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Pedestrian route choice in buildings: experiments and modelling

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Abstract

Understanding pedestrian behaviour is of obvious practical importance for facilitating pedestrian infrastructure in cities and promoting crowd evacuation in emergencies. Pedestrian route choice, as one of the key aspects, has received wide attention but has been investigated from different conceptual and methodological angles. By reviewing the literature, a systematic theoretical framework is presented in this thesis, which provides general decision-making processes and associated principles for pedestrian route choice across disciplines and contexts. However, how pedestrians perceive, integrate, respond to and decide upon information is not fixed but varies with the context.

This thesis especially focuses on pedestrian route choice in buildings that is directly relevant to building design and safety management. Virtual experiments are conducted to investigate how pedestrians respond to various environmental information and make spatial decisions in different buildings; Simulations are presented to explore how crowd dynamics emerge from individual interactions. Findings indicate the trade-offs among various environmental information, highlight the importance of contextual factors, and reveal the impacts of building layout properties on pedestrian route choice in buildings. However, participants only make one decision in these scenarios and how pedestrians make consecutive route choices, which frequently happens in complex buildings, remains unanswered. Another part of the thesis explores this issue by investigating sequences of pedestrian spatial decisions and establishing a different decision-making process in consecutive route choices, aiming to form the initial steps in understanding this essential but neglected topic.

This thesis aims to provide experimental and simulation investigations on how different factors shape pedestrian route choice behaviour in buildings and a starting point for future research on sequences of consecutive pedestrian spatial decisions.

Four papers based on the work in this thesis have been published in peer-reviewed journals.

Dedication and acknowledgements

Time flies and my time perception becomes dull as I get older. It was not until I finished this thesis that I realised that I had completed my doctoral journey and was about to bid farewell to my student days and enter an unknown new life stage. This is a milestone in my life anyway. All the sour, sweet, bitter and spicy moments I have had in the past few years, have been fermented into the best glass of wine I have ever tasted. This journey would have not been possible without the support of several people.

First of all, I would like to express my great thanks to my supervisor Dr Nikolai Bode, who always tried his best to support me to explore freely and was ready to provide help at any time, allowing me to have been following my most comfortable pace throughout the doctoral period and have never felt that I have to do something. I am very fortunate to be his student, and I sincerely hope that I could be such a supervisor in the future.

I would also like to thank Prof. Eddie Wilson, my annual process reviewer, who always gives positive feedback in every meeting, not only to provide new perspectives on my research but also to give valuable advice and recommendations for my academic career. Thanks Dr Christopher King for giving feedback on my thesis.

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Finally, I would like to thank my wife, Rong, whose love give me strength throughout these years - I hope she would feel in the same way during her PhD, my parents and my sister for supporting me all the time and my five-year-old niece who believes a doctor degree is cool, motivating me to earn one.

AUTHOR'S DECLARATION

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

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CHAPTER 1

INTRODUCTION

1.1 Motivation

Pedestrian route choice refers to the spatial decision individuals make between a set of options to reach their preferred destination. Pedestrians make route choices in a variety of scenarios such as in their daily lives where people choose a specific route to work or in emergencies where evacuees have to decide on which route to take for escape, which may happen unconsciously [105]. Understanding the environmental and psychological mechanisms behind this process is a fundamental research focus in many fields including engineering, physics, mathematics and social sciences [90]. These different disciplines focus on various aspects of this behaviour using a variety of techniques, making pedestrian route choice an interdisciplinary topic.

Pedestrian route choice can occur at different spatial scales, ranging from a room [69], a building [37] or even an entire area threatened by disasters [135]. Empirical knowledge of pedestrian route choice in buildings is especially important because it can help create friendly and efficient walking environments, which potentially encourage walking and thus benefit public health, and develop better evacuation strategies to prevent various pedestrian hazards [89]. For example, understanding pedestrian route choice can predict pedestrian demand in each zone of buildings to avoid crowd accidents in extreme situations [21].

How pedestrians choose their route in buildings has been investigated through experiments [195]. One of the paradigms is laboratory experiments where participants are asked to complete route choice tasks under controlled conditions. In such experiments, data are usually collected using video recordings and can be used to gain insights into pedestrian route choice in certain scenarios and calibrate pedestrian dynamic models. For example, [146] conduct several field experiments with social groups to calibrate a floor field cellular automata model based on a leader-follower rule. However, recreating realistic environments for participant spatial decisions is difficult, expensive, and time-consuming and will only be relevant to specific contexts. In contrast, virtual experiments are cheap, flexible and permit a highly controlled setting, which has been widely used in the field of pedestrian dynamics [72]. Various aspects of pedestrian route choice have been investigated using this paradigm, including how participants respond to various information (e.g., signs [44], fire [243] and obstacle position [225]) and pedestrian route choice behaviour in different contexts (e.g., rooms [111], buildings [3] and tunnels [113]).

