance metric \( d_j(t) \). \( \lambda \) controls pedestrian agents’ lower-level spatial knowledge. \( d_j(t) \) is given by

\[
d_j(t) = \frac{L - |x_p(t) - x_j|}{L} \quad (5.3)
\]

where \( L \) is the length of the road the pedestrian is walking on, \( x_p(t) \) is the position of the pedestrian agent, \( x_j \) is the position of crossing alternative \( j \). \( L \) is used to ensure that closer crossing alternatives have a higher value of \( d_j(t) \) and that values are scaled relative to the length of the road. The \( d_j(t) \) values and sampling probability for the two crossing alternatives as a pedestrian moves from one end to the other of the abstract road are shown in Figure 5.2. Low values of \( \lambda \) produce a more uniform probability distribution that represents a pedestrian agent with good spatial perception of all crossing alternatives. High values of \( \lambda \) strongly bias nearby crossings and represent a pedestrian agent with limited perception of crossings further away. With more even sampling of all crossing alternatives the pedestrian agent is better able to identify the crossing alternative that best suits its preferences.
Crossing Alternative Utility

Crossing alternative utility is defined as a weighted sum of a journey detour metric and a traffic exposure metric, representing a trade-off between preference for reducing walking distance and avoiding risk associated with road crossing. The weighting between these utility components is controlled by a parameter, $\alpha$, permitting differences in the perceived utility of crossing alternatives between pedestrian agents.

The activation accumulation process requires the magnitude of crossing alternative utility to be greater when the crossing alternative is more attractive (as opposed to utilities expressed in terms of costs). Additionally, crossing alternative attributes should be expressed on the same scale so that their weighting represents a trade-off between one and the other only and not any re-scaling.

The journey detour and traffic exposure attributes are given by the following metrics. The journey detour metric $U_{j}^{\text{detour}}(t)$ is

$$U_{j}^{\text{detour}}(t) = 1 - \frac{\Delta L_{j}(t)}{L}$$

(5.4).

where $L$ is the length of the road the pedestrian is walking on, and $\Delta L_{j}$ is a measure of the detour required to make use of crossing alternative $j$ given by the difference between walking distance to reach the destination via crossing alternative $j$ and the walking distance to reach the destination if the agent were to cross the road at their current location. Carriageway width is assumed to be the same at both crossing locations so differences in distance come from movement along the pavement. The fractional difference is used to scale the metric relative to road link, fixing values between 0 and 1 for all road links and crossing alternatives.

The vehicle exposure metric, $U_{j}^{\text{exposure}}(t)$ is based on the number of vehicles expected to pass through the crossing in the time it would take the agent to cross the road assuming constant vehicle velocity. To ensure the metric is expressed on the same scale as $U_{j}^{\text{detour}}(t)$, this metric returns a binary value of either 0 or 1, where
\[
U_j^{\text{exposure}}(t) = \begin{cases} 
0, & \text{if 1 or more vehicles would pass through the crossing} \\
1, & \text{otherwise}
\end{cases}
\] (5.5)

A fractional difference metric similar to \(U_j^{\text{detour}}(t)\) was not used for this attribute because it is not clear how the vehicle flow on a road link should be normalised in order to produce a metric whose values match the scale of the journey detour metric. Whilst the vehicle exposure metric is binary, the time averaged value lies in the range \(0 \geq x \geq 1\) due to variations in the numbers, speeds and positions (relative to crossing alternatives) of vehicles on the road link at each time step. This metric enables pedestrian agent decision making to respond to dynamic vehicle traffic.

These two crossing alternative attributes are combined to give the perceived crossing alternative utility \(U_j(t)\) as

\[
U_j(t) = \alpha U_j^{\text{detour}}(t) + (1 - \alpha)U_j^{\text{exposure}}(t)
\] (5.6)

where \(\alpha\) is a pedestrian agent parameter representing the pedestrian’s trade off between journey detour and vehicle exposure attributes. A high value of \(\alpha\) represents a risk taking pedestrian who values reduced journey detour more than avoiding vehicle exposure. Varying \(\alpha\) is the mechanism for representing different pedestrian preferences at the lower-level.

As the pedestrian agent moves along a road the attributes of crossing alternatives change depending on the location of the pedestrian and the flow of vehicles on the road. The variation of utility in combination with the stochastic sampling of crossing alternatives means that the rate of activation accumulation of crossing alternatives varies.

Figure 5.3 shows the behaviour of the attribute metrics and utilities for the abstract road scenario illustrated in Figure 5.1. Vehicles are added to the road on the far left-hand side at position \(x_v(0) = 0\) every 5 seconds and move to the far
right-hand side at $10\text{ms}^{-1}$ (around $22\text{mph}$). Only one lane of vehicle traffic is considered in this example. The pedestrian agent is similarly added to the road at the far left hand side such that $x_p(0) = 0$. For the marked crossing $U_{mkd}^{\text{exposure}}(t) = 1$ for all $t$ since the pedestrian agent expects vehicle agents to yield at this crossing. For the informal crossing, $U_{inf}^{\text{exposure}}(t)$ switches between 0 and 1 as new vehicles enter and move along the road link. When averaged over time $U_{inf}^{\text{exposure}}(t) < U_{mkd}^{\text{exposure}}(t)$ meaning the informal crossing alternative has reduced utility on the grounds of vehicle exposure.

The value of the journey detour metric for the marked crossing, $U_{mkd}^{\text{detour}}(t)$, is around 0.6 until the agent passes its destination at which point it increases linearly up to the maximum value of 1. This reflects the constant and then reducing detour distance of the marked crossing once the agent moves further away from its destination and towards the crossing. By definition, the journey detour metric value for the informal crossing is a constant value of 1. The overall crossing alternative utility is given by the weighted sum of these two metrics with $\alpha = 0.5$ representing a pedestrian which values journey detour and vehicle exposure equally. The utility of the informal crossing tends to be higher than the marked crossing initially but is overtaken by the marked crossing once the detour distance is sufficiently reduced, at which point the additional journey detour costs are outweighed by the benefits of lower vehicle exposure.

Figure 5.4 replicates this scenario but introduces greater variation in vehicle flow by creating a 10s pause in vehicle additions coinciding with the time the pedestrian agent passes their destination. This is illustrative of a scenario where a gap in traffic coincides with the pedestrian walking past its destination. This produces consistently higher utility for the informal crossing alternative during this gap, illustrating how the choice model is able to respond to short term variation in vehicle traffic.

**Crossing Alternative Selection**

Pedestrian agents choose a crossing alternative when the activation for the alternative reaches a threshold level determined by another parameter, $\varepsilon$. Figure 5.5
5.4. Lower-level route choice model

Figure 5.3: The attributes and utilities of two crossing alternatives as perceived by a pedestrian agent moving along the road. The position of the pedestrian agent’s destination, which is on the opposite side of the road, and the marked crossing are marked in the figure by dashed vertical lines. The number of vehicles on the road at each at time $t$ is shown by the dotted black line in the chart below.

Figure 5.4: The attributes and utilities of two crossing alternatives as perceived by a pedestrian agent for a varying vehicle flow scenario. Vertical dashed lines indicate the location of the pedestrian agent’s destination and the marked crossing alternative. The drop in vehicle numbers causes the perceived utility of the informal crossing option to remain high.
shows the activation for each crossing alternative as the pedestrian agent moves along the road for a constant (top) and varied (bottom) traffic scenario for $\alpha = 0.5$, $\varepsilon = 4$, $\lambda = 1$ and $\gamma = 0.9$.

In the constant traffic scenario the utilities of both crossing alternatives are comparably low due to the high vehicle exposure associated with the informal crossing and high journey detour associated with the marked crossing. As a result neither alternative accumulates sufficient activation to trigger a choice until the pedestrian agent is close enough to the marked crossing for the journey detour utility to improve. The marked crossing overtakes the informal crossing and reaches the threshold activation level, triggering the choice. In the varied vehicle flow scenario the gap in vehicle traffic is perceived by the pedestrian agent and leads to an increase in the utility of the informal crossing alternative. The informal crossing alternative accumulates sufficient activation to trigger the choice as the pedestrian passes its destination on the other side of the road. The choice of crossing location is reactive to the short term variations in vehicle flow, producing gap seeking road crossing behaviour as pedestrian agents move along the street. Due to the stochastic nature of the model the same choice will not be made in every case (the random seed is held constant in this example). Once a crossing alternative is chosen the activation accumulation process stops. However, in these diagrams activation continues to accumulate as if the pedestrian agent continues to walk along the road rather than cross; this is purely for illustrative purposes.

Finally, a time threshold parameter, $\tau$, is used to enforce a choice of crossing alternative in cases where the utility of all alternatives is not sufficiently high to reach the threshold $\varepsilon$ in a reasonable time frame given the decay factor $\gamma$. Once $\tau$ simulation ticks have passed the pedestrian agent is forced to choose the crossing alternative with the highest activation. The time threshold is only applied once agents are unable to progress on their route without choosing a crossing alternative. The time threshold is not expected to alter road crossing preferences because a) it should only come into effect in a small number of cases and b) the choice is still based on the activation level and therefore continues to reflect preferences.
5.5. Integration between upper-level and lower-level route choice

Having established the decision making and actions of lower-level route choice it is helpful to summarise how upper-level and lower-level choices are integrated. Firstly, upper-level paths shape lower-level choice construal. Upper-level paths that do not cross the current road link are treated as unchanged by low-level construal of this decision. In this case the lower-level way points are simply given by the pavement nodes at either end of the non-crossing upper-level pavement network link. Low-level construal of upper-level paths that do cross the current road link, via either a direct or diagonal crossing link, does change the decision making process.
5.5. Integration between upper-level and lower-level route choice

For direct crossings the crossing location choice is made from a stationary position at one side of the direct crossing link. For diagonal crossings, the pedestrian agent chooses a crossing alternative while moving along the pavement since diagonal crossings represent movement to the other end of the road as well as across the carriageway. In this case the agent is assigned the pavement node on the same side and far end of the road as the target way point. These two scenarios are illustrated in Figures 5.6a and 5.6b.

Secondly, lower-level route choice can shape upper-level route choice. When traversing a diagonal crossing link, the pedestrian may reach the end of the road before a crossing choice is made due to the crossing alternatives not providing sufficient utility to reach the activation threshold. At this point a new upper-level path is chosen due to the tactical planning horizon progressing. In this way, the initial choice to cross based on a high-level construal (upper-level, abstract, desirability based) is updated based on low-level construal (lower-level, detailed, feasibility based) and no crossing is made.
5.6 Pedestrian movement

A pedestrian movement model is used to move pedestrian agents between the chosen way points on their current road link, simply integrating lower-level route choice with pedestrian movement. Once the pedestrian agent is within 0.5\textit{m} of a way point the next way point becomes the agent’s target. Once the agent reaches a pavement node at the end of the road link, the agent’s perception of upper-level and lower-level environments progresses, prompting new upper-level and lower-level route choices. The agent’s destination is similarly treated as a way point and on the final link this is what the agent moves towards rather than the pavement nodes at the end of the link.

Pedestrian movement is modelled using the ‘cognitive heuristic’ model of pedestrian movement detailed in Moussaid et al. (2011). The basis of the model is two heuristics: 1) that pedestrians walk in a direction that allows the most direct path to their destination, accounting for obstacles and 2) that walking speed is chosen to maintain a minimum time to collision to an obstacle. Each time step, pedestrian agents identify their desired velocity by using these two heuristics to calculate their desired walking direction and speed. In the absence of obstacles (such as walls or other agents) this is the desired walking speed in the direction of the pedestrian agent’s destination. If a wall or other pedestrian agent, within a threshold distance, obscures the destination the desired direction of movement shifts to avoid these and the agent may reduce speed to maintain a minimum time to collision. Furthermore, collisions with obstacles are modelled with an additional term that represents physical contact forces.

The cognitive heuristic model was initially fully implemented but simplifications were later made to reduce the computational cost of simulation runs. Interactions between the environment and pedestrian agents were excluded by removing building boundaries from the model. Simulation results were compared with and without the inclusion of building walls (for both the small-scale experiments presented in this chapter and the large-scale experiments presented in Chapter 6) and were found to not significantly differ.
Table 5.1 lists the ‘cognitive heuristic’ model parameters. These are taken directly from Moussaid et al. (2011) apart from the angular resolution of the field of vision which was increased to reduce computational cost.

<table>
<thead>
<tr>
<th>Parameter Name</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta$</td>
<td>Angular field of vision</td>
<td>150deg</td>
</tr>
<tr>
<td>$d_{max}$</td>
<td>Maximum vision distance</td>
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</tr>
<tr>
<td>$\text{ang}_{res}$</td>
<td>Angular resolution of field of vision</td>
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</tr>
<tr>
<td>$k$</td>
<td>Interaction force constant</td>
<td>5000</td>
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<tr>
<td>$T$</td>
<td>Relaxation time - time required for ped to adjust velocity</td>
<td>0.5s</td>
</tr>
</tbody>
</table>

**Table 5.1:** Parameter values for the heuristic cognitive model of pedestrian walking. Apart from $\theta$, which was increased to reduce computational cost, values are taken from Moussaid et al. (2011). The parameter $T$ is referred to as $\tau$ in Moussaid et al. (2011) but I have used the symbol $T$ as in this thesis because $\tau$ refers to the time threshold in the *lower-level* route choice model.

## 5.7 Small-scale simulation experiments

Small-scale simulation experiments are used to test and verify the behaviour produced by the *lower-level* route choice model. The previous sections defined a sequential sampling discrete choice model used to choose between crossing alternatives at the *lower-level* and explained how *lower-level* route choices integrate with *upper-level* route choices. The object of these experiments is to verify that the *lower-level* route choice model produces road crossing behaviour that reflects the behaviours reported in the literature. Specifically, parameter sweeps across *lower-level* parameters $\alpha, \lambda, \gamma, \varepsilon$, and $\tau$ are used to identify the regions of parameter space in which the following behaviours are produced:

1. Pedestrian agents’ choice of crossing location is sensitive to vehicle traffic and crossing alternative attributes

2. Pedestrian agents can choose between crossing alternatives within a reasonable time frame
3. Pedestrian agents’ postpone crossing if no suitable crossing infrastructure is available

To do this pedestrian movement is modelled over just 1-2 road links. In both experiments upper-level route choice parameters, $PH$ and $MC$, are held constant and so variations in pedestrian agent behaviour are produced only by lower-level route choice. This allows the lower-level route choice model to be tested. In the following chapter, large-scale simulation experiments are performed which explore the pedestrian agent behaviour produced by the complete CLT route choice model.

In both experiments all pedestrian agents perform the same trip, from a single origin to a destination on the other side of the road. In Experiment 1 the destination is located on a neighbouring road link and in Experiment 2 the destination is located on the same road link as the origin. Experiment 1 therefore tests the integration of lower-level and upper-level route choice as well as road crossing behaviour. Experiment 2 only tests choices between crossing alternatives. In each simulation experiment vehicle traffic is produced by vehicle agents travelling on the road links pedestrian agents walk along. Vehicle traffic is unidirectional in both experiments. Two levels of vehicle traffic are considered, high and low, differentiated by the time average number of vehicle agents added to the environment.

5.7.1 Experiment 1: Setting epsilon and gamma parameter bounds

Parameters $\gamma$, $\varepsilon$, and $\tau$ control when a choice of crossing alternative is triggered. Experiment 1 seeks to identify value ranges for $\gamma$, $\varepsilon$, and $\tau$ that produce the behaviours listed above. In addition, $\varepsilon$ and $\gamma$ must satisfy $\varepsilon(1 - \gamma) \leq 1$ for it to be possible to reach activation threshold $\varepsilon$ given the maximum possible crossing alternative utility value of 1. Higher $\varepsilon$ values or lower $\gamma$ values inhibit decision making and can prevent crossing alternatives from being chosen. Similarly, low $\varepsilon$ and high $\gamma$ values will mean a crossing alternative can be chosen with very few sampling iterations, limiting the influence of pedestrian preferences or road traffic conditions on crossing choice.
Because of these relations, $\varepsilon$ and $\gamma$ are instrumental in enabling lower-level route choice to revise upper-level crossing decisions. If a pedestrian agent reaches the end of a road link before a crossing choice is made, the upper-level path is replanned due to the progression of the planning horizon. Raising the threshold for choosing a crossing alternative should increase the frequency of this occurring. At the same time, postponing crossing should only occur where the pedestrian agent perceives a lack of suitable crossing options and therefore should depend on the agent’s perception of the street environment. This simulation experiment seeks to identify the $\varepsilon$ and $\gamma$ bounds that balance these objectives.

The parameter $\tau$ affects when a crossing alternative choice is made by imposing a strict time limit for activation accumulation. Using a time threshold means that $\varepsilon(1 - \gamma) \leq 1$ is not strictly necessary for a choice to be made, but $\varepsilon$ and $\gamma$ values that do not satisfy this inequality are considered implausible as they mean all choices would be made after exactly $\tau$ model ticks. In this experiment $\tau$ is held at a constant high value because this parameters is not intended to influence crossing behaviour and only ensure that pedestrian agents can always complete their journeys.

5.7.1.1 Methods

Figure 5.7 illustrates the simulation environment used for this experiment. In each simulation run 40 pedestrian trips from from origin O to destination D are modelled. This number of pedestrian agent trips was deemed sufficient for establishing the behaviour produced by the parameters and initial conditions. Because all trips share the same initial conditions and traffic levels in both these small-scale experiments a higher number of trips was not deemed necessary to establish the effect of model parameters. Pedestrian agents are added to the simulation with a time period of $T_{ped} = 80s$, producing low densities of pedestrian agents such that crossing decisions are not affected by pedestrian-pedestrian interaction. Pedestrian movement is therefore effectively constant velocity motion towards the destination, which allows lower-level route choice to be verified in isolation from the cognitive heuristic model of pedestrian movement as well as upper-level route choice. In Chapter 6 all
three model components are brought together in a more comprehensive exploration of model behaviour.

Upper-level parameters are fixed ($MC = false$ and $PH = 100$) to produce agents that all choose the same initial upper-level path, shown in orange in Figure 5.7. This trip requires performing at least one road crossing. When the agent reaches the diagonal crossing link, lower-level route choice is used to choose a crossing location as the pedestrian agent walks along the pavement. The only crossing option available on this section of the road network is an informal crossing. Alternatively, the agent can continue walking to the end of the road at which point their upper-level route is re-planned, which might allow them to avoid crossing informally.

The origin and destination of the vehicle agents are the start and end points of the section of road network included in the model environment. Vehicles agents move in one direction only.

Lower-level parameters $\varepsilon$, $\gamma$, and $\lambda$ are varied between runs whilst the remaining parameters are held constant at $\alpha = 0.1$ and $\tau = 120$. Setting $\alpha = 0.1$ produces vehicle exposure averse agents that should avoid crossing informally. Coarse parameter sweeps are first performed, where $\gamma$ is increased from $0 - 1$ in 0.1 increments and $\varepsilon$ is increased from $0 - 12$ in 0.5 increments. Additionally, $\lambda \in [0.5, 1.5]$ is used to check the results for different lower-level spatial knowledge settings (the effect of $\lambda$ on road crossing is investigated more thoroughly in Experiment 2). For each route choice parameter setting, a high ($\bar{N}_v = 15$) and low ($\bar{N}_v = 1$) vehicle flow scenario is simulated. Following this, a more granular parameter sweep is performed with $\gamma \in [0.8, 0.9]$ and $\varepsilon$ increased from $4 - 12$ in 0.2 increments. Each simulation run corresponds to one set of parameter inputs so the coarse parameter sweep requires $11 \times 13 \times 1 = 1572$ simulation runs and the granular parameter sweep $2 \times 70 \times 2 \times 2 = 560$ runs. Table 5.2 summarises the parameter values and ranges used in this experiment.

The proportion of pedestrians that do not cross the road link marked RL1 in Figure 5.7 is recorded. High proportions indicate that pedestrian agents’ lower-level route choice is causing the upper-level to change in response to the lack of suitable
5.7. Small-scale simulation experiments

Figure 5.7: The GIS environment of Experiment 1. The upper-level path is shown in orange and crossing infrastructure in blue.

crossing infrastructure.

<table>
<thead>
<tr>
<th>Model Component</th>
<th>Name</th>
<th>Description</th>
<th>Possible Values</th>
<th>Experiment 1 Values</th>
<th>Experiment 2 Values</th>
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<tr>
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<td>1</td>
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<td>Agent Trips</td>
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<td>Number of pedestrian trips</td>
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<td>40</td>
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<td></td>
<td>$T_{ped}$</td>
<td>Pedestrian addition time period</td>
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<td>80</td>
</tr>
<tr>
<td></td>
<td>$\bar{N}_v$</td>
<td>Time average number of vehicle agents</td>
<td>N</td>
<td>1, 15</td>
<td>1, 15</td>
</tr>
<tr>
<td>Lower-level route choice</td>
<td>$\alpha$</td>
<td>Vehicle exposure and route detour utility weighting</td>
<td>(0, 1)</td>
<td>0.1</td>
<td>0 – 1</td>
</tr>
<tr>
<td></td>
<td>$\lambda$</td>
<td>Crossing alternative sampling distance sensitivity</td>
<td>R</td>
<td>0.5, 1.5</td>
<td>0 – 2</td>
</tr>
<tr>
<td></td>
<td>$\gamma$</td>
<td>Preference decay per time step</td>
<td>(0, 1)</td>
<td>0 – 1</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>$\varepsilon$</td>
<td>Preference choice threshold</td>
<td>R</td>
<td>0 – 14</td>
<td>5, 8</td>
</tr>
<tr>
<td></td>
<td>$\tau$</td>
<td>Model ticks choice threshold</td>
<td>R</td>
<td>120</td>
<td>120</td>
</tr>
</tbody>
</table>

Table 5.2: Simulation parameters used in experiments 1 and 2. Upper-level parameters are not shown because upper-level paths are constant across all simulation runs.
5.7.1.2 Results

Figure 5.8a shows the results from the coarse parameter sweep simulations. For $\varepsilon (1 - \gamma) > 1$ agents are unable to make a crossing choice due to $\gamma$ prohibiting the activation threshold, $\varepsilon$, from being reached. For low values of $\varepsilon$ and high values of $\gamma$ the pedestrian chooses an informal crossing location regardless of vehicle traffic level. This region of parameter space can equally be excluded because crossing choices should be sensitive to vehicle traffic.

A small section of parameter space close to the $\varepsilon (1 - \gamma) \leq 1$ boundary can be identified where pedestrian agents are sensitive to the traffic level and do not choose to cross informally in high vehicle flow scenarios. The granular parameter sweep (Figure 5.8b) shows that for $\gamma = 0.9$ and $5 \leq \varepsilon \leq 8$ pedestrian agents postpone crossing under high vehicle scenarios but cross informally in low vehicle flow scenarios. This behaviour is observed for both $\lambda = 0.5$ and $\lambda = 1.5$.

Fixing parameter ranges as $\gamma = 0.9$ and $5 \leq \varepsilon \leq 8$ therefore ensures the model produces the behaviours listed above. Under high vehicle flow scenarios these values enable feedback from the lower to upper-level of the route choice hierarchy.

5.7.2 Experiment 2: Setting alpha and lambda parameter bounds

Experiment 1 established $\varepsilon$ and $\gamma$ parameter bounds that ensure crossing choices can be made as well as postponed. Experiment 2 focuses on the choice between crossing alternatives and seeks to verify that lower-level route choice produces road crossing behaviour that is responsive to dynamic vehicle traffic, pedestrian preferences, and crossing alternative attributes. The design of the sequential sampling model is intended to respond to these factors in ways that are consistent with reported pedestrian road crossing behaviours, as discussed in Section 5.4. This is now verified by simulating a pedestrian agent’s choice between two crossing alternatives.