In addition to experiments, various models have been developed to examine pedestrian route choices [178]. A group of models focuses on how individuals make spatial decisions based on various attributes and aim to establish the trade-offs between these attributes that are usually associated with route properties, individual characteristics and contextual factors. For example, [78] propose mixed logit models that include the spatial distance to exits, the level of congestion around exits, and the visibility of the exit to quantitatively measure the contribution of each factor to individual route choice in evacuation. However, these models focus on route choice behaviour of pedestrians, which is an aspect of tactical-level decisions. In contrast, a group of models focuses on operational-level decisions that mainly involve collision avoidance [195]. These evacuation models are based on various mechanisms that aim to accurately replicate the complex and dynamic nature of crowd behaviour during an emergency evacuation. One widely used model is the social force model [85], which is driven by multiple physical forces, such as repulsion, attraction, and friction that determine how individuals move through a crowd. In addition, some models integrates distinct levels of decisions and thus can simulate crowd behaviour that emerges from the individual decision. For example, in social force models, besides the main component that describes individual movements, there is a separate part for pedestrian direction choice that allows each person may to either choose an individual direction or follow the average direction of neighbours, making it possible to explore crowd behaviour in evacuation. An example of where this is done is [85] which found the pedestrian following behaviour and the resulting unbalanced exit usage. Furthermore, benefiting from advances in computer technology, pedestrian and crowd dynamic simulators capable of multi-scale environments are increasingly being developed. An online survey revealed a total of 72 models presently employed. Among these models, 12 were identified as the most commonly utilized by researchers and practitioners in the field [144].

One of the essential aspects of pedestrian route choice is to investigate factors that contribute to individual spatial decisions, among which environmental information and contextual factors have been identified as key factors [17]. Environmental information can be classified into two principal categories: static information that does not change with time (e.g., obstacles) and dynamic information varying with time (e.g., spreading smoke or crowd movements) [20]. Previous research has established the impacts of various sources of environmental information on pedestrian route choice. For example, some studies have explored the influence of several aspects of signage on individual route choices such as position, colour, and display format [60, 184, 186, 227]. However, the findings on how individuals respond to information are diverse. For example, several empirical findings suggest participants tend to avoid others [81, 128] but other studies indicate individuals have the tendency of following the crowd [69, 163]. In terms of contextual factors, many potentially important influences have been identified and investigated extensively through modelling and experiments such as contexts with various characteristics (e.g., metro stations [49], tunnels [184] or airports [150]), motivation [107] and social interactions of pedestrians [235]. Previous work has established that pedestrians choose their routes based on various strategies associated with contexts. For example, pedestrians are more likely to choose the exit with a shorter distance in normal walking environments but prefer less crowded exits to minimum congestion time and thus improve evacuation efficiency in emergencies [74]. However, in stressful situations pedestrians tend to follow others due to the increasing stress [86]. Furthermore, a crucial but understudied contextual factor is the layout of buildings that measures the conditions of building elements and their spatial arrangements. Previous research has explored the role of various aspects of building layout in the human route choice process such as how pedestrians choose which route to take in scenarios with specific structures (e.g., obstacles in front of exits [95] and exit arrangement [198]). However, there is still a lack of a method for generating building structures with specific properties and sufficient empirical data for a deep investigation of the impacts of building layout on pedestrian route choice.

Some theories have been posited to account for pedestrian behaviours in the context of evacuations. For example, the theory of affordances, formulated by Gibson [153], has been used to model the links between exit design and route choice [169]. This theoretical framework proposes that objects are perceived by individuals in relation to the actions or opportunities they afford. In other words, an affordance represents what an object can offer an individual in terms of achieving their goals. For example, an emergency exit would not simply be seen as a door with a sign, but as a means of reaching safety. [84] later developed an extended version of this theory, which posits that the assessment of affordances can be made in relation to four distinct aspects: sensory, cognitive, physical, and functional. Models of bounded rationality assume that people are purposively rational, but that they are limited by the extent of their information and by their cognitive capacities for calculation, prediction and action [171]. To compensate, people satisfy rather than optimize. For example, it may be that people are strongly disposed to exit the same way that they entered, rather than evaluating all the possible exits. The theory of affiliation [91], a psychological concept that refers to the tendency of people to seek out the company of others in times of stress or uncertainty, suggests that individuals may be more likely to seek the company of others during an emergency evacuation, as they may feel a greater sense of fear and uncertainty. According to the theory of affiliation, individuals have an innate drive to form social connections and maintain relationships with others. This drive is thought to be especially strong in times of stress, as people seek out social support to help them cope with difficult situations. This support can come in the form of emotional support, practical assistance, or simply the presence of other people. In the context of evacuation, the theory of affiliation suggests that individuals may be more likely to seek out the company of others to help them cope with the stress and uncertainty of the situation [43].

While many studies have investigated single instances of decisions on routes, the fact that these processes often involve sequences of decisions has so far not been considered. For example, in pedestrian route choice models, individuals are usually assumed to either plan their routes in advance using specific principles or make an independent decision at each junction [241]. However, these assumptions cannot capture the impacts of previous route choice experience on subsequent decisions, which may be vital for the decision-making of pedestrians [25]. Therefore, insights into individual behaviour in consecutive choices are required, which can help predict pedestrian spatial decisions and facilitate safety management, especially in complex buildings where people have to make many route choices.

Route choice in the context of evacuations typically entails a sequence of spatial decision-making processes. However, modelling route choice can be particularly challenging in complex buildings or scenarios where multiple routes are available. In contrast, exit choice refers to the selection of exits by individuals when presented with a set of alternatives. Exit choice can be considered a subset of route choice and is often modelled using binary choices, which may be sufficient for simpler buildings with a limited number of exits on a given floor. It is worth noting that while the majority of the chapters in this thesis focus on exit choice, route choice also is involved.

The empirical investigation of route choice in evacuation has practical implications for the effective design and implementation of emergency evacuation plans. By gaining insights into the factors that influence individuals' exit decisions during an evacuation, emergency planners and building designers can devise strategies to enhance evacuation efficiency and alleviate potential congestion and bottlenecks. For instance, some studies have revealed that individuals have a proclivity to choose exits based on their proximity, irrespective of whether they are the optimal or safest choice. In light of this finding, emergency planners can develop evacuation routes that guide individuals towards exits that are not only in close proximity but also the most efficient and secure.

1.2 Objectives

This thesis focuses on pedestrian route choice in buildings and addresses these issues through literature reviews, experiments and modelling. The scope of our investigation is limited to emergency scenarios in which pedestrians are required to quickly locate and access an exit in order to avoid potential harm or disaster. The primary focus of this thesis is on the exit choice of pedestrians when presented with two possible exits. However, the scenarios that involve a sequence of route decisions are also investigated. Pedestrian movements, including collision avoidance, are taken into account, but are considered only as one component of the overall evacuation process. The simulation of these movements utilizes established methods that have been well-validated in previous research. The work presented here is hoped to serve as a starting point in developing a general theoretical framework for research across disciplines. It also aims to gain a deep understanding of how environmental information, contextual factors and building layout properties shape pedestrian route choice, explore pedestrian behaviour in sequences of route choices, expand the available data on pedestrian behaviour in buildings and ultimately help design appropriate pedestrian management strategies.

The specific research questions are addressed below.

RQ1: How can we develop a systematic framework for pedestrian route choice that can capture the essence of pedestrian route choice across disciplines? - Pedestrian route choice has long been a research focus and has received much attention in recent decades. A variety of disciplines are involved in different aspects of this topic. A systematic framework across disciplines can help researchers classify, contrast and analyse existing and planned research on pedestrian route choice and provide a structured theoretical starting point for interpreting or explaining observed pedestrian behaviours. This research does not purport to provide an exhaustive analysis of pedestrian route choice, as such an endeavour would likely be impractical given the varied scales and mechanisms involved. However, the study aims to offer a fresh perspective that may prove useful to researchers investigating a range of research questions in this domain.

RQ1.1: Where does the complexity of pedestrian route choice come from? - Route choice is involved across many aspects of pedestrian activity and can occur in a room, a building and even a city where pedestrians can have various goals such as tourists who prefer routes that can offer high-quality visual attractions and evacuees who tend to choose the routes via which they can escape as quickly as possible. Thus, identifying factors resulting in the complexity of pedestrian route choice can help gain a deeper understanding of this interdisciplinary topic and provides a solid basis for the establishment of a general theoretical framework that can address **RQ1.2**.

RQ1.2: What processes can be identified to describe pedestrian route choice across contexts? - Researchers from different disciplines are working on various aspects of pedestrian route choice and previous work has established the importance of contextual factors on pedestrian spatial decisions. Therefore, a general process of how pedestrians choose routes is necessary to bridge the gap between contexts and disciplines, which also can provide a basic framework to help identify key mechanisms in each process to answer **RQ1.3**.