5.7.2.1 Methods

Figure 5.9 illustrates the simulation environment used for this experiment. As with Experiment 1, in each simulation run 40 pedestrian trips from from origin O to
Figure 5.8: a) Proportion of pedestrian agents that postpone crossing. The black line marks the boundary $\varepsilon(1-\gamma) \leq 1$. Only a small region of the $\varepsilon-\gamma$ parameter space produces behaviour that is dependent on vehicle flow. b) A more granular parameter sweep focusing on the region where behaviour is vehicle flow dependent. Both figures show that in this scenario crossing choice is approximately independent of vehicle flow.

destination D are modelled. The upper-level path is a single diagonal crossing link leading from the origin to destination meaning pedestrian agents move along the road while choosing a crossing location. One marked crossing is located on the road and so the pedestrian agent perceives two crossing alternatives: a marked crossing and an informal crossing. Vehicle agents are spawned at the right of the road link of the road and travel to the left.

Two configurations of crossing infrastructure placement are considered. In one configuration the marked crossing lies between the pedestrian origin and destination, termed the between configuration, and in the other the marked crossing lies beyond the destination, termed the beyond configuration. As before, two levels of vehicle flow are considered: high ($\bar{N}_v = 15$) and low ($\bar{N}_v = 1$). Together this pro-
duces four different street environment scenarios in which pedestrian agents make road crossing choices.

Lower-level route choices in each of these environments should differ in ways that are consistent with the behaviours identified in the literature. Road crossing behaviour is compared between scenarios by performing parameters sweeps across lower-level parameters for each scenario. Regions of the parameter space that produce the required differences between scenarios can then be identified. Doing so verifies that lower-level route choice is able to produce the desired road crossing behaviour and helps define a suitable range for lower-level parameter values.

For each scenario lower-level parameters are stepped through the following ranges (summarised in Table 5.2): $\gamma = 0.9$, $\epsilon \in 5, 8$, $0 \leq \alpha \leq 1$, and $0 \leq \lambda \leq 2$. The fixed $\gamma$ value follows from Experiment 1, as does the two $\epsilon$ values taken from the extremes of the $\epsilon$ bounds established in Experiment 1. $\alpha$ and $\lambda$ are increased in increments of 0.1 and 0.2 respectively. Along with the two $\epsilon$ values this make for 242 simulation runs per scenario and a total of 4 scenarios (between/beyond crossing configuration and high/low traffic flow).

The proportion of pedestrians choosing to cross at the marked crossing is measured for each parameter setting. (The only other option is crossing informally so a high proportion choosing one implies a low proportion choosing the other.) Additionally, the trajectories of pedestrian agents are recorded and visualised to inspect the agents’ crossing locations.

5.7.2.2 Results

Figure 5.10 shows the proportion of pedestrian agents who chose to cross at an informal location in each of the four scenarios for each value of $\alpha$ and $\lambda$, $\epsilon \in 5, 8$, and $\gamma = 0.9$.

The figure shows that changes in $\alpha$ and $\lambda$ produce qualitative differences in crossing behaviour. Agents with low $\alpha$ and $\lambda$ predominantly choose the marked crossing, especially in the high vehicle flow scenarios. These parameter settings represent agents which value avoiding vehicle exposure and sample both crossing alternatives relatively equally. By considering both crossing alternatives equally
5.7. Small-scale simulation experiments

Figure 5.9: The GIS environment for Experiment 2. Pedestrian agents choose a route from origin O to destination D. Crossing infrastructure for ‘between’ and ‘beyond’ configurations is shown in dark and light blue respectively. Vehicle agents move along the road link indicated by the white line in the black carriageway.

these agents correctly identify the alternative that suits their preference (the marked crossing).

Increasing $\alpha$ increases the frequency of informal crossing. This follows from high $\alpha$ values producing agents that value shorter trip detours more than avoiding vehicle exposure. Increasing the value of $\lambda$ also increases the frequency of informal crossings because higher values of $\lambda$ produce pedestrian agents that are less able to consider crossing alternatives further away from them and are therefore biased towards the (by definition) nearby informal crossing alternative.

The level of vehicle flow also has a clear effect on crossing behaviour. Comparing high and low vehicle scenarios shows that increasing vehicle flow tends to reduce the proportion of informal crossing, although, this depends on agents’ preferences. If agents value reducing trip detour far more that avoiding vehicle exposure (high $\alpha$) increasing vehicle flow does little to change their crossing behaviour.

The location of the marked crossing also affects crossing behaviour. For parameter settings that produce agents with preference for journey detour savings
5.7. **Small-scale simulation experiments**

(high $\alpha$) we observe an increase in informal crossing in the beyond configuration compared to the between configuration. The effect is also much larger in the low vehicle flow scenarios where, for certain parameter values, the dominant road crossing behaviour switches from marked crossing to informal crossing from one crossing configuration to another. The $\varepsilon = 8$ setting also amplifies the difference between crossing configurations showing that a higher activation threshold can increase the effect of crossing preferences on crossing behaviour. Agents with these preferences change their choice of crossing in response to the additional detour required to use the marked crossing in the beyond configuration leading to an increase in (time optimal) informal crossings. However, when vehicle flow is high and $\varepsilon$ low the effect of crossing location is dampened.

![Figure 5.10: Proportion of pedestrian agents choosing to crossing at an informal location for a) $\varepsilon = 5$ and b) $\varepsilon = 8$.](image)

Finally, the pedestrian agents’ trajectories for a selection of parameter values are shown in Figures 5.11 and 5.12. Differences in pedestrian crossing choices between scenarios are clear, with more uniform sets of paths produced in runs with high vehicle flow and low $\alpha$, and more varied paths in scenarios with lower vehicle flow and high $\alpha$. Low $\alpha$ produces agents which prioritise avoiding vehicle exposure over journey detours and, as a result, their use of road space is more normative (crossing at a marked crossing) and ordered (less variety of paths). Conversely, preference for avoiding journey detours produces agent trajectories that are ‘non-compliant’ with road crossing norms. Figures 5.11 and 5.12 also illustrate the ability...
of lower-level route choice to generate road crossing at a variety of locations due to the continuous representation of space and definition of informal crossing location as the pedestrian agent’s current location.

In some cases a high proportion of pedestrian agents choose to cross at a marked crossing located behind them, requiring them to change direction and move back towards the start of the road link. This occurs because pedestrian agents accumulate activation as they walk along the pavement and may choose a marked crossing once they have walked past it. Additionally, because the pedestrian agents’ destination is located on the road link there isn’t the possibility of continuing onto the next road link if a crossing choice is not made, like in Experiment 2. The result is that street level trajectories are unrealistic for some parameter settings. However, this ‘back tracking’ does not affect the road crossing component of street level trajectories. The results in Figure 5.10 show that the road crossing behaviour produced by lower-level route choice reflects the characteristics of real road crossing behaviour recorded in the literature whilst the trajectories in Figures 5.11 and 5.12 show that the non-road crossing components of pedestrian agent trajectories are unrealistic in certain conditions. This is a limitation of lower-level route choice that is accounted for in subsequent analysis by not using the walking distance of pedestrian agents as a meaningful metric of behaviour, instead measuring behaviour using the chosen upper-level paths and lower-level crossing locations.

5.8 Discussion

The results show that lower-level route choice is able to generate some of the observed features of pedestrian road crossing behaviour such as dependence on traffic levels, trade offs between journey detour and vehicle exposure, heterogeneity between pedestrians, and dependence on crossing location. Additionally, they demonstrate the integration between lower and upper-level route choices, with high-level construal giving way to low-level construal as pedestrian agents move through the environment.

The parameter sweeps demonstrate the different roles the parameters $\alpha$, $\lambda$,
5.8. Discussion

Figure 5.11: A heat map of the trajectories of pedestrian agents in the between configuration. Lighter colours indicate more popular paths. Pedestrians move along the road according to a social force model which includes interactions between pedestrians and between pedestrians and the environment.

Figure 5.12: A heat map of the trajectories of pedestrian agents in the beyond configuration. Lighter colours indicate more popular paths.
5.8. Discussion

$\epsilon$ and $\gamma$ play in producing crossing location choices. Setting parameter values of $\gamma = 0.9$ and $5 \leq \epsilon \leq 8$ ensures crossing decisions are made and that low-level choice construal can change initial high-level decisions.

The $\alpha$ and $\lambda$ parameter sweeps in Experiment 2 show that the value ranges $0 \leq \alpha \leq 1$ and $0 \leq \lambda \leq 2$ enable lower-level route choice to range between high and low levels of informal crossing in response to both changes in the parameters and the environment. $\alpha$ is naturally bounded from above and below and so the range $0 \leq \alpha \leq 1$ encompasses all possible values. Low values of $\alpha$ produce agents which prioritise avoiding vehicle exposure rather than journey detour and therefore tend to cross at marked locations.

$\lambda$ is bounded from below by 0 but has no upper limit. Low values of $\lambda$ produce agents that consider all crossing alternatives evenly, interpreted as optimising their choice for their preferences, whereas high values of $\lambda$ produce agents that consider closer alternatives more frequently, limiting the ability to identify a suitable crossing alternative. The results show that for $\lambda \sim 2$ in the low vehicle flow scenarios pedestrian agents almost always cross informally, regardless of their preferences or marked crossing location. Permitting higher values of $\lambda$ would therefore increase the region of parameter space where the behaviour of pedestrian agents is insensitive to their preferences or the environment. For this reason the upper bound of $\lambda \leq 2$ is imposed.

Whilst the road crossing choices of agents respond in intuitive ways to model parameters and environmental conditions, the tendency to back-track in certain situations is not representative of real pedestrian behaviour. This limits the the lower-level choice models to providing a description of road crossing behaviour only, and not a complete description of street level trajectories.

This chapter has employed parameter sweeps to identify suitable parameter value ranges within which plausible road crossing behaviour is produced. The model has not been calibrated or validated against observations of pedestrian crossing choice. Doing so could establish distributions of parameters values that would simulate the heterogeneity of a real pedestrian population. An alternative approach
is taken in the following chapters, whereby sensitivity analyses across the whole parameter space are performed. This limits the applicability of the model for representing pedestrian behaviour in a well-defined situation in favour of exploring how multi-scale route choice determines pedestrian behaviour under a wide variety of behavioural settings.

5.9 Conclusion

This chapter presents the lower-level route choice model. Initially abstract upper-level route choices are re-construed at the lower-level where a specific road crossing location is chosen. Upper-level route choice shapes, but does not fully determine, lower-level route choice. This choice is made based on a continuous representation of the environment occupied by other agents and road crossing infrastructure. A sequential sampling approach is used to model a pedestrian’s gradual deliberation and eventual choice between discrete crossing alternatives. The activation accumulation process produces crossing location choices that respond to the local environment of the pedestrian agent as they move along the road. The integration of upper-level and lower-level route choices is also specified, as well as the integration of lower-level route choices with pedestrian agent movement. In this way, street level pedestrian route choice has been integrated with route choices over larger spatial scales following the hierarchical CLT modelling framework.

The behaviour produced by the lower-level route choice model is explored in two small-scale simulation experiments. These experiments are used to establish parameter bounds within which a wide range of plausible pedestrian road crossing behaviour is produced. The model reproduces some observed characteristics of pedestrian road crossing behaviour such as trade offs between journey detour and traffic exposure, sensitivity to traffic conditions, non-compliant (informal) crossing, and dependence of crossing choice on the proximity of crossing alternatives. By representing these sources of pedestrian heterogeneity the lower-level route choice model provides a rich description of pedestrian movement at the street level. The following chapter builds on this with simulations of pedestrian trips across an ur-
ban neighbourhood in which upper-level and lower-level route choice combine to produced varied pedestrian trajectories at multiple scales.
Chapter 6

Verifying multi-scale pedestrian route choice

6.1 Introduction

Having established the upper-level and lower-level route choice models, street level pedestrian movement across an urban neighbourhood can now be modelled. Chapters 4 and 5 demonstrate how the route choice models produce pedestrian agent trajectories in highly constrained situations comprising only a few different origin-destination trips. This chapter establishes how the CLT route choice parameters influence pedestrian agent behaviour when a greater variety of trips are modelled.

To address this question the CLT route choice model is implemented in an agent-based simulation (ABS) of pedestrian and vehicle trips in three different environments. Sensitivity analysis is used to establish the effects of route choice components on metrics of pedestrian agent movement at the street and neighbourhood level. This analysis builds on the small-scale experiments conducted in previous chapters by producing pedestrian trajectories for a variety of trips. This allows the influence of lower-level and upper-level route choice components on patterns of pedestrian movement at multiple scales and between environments to be compared, providing a more complete verification of the CLT route choice model. Additionally, the paths produced by the CLT route choice model are compared to an alternative route choice model - a network optimal least cost model - which helps
demonstrate the contribution of the CLT route choice model.

This chapter proceeds by detailing the spatial ABS used to simulate pedestrian movement in Section 6.2. The methods for the global sensitivity analysis and least cost model comparison are explained in Section 6.3 and the results presented in Section 6.4. Section 6.5 discusses these results before concluding in Section 6.6.

6.2 Agent-based simulation description

The CLT route choice model is verified by using the model to simulate the movement of pedestrians. The components of the ABS are described below following the structure proposed in Crooks et al. (2018).

6.2.1 Overview

The ABS consists of pedestrian and vehicle agents completing trips in a section of an urban road network. Each simulation run is defined by parameters that control the number and frequency of pedestrian and vehicle trips as well as the CLT route choice model used by pedestrian agents to navigate.

For each pedestrian agent we record its origin and destination pavement node, the pavement network links it traverses, and its road crossing locations. These observations are aggregated over the pedestrian population of each run and used to characterise the pedestrian behaviour produced by the input parameter values.

Parameter sweeps are used to identify parameter ranges that produce different road crossing behaviour and verify whether parameters are affecting pedestrian agent behaviour in the desired manner. From this conclusions are drawn regarding how pedestrian agent road crossing behaviour depends on interactions between components of the CLT route choice model and the simulation environment.

The assumptions made in developing the ABS are predominantly those of the CLT route choice model. Within the simulation, the uncertainty surrounding pedestrian decision making is represented by the range of CLT route choice parameters (representing levels of spatial knowledge and route preferences).

Aspects of pedestrian decision making that are absent from the route choice model will be absent from the ABS. Notably, this includes yielding decisions of
pedestrian agents. The CLT route choice model accounts for vehicle traffic in the choice of a crossing location, but subsequent decisions regarding whether or not to cross the road at a particular time are not included. These decisions are often referred to as ‘gap-acceptance’ decisions. Group effects (pedestrian agents belonging to a group) are also not represented.

The pedestrian behaviours that are represented by the CLT route choice model have been identified in the literature. In short, we assume that the ABS parameter space maps to a set of pedestrian agent routes that encompass the real set of routes that would be produced by pedestrians moving in the same urban space. This assumption is interrogated through the simulation experiments presented in this chapter by analysing what behaviour is produced by the extremes of the parameter distributions.

The ABS also makes simplifying assumptions about how vehicles move on urban streets but this should have limited consequences because vehicle movement impacts the outcomes of interest only through the vehicle exposure attribute of crossing alternatives. The vehicle exposure attribute is a coarse, binary measure and therefore is less sensitive to the details of vehicle movement.

The ABS is developed using open source Java software Repast Simphony (North et al., 2013) and is available at https://github.com/obisargoni/multiscale-ped-abm.

6.2.2 World

Each simulation tick corresponds to 1 second and the simulation environment is represented by a continuous GIS space.

Agent Trips

Activity schedules and choices around activity locations are treated as external to the ABS. Pedestrian and vehicle agents are simply assigned an origin and destination coordinate and move between them. Trip chaining is not included and vehicle agents do not park or pull over.

The number of pedestrian trips to model, $N_p$, is given as an input to the simulation. Pedestrian agents are added to the simulation with a fixed time period,
$T_p$, until $N_p$ have been added. The simulation ends once all pedestrian agents have completed their trips.

Vehicle agents are continually added to the simulation to produce the traffic conditions that pedestrian agents respond to. The level of vehicle traffic is given as a simulation input by setting the desired time average number of vehicle agents $\bar{N}_v$. Vehicle agents are added to the simulation when the total number of vehicle agents drops below $N_v$. Vehicle agents continue to be added to the simulation until the run ends.

**Simulation Environments**

Trips are simulated in three different environments: two synthetic grid environments and one environment built using real geometries, shown in Figure 6.1. Simulating pedestrian agents in different environments enables analysis of how route choices are dependent on the environment as well as on the route choice parameters.

The environments are designed to be comparable in terms of spatial extent and the number of road intersections. The real road network environment is a 1km catchment area (measured by road network distance) around Clapham Common tube station in South West London. Transport for London analysis reports that average daily walking distance was 1.2km in 2017/18 with *walk stages* (walks that form part of a larger trip - a walk to a metro station is a walk stage) comprising 0.5km of this average (Transport for London, 2018). Given this average, a 1km catchment area is considered to be a suitable upper limit of walking distance to a metro station.

The processed road network consists of 130 intersections, defined as nodes with degree 3 or greater, and 263 nodes in total. The high number of nodes with degree 2 is the result of breaking up curved road geometries into sequences of straight road links. (The processing of road network data is discussed in Section 4.2.)

The two synthetic road networks are both 1km catchment area grids with right-angle turns. The Uniform Grid environment has uniform link length of 125m in the horizontal direction and 100m in the vertical direction, 131 intersections and 159
nodes in total. The Quad Grid is produced using a quad tree algorithm (Eisenstat, 2011) that produces a variety of road link lengths. The Quad Grid network has link lengths from 15.6m to 500m (one road link is 500m, the next largest link length is 250m), 132 intersections and 153 nodes in total. In both synthetic grid environments carriageway width is set to 10m and the pavement width to 3m, apart from on the shortest links in the Quad Grid environment where these widths are halved. The pavement network is produced from the pavement polygons in the same way as for the Clapham Common environment.

**Crossing Infrastructure**

Marked crossing alternatives (MCAs) are added to the environment by placing straight lines between pavement polygons at the entrances to side roads and around 4-way intersections. This assumes pedestrians have right-of-way at these locations. This is based based on the UK Highway Code which states that pedestrians have right-of-way when crossing at side roads (The Highway Code, 2022a). The simulation does not include traffic lights and the placement of MCAs around 4-way intersections assumes pedestrian right-of-way where, in reality, right-of-way would typically alternate between vehicle and pedestrian flows.

Side roads are identified as those which join intersections approximately at a right angle to both adjacent road links. Strictly enforcing the right angle condition in the Clapham Common network results in few MCAs and so a more relaxed condition of $90 \pm 45^\circ$ is used. This produces a good coverage of MCAs which ensures
that pavements are well connected.

In the Uniform Grid environment MCAs are placed at either end of every road link owing to the uniform 90° angles between road links and uniform 4-way intersections. In the Quad Grid environment all 4-way intersections and side roads have MCAs but the irregular block sizes mean that there are long stretches of pavement that only have MCAs at either end or on one side of the road. Unlike the grid environments, in the Clapham Common environment the more irregular placement of MCAs means that for some trips informal crossings are necessary when following the shortest road network path.

**Trip Origins and Destinations**

The origins and destinations of pedestrian and vehicle trips are coordinates that are uniformly randomly distributed throughout the environment and referred to as ODs. Vehicle ODs are located at road network nodes. In each simulation environment 91 nodes are assigned as vehicle ODs and act as both sources and sinks for vehicle agents. These nodes are chosen from a uniform random distribution across all junction nodes in the road network with non-junctions nodes added if needed to make up 91 ODs in total. Vehicle agent trips origins and destinations are sampled from a uniform random distribution across all vehicle ODs.

All pedestrian trips share the same destination, a single OD located at the centre of each environment. This is the entrance to a metro station in the Clapham Common environment and can be similarly interpreted in the synthetic grid environments. Using a single, central destination creates unidirectional pedestrian flows to the metro station. (Appendix A includes simulation results for two-way pedestrian flows in the Clapham Common environment which, with the exception of a shift in average route length, are approximately the same as the one-way results.)

Pedestrian agent trip origins are sampled uniformly from the other pedestrian ODs. Pedestrian ODs are located on pavement polygons with 305 ODs in each environment. These are chosen by randomly selecting a sample of pavement polygons and choosing a random location in each polygon (to avoid ODs clustering close to one another). Pavement polygons within 50m of the destination OD were excluded.
In the Clapham Common, Quad Grid and Uniform Grid environments there are 333, 242 and 286 road links respectively; 305 ODs were chosen to provide good coverage across the road links in each environment.

In all simulation runs 200 pedestrian trips are modelled. This number was chosen to give a high coverage of trip origins across the environment. A higher number of trips would provide better coverage of the environment at the cost of longer simulation runs. At this stage of model verification it was desirable to have shorter runs to enable more expansive exploration of the parameters space. The implications of this are discussed at the end of this chapter, in Chapter 8 and, as mentioned above, in Appendix A.

Ten rounds of vehicle agent additions are performed to initiate traffic conditions before pedestrian agents are added.

### 6.2.3 Interactions

Pedestrian agents interact with the environment and vehicle agents through the CLT route choice model - at the upper-level through a choice of pavement network path and at the lower-level through a choice of crossing location. Additionally, physical interactions with other pedestrian agents and with the environment shape pedestrian movement through Moussaid et al. (2011)’s ‘cognitive heuristic’ model. Pedestrian agents do not physically interact with vehicle agents, they only interact through their perception of vehicle traffic when choosing a crossing location.

Vehicle agents similarly interact with the environment through their route choice decisions. Vehicle agents are constrained to move along the road centre line of OS-ITN road network links which constitutes another form of environment interaction. Vehicle agents interact with other vehicle agents through a simple car following model with no overtaking, adapted from Krauss (1998) and detailed further below. When vehicle agents reach an intersection they progress onto the next link once there is capacity for an additional vehicle. Vehicle agents also physically interact with pedestrian agents by yielding to them when they cross the road. Vehicle agents’ velocities are updated such that they never collide with a pedestrian agent. Pedestrian crossing can therefore cause vehicle queues and delays.
Through these interactions flows of pedestrian and vehicle agents are shaped by the environment and by the presence of other agents.

### 6.2.4 Agents

**Pedestrian Agents**

Pedestrian agents’ decisions are governed by *upper-level* and *lower-level* route choice which determines the way points the pedestrian agent moves between. Once these way points are chosen pedestrian agents move between them according to Moussaid et al. (2011)’s ‘cognitive heuristic’ model, as discussed in Chapter 5.

Pedestrian agents are defined by their walking speed, origin and destination and the route choice model parameter values they are initialised with. The pedestrian population in each run is homogeneous, meaning that all pedestrian agents are assigned the same values for route choice parameters, as this helps to isolate the effect of each parameter on pedestrian agents’ behaviour.

Pedestrian agents’ route choice parameters are detailed in Chapters 4 and 5 and can be summarised as follows. Parameters $PH$ and $MC$ control *upper-level* route choice and represent the high-level spatial knowledge and preferences of pedestrian agents. $\alpha$ and $\lambda$ represent risk taking and route optimising characteristics of the pedestrian agents at the *lower-level*; together they control which crossing alternatives are perceived as more attractive. $\gamma$ controls the rate of activation decay, $\varepsilon$ the activation threshold for alternative choice, and $\tau$ the maximum duration of activation accumulation; together they control how easily a choice is made.