RQ1.3: What are the principles of pedestrian route choice in each identified process? - The general processes of pedestrian route choice can provide a basic framework for research. However, the principles of decision-making mechanisms in each process require to be identified to complement this framework in detail and enable it to serve as a research tool for researchers in areas relevant to pedestrian route choice studies. Due to the complexity of pedestrian route choice, the principles cannot be identified exhaustively but should provide general knowledge across contexts and disciplines.

RQ2: How do various sources of directional information (e.g., signs and movements of others) impart pedestrian route choice in buildings? - Environmental information has been identified as one of the most crucial factors directing pedestrian route choice and has been investigated extensively through experiments and modelling [17]. Environmental information can be categorised into static information that remains unchanged such as signs in evacuation and dynamic information that varies with time such as the movement of the crowd. In this thesis, we focus on signs and the movement of others, which are essential environmental information affecting pedestrian route choice. Investigations into how pedestrians respond to various kinds of information can not only help gain a new understanding of pedestrian route choice but also help develop measures that can improve pedestrian safety in buildings.

RQ2.1: How do pedestrians trade off various sources of environmental information? - When pedestrians have various sources of direction information, they have to trade off between different options and decide which information to follow. [114] found that conflicting information has a negative effect on the pedestrian route choice process in a virtual tunnel fire evacuation. However, more empirical work is still needed to investigate the route choice of pedestrians when handling various information that indicates different directions in evacuation.

RQ2.2: Are responses of pedestrians to experimental information consistent in different contexts? If not, what contextual factors can be important? - Studies reveal pedestrians tend to follow the direction indicated by signs in different contexts such as tunnels and buildings, which suggests the consistency of pedestrian route choice across scenarios. However, other research indicates pedestrians behave differently across contexts. For example, [163] found that pedestrians have an innate preference for following others especially when the stress level is high while another work by [140] suggests that pedestrians are more likely to follow the minority and that increased stress levels or crowding amplify that behaviour [81]. The diverse results highlight the importance of identifying the contextual factors on pedestrian spatial decisions. The primary objective of this part is to obtain a deeper understanding of pedestrian behaviour in controlled experimental settings, with the understanding that additional research may be required to fully validate the applicability of our findings to real-world situations. However, compared to actual events, virtual experiments enable us to explore the impact of various factors in a more controlled and adaptable manner.

RQ3: How can building layout properties influence pedestrian route choice in buildings? - How building layout properties shape pedestrian route choice is directly related to building design and safety management. While building layout can significantly facilitate pedestrian movement and navigation, it is not the sole factor to consider in building design practice. Other practical considerations such as energy efficiency and cost control can play an important role in design decisions, which may limit the engineering feasibility of some research. Nevertheless, gaining a deep understanding of the impact of building layout on pedestrian evacuation is still valuable, as new techniques and technologies in the future may provide solutions to address these practical challenges. The present study proposes a method to systematically investigate building layout by addressing two questions:

RQ3.1: How to develop a method that can create buildings with different layout properties? - Due to the complexity of buildings in reality, it is challenging to identify factors that can capture building layout properties and conduct well-controlled experiments for investigating the influences of a specific layout property on pedestrian behaviour. Virtual experiments provide a potential solution to this issue as this paradigm can create carefully-designed virtual environments systematically and duplicate them for a large number of participants flexibly. However, to achieve this, a method for generating buildings with various layout properties that can be controlled by several parameters is required.

RQ3.2: What are some factors that can measure different aspects of building layout properties? - Building layout, reflecting conditions of building geometric elements and spatial arrangements among them, is a broad concept and can be quantified by different approaches. A widely accepted measurement is the InterConnection Density (ICD) defined by O'Neill [170], which can measure the density of available paths between places in buildings. While this measurement can capture an aspect of the entire building layout, other aspects of the entire building and layout properties for part of a building are important as well. The concept of affordance, which describes the interactions between an object and an individual's capacity to engage with it, has potential utility in qualitatively scrutinizing diverse system designs (e.g., building layout) to identify the most optimal system that aligns with the targeted design objectives [169]. Therefore, other measurements need to be identified for ensuring a broader range of possible layout properties to answer **RQ3**.

RQ4 Do pedestrians behave the same in single decisions and sequences of consecutive route choices? If not, how to establish the existence, nature and consequences of such changes? - Previous studies have widely studied how pedestrians respond to different environmental information in various contexts, especially where pedestrians only need to make one route decision. However, little is known about pedestrian behaviours in sequences of consecutive pedestrian route choices which probably occur in complex buildings such as shopping malls. Previous work suggests that a large number of spatial decisions increase pedestrian cognitive load during navigation [158]. However, whether such effects influence pedestrian route choice has not been investigated. Moreover, for every single decision-making in pedestrian dynamic models, pedestrians are usually assumed to choose routes based on the same mechanisms, without considering the influence of previous route choices on subsequent decisions. Thus, identifying pedestrian behaviour in route choice sequences and exploring its implications is essential to better understand pedestrian spatial decisions in complex buildings.

1.3 Method

In this thesis, three virtual experiments (Chapters 3-5) are conducted to collect data on participant route choice behaviours in certain scenarios and mathematics (Chapter 5) and agent-based models (Chapter 3) are used to explore how crowd behaviour emerges from individual interactions.

1.3.1 Virtual experiments

Field observations and laboratory experiments are the two main experimental paradigms for research on pedestrian decision-making. However, both methods have limitations that undermine their effectiveness [162]. For example, crowd data obtained from field observations usually require additional efforts for accurate quantification and are difficult to investigate the influences of specific factors in a well-controlled way. For laboratory experiments, they can implement well-controlled treatments in reality but recreating the experimental environments is expensive and organising large numbers of pedestrians is hard.

In contrast, another experimental paradigm, that presents participants with virtual environments where participants are able to look around, move and interact with the surroundings experiments, can tackle these issues [143]. Virtual technologies can be categorised into desktop VR where participants usually attend experiments displayed on a computer screen by using keyboards or/and mice, head-mounted display VR where participants are presented with visuals directly to their eyes via headsets or glasses, and Cave (Cave Automatic Virtual Environment) that allows participants to have lifelike visuals in large spaces [52]. All these technologies have been introduced in virtual experiments for pedestrian decision-making in a variety of scenarios such as tunnels, buildings and city streets. In addition, the selection of an appropriate locomotion mechanism is a crucial factor to consider in VR experiments, particularly when investigating evacuation scenarios [56]. The choice of locomotion mechanism can have significant effects on participants' behaviour and decision-making in the virtual environment [29]. For instance, using a point-and-click mechanism may limit participants' ability to make small adjustments, potentially hindering their capacity to avoid collisions with other virtual agents [172]. Conversely, physical movement within the virtual environment can create a more immersive experience and allow participants to make more precise movements, but may also increase the risk of physical injury without proper supervision [137]. Furthermore, the use of gamepads or treadmills may also influence participant behaviour and decision-making, as these mechanisms may impact the speed and fluidity of movement within the virtual environment [230].

In this thesis, the desktop virtual technology is used for three virtual experiments for the following two reasons. First, compared to others, desktop VR requires less equipment and allows participants to virtually attend, meaning data can be collected easily and remotely which is especially feasible for the virtual experiments with a large number of participants presented in Chapter 4. Second, desktop VR can present participants with a 2D top-down view of a virtual building, allowing the investigation on route choice behaviours of pedestrians who are assumed to have global knowledge about the building, which is one of the focuses in Chapter 4. If there were no limitations to time and financial resources, conducting 3D virtual experiments where participants wear VR equipment would be the ideal option in terms of immersiveness. However, considering the time and financial constraints of this research, desktop VR is the most suitable and sufficient option for investigating research questions.

The findings obtained from virtual experiments suggest how individuals make route choices in certain scenarios. However, the crowd behaviours emerging from individual interactions remain unclear and modelling provides a possible solution to this problem.

1.3.2 Modelling

Modelling is another essential methodology for research on pedestrian decision-making. A large variety of models have been developed to simulate pedestrian behaviours in various scenarios based on different approaches (see [242] for a review). The role of modelling in previous research varies. For example, some work aims to reproduce realistic pedestrian behaviour using modelling while other studies develop data-driven models for pedestrian route choice prediction [120]. Although many models need to be calibrated by empirical data, this paradigm can help describe pedestrian behaviour and simulate crowd dynamics.

In this thesis, two models are used for different purposes. The first model is an agent-based model based on queuing theory, which is used to investigate the crowd behaviour that emerged from individual interactions observed in the virtual experiment in Chapter 3. The second model, presented in Chapter 5, is a mathematical model that aims to formalise our hypothesis that pedestrians pay less attention to environmental information the more decisions they make in sequence, and explore its possible consequences.

While more empirical work is required to test whether the findings obtained from the virtual simulation results can be extended to common scenarios, the applications of modelling in this thesis expand the understanding of pedestrian route choice in buildings and can be severed as a starting point for future research.