Pedestrian agents’ speed is drawn from a lognormal distribution $v \sim \text{Lognormal}(1.5ms^{-1}, 0.3ms^{-1})$ (limited between $1.6kmph < v < 9.0kmph$) with skew $= 0.6$ (Willis et al., 2004). The positive skew of the lognormal distribution means below average speed pedestrian agents are more frequently added to the model.

**Vehicle Agents**

Vehicle agents are characterised by their origin and destination, maximum driving speed, acceleration, and deceleration. Vehicle agents follow the shortest path on the OS-ITN road network (link weight given by link length) from their
6.2. Agent-based simulation description

Vehicle agents move according to a car following model adapted from Krauss (1998) (the model is adapted slightly by removing random perturbations to vehicle velocity). Each simulation tick, with duration $\Delta t$, vehicle agents update their velocity and position according to:

\[
v(t + \Delta t) = \max(0, v_{\text{des}}(t)) \tag{6.1}
\]

\[
x(t + \Delta t) = x(t) + v(t)\Delta t \tag{6.2}
\]

$v_{\text{des}}(t)$ is the vehicle agents’ desired velocity. The desired velocity is the minimum of: the vehicle agent’s maximum allowed velocity, $v_{\text{max}}$; its velocity were it to accelerate as if in free flow conditions, $v(t) + a\Delta t$; or the safe following velocity, $v_{\text{safe}}(t)$. This means that in the absence of obstructions a vehicle agent will accelerate continuously until its maximum velocity is reached. However, the presence of obstacles such as other vehicle agents means the $v_{\text{safe}}(t)$ can be lower than $v_{\text{max}}$. In the case of vehicle following, $v_{\text{safe}}$ is given by:

\[
v_{\text{safe}}(t + \Delta t) = v_l(t) + \frac{g(t) - g_{\text{des}}(t)}{\bar{v} + r} \tag{6.3}
\]

where $v_l(t)$ is the velocity of the leader vehicle, $g(t)$ is the position of the vehicle agent, $g_{\text{des}}(t)$ is the desired following distance from the lead vehicle agent, $\bar{v}$ is the average of the two vehicles’ velocities, $b$ is a constant that represents the desired deceleration rate, and $r$ is a constant that represents the vehicle agent’s reaction time. Using $g_{\text{des}} = rv_l(t)$ ensures the vehicle maintains a safe following distance from other vehicle agents. When required to yield to pedestrian agents a fixed safe distance of $g_{\text{des}} = 2m$ and $v_l = 0ms^{-1}$ is used. Vehicle agents have a field of vision of 20$m$ and only adjust their speed with respect to objects within this distance. Remaining constants are taken from Krauss (1998): $r = 1s$, $a = 0.8ms^{-2}$, and $b = 4.5ms^{-2}$. $v_{\text{max}} = 11.2ms^{-1}$ (25mph) is chosen as a suitable speed limit for urban areas given the mixture of 20mph and 30mph urban speed limits in the
6.3 Methods

6.3.1 Global sensitivity analysis

The small-scale experiments in Chapter 5 verify the behaviour produced by lower-level route choice across just 1-2 road links. These experiments are expanded to enable verification of two additional aspects of the CLT route choice model:

- the effect of upper-level route choice on pedestrian behaviour
- whether lower-level route choice continues to affect pedestrian behaviour in the same way when enacted on multiple road links

Upper-level route choice parameters were held constant in the small-scale experiments. Expanding the spatial scale of the experiments creates a role for upper-level route choice, and therefore parameters $MC$ and $PH$, to affect pedestrian agent movement. The small-scale experiments were also conducted on only one section of the road network. Simulating movement over a larger section of the road network helps verify whether these findings - the way pedestrian agent behaviour responds to vehicle traffic and lower-level parameters - is sustained in a larger study area.

The use of the full CLT route choice model expands the parameter space that must be explored in these experiments. Global sensitivity analysis is used to navigate this challenge and ensure the parameter space is fully explored and the results reflect the influence of parameter values across the space equally. Output metrics are defined and used to characterise neighbourhood and street scale aspects of pedestrian agent movement.

6.3.1.1 Simulation inputs: model parameters and initial conditions

The ABM has 11 inputs, referred to as model or simulation parameters, which are listed in Table 6.2: 7 control the route choice model used by the pedestrians agents;
3 control the number and density of pedestrian and vehicle agents in the simulation, termed initial conditions; 1 parameter sets the random seed.

Table 6.2 lists the parameter bounds or fixed values used in the global sensitivity analysis. The bounds for of lower-level parameters $\varepsilon$, $\gamma$, $\alpha$, and $\lambda$ are set based on the results from Experiment 1 and 2 in Chapter 5. $\alpha$ is, by definition, bounded from below and above by 0 and 1 so the full range of this parameter is considered. $\lambda$ is naturally bounded from below by zero and the small-scale simulation experiments show that for $\lambda > 2$ pedestrian agents tend to cross informally irrespective of preferences and crossing location in lower vehicle flow settings. This is considered implausible so 2 is used as the upper limit of this parameter. Similarly, for values of $\varepsilon < 5$ or $\varepsilon > 8$ pedestrian agents did not adjust their road crossing choices in response to changes in the street environments so these are used as the bounds for the $\varepsilon$ parameter. Small-scale experiments found that fixing $\gamma = 0.9$ does not significantly limit the behaviour of pedestrian agents so this is retained here.

The bounds of the remaining lower-level parameter, $30 \leq \tau \leq 120$, are chosen based on the assumption that this permits a sufficient number of activation accumulation iterations for crossing alternative preference to be established. Pedestrian agent behaviour should not be sensitive to this parameter as it is intended to ensure pedestrian agents can always complete their journeys and not to influence road crossing behaviour. Using lower values of $\tau$ could influence crossing behaviour by forcing agents to choose prematurely while larger $\tau$ values could slow simulation runs without providing any benefit.

$N_v$ parameter bounds are set to produce sparse and dense traffic conditions at either extreme. At $N_v = 20$ all road links in each environment have high levels of capacity whilst at $N_v = 700$ a small large proportion of road links are close to or at full occupancy throughout the simulation. Beyond $N_v = 700$ the number of road links at full occupancy steeply increases in the Quad Grid environment, as shown in Table 6.1 which reports the occupancy level of road links for extreme $N_v$ values. This suggests that traffic starts to enter grid-lock with this level of vehicle agents. To avoid entering this traffic regime and producing very different traffic conditions
### 6.3. Methods

<table>
<thead>
<tr>
<th>$N_v$</th>
<th>Environment</th>
<th>50th</th>
<th>90th</th>
<th>99th</th>
</tr>
</thead>
<tbody>
<tr>
<td>20</td>
<td>CC</td>
<td>0.0</td>
<td>0.3</td>
<td>0.6</td>
</tr>
<tr>
<td></td>
<td>QG</td>
<td>0.1</td>
<td>0.4</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>UG</td>
<td>0.1</td>
<td>0.2</td>
<td>0.4</td>
</tr>
<tr>
<td>700</td>
<td>CC</td>
<td>0.9</td>
<td>7.8</td>
<td>47.0</td>
</tr>
<tr>
<td></td>
<td>QG</td>
<td>2.3</td>
<td>14</td>
<td>64.6</td>
</tr>
<tr>
<td></td>
<td>UG</td>
<td>2.7</td>
<td>7.8</td>
<td>24.2</td>
</tr>
<tr>
<td>750</td>
<td>CC</td>
<td>0.3</td>
<td>4.8</td>
<td>84.3</td>
</tr>
<tr>
<td></td>
<td>QG</td>
<td>1.4</td>
<td>16.7</td>
<td>88.0</td>
</tr>
<tr>
<td></td>
<td>UG</td>
<td>2.8</td>
<td>8.2</td>
<td>32.8</td>
</tr>
<tr>
<td>800</td>
<td>CC</td>
<td>0.2</td>
<td>3.4</td>
<td>89.6</td>
</tr>
<tr>
<td></td>
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<td>20.6</td>
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</tr>
<tr>
<td></td>
<td>UG</td>
<td>2.9</td>
<td>8.4</td>
<td>37.6</td>
</tr>
</tbody>
</table>

**Table 6.1:** The table shows the 50th, 90th and 99th percentile occupancy level of road links in each of the three environments under different vehicle number settings, $N_v$. The occupancy is calculated at the time average number of vehicles on a road links divided by its capacity, multiplied by 100. The 99th percentile values refer to the most congested road links in the environment, generally the most central links. For $N_v = 800$ the 90th percentile occupancy in the Quad Grid environment differs considerably from the other two environments, showing that vehicle agents are more congested in this environment.

between environments, the upper bound $N_v = 700$ is chosen.

The bounds for $T_p$ were similarly chosen to produce sparse and dense populations of pedestrian agents. This was judged using a visualisation of the simulation. The upper bound of $T_p = 80$ means that pedestrian agents rarely interact with one another whilst $T_p = 5$ produces a dense group of pedestrian agents that converge on the destination at a similar time.

$MC$ is defined as a Boolean and so the full set of possible values are accounted for in the following simulations. $PH$ is naturally bounded from below from 0 but this would mean agents are unable to perceive any of the pavement network which is unrealistic. The lower bounds of 20° is used instead. The $PH = 360°$ upper bound was chosen to provide near complete network knowledge for pedestrian agents. Based on the trips that pedestrian agents undertake in each environment, this upper bound provides optimal pavement network knowledge for all trips in the grid environments and 75% of trips in the Clapham Common environment.

Of the 11 simulation parameters 8 are varied between runs. In addition to $\gamma$
two other model parameters are fixed: \( N_{\text{ped}} = 200 \) and the random seed is held constant. This is so the same 200 pedestrian agent trips are modelled each run. This means that changes in pedestrian agents behaviour are attributable to changes in route choices alone.

<table>
<thead>
<tr>
<th>Model Component</th>
<th>Name</th>
<th>Description</th>
<th>Possible Values</th>
<th>Sobol GSA Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stochastic Processes</td>
<td>Seed</td>
<td>Random Seed</td>
<td>( \mathbb{N} )</td>
<td>1</td>
</tr>
<tr>
<td>Agent Trips</td>
<td>( N_p )</td>
<td>Number of pedestrian trips</td>
<td>( \mathbb{N} )</td>
<td>200</td>
</tr>
<tr>
<td></td>
<td>( N_v )</td>
<td>Time average number of vehicle agents</td>
<td>( \mathbb{N} )</td>
<td>20 – 700</td>
</tr>
<tr>
<td></td>
<td>( T_p )</td>
<td>Pedestrian addition time period</td>
<td>( \mathbb{N} )</td>
<td>5 – 80</td>
</tr>
<tr>
<td>Upper-level route choice</td>
<td>MC</td>
<td>Route choice heuristic</td>
<td>Boolean</td>
<td>{true, false}</td>
</tr>
<tr>
<td></td>
<td>PH</td>
<td>Planning horizon angular distance</td>
<td>( \mathbb{R} )</td>
<td>20 – 360</td>
</tr>
<tr>
<td>Lower-level route choice</td>
<td>( \alpha )</td>
<td>Vehicle exposure and route detour utility weighting</td>
<td>( (0, 1) )</td>
<td>0 – 1</td>
</tr>
<tr>
<td></td>
<td>( \lambda )</td>
<td>Crossing alternative sampling distance sensitivity</td>
<td>( \mathbb{R} )</td>
<td>0 – 2</td>
</tr>
<tr>
<td></td>
<td>( \gamma )</td>
<td>Preference decay per time step</td>
<td>( (0, 1) )</td>
<td>0.9</td>
</tr>
<tr>
<td></td>
<td>( \varepsilon )</td>
<td>Preference choice threshold</td>
<td>( \mathbb{R} )</td>
<td>5 – 8</td>
</tr>
<tr>
<td></td>
<td>( \tau )</td>
<td>Model ticks choice threshold</td>
<td>( \mathbb{R} )</td>
<td>30 – 120</td>
</tr>
</tbody>
</table>

Table 6.2: Simulation parameters.

6.3.1.2 Output metrics

Four metrics are used to quantify pedestrian agents’ routes: mean upper-level path length, percentage of pedestrian agents whose path length is equal to the shortest path length, mean frequency of postponing crossing, and percentage of road crossings that are at informal (rather than marked) crossing locations.

Mean upper-level path length for each simulation run, is given by

\[
\bar{L} = \frac{\sum_p l_{p,q}}{N_p}
\]

(6.4)

where \( l_{p,q} \) is the length of network link \( q \) in pedestrian agent \( p \)’s completed upper-level path and \( N_p \) is the number of pedestrians in the run. \( \bar{L} \) is an estimate
of the mean distance travelled by pedestrians in the simulation run (estimate since agents’ deviate from these links when crossing the road and avoiding other pedestrian agents).

Route choices are compared to the shortest path by calculating the percentage of pedestrian agents whose path length is equal to the shortest path length, $SP$. To ensure fair comparison to the agent’s path, shortest paths are constrained to the section of the pavement network that follows the agent’s road network path. Comparisons to the shortest path therefore reflect the effects of model parameters and not the effects of restricting upper-level paths to follow the shortest road network path.

The road crossing behaviour of pedestrian agents is measured in two ways. The mean frequency of postponing crossing, $\bar{P}$, is given by

$$\bar{P} = \frac{P}{N_p} \quad (6.5)$$

where $P$ is the number of times pedestrian agents postpone crossing in a run. This measures the frequency of lower-level route choice changing upper-level route choice. This is the same metric analysed in Experiment 1 in Chapter 5 (see Section 5.7.1.2).

The percentage of road crossings that are at informal (rather than marked) crossing locations, $I$, is also recorded. This is the same metric that was analysed in Experiment 2 in Chapter 5 (see Section 5.7.2.2).

Since the number of pedestrian agents and trips is held constant across all runs, variations in these metrics between runs are due to differences in path finding behaviour alone.

The sensitivity of $L$, $SP$, $\bar{P}$, and $I$ to each of these parameters is calculated using the total effect Sobol sensitivity indicator. Sobol indices (SIs) are a variance-based measure of sensitivity given by the conditional variance of output metric $Y$ with respect to input parameters $X_i$ (Saltelli et al., 2008). SIs are expressed as a proportion of total output metric variance. The total effect SI, $S_T$, measures the total sensitivity of an output metric to parameter $X_i$, accounting for all interactions between $X_i$
and other parameters. We use the SALib python library (Herman and Usher, 2017) to sample parameter values from the Sobol pseudo-random distribution to produce 256 estimates of $S_{T_i}$ for each model parameter $X_i$, requiring 2,560 simulation runs using the Satelli method for calculating Sobol indices.

GSA simulations were run on a Windows Server with a 3.30GHz processor and 128Gb of memory. The 2560 model runs took 120, 90 and 220 minutes to complete for the Uniform Grid, Quad Grid and Clapham Common environments.

### 6.3.2 Least cost model comparison

The CLT route choice model is compared to an optimal least cost route choice model to clarify the differences of this approach to other route choice methodologies.

In this model pedestrian routes are given by the least cost path on the pavement network. As with the CLT model the least cost path is constrained to the section of the pavement network that follows the agent’s road network path. This ensures that the same total amount of spatial information is available under each model. To account for road crossing and vehicle traffic we parameterise the weight of road crossing pavement network links as follows:

\[
\begin{align*}
    w_i &= \begin{cases} 
        l_i, & \text{if the link does not cross a road} \\
        l_i + k\rho_{v_j}, & \text{if the link crosses at location with crossing infrastructure} \\
        l_i + j\rho_{v_j}, & \text{if the link crosses at location without crossing infrastructure}
    \end{cases}
\end{align*}
\]

(6.6)

where $l_i$ is the length of link $i$, $\rho_{v_j}$ is the time average vehicle density of the road the pavement network link crosses (calculated from vehicle trajectories produced in the simulations) and $k, j \in \{0, 500, 1000, 1500, 2000\}$. For each level of vehicle flow represented in the 2560 runs performed in the GSA and all combinations of $j$ and $k$, a total of 6400 parameter settings, we compute the least cost pavement network paths for every unique pedestrian trip simulated in the GSA. In the Clapham Common environment the median increase in the weight of road crossing links ranges from $0.2 - 2.1\%$ between parameter settings, with maximum increases ranging from
6.4 Results

6.4.1 Global sensitivity analysis

The results of the global sensitivity analysis simulations are summarised in the following figures: Figure 6.2 shows the origins and destinations of pedestrian trips and the proportion of pedestrian agents travelling on each road link; Figure 6.3 plots the output metrics against parameter values for every model run with a trend line to show the relationship; Figure 6.4 provides an aggregate view of these plots with histograms showing the distribution of $\bar{L}$, SP, $\bar{P}$, and I across simulation runs and the sensitivity of each metric to each model parameter (zero sensitivity is equivalent to a flat trend line).

Across all environments and output metrics, parameters $\tau$ and $T_p$ had minimal impact, as show by the sensitivity indices in Figure 6.4. For this reason they have been omitted from Figure 6.3.

Route Length
6.4. Results

Routes are typically longest in the Uniform Grid environment and shortest in the Clapham Common Environment. \( \bar{L} \) has a similar range in all three environments, but is least varied in the Quad Grid environment.

\( \bar{L} \) tends to be most sensitive to \( MC, PH \) and \( \epsilon \), although in Uniform Grid environment \( \bar{L} \) is not sensitive to \( MC \) at all. Increasing \( PH \) decreases \( \bar{L} \). Setting \( MC = true \) and increasing \( \epsilon \) increases \( \bar{L} \).

\( \bar{L} \) is also sensitive to \( \alpha \) and \( N_v \) to a lesser degree. Increasing \( \alpha \) tends to decrease route lengths. This follows from high \( \alpha \) values making pedestrian agents’ crossing choices based more on trip distance than vehicle exposure. Similarly, increasing \( N_v \) increases route lengths.

Shortest path similarity

\( SP \) is similarly distributed in the three environments, ranging from 8% to 38% in the Uniform Grid, 4% to 34% in the Quad Grid, and 2% to 37% in the Clapham Common environment. Since these shortest paths are constrained to follow the same road links as the pedestrian agents, agents following these shortest paths have similar \( \bar{L} \) values to those that do not, with a maximum difference in \( \bar{L} \) of between 6.4% (Uniform Grid) and 9.1% (Clapham Common).

As with \( \bar{L}, PH, MC \) and \( \epsilon \) account for most of the variance of \( SP \). Increasing \( PH \) increases \( SP \) while increasing \( \epsilon \) and setting \( MC = true \) decreases \( SP \). Again, \( \alpha \) and \( N_v \) have a slight effect for the same reasons that these parameters affect \( \bar{L} \).

Crossing behaviour

The distribution of \( \bar{P} \) is similar across all three environments. Postponements occur most frequently in the Uniform grid environment (mean \( \bar{P} = 1.4 \)) and least frequently in the Clapham Common environment (mean \( \bar{P} = 0.68 \)). In all environments a large region of parameter space produces \( \bar{P} > 1 \). For context, pedestrian agents perform an average of between 4.4-5.7 road crossings in each environment with the maximum only ranging from 5.7 to 7.4. Therefore, postponing one road crossing corresponds to around 20% of an agent’s upper-level road crossing decisions being altered by lower-level decision making.

\( \bar{P} \) is approximately equally sensitive to \( \epsilon, PH, \) and \( MC \) in all three environ-
ments, with increases in $\varepsilon$ increasing $\bar{P}$. Increasing $PH$ tends to increase $\bar{P}$ and setting $MC = true$ tends to decrease $\bar{P}$, though again $MC$ has no effect in the Uniform Grid environment. $PH$ has a far greater effect on postponements in the grid environments.

The results for $I$ show a wide range of informal crossing rates in all three environments. $I$ ranges from 0% to 72% in the Uniform Grid, 7% to 82% in the Quad Grid, and 32% to 77% in the Clapham Common environment, with an average of 23%, 41%, and 55% in respectively. The higher frequency of informal crossing in the Clapham Common environment reflects the reduced availability of marked crossing infrastructure in this environment.

$I$ shows higher sensitivity to lower-level parameter $\alpha$ and $N_v$ than other metrics, with increases in $\alpha$ and decreases in $N_v$ producing higher rates of informal crossing. Upper-level parameters $PH$ and $MC$ also contribute to the variation of $I$, particularly in the Quad Grid environment, with increases in $PH$ also increasing the rate of informal crossing.

### 6.4.2 Least cost model comparison

As with the CLT model, the least cost path model distinguishes between the presence and absence of crossing infrastructure and levels of vehicle traffic. The resulting routes show a similar level of variation in $\bar{L}$ as shown by the results in Table 6.3.

<table>
<thead>
<tr>
<th></th>
<th>Uniform Grid Mean $\bar{L}$</th>
<th>STD</th>
<th>Quad Grid Mean $\bar{L}$</th>
<th>STD</th>
<th>Clapham Common Mean $\bar{L}$</th>
<th>STD</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLT</td>
<td>743m</td>
<td>6.6m</td>
<td>732m</td>
<td>5.2m</td>
<td>682m</td>
<td>6.4m</td>
</tr>
<tr>
<td>Least Cost</td>
<td>733m</td>
<td>6.0m</td>
<td>697m</td>
<td>6.6m</td>
<td>658m</td>
<td>6.5m</td>
</tr>
</tbody>
</table>

*Table 6.3:* Comparison of $\bar{L}$ mean standard deviation and variance calculated over parameter settings.
6.5 Discussion

6.5.1 Global sensitivity analysis

The pedestrian behaviour produced by the CLT route choice model has been explored with GSA. The results show that the model is able to produce a wide range of pedestrian trajectories spanning an urban neighbourhood. This is shown by the distribution of $\bar{L}$ and $SP$ across model runs, produced through variations in pedestrian agents’ route choices and levels of vehicle traffic. Additionally, integrating street level and neighbourhood level decisions reveals multi-scale influences on road crossing behaviour.

The variation in metrics $\bar{L}$, $SP$, and $\bar{P}$ is predominantly due to three parameters: $MC$, $PH$, and $\varepsilon$. As $PH$ increases $\bar{L}$ tends to decrease, showing that increasing spatial knowledge enables agents to identify more optimal routes. Choosing to min-
6.5. Discussion

Figure 6.4: Histograms of output metrics across multiple simulation runs, with the y-axis showing the number of runs which produced values in each bin. Below the histograms are the total effect sensitivity indices of each metric and parameter. Confidence intervals are given by the variation across the 256 indices values produced from the 2560 simulation runs.

Figure 6.5: Comparison between paths produced by the hierarchical CLT model and a constrained least cost path model. Each path corresponds to a different parameter setting. In this case the standard deviation is 12m for CLT path lengths and 5.1m for least cost path lengths.

imise the number of road crossings ($MC = true$) rather than route length increases $\bar{L}$. Higher values of $\varepsilon$ also increase route lengths by make it harder for agents to choose a crossing location, causing agents to postpone crossing more frequently and not follow their desired upper-level path.

These parameter effects are also reflected in variations in $SP$. For high $PH$ and
MC = false settings nearly all pedestrian agents should choose optimum upper-level paths. However, in all environments a maximum of only around 40% of agents follow the shortest path. This demonstrates that pedestrian agents deviate from optimal paths as a result of lower-level route choices. High ε values inhibit a pedestrian agents’ choice of crossing alternative, shown by the increase in $\bar{P}$. Additionally, high levels of vehicles traffic, $N_v$, combined with sensitivity to traffic levels (low $\alpha$) reduce the ability of pedestrian agents to follow shortest paths. Ultimately, it is the interaction between these lower-level parameters that affects agents’ choices.\(^1\)

The model produces a broad set of street level trajectories. The wide range of $I$ values across model runs shows that pedestrian agents can be made to the cross road at marked locations to a greater or lesser degree, particularly in the grid environments due to the increased coverage of crossing infrastructure. $I$ also responds to model parameters in intuitive ways. Firstly, it is far more sensitive to lower-level parameters $\alpha$, $\lambda$ and $N_v$ that other metrics meaning these parameters tend to affect lower-level decisions only and play less of a role in altering upper-level decisions. Increasing $\alpha$ increases the importance of the journey time attribute of a crossing location and this is reflected in the increase in the rate of informal crossing. As $N_v$ decreases the frequency of informal crossing also increases showing that pedestrian agents are perceiving lower levels of vehicle flow and adjusting their road crossing behaviour accordingly. This demonstrates that lower-level decision making is producing the intended road crossing behaviour when implemented in a larger scale simulation.

Integrating street and neighbourhood navigation decisions into a single modelling framework has enabled comparisons of the effects of decision making at each of these scales on pedestrian agent behaviour. Metrics $\bar{L}$ and $SP$ are calculated from pedestrian agents’ upper-level routes on the pavement network. It follows that these metrics are predominantly sensitive to upper-level parameters $MC$ and $PH$. However, non-zero values for lower-level parameter sensitivity indices show routes are also impacted by street level decision making.

\(^1\)The variation in sensitivity indices indicated by the error bars is due to the sensitivity of the outputs to a particular parameter also depending on the values of the other parameters.
This is further evidenced by \( \bar{P} \) which measures the frequency of lower-level decision making changing upper-level routes. This is the process by which lower-level parameters produce variance in \( L \) and \( SP \). In all environments \( \bar{P} \) is highly sensitive to \( \varepsilon \). Higher \( \varepsilon \) values mean a higher activation threshold must be reached to trigger a choice of crossing location, therefore making it harder for a choice to be made before the agent reaches the end of the road link. In the Clapham Common environment \( \bar{P} \) is also highly sensitive to \( \alpha, N_v, \) and \( MC \) which shows that, in this environment in particular, pedestrian agents are postponing crossing to avoid vehicle exposure. These results show the framework is producing core behaviours outlined by CLT: the re-construal of initially abstract high-level decisions when psychological distance between the decision maker and the object of the decision is reduced.

The model also produces interaction from upper to lower-level decision making. This is most clearly demonstrated by \( I \), the rate of informal crossing, being sensitive to upper-level parameters despite crossing location being chosen at the lower-level. This sensitivity means that the frequency of informal crossings depends on the route chosen at the upper-level (i.e. the pavement network route). For example, increasing \( PH \) tends to increase the rate of informal crossing in the Quad Grid environment. Increasing the spatial knowledge of agents changes their crossing behaviour by changing which road links upper-level paths cross at. Interestingly, \( \bar{P} \) is also sensitive to upper-level parameters meaning that the process of lower-level decision making affecting upper-level routes is itself dependent on the upper-level routes. The hierarchical CLT framework has therefore enabled multi-scale influences on road crossing behaviour to be identified.

Comparisons between road network environments reveal how components of the CLT model are dependent on the environment. \( MC \) is the only parameter to affect an output metric (\( I \)) in opposite ways between environments. Agents which minimise the number of crossings in upper-level paths perform fewer informal crossings in the Clapham Common environment but more in the Quad Grid environment (as a proportion of their road crossings). This can be explained by differences
in the locations of crossing infrastructure between the environments. In the Quad Grid environment minimising crossings at the upper-level leads agents to cross road links with less crossing infrastructure which biases the informal crossing option.

Additionally, $MC$ has far less effect on all output metrics in the Uniform Grid environment than in the other two environments. This follows from the Uniform environment having multiple paths that satisfy both the shortest distance and fewest crossings heuristics, making the choice of path more indifferent to which heuristic is used. As the road network becomes less uniform in the Quad Grid and Clapham Common environments, $MC$ tends to become more influential. Conversely, $PH$ tends to be more influential in the grid environments where the more uniform pavement network link lengths required larger planning horizons to identify more optimal upper-level paths. (Clear discontinuities in the plot of $\bar{L}$ against $PH$ in Figure 6.3 can also be seen at 90° for the grid environments, a result of having uniform 90° turns in the grids.) The varied link lengths (e.g. different link lengths on either side of the road) in the the Clapham Common environment mean optimal paths can be identified even with a minimal planning horizon (e.g. by avoiding walking on a longer side of the road).

Another notable difference between environments is the greater sensitivity of output metrics to $\varepsilon$ in the Uniform Grid environment. This is due to the uniform length of road links in this environment which allow for $\varepsilon$ to determine lower-level route choice more systematically. In the more realistic environments $\varepsilon$ has less of an effect.

### 6.5.2 Least cost model comparison

Comparison to the least cost route choice model shows both models can produce a similar level of variation in upper-level route lengths. The least cost model produces a variety of routes by using historic vehicle count data in combination with two parameters to weight different network links. The CLT route choice model has produced a similar variation in route lengths through the dynamic decision making of agents moving through and responding to their environment. Figure 6.5 compares the paths produced by these two models for one OD pair. For this OD pair, the CLT
route choice model distributes pedestrian agents more evenly across the pavement network, also producing a larger standard deviation in route lengths (12m compared to 5.1m). Comparing the methods for individual trips reveals differences between the two methods that are obscured by the statistics calculated over all trips in Table 6.3. Additionally, the least cost model with the narrower parameter range of $k, j \in \{0, 100, 200, 300, 400, 500\}$, shown in Appendix A Section A.2, produces a smaller standard deviation of route length than the CLT route choice model. Together, these results show that the CLT route choice model produces pedestrian route alternatives that are qualitatively different to those produced by a least cost model, doing so through a combination of heuristics, bounded rationality, and dynamic route choice.

### 6.5.3 Validity of parameter bounds

The effect of different pedestrian preferences on movement have been explored using GSA. The choice of parameter bounds was intended to fully encompass the pedestrian agent behaviour that can be produced by the model. The results provide some indication this has been achieved. Figure 6.3 shows the response of all output metrics to $PH$ appears to taper off towards the upper $PH$ bound, suggesting that pedestrian agent behaviour changes little beyond this limit. The largest change in $SP$ in response to $PH$ occurs for lower-mid PH values, again suggesting that increasing the upper or lower bound will have minimal impact on the results.

The response of metrics $\bar{L}$, $SP$, and $\bar{P}$ to $\epsilon$ appears to taper at upper bound, suggesting that pedestrian agent behaviour changes little for $\epsilon > 8$. Changes in pedestrian agent behaviour may be observed beyond the lower $\epsilon$ bound, but as discussed in Chapter 5 this could limit the ability of pedestrian agents to respond to traffic levels.

$I$ shows a clear tapering in response to high $N_v$ values, suggesting the upper limit of vehicle traffic is producing near minimal informal crossing. However, higher $N_v$ values may continue to produce changes in $\bar{L}$, $SP$, and $\bar{P}$. The results that only a maximum of 40% of pedestrian agents followed the shortest path suggests that the lower $N_v$ bound could be reduced further to better test the model. By definition, pedestrian agents should all follow the shortest path for certain route
choice settings (high $PH$, $MC = false$, low $\epsilon$, high $\alpha$). To observe 100% of pedestrian agents following the shortest path the level of vehicle traffic may need to be lower than considered in these experiments.

The remaining parameters, $\tau$, $\lambda$, and $T_p$, were found to have minimal effects of the output metrics for the range of values used in simulations. A more parsimonious model is therefore possible, where values for these parameters are fixed.

6.5.4 Limitations

A number of assumption and simplifications were made in developing the simulation used to explore the behaviour produced by the CLT route choice model. I discuss these below and the effect they are likely to have had on the results.

Absence of noise in vehicle agent movement model

The car following model used to control the movement of vehicle agents does not include random perturbations to vehicle speed. Random perturbations to vehicle speed are typically needed to reproduce stop-go traffic waves at higher vehicle densities (for example in canonical single infinite lane traffic simulations). The absence of random perturbations to vehicle speed in this simulation produces unrealistically consistent vehicle speeds and potentially reduces the occurrence of gaps in vehicle traffic which, in turn, potentially limits pedestrian road crossing. However, the simulation does contain other ways vehicle agents’ speed can be interrupted: vehicle agents slow down or stop for crossing pedestrians and must wait at junctions for capacity on connecting road links. Because of this, the impact of excluding random perturbations to vehicle speed is expected to be small.

Role of the cognitive heuristic model of pedestrian movement

The movement of pedestrian agents is controlled by the cognitive heuristic model, detailed in Section 5.6. The simulation experiments in this chapter build on those in Chapter 5 by varying pedestrian agent densities (through the $T_{ped}$ parameter), in principle warranting the use of this more detailed model of pedestrian movement and interaction. However, given the low number of pedestrian agents added to the simulation (200) and the shortest time period of $T_{ped} = 5s$ pedestrian agent densities remain low in all simulation runs. Additionally, interactions with
the environment (walls) were excluded to reduce computational cost (this simplification is discussed in Section 5.6. As a result, pedestrian agents effectively move at constant speed towards their destination meaning that the cognitive heuristic model of pedestrian movement is mainly redundant. I expect similar results would be obtained by modelling pedestrian agents’ movement as a constant velocity straight line without having a significant effect on the results. The cognitive heuristic model would have an effect if higher pedestrian densities were simulated. This would also require using a smaller model time step (see below). At low pedestrian densities the pedestrian movement model is currently introducing unnecessary computational cost.

**One second time step**

A 1s time step is too coarse to effectively model high density pedestrian movement. At high densities smaller time steps of $< 0.1s$ are required to avoid very high collision forces that displace pedestrian agents large distances in a single step (a model artefact commonly observed when too large a time step is used). That these are not observed is a further illustration that simulated pedestrian densities are too low for the cognitive heuristic model to have an effect.

**Varying pedestrian speeds**

Pedestrian agents are assigned different desired walking speeds using a log-normal distribution. The lower-level route choice model accumulates activation at a constant rate of once per time step. When a diagonal pavement crossing link is chosen, faster moving pedestrian agents will have fewer opportunities to accumulate activation due to reaching the end of the road in fewer time steps. This creates an unintended causal link between walking speed and road crossing choices, the impact of which will be for faster moving pedestrian agents to tend to cross further towards the end of the road and to postpone crossing more often. To correct for this the rate of activation accumulation could be adjusted to account for pedestrian agent speeds, creating a consistent activation accumulation process across all pedestrian agents. (It is possible that faster moving pedestrians do tend to cross in systematically different locations, which would be an interesting model prediction
Constant random seed

The activation accumulation process of lower-level route choice uses randomness when sampling crossing alternatives. To properly account for the effect of randomness on model outcomes, multiple experiments should be performed with different random seeds rather than the single fixed random seed used in this chapter and in Chapter 5. The crossing alternative sampling probability, given by Equation 5.2, is implemented using a pseudo-random uniform number distribution whose sequence is determined by the random seed. The risk of not performing replicate simulation runs with different random seeds is that the results are contingent in some way on the particular sequence of random numbers produced by the chosen random seed. However, because each pedestrian agent samples crossing alternatives many times to make a crossing decision and because the order in which agents will sample alternatives changes based on other model parameters (for example changing upper-level parameters will change when pedestrian agents attempt to cross the road) it is unlikely that measurably different crossing behaviour would be observed with different random seeds. Nonetheless, the lack of replicate simulations is a limitation that should be addressed going forward.

6.5.5 Future work

To develop this work further it is necessary to validate the model. Given the complexity of the model - typical of ABMs and micro-simulations that produce high-level patterns ‘from the bottom up’ - there is not a single, well defined approach to validation. instead, there are multiple model components that require different approaches to validation. A central premise of the model is that road crossing decisions are reconstrued from a high to a low level in a manor in-keeping with CLT. To validate this process - represented in the model by the interaction of upper and lower-level route choice would require a bespoke experimental design that seeks to measure peoples cognition and/or decision making in real or simulated urban environments. For example, by replicating the experiments used to validate choice construal (Fujita et al., 2006; Liberman and Trope, 1998; Yan et al., 2016) in an
6.5. Discussion

Validating this aspect of the model more closely aligns with its purpose as a tool for studying pedestrian cognition and perception rather than a tool for transport planning.

Alternatively, validating the upper and lower-level route choice models by observing pedestrian road crossing choices in urban settings would be more aligned with providing useful insight for transport planning and street design. For example, the virtual game-like experimental methodologies Wang et al. (2021) or field observations (Wang et al., 2010) can be used to validate road crossing models and are also applicable to the lower-level route choice model presented in this thesis. Similarly, the detailed origin to destination recording of people’s road crossing behaviour used by (Papadimitriou, 2016) to study pedestrian road crossing could also be used to verify the routes produced by the CLT route choice model. By emulating these validation methodologies different models of road crossing could be compared to the CLT route choice model (as well as to other versions of the CLT route choice model that use different crossing alternative choice sets or upper-level route choice heuristics), helping to establish which is most accurate in a particular context and ultimately to better anticipate people’s behaviour when designing urban streets.

Finally, the computational cost of the model may be reduced through simplifying or removing components of the model, the most computationally expensive of which is, firstly, the ‘cognitive heuristic’ pedestrian movement model (discussed in Section 6.5.4 above) and, secondly, the sequential sampling crossing location choice model.

By addressing these limitations the CLT route choice framework could be used for a more granular appraisal of traffic management and urban design. Walkability (Talen and Koschinsky, 2013) and pedestrian quality-of-service (Macdonald et al., 2018; Anciaes and Jones, 2016a) analysis could be extended to account for a broader set of possible pedestrian trajectories that are responsive to the movements of other road users.
6.6 Conclusion

The CLT route choice model presented in Chapters 4 and 5 represents specific characteristics of pedestrian route choice and road crossing, broadly grouped into ‘spatial knowledge’ and ‘route preferences’ categories. The experiments we perform in this chapter and Chapter 5 robustly test the CLT route choice model by examining behaviour at two spatial scales (street level and neighbourhood level), simulating trips in multiple environments, and widely exploring the parameter space. While the route choice model may fail to represent or parameterise some additional aspects of pedestrian decision making, the model verification performed in this chapter extensively tests the components that have been incorporated.

This chapter verifies that components of upper-level and lower-level route choice models are producing the intended pedestrian behaviour when used to model a variety of pedestrian trips in an urban neighbourhood. To do this, we implemented the CLT route choice model in a spatial ABS and perform global sensitivity analysis for three simulation environments. Pedestrian trips in three environments were simulated to verify which aspects of pedestrian agent behaviour are shaped by the environment independently to the route choice model.

The results show that movement at both the neighbourhood and street level is affected by decision making at both scales, although upper-level parameters $MC$ and $PH$ predominantly control measures of upper-level paths $\bar{L}$ and $SP$. Comparison to an optimal least cost route choice model demonstrates the CLT route choice model is able to produce a similarly wide variety of routes, predominantly through upper-level route choice. Additionally, the model produces a wide variety street level trajectories due to the representation of informal crossing behaviour.

The CLT route choice model could therefore serve as an alternative source of pedestrian route alternatives, both at the neighbourhood and street scale. The advantages of such a method would be the increased granularity of the route alternatives and their interpretability in theoretically robust psychological terms. Additionally, by connecting granular pedestrian movement with larger scale navigation the CLT route choice model could support more detailed assessments of pedestrian walk-
ing experience and street infrastructure. This is developed in the following chapter, Chapter 7, where different road crossing restrictions are simulated and compared.
Chapter 7

Incorporating multi-scale pedestrian movement into street infrastructure appraisal

7.1 Introduction

In Chapter 6 we used global sensitivity analysis to explore the pedestrian agent behaviour produced by the CLT route choice model in three simulation environments. This chapter builds on this analysis by introducing policies that restrict pedestrian road crossing behaviour, using the simulation methodology developed in Chapter 6 to analyse the effects of these policies.

In urban street environments road user movement is coordinated through a mixture of physical infrastructure, laws, rules, and social norms (Tennant et al., 2021). These multiple layers have developed over time, often in direct response to increasing volumes of vehicle traffic (Moran, 2006, 2010), and constitute both ‘bottom-up’ (for example emergent social norms) and ‘top-down’ (for example infrastructure delivered by a central authority) influences. This is typical of socio-technical systems in which practices, regulations, maintenance networks, and infrastructure, are aligned to a particular technology and successfully perform societal functions such as the movement of people (Geels, 2002).

The transition to more sustainable urban transport systems is motivating
changes to socio-technical configurations that govern road users. Plans to increase walking and cycling in urban areas (Department for Transport, 2021) demand changes to infrastructure and urban street space allocation (Gössling, 2020; Cervero et al., 2019). Micro-mobility (encompassing e-scooters, dockless bicycles and other new single rider vehicles) can compete for street space with pedestrians (Zhang et al., 2023) and may require additional infrastructure (Zagorskas and Burinskienë, 2020) and regulations (Sareen et al., 2021) regarding their operation. At the same time, autonomous vehicles could make new demands of street infrastructure to help facilitate their operation (Tennant and Stilgoe, 2021).

Among these competing and changing demands of urban roads, attempts to ensure both mobility and safety exemplify tensions between different road users and values. Mobility is a core function that roads perform (Jones and Boujenko, 2009) as reflected in the evaluation of roads in terms of vehicle speed and throughput metrics (Jones and Anciaes, 2018). Simultaneously ensuring the safety of road users is a challenge that has been addressed in different ways. Traditional approaches to traffic engineering seek to design out interactions or potential conflict points between road users. However, this can lead to environments that, by providing additional space for cars, encourage high vehicle speeds which ultimately reduce the safety of the environment (Ewing and Dumbaugh, 2009) and walking intentions (Anciaes et al., 2019). Alternative approaches view vehicle speeds and traffic levels as the principle (inversely proportional) determinants of road safety. Accordingly, speed limits may be reduced and roads designed to encourage lower speeds, for example by increasing the potential for conflicts between road users in the hope that drivers adjust their behaviour accordingly (Dumbaugh and Gattis, 2005). Such interventions improve the safety for road users partially the expense of vehicle mobility, highlighting how tensions between safety and mobility may be more accurately expressed as tensions between vehicular and active transport modes.

Interventions related to safety and mobility tend to be made in relation to different spatial scales as well as in relation to different transport modes. A network-level perspective is generally considered necessary for assessing and improving the link
function of urban roads. Studies argue that cycle infrastructure investments should be prioritised based on network connectivity (Natera Orozco et al., 2020; Szell et al., 2021) and that the effects of increases to road network capacity on vehicle traffic are determined by the intervention location relative to the rest of the network (Sloman and Hopkinson, 2020). Similarly, walkability assessments include assessments of the connectivity of road networks (Southworth, 2005; Dhanani et al., 2017; Sevtsuk et al., 2016). Analysis of road safety takes a less explicitly network-level perspective with high risk areas identified based on the locations of incidents without consideration of the routes being taken by those at risk (Xie et al., 2017; Wang and Kockelman, 2013; Lovelace et al., 2016). Interventions to improve infrastructure safety are generally assessed at the link level (Anciaes et al., 2018; Cantillo et al., 2015; Hensher et al., 2011). Assessing street infrastructure interventions at both the link-level and neighbourhood level could provide a more thorough and integrated assessment of the impacts on safety and mobility.

In this chapter the agent-based simulation (ABS) developed through this thesis is used to explore the potential trade-offs between mobility and safety and how interventions to street infrastructure affect these. This agent-based approach can be contrasted to existing methods designed to assess the effect on pedestrians of changes to street infrastructure. Anciaes et al. (2018) propose a methodology to appraise the value of infrastructure designed to reduce the barrier effect of roads such as pedestrian crossings. This detailed and thorough method is limited to considering interventions at single specific sections of road or intersections. This narrow geographical focus prevents analysis of how the impacts of interventions are shaped by movement patterns across multiple scales - from link level to the wider urban area - or the impacts of interventions covering multiple locations. Papadimitriou’s work models pedestrian road crossing choices across multiple road links (Papadimitriou, 2012, 2016), but does not consider how interventions to street infrastructure could change pedestrian and vehicle behaviour. Elsewhere, simulations have been used to explore the effects of different traffic management policies on pedestrian and vehicle behaviour but have used simple and homogeneous models of pedestrian
7.2. Methods

The multi-scale model of pedestrian movement that has been developed in this thesis can be leveraged to address these gaps. This agent-based approach can provide a richer description of how the impacts of such ‘top-down’ interventions emerge through the actions of individual agents and their interactions with one another and with street infrastructure. Additionally, the ABS incorporates a wide range of pedestrian route choice behaviours. This provides a source of pedestrian heterogeneity which can improve impacts assessments by broadening the set of behaviours that interventions are tested under.

The following section explains how the ABS is adapted to the tasks of exploring the impacts of changes to street infrastructure, specifically interventions that limit where pedestrians are able to cross the road. In Section 7.3 the results of the simulation experiments are presented and in Section 7.4 they are discussed. Section 7.5 concludes this chapter.

7.2 Methods

7.2.1 Simulation scenarios

We use the ABS of multi-scale pedestrian movement developed in this thesis to explore the impacts of three policies that restrict pedestrian agents’ road crossing ability. Specifically, pedestrian agents are prevented from crossing roads informally to varying degrees in each of the policies. These are intended to represent the effect of laws or infrastructure (for example guard rails) that ensure pedestrians cross the road at marked crossing only. These policies can be contrasted to the CLT route choice model parameters which produce more or less informal road crossing through the preferences of individual pedestrian agents\(^1\).

By restricting informal crossings, the policies confine pedestrian-vehicle inter-

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\(^1\)The CLT route choice model assumes all pedestrians evaluate an informal crossing option. The policies to restrict informal crossing could therefore also be interpreted as representing different kinds of pedestrian agents that do not consider crossing informally on all road links. Here we do not distinguish between these two cases - pedestrians themselves deciding to to entertain an informal crossing option and physical barriers removing such an option - and instead focus on the effects of such differences in road crossing behaviour.
actions to a predetermined set of locations. Under certain traffic engineering perspectives this helps ensure safety by reducing the potential locations of pedestrian-vehicle conflicts, but, as discussed above, ‘shared-space’ designs are based on an opposing philosophy. Where pedestrians can be expected to cross the road gains significance in the context of autonomous vehicle testing and deployment. Studies argue that validating autonomous vehicle performance requires establishing the operational design domain (ODD) of the vehicle (Weissensteiner et al., 2023; Stilgoe, 2021) which in urban areas will include the behaviour of other road users (Vinkhuyzen and Cefkin, 2016; Domeyer et al., 2020). Simulating policies that restrict pedestrian road crossing behaviour at the neighbourhood scale helps to understand how the impacts of such policies are contingent on a particular urban environment, thereby addressing questions regarding the wider social and behavioural impacts of vehicle automation (Borenstein et al., 2017; Cavoli et al., 2017).

The effects of these policies are investigated by simulating pedestrian agent trips under each in three different road network environments and under a range of trip and route choice parameter settings. As in Chapter 6, for each simulation run output metrics characterising the behaviour of pedestrian and vehicle agents are produced which are used to compare the effects of the three policies.

The three simulation environments used in Chapter 6 are used again in this analysis: Clapham Common, Quad Grid, and Uniform Grid. This allows analysis of how the effects of these policies could be contingent on the road network morphology and associated road crossing infrastructure of each environment. The locations of marked crossings are also unchanged: placed at the entrance to side roads and around junctions with four or more entries and exits (i.e. road nodes with degree 4 or higher).\(^2\)

Three crossing restriction policies are considered: ‘always’, ‘sometimes’ and ‘never’. The ‘always’ policy permits informal crossing on all road links and corresponds to the implementation of the CLT route choice model presented thus far.