1.4 Contributions

1.4.1 Contributions of this thesis

Understanding how pedestrians find and choose routes in buildings is an important topic that is directly associated with building design and safety management. Given the interdisciplinarity and complexity of pedestrian route choice, it is difficult but essential to establish a systematic theoretical framework for research across disciplines and contexts. The first contribution of this thesis is to establish general decision-making processes of pedestrian route choice and identify the principles that can capture the key mechanisms of each process (Chapter 2). The findings provide a systematic overview of the field of pedestrian route choice and help facilitate bridging across disciplines, which attempts to answer **RQ1** and its sub-questions in Section 1.2.

The route choices of pedestrians can be viewed as their integration and subsequent response to environmental information and internal information. Due to the controllability of environmental information, insights into how pedestrians respond to environmental information can help develop pedestrian management strategies, especially in complex building evacuation. The second contribution of this work is to investigate the trade-offs between various sources of environmental information (Chapter 3 and 5 for **RQ2**) and the impacts of contextual factors (Chapter 3 for **RQ2**) and building layout properties (Chapter 4 for **RQ3**) on pedestrian route choice via virtual experiments and modelling. Results indicate the dominant role of signs and maps compared to the movement of others, establish the influences of several building layout properties, and highlight the importance of contextual factors in directing pedestrian spatial decision-making.

Compared to fruitful findings of single instances of pedestrian decisions on routes, little attention has been paid to pedestrian behaviour in sequences of consecutive route choices. The third contribution of this thesis is to form the hypothesis that pedestrians tend to respond less to experimental information as they make more route decisions and find evidence for it via a virtual experiment and case study (Chapter 5). Simulation results suggest that it can be applicable to certain scenarios and may result in more predictable route choice dynamics. More importantly, the findings indicate that pedestrians may have different decision-making processes in sequences of route choices, which is worth further investigation, which explores **RQ4** and its sub-questions.

Except for the theoretical framework developed in Chapter 1 provides a foundation for our research on pedestrian route choice in buildings, the majority of our findings are based on experimental settings. While steps were taken to eliminate extraneous variable, it is technically impossible to completely avoid these issues. While we can gain insights into pedestrian behaviour by analysing data using statistical techniques, further validation is necessary to determine the extent to which our findings can be applied to real-life scenarios.

This thesis aims to develop a possible systematic framework for pedestrian route choice, investigate how environmental information, contextual factors and building layout properties shape individual spatial decisions, explore how pedestrian decision-making changes in sequences of route choices, and expand the empirical data on pedestrian route choice in buildings.

1.4.2 Publications

Four peer-reviewed journal papers have been published based on the work in this thesis and for all of the publications I led every single stage of the project with input from my lead supervisor Dr Nikolai Bode.

1. Y. TONG AND N. W. BODE, *The principles of pedestrian route choice*, Journal of the Royal Society Interface, 19 (2022), p. 20220061 [221], presented in Chapter 2.

2. Y. TONG AND N. W. BODE, *An investigation of how context affects the response of pedestrians to the movement of others*, Safety Science, 157 (2023), p. 105919 [223], described in Chapter 3

3. Y. TONG AND N. W. BODE, *How building layout properties influence pedestrian route choice and route recall*, Transportmetrica A: Transport Science, (2022), pp. 1 [220], shown in Chapter 4.

4. Y. TONG AND N. W. BODE, *The value pedestrians attribute to environmental information diminishes in route choice sequences*, Transportation Research Part C: Emerging Technologies, 124 (2021), p. 102909 [219], introduced in Chapter 5.

The following publications are associated with pedestrian behaviour but are not included in this thesis due to different reasons. Paper 5 uses a stated choice method for data collection which is a different main method in this thesis; Papers 6 and 7 involve pure simulations research without any empirical data and Paper 8 is a research story other than a research work.

5. Y. TONG AND N. W. BODE, *Higher investment levels into pre-planned routes increase the adherence of pedestrians to them*, Transportation Research Part F: Traffic Psychology and behaviour, 82 (2021), pp. 297–315 [218].

6. Y. TONG AND N. W. BODE, *Simulation investigation on crowd evacuation strategies for helping vulnerable pedestrians at different stages of egress*, International Journal of Disaster Risk Reduction, (2022), p. 1034 [222].

7. Y. TONG, C. KING, AND Y. HU, *Using agent-based simulation to assess disease prevention measures during pandemics*, Chinese Physics B, 30 (2021), p. 0989 [224].

8. Y. TONG, *My writing journey*, Science, 375 (2022), pp. 1062–106 [217].

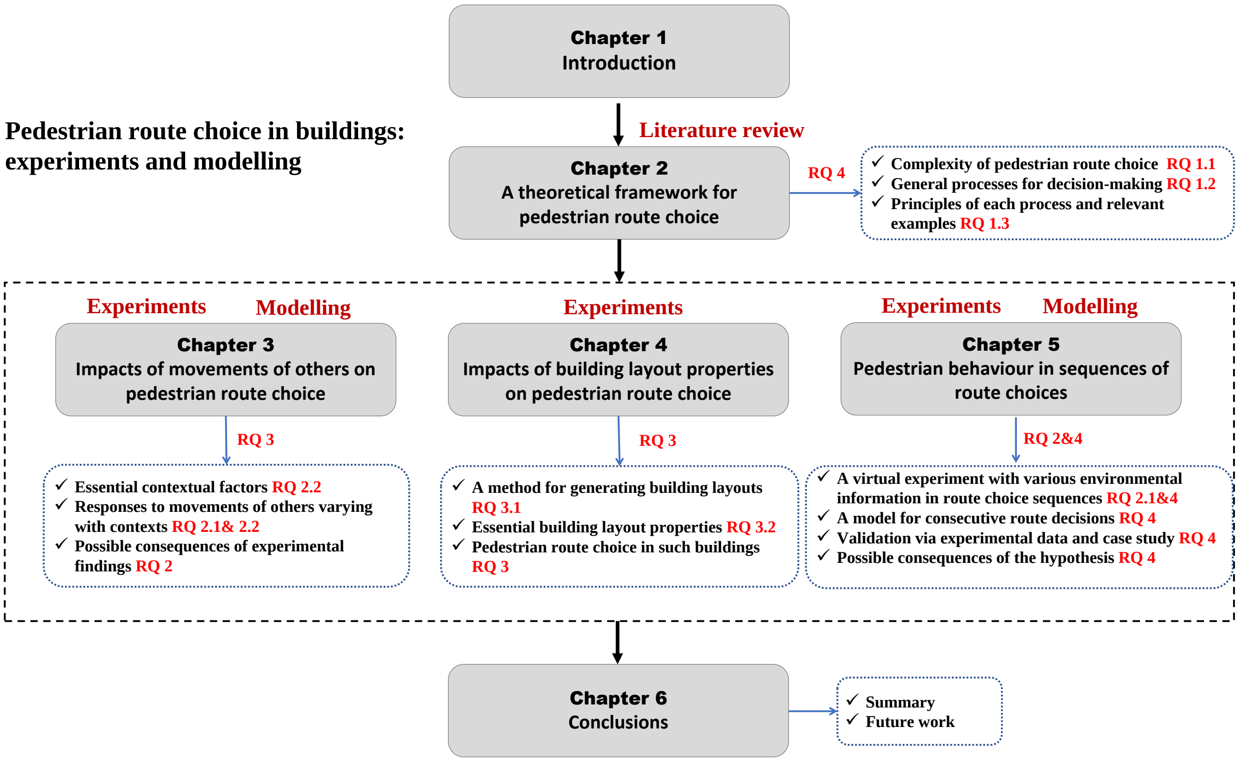


Figure 1.1: The outline of this thesis.

1.5 Outline

This thesis is organised into six chapters, as shown in Figure 1.1. Chapter 1 introduces the general background of pedestrian route choice. Chapters 2-5 are the main parts of this work, each one aims to answer one or more research questions summarised in Section 1.2 and is associated with a published paper. Chapter 6 summarised the findings of this thesis and suggests potential avenues for future work.

Chapter 2

A theoretical framework for pedestrian route choice

This chapter describes a theoretical framework for pedestrian route choice across disciplines which explores **RQ1**, and its associated sub-questions described in Section 1.2. Section 2.1 summarises the reasons that make pedestrian route choice a complicated topic which seeks to answer **RQ1.1**. Section 2.2 presents a general decision-making process of pedestrians across contexts, identifies the principles that capture the essence of each process and illustrate how each principle operates across disciplines by giving examples. This section aims to address **RQ1.2** and **RQ1.3**. Section 2.3 summarises the main findings of this chapter and discusses opportunities for future research.

The work presented here has been published in the Journal of the Royal Society Interface: Y. TONG AND N. W. BODE, *The principles of pedestrian route choice*, Journal of the Royal Society Interface, 19 (2022), p. 20220061 [221].

2.1 Introduction

Imagine that you are exploring a city for the first time. Fortunately, you have a map that precisely shows the correct information to get you where you would like to go. However, there are several routes, including direct and short ones, and scenic ones that are indirect and pass through narrow lanes. Which route will you take? Now imagine that you visit a museum for the first time when the fire alarm starts to sound. When you are looking for a way out, you probably do not consider how scenic the way is. Instead, you may be looking for evacuation signs and where others are going, but it may be dark, or worse, rooms may be filled with smoke. When all cues suggest the same route, it is not difficult to decide in these situations. If not, you will have to somehow trade off different route properties that you are aware of. While these two scenarios are probably not an everyday occurrence, pedestrian route choice is involved in many aspects of our daily lives, such as commuting, for example. We go to work on a specific route and go home on the same or another route. This route choice has already taken place many times, it may not be a conscious decision sometimes, and it may be determined by choice inertia. Regardless of the specific mechanisms for how we select routes, they shape our spatial behaviour.