---

\(^2\)One additional marked crossing was manually added to a junction in the Clapham Common environment. This was required because, when preventing informal crossing under the “never” policy, a small number of pedestrian agents were unable to progress past this junction in some simulation runs.
Under this policy pedestrian agents always perceive an informal crossing alternative when choosing a crossing location under lower-level route choice (in addition to the marked crossing alternatives represented by line geometries).

The ‘sometimes’ and ‘never’ policies restrict the ability of pedestrian agents to perform informal crossings. Under the ‘never’ policy, informal crossing is prevented on all road links. The ‘sometimes’ policy represents a more balanced approach to regulating the movements of pedestrians in which informal crossing is only prevented on the busiest roads. In the Clapham Common environment, informal crossing is prevented on roads classed as A-Roads (in the UK road classification system A Roads have regional strategic importance and typically high levels of vehicle traffic), a total of 54 links connected to 54 intersections. To replicate this in the synthetic grid environments stretches of road that pass through and around the centre of the road network are treated as A-Roads; 48 links connected to 45 intersections in the Uniform Grid environment and 47 links connected to 45 intersections in the Quad Grid environment. Figure 7.1 shows the road network for each environment and the roads on which informal crossing is prevented under the ‘sometimes’ policy.

Pedestrian agents are prevented from crossing informally in the simulation by making an adjustment to the upper-level and lower-level route choice models. At the lower level an informal crossing alternative is not included in the crossing alternative choice set on road links where informal crossing is prevented. At the upper-level the pavement network is edited to reflect the unavailability of informal crossing. Road crossing pavement network links are removed if it is not possible for pedestrian agents to cross (road links without marked crossings and where informal crossing is prevented). This prevents pedestrian agents choosing an upper-level path they would be unable to traverse at the lower-level.

In the original upper-level route choice model, paths on the pavement network are constrained to follow the shortest road network path from origin to destination. (Recall that pedestrian agents first choose a path on the road network and that their perception of the pavement network is defined by the number of road network links
that lie within their planning horizon.) When informal crossing is restricted, this route can become impossible for a pedestrian agent to complete due to the edits to the pavement network. The road network is not edited since a pedestrian agent starting on a different side of the road might still be able to follow the shortest road network path without crossing informally.

To ensure all pedestrian agent trips can be completed a further adjustment to upper-level route choice is made. If no pavement network path to the end of a pedestrian agent’s planning horizon exists, the constraint to follow the shortest road network path is removed and the pedestrian agent chooses an upper-level path to their destination with complete knowledge of the pavement network. In practice, this never occurs in the grid environments due to the availability of marked crossings at either end of each road link but does occur in the Clapham Common environment due to the lower coverage of marked crossings.

The need to re-plan upper-level paths in this way reflects the severity of preventing informal crossings, particularly where the coverage of marked crossings is sparse or uneven. In real urban environments informal crossing is rarely impossible, even if it is illegal or uncustomary. But for this study, the restriction serves as a way to highlight the extent to which informal crossing behaviour is necessary to avoid significant detours given the placement of marked crossings. Because informal crossings increase the potential for conflicts between road users the effect of these policies can be related to balancing safety and mobility afforded by urban roads.

The three environments (Uniform Grid, Quad Grid, Clapham Common) combined with the three policies (‘always’, ‘sometimes’ and ‘never’) produces 9 scenarios. For each scenario 2,560 model runs are performed. Each run uses a different set of parameter values which determine the path-finding behaviour of the pedestrian agents, the trip frequencies of pedestrian agents and the time average number of vehicle agents travelling in the environment. Parameter value ranges are the same as those used in Chapter 6, shown in Table 6.2. Parameter values are sampled using the Sobol pseudo-random number sequence (Saltelli et al., 2008) using a uniform
7.2. Methods

Figure 7.1: The road network for each of the model environments. Informal crossing is prevented on the highlighted links in under the ‘sometimes’ policy.

distribution across each parameter’s value range.

7.2.2 Evaluation metrics

Five metrics are used to analyse the effects of the policies: mean upper-level path length, $\bar{L}$; total number of road crossings, $N_C$; crossing location entropy, $CLE$; crossing location dispersion $CLD$; and the average speed of vehicle agents, $\bar{S}_V$. Metrics $N_C$, $CLE$, and $CLD$ measure lower-level pedestrian movement and road crossing behaviour and $\bar{L}$ measures upper-level route choices. $\bar{S}_V$ is used to measure interactions between pedestrian and vehicle agents.

$\bar{L}$ is given by

$$\bar{L} = \frac{\sum_{p,q} l_{p,q}}{N_p}$$

(7.1)

where $l_{p,q}$ is the length of network link $q$ in pedestrian agent $p$’s completed upper-level path and $N_p$ is the number of pedestrians in the run. This metric was used in Chapter 6 to analyse pedestrian agent route choices.

$CLE$ is a measure of the diversity of road crossing locations in each run. This metric is determined by street-level movement patterns of pedestrian agents. To calculate $CLE$, first the diversity of crossing locations on each road link in a given simulation run is calculated. Each road link is divided into $2m$ segments, with the

\[3\] The analysis was repeated with $5m$ segments. $5m$ segments were found to be too course and did not identify changes in road crossing behaviour.
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The number of crossings in each segment is counted and divided by the total number of crossings on that link to give $p_{t,i}$, the probability of a crossing taking place in segment $i$ on link $l$. The diversity of crossing locations on that link is then calculated using the Shannon Entropy formula $H = -\sum p_i \log(p_i)$ (Shannon, 1948) to give $CLE_l$, the crossing location entropy of link $l$.

Links on which all road crossings occurred in the same segment $i$ will have a low $CLE_l$ value where as links on which pedestrian agents crossed at a variety of locations will have a high $CLE_l$ value. To illustrate this, the simulation results from Chapter 4 are presented again in Figure 7.2 below.

Individual links’ entropy values are then averaged to give $CLE$. Road links typically vary in length which means that the number of 2m segments, $n_l$, will vary. This raises the issue of how to average the entropy values of different road links. One approach is to normalise each link’s entropy by the maximum possible value for that link, $\log(n_l)$, as per the normalisation method used by Marin et al. (2022) for comparing entropy values between network components of varying size. However, in this case normalisation is not appropriate. Consider the $CLE_l$ value for two road links with different lengths - $L_1$ is 4m long and $L_2$ is 10m long - where on both links crossings are evenly split between the first and second 2m segments. The unnormalised $CLE_l$ values would be equal:

\[ CLE_{L_1} = CLE_{L_2} = -(0.5 \times \log(0.5) + 0.5 \times \log(0.5)) \] (7.2)

but the normalised values would not:

\[ |CLE_{L_1}| = \frac{-(0.5 \times \log(0.5) + 0.5 \times \log(0.5))}{\log(2)} = 1 \] (7.3)

\[ |CLE_{L_2}| = \frac{-(0.5 \times \log(0.5) + 0.5 \times \log(0.5))}{\log(5)} = 0.43 \] (7.4)

By averaging the unnormalised values $CLE$ measures how spread out in space road crossings are rather than how spread out relative to the length of each road.
7.2. Methods

Crossing locations in two scenarios with brighter colours indicating a greater density of road crossings at that location. Where crossings are more evenly spread along a road link CLE is higher.

Figure 7.2: Crossing locations in two scenarios with brighter colours indicating a greater density of road crossings at that location. Where crossings are more evenly spread along a road link CLE is higher.

CLE is given by the average distance of crossing locations from the centre of all crossing locations (given be the mean latitude and longitude of all coordinates) (Rey et al., 2020). A low dispersion value indicates a higher proportion of crossings occurring in the centre of the environment, whereas a higher dispersion value indicates that crossings are made widely spread out from the centre.

The fifth evaluation metric is the average speed of vehicle agents in the simulation run, \( \bar{S}_V \). In the simulation, all vehicle agents adhere to the same maximum speed limit and in the absence of other agents will only decelerate to avoid exceeding this limit. In the presence of other agents, vehicle agents will reduce their speed to match the speed of the vehicle ahead of them and to yield to crossing pedestrian agents. Because of this, changes in average vehicle agent speed between runs are almost entirely produced through interactions with other agents\(^4\). Average vehicle agent speed, \( \bar{S}_V \), is therefore used to measure the extent of competition for carriageway space.

\(^4\)It takes vehicle agents 14s to reach the maximum speed. Depending on the distribution of vehicle origins and destinations, it’s possible for slight differences in average speed to occur without interactions as a result of the accelerating period of a vehicle agent’s journey comprising a greater or lesser share of the whole journey. However, this effect is negligible because the distribution of vehicle origins and destinations being constant across simulation runs.
7.2.3 Analysis

First, we assess effect of the policies on pedestrian agent behaviour. Then, we assess the effect of the policies on competition for carriageway space. Building on this, the causal pathways from policy setting to pedestrian agent behaviour to changes in carriageway competition are investigated in order to explain how the polices change pedestrian-vehicle interactions when sharing carriageway space.

The metrics $L$, $CLE$, and $CLD$ are used to assess the effects of crossing restriction policies on pedestrian agent behaviour, summarised by the hypothesis $H_1$ below:

- $H_{1.0}$: Restricting informal crossing does not affect pedestrian behaviour, as measured by $L$, $NC$, $CLE$, and $CLD$

- $H_{1.1}$: Restricting informal crossing does affect pedestrian behaviour, as measured by $L$, $NC$, $CLE$, and $CLD$

By measuring street-level pedestrian trajectories, $CLE$ should exhibit a clear trend between crossing restriction policies, since the policies directly affect street-level pedestrian behaviour. The effect of policies on $L$, $NC$, and $CLD$ is less evident from the policy definition. These are metrics of pedestrian movement at the scale of the whole environment and are shaped by neighbourhood-level features such as network morphology and street-level features such as marked crossing infrastructure. How policies to restrict pedestrian behaviour at the street-level manifest to neighbourhood-scale patterns are best revealed through the simulation methodology used here.

These hypotheses will be tested with linear regression models in which $L$, $NC$, $CLE$, and $CLD$ are the dependent variables and the policy setting is an independent variable. The policy setting is represented with a one-hot encoding consisting of two categorical variables $sometimes$ and $never$ representing these two policies. Equation 7.5 gives the regression model equations used to test these hypotheses. Because the exact same set of simulation parameter values ($\alpha, \epsilon, \tau, \lambda, MC, PH, T_p, N_v$) are used when simulating each policy setting, these parameters do not need to be included
as controls in the regression models to identify the effect of the policies on the evaluation metrics.

\[
\begin{align*}
L \\
N_C \\
CLE \\
CLD
\end{align*}
\sim \text{sometimes} + \text{never} + \text{const} \\
(7.5)
\]

While the environments are designed to be similar in certain respects, direct comparisons of the output metrics between environments cannot be easily interpreted, in particular when comparing the Clapham Common environment to the two grid environments. Instead, the analysis focuses on comparing the differences between the effect of the policies on the output metrics between environments. As in Chapter 6, the distribution of each metric across all simulation runs is visualised to further compare policy settings. This compares the range of values produced by varying simulation parameters \((\alpha, \varepsilon, \tau, \lambda, MC, PH, T_p, N_v)\) between each policy setting and between environments.

Despite \(CLE\) and \(CLD\) measuring road crossing behaviour, the results of the above hypothesis tests do not inform whether interactions between pedestrian and vehicle agents are changed by restricting informal crossing. To answer this question, \(\bar{S}_V\) is must be compared between policy settings. Furthermore, because the policies only affect pedestrian agents, any change in \(\bar{S}_V\) due to the policies should be explainable in terms of changes in pedestrian agent behaviour. The directed acyclic graph (DAG) shown in Figure 7.3 illustrates this argument. Changes in \(\bar{S}_V\) are only produced by conflicts between agents and there are two ways that agent conflicts can be affected. \(\bar{N}_v\) directly affects conflicts by changing the number of vehicle agents in the simulation and therefore the competition for carriageway space. Conflicts are also affected by changes in pedestrian agent road crossing behaviour, which in turn will be affected by crossing restriction policies. The only causal path through which the policies can affect \(\bar{S}_V\) is through pedestrian agent behaviour. The question of whether the policies affect \(\bar{S}_V\) in this manner is summarised by the following
hypotheses:

• $H_2.0$: Restricting informal crossing does not affect vehicle speed

• $H_2.1a$: Restricting informal crossing affects vehicle speed by changing the number of pedestrian road crossings

• $H_2.1c$: Restricting informal crossing affects vehicle speed by changing the dispersion of pedestrian road crossings

• $H_2.1b$: Restricting informal crossing affects vehicle speed by changing the crossing location entropy of pedestrian road crossings

$H_2.0$ addresses whether or not the informal crossing policies affect $\bar{S}_V$. The three alternative hypotheses, $H_2.1a$, $H_2.1c$, and $H_2.1b$ address how the policies affect $\bar{S}_V$. The alternative hypotheses each identify a different aspect of pedestrian crossing as the mediator between the policies and pedestrian-vehicle conflicts. $H_2.1a$ considers the number of crossings, a non-spatial metric of pedestrian crossing behaviour. $H_2.1c$ considers crossing dispersion, a global spatial measure of crossing locations. $H_2.1b$ considers crossing location entropy, a local spatial measure of crossing locations.

These hypotheses are tested also with linear regression models. $H_2.0$ is tested by taking $\bar{S}_V$ as the dependent variable and the policies as the independent variables, as shown in Equation 7.6.

$$\bar{S}_V \sim \text{sometimes} + \text{never} + \text{const} \quad (7.6)$$

The regression model defined by Equation 7.6 can only indicate whether or not policies affect pedestrian-vehicle interactions. Hypotheses $H_2.1a$, $H_2.1c$, and $H_2.1b$ each propose a different explanation for how policies affect these interactions. Each of these hypotheses are tested with a two-stage least squares regression (2SLS) instrumental variable (IV) analysis (Huntington-Klein, 2021; Pokropek, 2016), summarised by the equation pairs 7.7, 7.9, and 7.8. 2SLS consists of performing two linear regressions. The first regression is used to predict the ‘treatment’
Figure 7.3: A directed acyclic graph illustrating the possible causal paths affecting $\bar{S}_V$. $\bar{N}_v$ affects conflicts indirectly, because pedestrian agent route choices respond to the level of vehicle traffic, and directly, because higher levels of vehicle traffic increases competition for carriageway space.

variable ($N_C$, $CLE$, or $CLD$) with the policy (which acts as the ‘instrument’). This first stage is given by the regression models given by Equation 7.5. The predicted treatment variables, $\hat{N}_C$, $\hat{CLE}$, and $\hat{CLD}$, isolate the variation in $N_C$, $CLE$, and $CLD$ due to the policies. In the second regression, $\bar{S}_V$, is modelled as dependent on the predicted treatment variable and the controls. The second regression provides the effect size of the association between changes in pedestrian agent behaviour due to the policies and changes in $\bar{S}_V$ due to the policies. Comparing these effect sizes, in combination with the results from the first stage regression (Equation 7.6) explains how the policies affect $\bar{S}_V$ through changes in pedestrian agent behaviour.

$$H2.1a:\quad N_C \sim sometimes + never + const$$
$$\bar{S}_V \sim \hat{N}_C + const$$

$$H2.1b:\quad CLE \sim sometimes + never + const$$
$$\bar{S}_V \sim \hat{CLE} + const$$
7.3 Results

Each simulation experiment produces 2,560 values for output metrics $L$, $N_C$, $CLE$, $CLD$, and $\hat{S}_V$. Table 7.1 presents the mean and standard deviation of each metric across simulation runs, an aggregation over route choice and trip frequency parameters. The distribution of these metrics across simulation runs is shown for each experiment in Figures 7.4 - 7.6. These distributions show that the effects of model parameters on outputs varies between scenarios. (See Appendix B for figures showing the sensitivity indices of evaluation metrics to simulation parameters under the three policy settings.) Comparisons between policy settings help explain how the policies are affecting agent behaviour.

\[
H2.1c : \quad CLD \sim \text{sometimes} + \text{never} + \text{const} \\
\hat{S}_V \sim CLD + \text{const} \quad (7.9)
\]

All simulation parameters are normalised using min-max rescaling (suitable since these are sampled from uniform distributions) and metrics $\hat{S}_V$, $N_C$, $CLE$, and $CLD$ are normalised by z-score rescaling (subtracting the mean and diving by the standard deviation).

Through this analysis the simulation is used to explore how top-down restrictions on pedestrian behaviour could change competition for carriageway space. By simulating each policy for a broad range of pedestrian agent and traffic settings, any identified differences between policies should be robust to uncertainties in pedestrian behaviour. The multi-scale nature of the simulation allows both global and local features of road crossings, as well as crossing frequency, to be measured and their effect on pedestrian-vehicle interaction quantified. Measuring competition for carriageway space is directly relevant to competing theories of pedestrian safety, such as whether conflicts should be designed out of or into urban roads (Ewing and Dumbaugh, 2009; Hamilton-Baillie, 2008). Here, we use crossing restriction policies to restrict the potential locations of pedestrian-vehicle interactions and observe how this changes the competition for road space ‘from the bottom up’.
### Table 7.1: Descriptive statistics for the five output metrics in each of the simulation experiments. Values are coloured to indicate within environment rank: green=largest, yellow=middle, red=lowest. If values are tied no colour is applied.

<table>
<thead>
<tr>
<th>Environment</th>
<th>Policy</th>
<th>( L )</th>
<th>( \sigma_{\bar{L}} )</th>
<th>( N_C )</th>
<th>( \sigma_{N_C} )</th>
<th>( CLE )</th>
<th>( \sigma_{CLE} )</th>
<th>( CLD )</th>
<th>( \sigma_{CLD} )</th>
<th>( S_V )</th>
<th>( \sigma_{SV} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clapham</td>
<td>always</td>
<td>682</td>
<td>6.4</td>
<td>5.3</td>
<td>1.2</td>
<td>0.46</td>
<td>0.11</td>
<td>313</td>
<td>10</td>
<td>9.3</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>sometimes</td>
<td>717</td>
<td>6.4</td>
<td>5.5</td>
<td>0.8</td>
<td>0.38</td>
<td>0.1</td>
<td>308</td>
<td>9</td>
<td>9.4</td>
<td>0.4</td>
</tr>
<tr>
<td></td>
<td>never</td>
<td>742</td>
<td>16.7</td>
<td>5.3</td>
<td>0.5</td>
<td>0.18</td>
<td>0.05</td>
<td>306</td>
<td>6</td>
<td>9.4</td>
<td>0.4</td>
</tr>
<tr>
<td>Quad</td>
<td>always</td>
<td>732</td>
<td>5.2</td>
<td>4.4</td>
<td>0.8</td>
<td>0.26</td>
<td>0.12</td>
<td>394</td>
<td>17</td>
<td>8.7</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>sometimes</td>
<td>730</td>
<td>5.0</td>
<td>5.0</td>
<td>0.4</td>
<td>0.17</td>
<td>0.10</td>
<td>380</td>
<td>5</td>
<td>8.7</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>never</td>
<td>725</td>
<td>7.6</td>
<td>5.2</td>
<td>0.2</td>
<td>0.17</td>
<td>0.07</td>
<td>386</td>
<td>3</td>
<td>8.7</td>
<td>0.7</td>
</tr>
<tr>
<td>Uniform</td>
<td>always</td>
<td>743</td>
<td>6.6</td>
<td>5.7</td>
<td>0.0</td>
<td>0.17</td>
<td>0.15</td>
<td>321</td>
<td>6</td>
<td>9.7</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>sometimes</td>
<td>741</td>
<td>6.3</td>
<td>5.7</td>
<td>0.0</td>
<td>0.15</td>
<td>0.12</td>
<td>325</td>
<td>6</td>
<td>9.7</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>never</td>
<td>735</td>
<td>8.2</td>
<td>5.7</td>
<td>0.0</td>
<td>0.14</td>
<td>0.08</td>
<td>329</td>
<td>9</td>
<td>9.6</td>
<td>0.3</td>
</tr>
</tbody>
</table>

First stage 2SLS results are shown in Table 7.2 and second stage results are shown in Tables 7.3, 7.4, and 7.5. These tables report the regression coefficients and their standard errors. Because these results are produced with simulated data p-values are not reported. Simulated data lacks a clear distinction between the sample and global population that the interpretation of p-values is based on. The sample size can be arbitrarily increased by running more simulations and indeed simulation experiments typically involve large numbers of simulation runs. Large numbers of simulation runs can inevitably lead to low p-values without necessarily providing greater insight into the phenomena being simulated. Instead we focus on reporting effect sizes (in the form of regression models coefficients) and their variability between runs (in the form of coefficient standard errors).

### 7.3.1 Pedestrian behaviour

#### 7.3.1.1 Path Length

The effect of restricting informal crossing on \( \bar{L} \) differs between environments. The largest change is observed in the Clapham Common environment, where \( \bar{L} \) increases from an average of 682\,m in the ‘always’ scenario, to 717\,m in the ‘sometimes’ scenario, to 742\,m in the ‘never’ scenario. In the grid environments restricting informal crossing tends to slightly reduce \( \bar{L} \). In the Quad Grid environment, \( \bar{L} \) decreases from an average of 732\,m in the ‘always’ scenario, to 730\,m in the ‘sometimes’ scenario, to 725\,m in the ‘never’ scenario. In the Uniform Grid the decrease is from 743\,m,
to 741m, to 734m. The  $\bar{L}$ regression coefficients in Table 7.2 further confirm that restricting informal crossing increases trip length in the Clapham Common environment and decreases it in the grid environments, with effect sizes increasing with increasing restrictions and errors remaining small compared to coefficient values. The larger ‘sometimes’ and ‘never’ regression coefficients and adjusted $R^2$ value in the Clapham Common environment confirms the greater effect of the policies here.

The distributions of $\bar{L}$ in Figures 7.4-7.6 show that the relative influence of simulation parameters and policy setting also differ between environments. In the Clapham Common environment very little overlap in the distributions of $\bar{L}$ is observed. This means that, while route choice parameters do vary route choice, the policies tend to have a greater effect. Again, this results from the need for pedestrian agents to follow different road network paths when informal crossing is restricted.

In both grid environments the distributions of $\bar{L}$ in different policy settings are highly overlapping. Furthermore, in the ‘never’ setting high frequencies of minimal and maximal $\bar{L}$ values are observed. In these environments model parameters, rather than the policy setting, predominantly determine $\bar{L}$. Again, this follows from the

<table>
<thead>
<tr>
<th>Metric</th>
<th>Environment</th>
<th>sometimes</th>
<th>never</th>
<th>const</th>
<th>Adj R2</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\bar{L}$</td>
<td>Clapham</td>
<td>1.31 ± 0.01</td>
<td>2.23 ± 0.01</td>
<td>−1.18 ± 0.01</td>
<td>0.836</td>
</tr>
<tr>
<td></td>
<td>Quad</td>
<td>−0.39 ± 0.03</td>
<td>−1.07 ± 0.03</td>
<td>0.48 ± 0.02</td>
<td>0.194</td>
</tr>
<tr>
<td></td>
<td>Uniform</td>
<td>−0.28 ± 0.02</td>
<td>−1.07 ± 0.02</td>
<td>0.45 ± 0.02</td>
<td>0.204</td>
</tr>
<tr>
<td>$N_C$</td>
<td>Clapham</td>
<td>0.20 ± 0.03</td>
<td>0.06 ± 0.03</td>
<td>−0.09 ± 0.02</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>Quad</td>
<td>0.88 ± 0.02</td>
<td>1.28 ± 0.02</td>
<td>−0.72 ± 0.02</td>
<td>0.284</td>
</tr>
<tr>
<td></td>
<td>Uniform</td>
<td>0.03 ± 0.02</td>
<td>−1.25 ± 0.02</td>
<td>0.41 ± 0.02</td>
<td>0.359</td>
</tr>
<tr>
<td>$CLE$</td>
<td>Clapham</td>
<td>−0.57 ± 0.02</td>
<td>−1.91 ± 0.02</td>
<td>0.82 ± 0.01</td>
<td>0.639</td>
</tr>
<tr>
<td></td>
<td>Quad</td>
<td>−0.80 ± 0.03</td>
<td>−0.85 ± 0.03</td>
<td>0.55 ± 0.02</td>
<td>0.151</td>
</tr>
<tr>
<td></td>
<td>Uniform</td>
<td>−0.12 ± 0.03</td>
<td>−0.21 ± 0.03</td>
<td>0.11 ± 0.02</td>
<td>0.007</td>
</tr>
<tr>
<td>$CLD$</td>
<td>Clapham</td>
<td>−0.64 ± 0.03</td>
<td>−0.78 ± 0.03</td>
<td>0.47 ± 0.02</td>
<td>0.116</td>
</tr>
<tr>
<td></td>
<td>Quad</td>
<td>−1.18 ± 0.02</td>
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<td>0.62 ± 0.02</td>
<td>0.233</td>
</tr>
<tr>
<td></td>
<td>Uniform</td>
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<td>1.00 ± 0.03</td>
<td>−0.51 ± 0.02</td>
<td>0.165</td>
</tr>
<tr>
<td>$\bar{s}_V$</td>
<td>Clapham</td>
<td>0.23 ± 0.03</td>
<td>0.37 ± 0.03</td>
<td>−0.20 ± 0.02</td>
<td>0.022</td>
</tr>
<tr>
<td></td>
<td>Quad</td>
<td>−0.05 ± 0.03</td>
<td>−0.08 ± 0.03</td>
<td>0.04 ± 0.02</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>Uniform</td>
<td>0.02 ± 0.03</td>
<td>−0.06 ± 0.03</td>
<td>0.01 ± 0.02</td>
<td>0.001</td>
</tr>
</tbody>
</table>

Table 7.2: Normalised variable coefficients and adjusted $R^2$ values for the regression models given by Equations 7.5 and 7.6 for each simulation environment. These results compare the effects of policies on $\bar{L}$, $N_C$, $CLE$, $CLD$, and $\bar{s}_V$. 

7.3. Results


greater coverage of marked crossings in these environments.

An increase in the standard deviation of $\bar{L}$ distributions between the permissive ‘always’ setting and restrictive ‘never’ setting is also observed; from $6.4m$ to $17m$ in the Clapham Common environment, $5.2m$ to $7.6m$ in the Quad Grid environment, and $6.6m$ to $8.2m$. This means that simulation parameters have greater impact on upper-level paths when informal crossing is prevented.

The large increase in $\bar{L}$ with crossing restrictions observed in the Clapham Common environment is due to the incomplete coverage of marked crossings, which requires pedestrian agents to take detours along different road links in the ‘sometimes’ and ‘never’ policy settings. In the grid environments marked crossings are more evenly distributed across the environment and so preventing informal crossing does not prevent the pedestrian agents from traversing any particular road link. The decrease in $\bar{L}$ can only be explained by pedestrian agents’ routes comprising more ‘diagonal crossing’ links when informal crossing is prevented, since these links traverse the space more efficiently. (The difference in $\bar{L}$ between policy settings is approximately the same in both grid environments - another indication this result is due to the diagonal link effect and not some other feature of the environment.) Because pedestrian agents do not walk along diagonal crossing links this gives a false impression that their journeys are shorter when in fact their trip lengths are virtually unchanged by the policies. The reduction in $\bar{L}$ between policy settings in the grid environments is an artefact of the model and does not represent a real change in trip length.

### 7.3.1.2 Crossing behaviour

#### Numbers of crossing

The effect of restricting informal crossing on $N_C$ also differs between environments. In the Clapham Common environment restricting informal crossing tends to increase $N_C$, however, the ‘sometimes’ policy has a larger effect than the ‘never’ policy. The regression coefficient for the ‘sometimes’ policy is $0.2 \pm 0.03$ while the coefficient for ‘never’ is $0.06 \pm 0.03$. This inconsistent relationship with crossing restriction is reflected in the low adjusted $R^2$ of $0.007$. 
In the Quad Grid environment a more consistent response is observed, with $N_C$ increasing as informal crossing is restricted; from an average of 4.4 crossings per pedestrian agent under the ‘always’ setting, to 5.0 under the ‘sometimes’ setting, to 5.2 under the ‘never’ setting. This consistent increase is reflected in a high adjusted $R^2$ value for the $N_C$ regression model in this environment.

In both the Clapham Common and Quad Grid environments restricting informal crossing narrows the distribution of $N_C$ values, as shown by Figures 7.4 and 7.5. This means that preventing informal crossing reduced the influence of simulation parameters on the number of crossings pedestrian agents perform.

In the Uniform Grid environment the number of crossings changes very little - either in response to the policies or simulation parameters - due to the regularity of the environment. While the ‘never’ policy does produce a slight reduction in the number of crossings, the average number of crossings only falls from 5.685 under the ‘always’ setting to 5.676 under the ‘never’ setting and is therefore not considered to be a material difference in pedestrian agent behaviour.

**Crossing location entropy**

In all three environments crossing locations become more ordered as restrictions are increased. The Clapham Common environment exhibits the greatest change in CLE in response to crossing restrictions, decreasing from 0.46 in the ‘always’ setting to 0.18 in the ‘never’ setting. The change is less in the grid environments; from 0.26 to 0.17 in the Quad Grid and from 0.17 to 0.14 in the Uniform Grid. This differences is reflected in the larger adjusted $R^2$ of the CLE regression model for the Clapham Common environment.

The distributions of CLE values further illustrate the effects of the policies. The large overlap between ‘sometimes’ and ‘always’ distributions in all three environments shows that when informal crossing is partially restricted disordered road crossing locations on the unrestricted road network dominate the overall pattern, leading to a distribution similar to that of the ‘always’ policy. The wide range of CLE values under the ‘sometimes’ and ‘always’ policies shows the CLT route choice model is able to produce road crossing behaviour encompassing both highly
7.3. Results

disordered and ordered crossing locations, demonstrating the model’s ability to produce heterogeneous pedestrian paths at the street level. This is particularly the case in the grid environments, where a larger overlap between the ‘never’ distribution and the other two distributions is observed compared to the Clapham Common environment. This shows that in the grid environments large regions of the parameter space produce equally as ordered road crossing behaviour as preventing informal crossing with a ‘top-down’ intervention. The limited overlap with the ‘never’ policy in the Clapham Common environment shows that, in this environment, the policy is producing behaviour rarely produced by the route choice model.

The ‘never’ distribution is also narrower in all three environments. This means that the influence of simulation parameters on \( CLE \) is reduced when informal crossing is prevented. This differs from \( \bar{L} \), which exhibits a broadening distribution as informal crossing is prevented. Route choice parameters’ ability to produce changes in \( CLE \) is diminished when informal crossing is prevented.

On the whole, preventing informal crossing suppresses the effect of model parameters on road crossing behaviour and produces more ordered crossing locations. The overlap between all three distributions shows that highly ordered road crossing locations can be produced through both top-down restrictions and bottom-up decision making of pedestrian agents.

Crossing location dispersion

Crossing restrictions tend to decrease \( CLD \) in the Clapham Common and Quad Grid environments and increase \( CLD \) in the Uniform Grid environment. The size of the policy effects are comparable between the environments, but with differences in the relative impacts of the ‘never’ and ‘sometimes’ policies. In the Clapham Common and Uniform Grid environments increasing the level of restriction increases the effect on \( CLD \), albeit in different directions. In the Quad Grid environment \( CLD \) is reduced more by the ‘sometimes’ policy than the ‘never’ policy. This suggests that preventing all informal crossing makes pedestrian agents tend to cross more towards the start of their journeys than when informal crossing is only partially prevented.

As with both \( N_C \) and \( CLE \), restricting informal crossings narrows the distribu-
7.3. Results

Figure 7.4: Results for the Clapham Common environment.

The results for the Clapham Common environment, particularly for the Quad Grid environment, showing again that these restrictions limit the influence of simulation parameters on pedestrian agent road crossing behaviour.

Comparing the regression coefficients between regression models reveals which metric between $N_C$, $CLE$, and $CLD$ is most strongly affected by the policies in each environment. In the Clapham Common environment the ‘never’ policy has the greatest effect on $CLE$, followed by $CLD$ and $N_C$. In the Quad Grid environment, the ‘never’ policy has the greatest effect on $N_C$, followed by $CLE$ and $CLD$, though the coefficient values for $CLE$ and $CLD$ are close to one another. Finally, in the Uniform Grid, the ‘never’ policy has the greatest effect on $N_C$, followed by $CLD$ and $CLE$. However, this is predominantly due to simulation parameters having nearly zero effect on $N_C$ in this environment; any small effect due to the policy produces a large effect size.
7.3. Results

Figure 7.5: Results for the Quad Grid environment.

7.3.2 Pedestrian-vehicle interactions

In this section the effects of the policies on $S_V$ are presented along with the results of the 2SLS analysis that attempts to explain these effects in terms of road crossing behaviour. Unlike the pedestrian behaviour metrics, the mean $S_V$ values in Table 7.1 show very little variation between policy settings. This is illustrated by the highly overlapping $S_V$ distributions between policies in all three environments shown in Figures 7.4-7.6.

The sensitivity indices for $S_V$ (see Figures B.1-B.3 in Appendix B) show why this is the case - $S_V$ is almost entirely determined by the number of vehicle agents in the simulation, $N_v$. $S_V$ is only slightly sensitive to parameters related to pedestrian agent behaviour and it follows that policies that affect pedestrian agent behaviour will have a limited effect on $S_V$ compared to variations in $N_v$.

Nonetheless, the results in Table 7.2 show small effects of the policies on $S_V$. In all three environments, the effect size of the ‘never’ policy is greater than the ‘some-
times’ policy, showing that preventing all informal crossing has a greater effect than preventing some. The direction of influence differs between environments. In the Clapham Common environment restricting informal crossing tends to increase $\bar{S}_V$ but in the Quad Grid environment it tends to decrease $\bar{S}_V$. The effect of the policies is inconsistent and weaker in the Uniform Grid environment. The ‘sometimes’ and ‘never’ coefficients are smaller than in the other environments, the coefficients have opposing signs, and the standard error is high.

Based on the regression results H2.0 is rejected for the Clapham Common and Quad Grid environments. In the Uniform Grid environment, the weak and inconsistent relationship between policies and $\bar{S}_V$ does not warrant further investigation - H2.0 is not rejected for this environment. While the coefficient standard errors are also high for the Quad Grid environment the inconsistent direction of the effect differentiates the Uniform Grid result.

The results of the 2SLS used to investigate hypotheses H2.1a, H2.1b, and
H2.1c are shown in Tables 7.3-7.5 for both stage 1 and stage 2 regression models. (The stage 1 results are the same as those shown in Table 7.2.) The stage 2 regressions correlate the change in $N_C$, $CLE$, and $CLD$ due to the policies with $\bar{S}_V$. The magnitude of the stage 2 regression coefficients together with the adjusted $R^2$ values indicate which metric of pedestrian road crossing behaviour provides the best explanation for the change in $\bar{S}_V$.

These results are also shown in Figure 7.7 in which the predicted values $\hat{N}_C$, $\hat{CLE}$, and $\hat{CLD}$ are correlated with $\bar{S}_V$. The trend-lines on these figures show the association between changes in these three metrics of crossing behaviour due to the policies and changes in $\bar{S}_V$ due to the policies. The figures show only small changes in $\bar{S}_V$ between policy settings compared to the large range of values produced within each policy setting (within policy variation is predominantly caused by the number of vehicle agents in the simulation run).

In the Clapham Common environment $\bar{S}_V$ increases with increasing crossing restrictions. At the same time $N_C$ increases, $CLE$ decreases, and $CLD$ decreases. The stage 2 regression coefficient for $\hat{N}_C$ is $0.29 \pm 0.06$; the coefficient for $\hat{CLD}$ is $-0.17 \pm 0.02$; and the coefficient for $\hat{CLE}$ is $-0.07 \pm 0.01$. The highest second stage adjusted $R^2$ value is 0.022 for $\hat{CLD}$, followed by 0.020 for $\hat{CLE}$, and 0.004 for $\hat{N}_C$.

While the coefficient for $\hat{N}_C$ is highest, this metric provides a poor explanation for the increase in $\bar{S}_V$. First, all else being equal, increases in the number of road crossings should decrease vehicle speed due to the greater competition for carriageway space. The observed association between the increase in $N_C$ with increases in $\bar{S}_V$ must be due to other aspects of pedestrian road crossing behaviour changing at the same time. Second, the lower adjusted $R^2$ value for this metric is due to $N_C$ increasing under the ‘sometimes’ policy more than under the ‘never’ policy (this is also reflected in the low adjusted $R^2$ value of 0.01 in the first stage regression for $N_C$). This does not align with the change in $\bar{S}_V$, which increases more under the ‘never’ policy than under the ‘sometimes’ policy.

The $CLD$ second stage regression exhibits the second largest coefficient. Addi-
tionally, $CLD$ is reduced more by the ‘never’ policy than by the ‘sometimes’ policy and therefore produces a higher $R^2$ value in the second stage regression. $CLE$ second stage regression has the smallest magnitude coefficient but a similar adjusted $R^2$ value to $CLD$. Changes in the dispersion of pedestrian agents’ crossing locations and the crossing location entropy both provide a good explanations for the change in vehicle speed due to crossing restriction policies. Preventing informal crossing tends to make crossings more concentrated in the centre of the Clapham Common environment and occur at more ordered locations on each road length. The centralisation and greater order of pedestrian crossings produced by the policies changes pedestrian-vehicle conflicts in a way that increases $\bar{S}_V$, despite slight increases in the number of crossings.

In the Quad Grid environment $\bar{S}_V$ decreases with increasing crossing restrictions. At the same time $N_C$ increases, $CLE$ decreases, and $CLD$ decreases. The stage 2 regression coefficient for $\hat{N}_C$ is $-0.04 \pm 0.01$; the coefficient for $\hat{CLD}$ is $0.03 \pm 0.02$; and the coefficient for $\hat{CLE}$ is $0.05 \pm 0.02$. The variability in effect sizes between runs is far higher in this environment as indicated by the high errors. The adjusted $R^2$ values are $0.001$ for $\hat{N}_C$, $0.001$ for $\hat{CLE}$, and $0.000$ for $\hat{CLD}$.

In the Quad Grid environment the magnitude of the second stage regression coefficients is similar for $\hat{N}_C$, $\hat{CLE}$, and $\hat{CLD}$. In this environment $N_C$ increases more strongly and consistently with increasing crossing restrictions than in the Clapham Common environment. The response of $CLE$ and $CLD$ to crossing restrictions is similar in magnitude and direction to the Clapham Common environment, apart from $CLD$ which decreases less in the ‘never’ setting than in the ‘sometimes’ setting.

These results help explain why in the Quad Grid restricting informal crossing tends to slightly reduce vehicle speed. Firstly, restricting informal crossing produces a large and more consistent increases in the number of road crossings. Secondly, the effect of restrictions on $CLD$, which in the Clapham Common environment was most strongly associated with an increases in vehicle speed, is inconsistent in this environment leading to a lower $\hat{CLD}$ coefficient. The magnitude of the
7.4 Discussion

We have performed a series of simulation experiments which explore the effects of three crossing restriction policies on the metrics $\bar{L}$, $N_C$, $CLE$, $CLD$, and $\bar{S}_V$ across three environments. Pedestrian agents navigate according to the CLT route

<table>
<thead>
<tr>
<th>Stage</th>
<th>Y</th>
<th>Scenario</th>
<th>$N_C$</th>
<th>sometimes</th>
<th>never</th>
<th>const</th>
<th>Adj R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>N_C</td>
<td>Clapham</td>
<td>0.2 ± 0.03</td>
<td>0.06 ± 0.03</td>
<td>-0.09 ± 0.02</td>
<td>0.007</td>
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<td></td>
<td></td>
<td>Quad</td>
<td>0.88 ± 0.02</td>
<td>1.28 ± 0.02</td>
<td>-0.72 ± 0.02</td>
<td>0.284</td>
<td></td>
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<tr>
<td>2</td>
<td>(\bar{S}_V)</td>
<td>Clapham</td>
<td>0.29 ± 0.06</td>
<td>9.35 ± 0.01</td>
<td>0.004</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Quad</td>
<td>-0.04 ± 0.01</td>
<td>8.72 ± 0.01</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 7.3: 2SLS IV regression model results for treatment variable $N_C$.

<table>
<thead>
<tr>
<th>Stage</th>
<th>Y</th>
<th>Scenario</th>
<th>$CLE$</th>
<th>sometimes</th>
<th>never</th>
<th>const</th>
<th>Adj R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CLE</td>
<td>Clapham</td>
<td>-0.57 ± 0.02</td>
<td>-1.91 ± 0.02</td>
<td>0.82 ± 0.01</td>
<td>0.639</td>
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<td></td>
<td></td>
<td>Quad</td>
<td>-0.80 ± 0.03</td>
<td>-0.85 ± 0.03</td>
<td>0.55 ± 0.02</td>
<td>0.151</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>(\bar{S}_V)</td>
<td>Clapham</td>
<td>-0.07 ± 0.01</td>
<td>9.35 ± 0.00</td>
<td>0.020</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Quad</td>
<td>0.05 ± 0.02</td>
<td>8.72 ± 0.01</td>
<td>0.001</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 7.4: 2SLS IV regression model results for treatment variable $CLE$.

$CLE$ regression coefficient is similar in the two environments and so there are not additional changes in $CLE$ in the Quad Grid environment to counteract the effect of the increased number of crossings.

Based on the comparison of the first and second stage regression results within and between environments, it appears that the increase in $\bar{S}_V$ with restrictions in informal crossing in the Clapham Common environment is driven primarily by the reduction in $CLD$ (accept H2.1b) and further supported by the reduction in $CLE$ (accept H2.1c). In the Quad Grid environment, a slight decrease in $\bar{S}_V$ is observed due to an increase in $N_C$ with crossing restrictions that is not countered by the reductions in $CLD$ and $CLE$ suggesting that here all three hypotheses have validity but that H2.1a dominates the overall pattern.

7.4 Discussion

We have performed a series of simulation experiments which explore the effects of three crossing restriction policies on the metrics $\bar{L}$, $N_C$, $CLE$, $CLD$, and $\bar{S}_V$ across three environments. Pedestrian agents navigate according to the CLT route

<table>
<thead>
<tr>
<th>Stage</th>
<th>Y</th>
<th>Scenario</th>
<th>$CLD$</th>
<th>sometimes</th>
<th>never</th>
<th>const</th>
<th>Adj R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>CLD</td>
<td>Clapham</td>
<td>-0.64 ± 0.03</td>
<td>-0.78 ± 0.03</td>
<td>0.47 ± 0.02</td>
<td>0.116</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Quad</td>
<td>-1.18 ± 0.02</td>
<td>-0.70 ± 0.02</td>
<td>0.62 ± 0.02</td>
<td>0.233</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>(\bar{S}_V)</td>
<td>Clapham</td>
<td>-0.17 ± 0.02</td>
<td>9.35 ± 0.00</td>
<td>0.022</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Quad</td>
<td>0.03 ± 0.02</td>
<td>8.72 ± 0.01</td>
<td>0.000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 7.5: 2SLS IV regression model results for treatment variable $CLD$. 
7.4. Discussion

Figure 7.7: Scatter plots showing how changes in metrics $N_C$, $CLE$ and $CLD$ between crossing restriction policies correlate with changes in $S_V$ between policies. The x-axes show normalised road crossing metric values predicted by the informal crossing policy (equivalent to the mean value for each policy). The y-axes show $S_V$ for each simulation run. Triangles indicate the mean $S_V$ and crossing metric value under each policy. Linear trend-lines, their equations, and p-values for the crossing metrics are shown in black. Regression equation coefficients, adjusted $R^2$ values, and p-values are rounded to 3 decimal places.

choice model developed in this thesis. A core component of this model is a pedestrian agent’s choice between a marked and informal crossing location under lower-level route choice. The results show the policies affect pedestrian movement and pedestrian-vehicle interactions and that these effects are dependent on both the environment and the (multi-scale) behaviour of pedestrian agents. This suggests that representing multi-scale pedestrian route choice can contribute to an understanding of how transport outcomes related to mobility and safety are produced and could be affected by interventions to street infrastructure. The following discussion elaborates on this conclusion.

7.4.1 Pedestrian behaviour

The differences in $L$ between policy settings reveals the extent to which pedestrian accessibility is dependent on informal crossing in each environment. The reduced
availability of marked crossings in the Clapham Common environment produces a larger change in $\bar{L}$ compared to the grid environments. This result demonstrates a contribution of the multi-scale CLT route choice model with regards to assessing pedestrian accessibility. Additionally, the route choice model enables the effect of policies on different components of decision making to be represented. For example, in all three environments permitting informal crossing reduces the influence of $PH$ on $\bar{L}$ (see Figure B.1 in Appendix B), meaning that pedestrian agents’ knowledge of the road network is less important when roads can be more easily crossed.

Road crossing behaviour was analysed with metrics $N_C$, $CLE$, and $CLD$. $N_C$ is minimally affected by the policies in the Clapham Common and Uniform Grid environments but increases due to restrictions on informal crossing in the Quad Grid environment.

$CLE$ measures how regular pedestrian crossing locations are, with highly ordered trajectories across the carriageway producing low $CLE$ values. The ‘never’ policy has the greatest effect on $CLE$ in the Clapham Common environment; compared with both the ‘always’ policy and ‘sometimes’ policies, the ‘never’ policy produces more ordered crossing locations for almost every parameter setting. However, in the grid environments, particularly the Uniform Grid, the effect of the policies is less distinct from that of CLT route choice parameters. In the Uniform Grid, highly ordered crossing locations can arise through agent decision making as well as through ‘top-down’ restrictions. Increasing the coverage of marked crossings in the Clapham Common environment could increase the overlap between ‘always’ and ‘never’ distributions. In this way, the CLT route choice model could inform the placement of crossing infrastructure to encourage more ordered road crossing behaviour through pedestrian decision making rather than through direct restrictions.

$CLD$ is reduced by restricting informal crossing in the Clapham Common and Quad Grid environments but increases in the Uniform Grid environment. Given that all pedestrian agents move to a single destination in the centre of each environment, a reduction in $CLD$ implies a higher proportion of road crossings being made towards the end of pedestrian agent trips.
By identifying different effects of pedestrian behaviour between environments, these results demonstrate a contribution of modelling multi-scale pedestrian movement using the CLT route choice model. CLE depends on street level pedestrian behaviour and so the effect of the policies is broadly the same in each environment - a reduction in CLE as informal crossing is restricted. Yet, notable differences are also observed. The availability of crossing infrastructure in the grid environments makes the impacts of the ‘never’ policy less distinct from the ‘always’ policy compared to the Clapham Common environment.

The $\bar{L}$, $N_C$ and $CLD$ metrics are dependent on neighbourhood level pedestrian behaviour, not just street-level behaviour as is the case with CLE. As a result, they exhibit greater differences between environments. Differences in crossing availability drive the different responses of $\bar{L}$ to the policies. In the Quad Grid the average number of crossings changes in response to the policies far more than in the other environments. In the Clapham Common and Quad Grid environments CLD is reduced by restricting informal crossing but increased in the Uniform Grid environments. Additionally, CLD is affected more by the ‘never’ policy than the ‘sometimes’ policy in the Clapham Common environment but not in the Quad Grid environment.

Because the policies only directly affect street-level route choices, these differences can only be identified through a multi-scale model that connects street-level and neighbourhood-level route choices. Whilst the choice of crossing location is made at the street-level only, the availability of crossing infrastructure depends on the structure of the road network. Network morphology also affects how pedestrians travel to reach their destination. These two influences combine to produce the observed differences between environments.

The CLT route choice model also enables the effects of policies on different components of decision making to be represented (in addition to policy effects on agent behaviour). For example, the increased sensitivity of output metrics to $PH$ in the ‘sometimes’ and ‘never’ policy settings show that policies will have a differential affect across the pedestrian agent population based on their knowledge.
of the road network. This is an advantage of adopting a modelling approach in which model structure is based on relevant psychological theory. An alternative model such as a network optimal least-cost route choice model is less able to explain pedestrian agent behaviour in psychological terms.

7.4.2 Pedestrian-vehicle interactions

Having established how restricting informal crossing affects pedestrian route lengths and road crossing behaviour, we now discuss the way these changes affect pedestrian-vehicle interactions. Pedestrian-vehicle interactions are measured by $\bar{S}_V$. Reductions in $\bar{S}_V$ must result from increased competition between agents for carriageway space. Since the policies only affect pedestrian agent behaviour any difference in $\bar{S}_V$ between policy settings is due to changes in pedestrian agent road crossings.

The first point to highlight is that $\bar{S}_V$ is predominantly determined by the number of vehicle agents $N_v$. As a result only slight differences in $\bar{S}_V$ are observed between policy settings. However, the direction and magnitude of these differences varies between environments. As restrictions on informal crossing increase, $\bar{S}_V$ tends to increase in the Clapham Common environment and decrease in the Quad Grid environment. (A small and inconsistent change in $\bar{S}_V$ was observed in the Uniform Grid environment.) This shows that in these simulations street-level restrictions produce different neighbourhood-level impacts through the emergent use of carriageway space by pedestrian agents.

The different effects of the policies on $\bar{S}_V$ between environments are explained by drawing on the 2SLS results. In the Clapham Common environment the reduction in $CLD$ with increasing crossing restrictions provides the best explanation for the increase in $\bar{S}_V$. This suggests that concentrating pedestrian agent road crossings at the centre of the environment increases the average vehicle speed.

In the Quad Grid environment $N_C$ increases in response to restricting informal crossing more than in the Clapham Common environment, and this provides the best explanation for the small decrease in $\bar{S}_V$. $CLD$ decreases in response to crossing restrictions in this environment. In the Clapham Common environment
the reduction in CLD is associated with an increase $\bar{S}_V$, however, in the Quad Grid environment this change in pedestrian agent behaviour appears to be out-weighted by the increase in the number of crossings.

These results show that pedestrian-vehicle interactions across an urban neighbourhood are produced through multiple, competing components of pedestrian agent behaviour. At the lower-level the policies have the same effect on pedestrian behaviour - CLE reduces in all environments showing that crossings become consistently more ordered at the street level. However, the effect on $\bar{S}_V$ differs, which means that, at the neighbourhood scale, the aggregate impacts of pedestrian-vehicle competition for carriageway space is shaped by environmental components such as network morphology and crossing infrastructure. These differences are emergent phenomena, not apparent from the model or policy definition, which show that, within the simulation, street level interactions between pedestrian and vehicle agents are influenced by the wider environment.

### 7.4.3 Implications for transport planning

Adopting a complexity science approach to studying urban transport systems (Crooks et al., 2018) has helped to bridge the gap between small-scale and system wide analyses of pedestrian behaviour. Existing research has linked system wide interventions such as congestion pricing to street level outcomes of pedestrian safety through, for example, the use of a system dynamics model of congesting pricing (Naumann et al., 2022). The contribution of our analysis is to focus on how different road network and crossing infrastructure designs produce different behaviour.

Camara et al. (2020)’s review of models of pedestrian behaviour highlights the importance of accounting for psychological and human factors in the development of autonomous vehicles. These factors are instrumental in producing pedestrian-vehicle interactions (Markkula et al., 2022) but are typically only modelled in scenarios consisting of single intersections or road links (Camara et al., 2020; Tian et al., 2020; Ridel et al., 2018). We have used a pedestrian route choice model based on theory and models from the psychology literature to generate pedestrian-vehicle
interactions across a whole urban neighbourhood.

This approach has revealed differences in pedestrian-vehicle interactions between a grid based road network, typical of planned cities designed around the automobile (Quad Grid), and an older, less planned road network typical of European cities (Clapham Common) (Boeing, 2019). Simulations of AV taxis in different cities (for example Lisbon (Martinez, 2015), Singapore (Azevedo et al., 2016), and Austin (Fagnant and Kockelman, 2018)) incorporate different trip distributions and transport networks, but not differences in pedestrian-vehicle interactions between these environments. Our results address this gap in two ways. First, with no restrictions on road crossing pedestrian agents’ crossing locations are more ordered in the grid environments. This suggests that pedestrian behaviour may be more predictable or easily navigated in these environments. Second, preventing informal crossing has less of an impact on pedestrian accessibility and road crossing behaviour in the grid environments (as indicated by the greater overlap of the distribution of output metric values between policy settings). Imposing such restrictions in a natural road network, for example with the objective of making pedestrian behaviour more predictable, may require additional investment in crossing infrastructure to avoid reductions in pedestrian accessibility and even then may always host less ordered road crossing locations (CLE values for the Clapham Common environment are higher than the Quad Grid environment under the ‘sometimes’ policy and about equal under the ‘never’).

Performing simulations over a range of CLT route choice model parameters provides a robust assessment of the policy impacts on the evaluation metrics $\tilde{L}$, $N_C$, $CLE$, $CLD$, and $\tilde{S}_V$. Simulation parameter value ranges encompass a wide range of plausible pedestrian behaviour, producing behavioural heterogeneity between simulation runs. This heterogeneity may be representative of the real heterogeneity in pedestrian behaviour, but without empirical validation (as is the case here), is better interpreted as accounting for the uncertainty regarding real pedestrian behaviour. For example, in the Clapham Common environment the $\tilde{L}$ distributions under the ‘always’ and ‘sometimes’ settings share virtually no overlap. The conclusion that
restricting informal crossing on some road links reduces pedestrian accessibility is therefore robust to uncertainty in pedestrian behaviour. This is not the case in the grid environments where large overlaps between policy distributions show that behaviour change could compensate for changes in $\bar{L}$ due to the loss of informal crossing. The same pattern is found for the $CLE$ metric, which displays less overlap between distributions in the Clapham Common environment than the grid environments.

Existing research has accounted for crossing availability (Rhoads et al., 2021) and spatial cognition (Manley et al., 2021) in assessments of pedestrian accessibility. This study builds on these approaches by integrating the two via the CLT route choice model and its implementation in an agent-based simulation. This provides a method for ‘opening-out’ uncertainties related to pedestrian behaviour (Lyons and Marsden, 2021) in ways that could make assessments of interventions to urban mobility systems more robust to uncertainties inherent to complex systems. It could also contribute to testing of autonomous vehicles. Studies have used simulation methods to generate and run simulation scenarios to test autonomous vehicles (Mullins et al., 2018). Nishiyama et al. (2020) simulate “behaviorally diverse traffic participants” to better test the autonomous systems but do not represent pedestrians. Such approaches could be improved by incorporating a source of diverse pedestrian behaviour that extends across multiple road links.

A key area of improvement for this analysis is the placement of road crossing locations. Crossing locations were set with a simple method applied in all three environments. Alternatively, the locations of marked crossing in the Clapham Common environment could be based on the locations of real crossing infrastructure. The simulation could then be used to explore how different arrangements of crossing locations and pedestrian rights of way produce different outcomes compared to an empirical base case. Using the real locations of crossing infrastructure in the Clapham Common environment could also provide a fairer comparison between environments. This would likely reduce the impact of restricting informal crossing in the Clapham Common environment, although a reduced impact would still be
expected in the grid environments given their regularity. A full discussion of study limitations and future work is given in Chapter 8.

The complexity of the simulation presented in this chapter poses a challenge to validation, as discussed in Section 3.3. In this chapter the CLT route choice model is used to explore the impact of restricting where people can cross the road. Validating the model outcomes requires an experiment that replicates, to some extent, these policies, by collecting data on pedestrian crossing locations to measure how well these correspond with the crossing locations of pedestrian agents in the simulation. This is a different form of validation to seeking to validate the reconstrual of route choice decisions, discussed in Section 6.5.5. However, separately validating these different components of the model is called for under Pattern Oriented Modelling (POM) (Grimm et al., 2005) as a way to robustly validate complex models. Validating the different model components can help to build confidence in model outcomes when simulating novel transportation scenarios such as new street designs for which historic data on crossing behaviour may be unavailable or irrelevant.

7.5 Conclusion

The multi-scale CLT route choice model developed through this thesis is implemented in a series of simulation experiments that explore the impacts of ‘top-down’ restrictions to pedestrian behaviour. Specifically, three policies are simulated in which informal crossing (i.e. jaywalking) is ‘always’, ‘sometimes’, and ‘never’ permitted. Through comparisons between policy settings and simulation environments (Clapham Common, Quad Grid, and Uniform Grid) the impacts of the policies are assessed.

By considering the effect of the policies on pedestrian mobility the experiments highlight how pedestrian accessibility is dependent on informal crossing behaviour. Whilst the idealised simulation environment and simple methodology for placing crossing infrastructure exaggerates the effect of the polices in this instance, the results demonstrate how this methodology could be usefully applied to inform the placement of street infrastructure. The results also show that the impacts of the
policies on pedestrian-vehicle interactions depend on both local and global characteristics of pedestrian road crossing behaviour. To explain the differences in the effects of policies on pedestrian-vehicle interaction between environments requires accounting for behaviour at both scales.

Designs and appraisals of urban streets could be supported by this simulation methodology. The representation of heterogeneity and uncertainty in pedestrian behaviour indicate the extent to which the impacts of policies are contingent on changes in pedestrian behaviour. Additionally, the results show that the impacts of policies are contingent on multi-scale components of pedestrian route choice. Incorporating a representation of multi-scale pedestrian route choice into such appraisals could therefore better identify the impacts of proposed interventions to urban streets or of novel transport technology such as autonomous vehicles.
Chapter 8

Conclusion

A novel model of pedestrian navigation and movement has been presented and implemented in a spatial agent-based simulation (ABS). In the following sections the main findings and contributions of the thesis are summarised. Following this a critique of the methodology and analysis is given before discussing areas of future work. The thesis ends with some closing thoughts about this work’s contribution to pedestrian modelling and sustainable transport planning more broadly.

8.1 Main findings

In this section the thesis objectives set out in the Introduction are restated with a brief discussion of how each objective is met.

Objective 1. Critically review research into the determinants of pedestrian behaviour on urban roads and the representation of this behaviour in models.

This objective is addressed in Chapter 2, Literature review, in which research on the determinants of pedestrian behaviour in urban areas is categorised into two groups: the built environment and and vehicle traffic. Studies discussed under the built environment determinants of pedestrian behaviour focused on the role of the arrangement of buildings and roads in cities influences behaviour, drawing connections between the organisation of the built environment and the people’s internal cognitive representation of such spatial information. These determinants of behaviour were contrasted to those related to interactions between road users, in particular between pedestrians and vehicles. These interactions are mediated by the
8.1. Main findings

The review of these determinants of pedestrian behaviour and experience informed the criticism of existing models of pedestrian movement in urban areas. This critique finds that models tend to represent pedestrian decision making at a single spatial scale. In most studies pedestrian decisions are modelled as being based on knowledge of their immediate environment or based on knowledge of the global environment. Very few models integrate decisions across these scales, with no known examples of models that do so at the granularity and scale to represent road crossing behaviour across an urban neighbourhood.

The review therefore identifies, firstly, that pedestrian behaviour is determined by factors that act at multiple spatial scales, and, secondly, that the connection between street level road user interactions and navigation across the urban environment is not represented in pedestrian models. Given the significant role of pedestrian-vehicle interactions in affecting multiple aspects of pedestrian experience, the importance of walking to sustainable urban transport, and the prospect of autonomous vehicles creating new tensions between road users, improving the representation of pedestrian behaviour in transport simulations is a relevant and potentially impactful avenue of research.

**Objective 2. Identify a suitable theoretical approach to modelling pedestrian navigation and movement at multiple spatial scales.**

This objective is addressed in Chapter 3, Modelling framework. The framework identifies construal level theory (CLT) as a suitable theory for guiding the development of a multi-scale pedestrian model. CLT was introduced in Chapter 2 as part of the discussion of spatial cognition and its role in determining pedestrian behaviour. In contrast to cognitive map theory, CLT makes distinctions between decision hierarchies based on psychological distance, an egocentric distance metric that incorporates spatial, temporal, and social components. The incorporation of
a temporal component into this hierarchical theory of decision making was argued to make CLT suitable for modelling pedestrian decision making at the street and neighbourhood level because of the influence of interactions between road users, which requires a dynamic as well as spatial representation of the environment.

Alongside establishing a suitable theory to base multi-scale pedestrian decisions on, the framework outlines the need for the model to represent heterogeneity in pedestrians’ decision making. Accounting for heterogeneity allows the model to produce a wide variety of route choices, and therefore trajectories. Given the potential for behaviour change, the need to produce a wide range of behavioural scenarios was identified as an important feature of the model for enabling an exploratory and descriptive modelling approach. This way, the model can be used to evaluate transport outcomes against a wide range of scenarios, aligning with the methods for accounting for uncertainty making identified in the literature review. The framework identifies differences in spatial knowledge and reasoning and route choice preferences as two sources of heterogeneity in pedestrian behaviour that should be represented in the route choice models.

Having established these principles, the approach to modelling multi-scale route choices was set out. Following CLT’s distinction between high-level and low-level choice construal, the framework distinguished between two levels of pedestrian decision making: upper-level route choice and lower-level route choice. Upper-level route choice concerns navigation to locations that are psychologically distant and is based on high-level choice construal - abstract and goal oriented. Lower-level route choice concerns navigation to locations that are psychologically proximate and is based on low-level choice construal - detailed and feasibility oriented. Integration between these two levels is achieved through the reconstrual of upper-level decisions at the lower-level, made possible by the movement of pedestrians bringing initially psychologically distant locations closer.

Objective 3. Develop a model of pedestrian movement in urban areas based on the outcomes of objectives 1 and 2.

This objective is addressed in Chapters 4, Upper-level route choice, and 5
Lower-level route choice which together present a novel model of multi-scale pedestrian route choice. Following the modelling framework established in Chapter 3, the route choice model comprises upper-level route choice, lower-level route choice, and their integration (predominantly discussed in Chapter 5). Both upper and lower-level route choices represent road crossing decisions but, following CLT, these choices are made based on different information and methods.

The modelling framework identifies two sources of pedestrian heterogeneity that should be incorporated into the route choice models: spatial knowledge and route choice preferences. At the upper-level, this is achieved by limiting pedestrian agents’ knowledge of the pavement network (the abstract representation of the environment upper-level route choices are based on) and by either choosing paths that minimise distance or the number of crossings (representing two different route choice preferences). At the lower-level this is achieved through agents’ sampling of crossing location alternatives and their perception of alternatives’ utility based on a weighing of vehicle exposure and journey detour attributes.

Upper and lower-level route choice models are designed to produce a wide variety of plausible pedestrian agent paths, depending on the models’ parameter values. This is verified in a limited way in these chapters by producing upper and lower-level paths between only two origin-destination pairs at each level. Based on these verifications, lower-level parameter bounds were imposed. This limited verification of route choice behaviour is expanded upon in Chapter 6.

Objective 4. Explore the behaviour produced by the pedestrian model and apply it to an assessment of the impacts of street infrastructure on pedestrian-vehicle interactions.

This objective is addressed in Chapter 6 and 7. Chapter 6, Verifying multi-scale pedestrian route choice, provides a comprehensive verification of the pedestrian agent behaviour produced by the CLT route choice model. This is achieved by implementing the route choice model in a spatial agent-based simulation of pedestrian and vehicle trips in three different environments. The results of these simulation experiments demonstrate that:
8.1. Main findings

- the route choice model can be tuned to produce pedestrian agents that almost entirely cross either at marked crossings or at informal locations

- the route choice model produces street level road crossing behaviour is sensitive to the level of vehicle traffic (this was verified for a single road link in Chapter 5 but Chapter 6 shows this behaviour is maintain over multiple links)

- upper-level routes are sensitive to vehicle traffic, meaning that 1. the model achieves feedback from lower to upper levels as well as upper to lower and 2. the model produces the barrier effect as an emergent phenomenon through the decision making of individual agents

Together these findings demonstrate the suitability of the CLT route choice model as a method for generating route alternatives with the primary advantage over an optimal weighted network path model being the combination of scale and granularity of trajectories and interpretability in terms of theoretically robust psychological parameters.

Chapter 7, Incorporating multi-scale pedestrian movement into street infrastructure appraisal, builds on Chapter 6 by applying the same simulation experiment methodology to an assessment of the impacts of restrictions to pedestrian road crossing behaviour. Pedestrian trips are simulated under three policies that restrict, to varying degrees, the ability of pedestrian agents to cross the road informally (i.e. to jaywalk). These policies only directly affect lower-level route choices. However, their impact on pedestrian-vehicle interactions differs between the environments due to differences in road network morphology and the related distribution of road crossing infrastructure. These differences emerge from the multi-scale navigation and movement of pedestrian agents, demonstrating the potential for modelling pedestrian behaviour at these scales to reveal influences on the environment on road crossing behaviour and to provide a more comprehensive assessment of the impacts of interventions to street infrastructure.

Chapter 7 used a causal inference methodology - two-stage linear regression - to identify how the policies changed pedestrian-vehicle competition for carriage-
way space. Without this additional analysis, the results would only indicate that there was a change in competition, but not which aspect of pedestrian behaviour was responsible for this change. The simulation experiment methodology used in Chapters 6 and 7 is well suited to such analysis because the causal paths (illustrated by the directed acyclic graph shown in Figure 7.3 in Chapter 7) are known to the modeller but their relative influence on simulation outcomes is not. This is because the outcomes result from the complex interactions produced by the simulation. Additional ‘meta-modelling’ is required, in this case two-stage linear regression, to provide detailed explanations of how these outcomes are produced.

8.2 Thesis contributions

The research contributions of this thesis are summarised below.

Chapter 3: Construal level theory route choice framework.

• Section 3.4: Novel application of the construal level theory as a basis for integrating pedestrian route choice decisions across street and neighbourhood urban environments.

Chapter 4: Developing a novel pedestrian route choice model for trips across multiple urban roads.

• Section 4.2.1: An assessment of the coverage of OSM ‘footways’ data across 100 UK cities.

• Section 4.2.2: A novel methodology for the production of a ‘pavement network’ from Ordnance Survey vector GIS data.

• Section 4.3: A novel pedestrian route choice model that makes use of the detailed representation provided by the ‘pavement network’. The model uses bounded spatial knowledge and heuristics to produce route heterogeneity.

Chapter 5: Modelling road crossing location choice and integrating this with neighbourhood level route choice.
8.2. Thesis contributions

• Section 5.4: A novel model of pedestrian road crossing location choice that accounts for informal road crossing, dynamic interaction between road users, and bounded spatial reasoning.

• Section 5.5: Integration of street-level (lower-level) and neighbourhood-level (upper-level) route choice models according to the CLT framework presented in Chapter 3.

• Section 5.7: A bespoke parameter sweep methodology for identifying suitable values ranges for lower-level route choice parameters.

Chapter 6: Simulating multi-scale pedestrian movement.

• Section 6.2.2: Development of synthetic road network environments and a method for locating crossing infrastructure based on network morphology.

• Section 6.3.1 & 6.4.1: Application of a global sensitivity analysis methodology to compare pedestrian road crossing and route choice behaviour between environments and to identify the relative influence of each component of the CLT route choice model.

• Section 6.3.2 & 6.4.2: Comparison of the CLT route choice model to a least cost weighted network model to clarify the contribution of the CLT model.

Chapter 7: Using the multi-scale pedestrian simulation to explore the impact of crossing restriction policies.

• Section 7.2.1: Development of policy scenarios based on the partial and complete restriction of informal road crossing based on road classification.

• Section 7.2.2: Novel ‘crossing location entropy’ metric used to measure the regularity of pedestrian agent crossing locations.

• Section 7.2.3: Application of two-stage least squares regression to test hypotheses regarding how (in addition to whether) the policies produce the observed changes in pedestrian agent behaviour.
8.3. Critique of the methodology

The criticisms of the thesis offered below focus on two central components:

- the assumptions embedded in the CLT route choice model
- the representation of the simulation environment used to explore the behaviour produced by the CLT route choice model
- model calibration and validation

Other aspects of the analysis, such as the design of the simulation experiments and accompanying analysis use comparatively well-established methods that, while not without limitation, do not warrant detailed criticisms here.

8.3.1 Assumptions and limitations of the CLT route choice model

The upper-level and lower-level route choice models embed a number of assumptions about pedestrian decision making that limit what pedestrian behaviour can be produced by the models.

Upper-level route choice permits a wide variety of pavement network paths to be chosen but these are restricted to follow the shortest road network path. This prevents differences in pedestrians agents’ planning horizons or upper-level route preferences from producing paths that follow different road links. As such, the model makes limited use of the pavement network as an improved representation of the urban environment from a pedestrian perspective. Addressing this restriction would mean pedestrian agents’ choices of which roads to walk down are based on a more realistic representation of the environment and could produce different outcomes compared to a road network representation - highlighting the implications of
choices made when representing the environment as a network. Redesigning upper-level route choice would require an alternative way of defining a pedestrian agent’s planning horizon and the end node(s) of candidate upper-level paths. Without careful design this would greatly increase the computational cost of the model.

*Lower-level* route choice presents a novel method for modelling a pedestrian’s choice of road crossing location. This model produces some unrealistic street level pedestrian trajectories. Pedestrian agents can choose to cross at a location they have already walked past, meaning agents turn and walk back along the pavement to get to their crossing location. Because of this only the road crossing locations of pedestrian agents were analysed and not their street-level trajectories. A more realistic integration of road crossing decisions and pedestrian movement is required to better represent the real walking distances of pedestrians in urban environments.

**Sequential sample model and its parameters**

The discrete choice methodology used for *lower-level* route choice is based on sequential sampling models developed in the mathematical psychology literature. Similar modelling approaches have been applied to pedestrian road crossing decisions (see discussion of existing models towards the end of Section 5.2) and the thesis methodology does not provide a robust comparison of these different approaches. Doing so would help guide the development of robust models of pedestrian road crossing behaviour.

Related to this is a critique of the validity of *lower-level* route choice parameters as representing real components of pedestrian decision making. The parameter $\alpha$ controls the relative weighting of vehicle exposure and detour attributes of crossing alternatives. The tendency for pedestrians to primarily consider these features of crossing infrastructure is well established in the literature and in road crossing models. *Lower-level* parameters $\varepsilon$ - the activation threshold - and $\lambda$ - controlling the relative salience of nearby crossings - also influence route choices. The use of activation thresholds for triggering choices is well established in sequential sampling models of decision making, but more evidence is required to establish whether this form of model is suitable for road crossing decisions. Similarly, the literature re-
view in Chapter 5 identified that the proximity of a crossing influenced pedestrians’ choice but whether the $\lambda$ parameter correctly represents this effect has not been established here. Establishing whether these are meaningful parameters through comparisons between models or model validation (see Section 8.3.3 below) is a necessary step to progressing the model from being a descriptive tool to providing explanatory or predictive capabilities.

**Representation of time in the route choice model**

The representation of time in the CLT route choice model also warrants further discussion and critique. Journey time differs from journey distance in ways that can be meaningful to pedestrians when choosing between alternative routes. The upper-level route choice model does not represent this distinction, with route alternatives characterised by their length and number of crossings only. An implication of this is the absence of crossing wait times from the model. Waiting to cross the road is common in busy urban areas and routes of equal distance may incur different journey times due to different crossing waits. Crossing waits may be longer at roads with higher levels of traffic, so their inclusion is directly relevant to the themes of the barrier effect and road crossing behaviour addressed in this thesis.

Representing journey time would enable modelling a pedestrian’s desire to take the fastest, rather than the shortest, route. This could produce a different set of trajectories - pedestrians with a preference for the fastest route may avoid crossing certain roads due to an expectation of longer wait times at those locations - and therefore better account for how vehicle traffic affects pedestrian trajectories. Additionally, accounting for crossing wait times as part of a journey time route attribute helps distinguish wait time from other aspects of pedestrians’ perceptions of road crossings - such as safety - and their influence of route choice.

This is also the case in lower-level route choice, where the absence of wait time as a crossing alternative attribute means the vehicle exposure attribute - calculated base on vehicle agent movements - doesn’t distinguish between the effects of crossing safety and crossing wait time on road crossing decisions. This is an important distinction: signalise crossings can increase safety but may require longer wait
8.3. Critique of the methodology

Times that crossing informally.

However, the dynamic nature of lower-level route choice (sequential sampling, changing traffic conditions, changing pedestrian location) means that time is implicitly represented despite the absence of journey time as an explicit attribute of choice alternatives. The representation of time is apparent in the activation accumulation process which provides pedestrian agents with a memory of past road conditions but allows them to update their preferences based on more recent information. Extending lower-level route choice to incorporate crossing wait times requires that pedestrian agents anticipate future road conditions as well as remember past ones. How should this anticipation be modelled? The challenge of calculating route attributes is acknowledged in the route choice framework by choices made with limited planning horizon or spatial knowledge. Crossing wait times are uncertain and challenging to calculate and therefore a model of wait time anticipation would also need to facilitate this distinction. Alongside anticipating future waits, pedestrian agents would need to wait at crossings for a suitable crossing opportunity rather than crossing as soon as they reach their crossing locations as they do currently. This suggests the integration of an additional gap acceptance mode into the route choice framework that is used to both anticipate and produce pedestrian agent waits.

Incorporating wait times, and journey time more broadly, would better reflect a purposeful comparison of crossing location options based on anticipation of near future traffic conditions. At the lower-level, I expect this would change pedestrian agent behaviour by motivating more informal crossings in cases where a longer crossing wait is anticipated at a marked crossing option. At the upper-level, I expect modelling pedestrians as choosing fastest routes would produce more trips that avoid large junctions, possibly leading to more road crossing on smaller roads.

A final criticism of the representation of time in the model relates to the choice of a 1s time step. This limitation is discussed in Chapter 6.5.4 and is briefly reiterated here for completeness. The 1s time step is too coarse to model high pedestrian and vehicle densities which renders the use of a social force model of pedestrian movement somewhat redundant. To apply the model to higher pedestrian densities
8.3. Critique of the methodology

the time step would need to be reduced.

8.3.2 Simulation environment and initial conditions

Street infrastructure

The simulation environment provides a highly simplified representation of real road environments. This representation is sufficient for the objectives of this thesis in that it represents pedestrian and vehicle movement and the interactions that result from the decisions of these agents. However, the movement of pedestrians and vehicles and their interaction is also mediated by infrastructure that is not represented in the simulation. Specifically, traffic lights and road crossing signals which coordinate the shared use of carriageway space by pedestrians and vehicles are not represented.

Because of this lack of detail in the representation of the environment, the simulation results, particularly those in Chapter 7 which measure competition for carriageway space between pedestrian and vehicle agents, do not provide a realistic measurement of vehicle speed and the frequency of pedestrian-vehicle interactions. Instead, the differences in results between environments and policy settings provide an initial indication of the value of integrating street-level and neighbourhood-level pedestrian movement.

Synthetic road networks

Related to the limited realism of the simulation environments is the use of synthetic road networks to compare to the real Clapham Common road network environment. The synthetic networks enable a controlled comparison between road network morphologies, while keeping trip distributions constant across the environments. This is a useful way of verifying how pedestrian behaviour depends on the road network. However, this also means results from the simulation experiments do not have direct application to the design of any real urban environments. Simplified representations of the environment have allowed a detailed assessment of the CLT route choice model but more realistic representations are needed to make the model useful for sustainable transport planning.

Pedestrian and vehicle trips
The pedestrian and vehicle trips that are simulated are a greatly simplified representation of real travel behaviour. Only a small sample of pedestrian trips (200 in each simulation run) with a shared destination are modelled in both Chapters 6 and 7. Appendix A Section A.1 reports that the conclusions in Chapter 6 are not changed when a larger sample of 300 trips heading both to and from the metro station are modelled (600 trips in total). However, a different distribution of trip lengths was observed and repeating these simulation experiments with a larger number of more diverse pedestrian trips may still produce different results. For example, the crossing location dispersion (CLD) metric used to analyse crossing behaviour in Chapter 7 can be expected to vary with changes to pedestrian trip origins and destinations. This is because CLD is a measure of where crossings take place across the whole environment. Different trips will result in trajectories along different sets of road links, in turn changing the road links on which pedestrian agents cross the road. In the $N = 200$ trips to the central metro station scenarios modelled in Chapter 7, restrictions to informal road crossing increased and decreased CLD in the Clapham Common and Quad Grid environments. If the trips were all from the central location, these trends may be reversed. If trips between other locations were included CLD may no longer change in relation to crossing location restrictions. It is therefore necessary to consider a broader, more realistic range of pedestrian trip origins and destinations to more accurately model how restrictions to road crossing would impact pedestrian-vehicle interactions.

### 8.3.3 Model calibration and validation

A notable absence in this thesis is calibration or validation of pedestrian agent behaviour against observations of real pedestrian route choices, at either the street or neighbourhood level. Chapters 4 and 5 established CLT route choice parameter ranges that met some basic assumptions about what constitutes plausible pedestrian behaviour. Building on this Chapter 6 verified that these pavement value ranges produce a wide range of pedestrian street-level trajectories.

I argue this verification of pedestrian behaviour is sufficient given the descriptive modelling purpose set out in the modelling framework of Chapter 3. Evaluating
the impact of crossing restriction policies under the wide range of pedestrian agent behaviour produced by these parameter ranges, Chapter 7 provides a robust assessment of how the impact of the policies differs between environments. However, without calibrating the model against observations, it is not possible to say how the breadth of pedestrian behaviour used in these analyses compares to the breadth of behaviour found in the Clapham Common area, or any other other urban area. Incorporating a wide range of behaviour when assessing the impacts of interventions is a useful way of acknowledging and accounting for uncertainties resulting from the potential for behaviour change. At the same time, calibration is needed to ground such assessments so that the extent to which modelled behaviour deviates from observed behaviour can be made explicit.

8.4 Future work

Some future directions of research are now suggested. These address the above criticisms as well as proposing ways in which this research could be applied to real transport planning problems.

8.4.1 Modelling pedestrian behaviour

Decision construal in urban areas

CLT is proposed in this thesis as a suitable way to model pedestrian decision making in relation to navigation and movement in urban areas. To progress this approach to modelling pedestrian behaviour evidence of choice reconstrual in the context of pedestrian route choice needs to be established. CLT and spatial cognition theory share a hierarchical representation of cognition and decision making. CLT offers a more general theory by distinguishing between hierarchy levels based on psychological distance, which, alongside spatial distance, incorporates temporal distances, social distances, and levels of certainty. To what extent do these additional factors shape people’s perception of and decision making in urban areas? Investigating the role of dynamic components of the environment, such as the movement of other road users, in defining cognitive hierarchies would help to align CLT with the existing, robust application of spatial cognition to wayfinding and naviga-
8.4. Future work

This could be investigated with surveys and interviews in which people explain how they make route choice decisions that are dependent on interactions with other road users as well as comparisons of peoples’ routes between busy and empty street environments.

**Comparing and integrating models of pedestrian road crossing**

A broader objective of future work is to compare and integrate different approaches to modelling pedestrian behaviour. The need to integrate multiple models of pedestrian decision making in order to produce a variety of known road crossing behaviour is highlighted by Markkula et al. (2022), arguing “that to reproduce a set of well-established empirical phenomena in naturalistic driver-pedestrian interaction, we need to combine a large number of existing psychological models, integrating theories of sensory noise, Bayesian perception, evidence accumulation decision-making, long-term valuation of action affordances, behavioural game theory, and theory of mind.” The set of “well-established empirical phenomena” the authors refer to are five behaviours related to pedestrian and vehicle yielding at marked crossings. A central tenant of this thesis is that outcomes for pedestrians related to such street level interactions manifest across larger spatial scales (for example the barrier effect). To this list of five behaviours and the multiple theories employed to model them we might add how pedestrians choose where to cross the road and how these choices relate to larger scale movement.

This thesis makes an initial attempt to integrate these different scales. A complete model of pedestrian decision making is an unrealistic and impractical objective. But without attempting to integrate different approaches it is not possible to establish how different components of the environment and pedestrian decision making interact to produce meaningful outcomes for pedestrians. This view follows from the arguments for a adopting a descriptive modelling purpose (Edmonds and Moss, 2005) whereby when modelling complex systems, the representation of the system should only be simplified once there is confidence that the simplification does not exclude meaningful interactions or impacts.
8.4.2 Appraising changes to urban streets

The work presented in this thesis can also be extended to address more applied research questions related to the design and management of urban streets. Below we discuss two specific, and related, areas: crossing infrastructure and autonomous vehicles.

Crossing infrastructure

Chapter 7 applies the CLT route choice model to compare the effects of restricting informal crossing in different environments. One of the primary causes of differences between the environments are the differences in the coverage of marked crossing infrastructure. A clear extension of this work is to analyse different strategies for marked crossing placement, observing the differences between different arrangements of crossing infrastructure for pedestrian outcomes. This could provide an alternative method for identifying and addressing the barrier effect in urban areas, one that is based on network level connectivity rather than choosing between different interventions for a single location. This would compliment attempts to reduce the barrier posed by specific roads by identifying whether and where pedestrian accessibility can be improved through the cumulative effect of reduced barriers across whole trips.

The development of a pavement network representation of the urban environment, built from Ordnance Survey data, is a thesis contribution which could be exploited to greater effect in such assessments. The methodology for producing the pavement network can be used to produce networks representing the availability and connectivity of pavement infrastructure for urban areas across the UK. Ordnance Survey data does not include the locations of crossing infrastructure. These are held by local transport authorities and are not generally available free of charge. Open Street Map may be a suitable alternative resource, from which crossing infrastructure locations could be extracted and used in combination with the pavement network to develop pedestrian simulations in multiple UK towns and cities. Using established transport simulation tools such as PTV VISSIM (Vissim, 2022) or Sumo (Lopez et al., 2018) would enable a more realistic representation of the
environment, within which the pedestrian agents move and interact.

**Autonomous vehicles**

Another related area this work could be applied is in the development and testing of autonomous vehicles - one of the motivations for developing a multi-scale pedestrian model. The results from Chapter 7 suggests that preventing informal crossing could change pedestrian-vehicle interactions in different ways between environments, in particular between grid environments typically of modernist, planned cities and more natural road networks found in older cities. Restricting informal crossing had a greater effect on pedestrian route lengths and vehicle speed in the Clapham Common environment than either of the grid environments. These results suggest that attempts to restrict street level pedestrian behaviour can have knock-on effects for pedestrian mobility over multiple road links.

The operation of autonomous vehicles may be contingent on certain behaviours or rules that are specific to certain regions. For example, Waymo’s autonomous vehicles have been predominantly operated in Tempe, Arizona, an American suburb built around vehicle mobility. Switching from one context to another could therefore require additional testing to understand if the limitations of the vehicles differ in the new location. Interactions with pedestrians may appear unchanged if modelled at only small-scales, involving small numbers of pedestrians on single roads. But the collective effect of multiple vehicles and pedestrians moving around a neighbourhood could impose different limitations or contingencies to the vehicles’ operation, as suggested by the differences in pedestrian-vehicle carriageway competition found in Chapter 7. By integrating street-level and neighbourhood-level pedestrian decision making simulation tools may be better able to anticipate the challenges posed by adopting autonomous vehicle technology from one region or city to another.

**8.5 Final conclusion**

Against a trend of falling carbon emissions across many sectors of the UK economy, transport related emissions have yet to fall. Transport decarbonisation plans
explicitly state the need for widespread changes in travel behaviour. In this context, models based on extrapolating historic trends can act as barriers to change by treating necessary changes as outlier events. An alternative approach is to focus on the behaviour of individuals from which travel patterns emerge, a complex systems perspective in which plausible and diverse future scenarios are generated through the actions and interactions of individuals. This project has adopted this approach to modelling pedestrian road crossing. We have integrated street-level road crossing decisions with neighbourhood-level route choices to explore how interactions between pedestrians and vehicles emerge from route choices that are shaped both by the environment and the agents within the environment. In combination with other methods, such models can support endeavours to design pedestrian-friendly urban environments.
Appendix A

A.1 Two-way pedestrian flows

An additional simulation experiment was performed to test whether global sensitivity analysis (GSA) results change when bidirectional pedestrian flows are simulated. The same GSA methodology described in Chapter 6 was used (same range of parameter values and 2560 simulation runs) but with a different set of pedestrian trips. N=600 pedestrian trips were simulated, with trips both to and from the central metro station (all trips either began or ended at the metro station, no trips between non-metro ODs were simulated). As before, the ODs of trip origins and destinations were chosen randomly based on a uniform probability distribution across all candidate locations, with a total of 305 pedestrian ODs created.

The comparison between one-way and two-way pedestrian results in Figure A.1 shows that the sensitivity indices of the four output metrics to model parameters are not materially changed by the introduction of bidirectional pedestrian flows, other than $\bar{L}$ which has changed due to a different set of trips being simulated.

A.2 Least cost model comparison with alternative parameters

Chapter 6 also presents results of a comparison between the CLT route choice model and a least cost route choice model (see Section 6.4.2. The least cost model results in Chapter 6 are produced by using parameter values $k, j \in \{0, 500, 1000, 1500, 2000\}$. Here results for a narrower range of parameter values are presented, $k, j \in \{0, 100, 200, 300, 400, 500\}$, which helps establish how the CLT route choice model
A.2. Least cost model comparison with alternative parameters

Figure A.1: Comparison of results for one-way (unidirectional) and two-way (bidirectional) pedestrian flows in the Clapham Common environment

differs from a least cost model. In the Clapham Common environment, this range of parameter values produces median increases in the weight of road crossing links ranging from $0.03 - 5.4\%$, with maximum increases ranging from $3.5 - 1400\%$.

Table A.1 shows the mean and standard deviation of upper-level path lengths. The CLT results are the same as those shown in Table 6.3 in Chapter 6 but the least cost model results are those produced with this alternative parameter range. The main difference to the results in Chapter 6 is that the standard deviation of the least cost path lengths is now lower than that of the CLT path lengths where as before the standard deviations of the two methods were similar. Given the wide parameter range of $k, j \in \{0, 500, 1000, 1500, 2000\}$ used in Chapter 6, this suggests that the range of path lengths produced the CLT route choice model represents an upper bound of route length variation achievable by shortest path methods.

<table>
<thead>
<tr>
<th>Model</th>
<th>Uniform Grid</th>
<th>Quad Grid</th>
<th>Clapham Common</th>
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<td></td>
<td>Mean $\bar{L}$</td>
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<td>Mean $\bar{L}$</td>
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<tr>
<td>CLT Least Cost</td>
<td>743m</td>
<td>6.6m</td>
<td>732m</td>
</tr>
<tr>
<td></td>
<td>729m</td>
<td>1.5m</td>
<td>692m</td>
</tr>
</tbody>
</table>

Table A.1: Comparison of $\bar{L}$ mean standard deviation and variance calculated over parameter settings for $k, j \in \{0, 100, 200, 300, 400, 500\}$
Appendix B

B.1 Incorporating multi-scale pedestrian movement into street infrastructure appraisal: sensitivity indices results

Chapter 7 uses the CLT route choice model to explore the impact of restricting informal crossings. The results presented in the chapter focus on the effect of the policies on the pedestrian behaviour, as measured by $\bar{L}, N_{C}, CLE, CLD,$ and $\bar{S}_v$.

In this appendix additional results produced by these simulation experiments are presented. These results are the sensitivity indices of each outcome metric to each simulation parameter, compared between the ‘always’, ‘sometimes’, and ‘never’ policy settings. The sensitivity indices show how the policies change the influence of different components of the CLT route choice model.

B.1.1 Pedestrian behaviour

B.1.1.1 Path length

The sensitivity indices shown in Figures B.1-B.3 provide additional information about how upper-level paths are affected by each policy. In all three environments restricting informal crossings reduces the sensitivity of $\bar{L}$ to lower-level route choice parameters. The policies reduce the influence of lower-level route choice by removing informal crossing alternatives from the choice set. Accordingly, output metrics should become less sensitive to lower-level parameters, as observed.

Sensitivity to $PH$ increases greatly as informal crossing is restricted. A larger $PH$ value helps pedestrian agents choose paths which have crossing infrastructure
B.1. Incorporating multi-scale pedestrian movement into street infrastructure appraisal: sensitivity indices results

Figure B.1: Sensitivity of each output metrics to model parameters for the Clapham Common environment scenarios.

which explains why this parameter becomes more influential. Recall also that sensitivity indices measure the proportion of variation in an output metric that is attributable to changes in each input parameter. It follows that decreased sensitivity to some parameters is matched by increased sensitivity to others, and this also contributes to the rise in \( PH \) sensitivity. The increased standard deviation of \( \bar{L} \) between the ‘always’ and ‘never’ settings shows that \( PH \) gains absolute and well as relative influence over \( \bar{L} \). This is particularly true in the Clapham Common environment, in which \( PH \) sensitivity and \( \bar{L} \) standard deviation increase the most, due to the reduced coverage of marked crossings.
B.1. Incorporating multi-scale pedestrian movement into street infrastructure appraisal: sensitivity indices results

Figure B.2: Sensitivity of each output metrics to model parameters for the Quad Grid environment scenarios.

On the other hand, $\bar{L}$ becomes less sensitive to upper-level parameter $MC$ as informal crossing is restricted. It appears that whether agents prioritise minimising crossings or route length becomes less influential when confronted with detours due to the unavailability of crossing infrastructure. The large decrease in $MC$ sensitivity observed between ‘always’ and ‘sometimes’ policy settings in the Clapham Common environment may also explain the increased sensitivity to $\varepsilon$ between these policies, a change that is inconsistent with the other environments.

In the Uniform Grid environment the only influential upper-level parameter is $PH$. It follows that decreasing influence of lower-level parameters increases the
B.1. Incorporating multi-scale pedestrian movement into street infrastructure appraisal: sensitivity indices results

Figure B.3: Sensitivity of each output metrics to model parameters for the Uniform Grid environment scenarios.

relative influence of $PH$. In the Quad Grid environment, the variation of link length and block size creates some variation in the coverage of marked crossings - there are road links without any mark crossings within the study area. Therefore, as with the Clapham Common environment $PH$ gains importance as informal crossing is restricted. However, this does not translate to large variations in $\bar{L}$ between policy settings because of the coverage of marked crossings remains high.

B.1.1.2 Crossing behaviour

Numbers of crossing

The sensitivity of $N_C$ to simulation parameters changes less between pol-
B.1. Incorporating multi-scale pedestrian movement into street infrastructure appraisal: sensitivity indices results

icy settings than other pedestrian behaviour metrics. In both the Quad Grid and Clapham Common environments $N_C$ is predominantly sensitive to $MC$ and this doesn’t change much between policy settings. $N_C$ is only very slightly sensitive to lower-level parameters in the ‘always’ setting and not at all when informal crossing is restricted.

The biggest change in sensitivity between policy settings is in the Clapham Common environment where sensitivity to $PH$ greatly increases as informal crossing is prevented. This follows from the planning horizon becoming more important to the route length of pedestrian agents when informal crossing is restricted and longer routes resulting in more crossings.

The standard deviation of $N_C$ across simulation parameters is approximately 0 in the Uniform Grid environment and so these sensitivity indices are not meaningful.

**Crossing location entropy**

Turning to the sensitivity indices for the $CLE$ metric, similar trends to the $\bar{L}$ metric are observed - the reduced influence of lower-level parameters and increased influence of the upper-level $PH$ parameter. As with $\bar{L}$ this is due to the restrictions limiting the influence of lower-level route choice - where informal crossing is prevented there is no way for vehicle traffic to influence pedestrian agents’ routes.

Another shared trend is the decreasing sensitivity to $MC$ and increasing sensitivity to $PH$ with increased crossing restrictions. $MC$ is predominantly responsible for controlling the number of crossings performed. In the ‘always’ setting these can occur at any location and so high crossing frequencies translates to high $CLE$, making $CLE$ sensitive to $MC$. As informal crossing is restricted $MC$ continues to drive crossing frequency but the locations of these crossings become more ordered and therefore affect $CLE$ less. Conversely, $CLE$ becomes more sensitive to $PH$ as pedestrian agents are prevented from crossing informally; in the Clapham Common environment, $CLE$ switches from being more sensitive to $MC$ than $PH$ to being more sensitive to $PH$ than $MC$.

The standard deviation of $CLE$ reduces as informal crossing is restricted, meaning that the route choice parameters have less influence overall. The wider
range of CLE values produced in the ‘always’ setting suggests that route choice components amplify one another to produce highly ordered and disordered crossing behaviour.

**Crossing location dispersion**

The sensitivity indices for CLD respond differently to the informal crossing policies between the environments. In the grid environments sensitivity to lower-level parameters decreases as informal crossing is restricted and sensitivity to PH increases. Sensitivity to MC is generally unchanged, apart from increasing under the ‘sometimes’ policy in the Quad Grid environment. When informal crossing is permitted in these environments, crossing dispersion is as sensitive to lower-level parameters as upper-level parameters, showing that street level route choice decisions have an impact of the global distribution of crossing locations. This changes as informal crossing is prevented, showing that the restrictions limit the ability for lower-level route choice to affect crossing behaviour across larger spatial scales.

Conversely, in the Clapham Common environment sensitivity to lower-level parameters $\alpha$ and $\epsilon$ increases when informal crossing is completely restricted. In this environment CLD is predominantly sensitive to upper-level parameters in all policy settings but particularly in the ‘always’ and ‘sometimes’ settings. The increased sensitivity to $\alpha$ and $\epsilon$ in the ‘never’ setting can only be explained as the result of the large decrease in sensitivity to MC, which means that these parameters’ gain relative importance. In the Clapham Common environment street-level route choices do not affect the global distribution of crossing locations, which is far more strongly determined by MC when informal crossing is allowed and PH when it isn’t.

**B.1.2 Pedestrian-vehicle interactions**

The sensitivity indices for $S_v$ are approximately the same between policy settings and between environments. $S_v$ is predominantly sensitive to $N_v$ and this is unchanged by restricting informal crossing. In the Clapham Common environment sensitivity to $T_{ped}$ and PH increases when informal crossing is prevented. The change in sensitivity indices indicates a small change in pedestrian-vehicle inter-
B.1. Incorporating multi-scale pedestrian movement into street infrastructure appraisal: sensitivity indices results
actions but this is better shown by the linear regression models and t-tests applied in Chapter 7.
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