The above examples illustrate realistic route choices people may face. Route choice is the spatial choice pedestrians make between a set of alternatives with the goal of reaching the desired destination, a process people have to deal with on a daily basis or in emergencies [37, 97]. It is regarded as one of the fundamental abilities of humans and is processed automatically within the brain and without the necessity of explicit thoughts in many cases [105]. The cognitive process of route choice is relevant to motor vehicle operators, cyclists, pedestrians and other transport users. Three reasons motivate us to focus on pedestrians. First, compared to other transport users who typically travel on road or other transport networks, pedestrians access a wide range of facilities, including commercial, residential, educational, and entertainment venues, for different reasons meaning their movement is more widely relevant to research areas beyond transportation, including architecture, safety engineering and retail, for example [90] . Second, compared to car drivers who cannot leave the road to take shortcuts, pedestrians are much less constrained by traffic rules and legal regulations and thus have a high degree of movement freedom and choice flexibility, which poses another big challenge for modelling. Third, walking is considered to be one of the most sustainable and green transport modes, especially in cities [89]. An understanding of pedestrian route choice can help the development of pedestrian facilities that provide attractive and efficient walking environments which are an essential requirement for sustainable urban transport and have additional benefits in terms of public health and avoiding social isolation [27]. Therefore, we focus on pedestrian route choice here.

Pedestrian route choice has long been a research topic and has drawn much attention in recent decades. As shown in Figure 2.1, the number of publications on this topic has been increasing substantially since the early 2000s and over 7000 studies have contributed to this research object. When reviewing work on pedestrian route choice, we found two main reasons that make it complex.

The first reason is that researchers from different disciplines are working on different topics related to pedestrian route choice using a variety of approaches. Figure 2.1 illustrates the percentage of all publications on this topic in different disciplines. For example, transportation scientists may develop route choice models calibrated on empirical data that involve interactions between pedestrians and vehicles with the goal of predicting future traffic conditions which in turn will support transportation control and planning in cities [177]. By contrast, neurologists might be interested in physiological structures responsible for spatial cognition, such as the parietal cortex, and may conduct controlled experiments using neurological methods [66]. Furthermore, pedestrian route choice plays a different role in the framework of each research topic. In pedestrian dynamics, pedestrian route choice is a ‘tactical-level’ decision on which route to use, distinguished from higher level ‘strategical-level’ decisions on selecting destinations and lower level ‘operational-level’ decisions on avoiding collisions with others and obstacles [195]. In transportation, route choice is the fourth step in the conventional transportation forecasting model, following trip generation, trip distribution and mode choice [156]. In psychology, the cognitive process of route choice is studied in its own right, considering what information is considered and how it is processed [209].

The second reason that adds to the complexity of studying pedestrian route choice is that it can occur on different temporal and spatial scales. For example, in evacuations pedestrians are often determined to reach a safe destination as quickly and as efficiently as possible, whereas tourists may choose scenic routes that may be less direct. In terms of spatial scales, evacuations from a smoky room [69], an entire building [37], or even a whole region that is threatened by a hurricane [13], all present situations that require individuals to choose routes, but over different distances. These different spatial and temporal scales may require different cognitive processes and especially when completing longer routes, pedestrians may update their decisions several times as they acquire new information, resulting in a sequence of route choices.

Previous reviews have covered specific aspects relevant to pedestrian route choice. For example, some studies review pedestrian decision-making but only focus on a specific scenario such as wayfinding, defined to be the process of completing short routes [5], the context of evacuations [195], or transport [178]. Other researchers review models used for reproducing realistic pedestrian behaviour and cover route choice as part of this [45, 120], or they analyse the external or internal factors that affect how pedestrians make spatial decisions [12]. However, all literature reviews to date consider route choice alongside other behaviours of pedestrians, often in specific contexts, and there is no study on this topic that presents a general perspective that is relevant and useful across research disciplines.

The discussion above highlights the importance of identifying the key mechanisms in pedestrian route choice and their relevance across contexts. In this contribution, we propose that the essential principles of pedestrian route choice are information perception, information integration, information response and mechanism of decision-making. We discuss how these principles are affected by and operate in different contexts. Our aim is to establish key principles in pedestrian route choice and their relevance across disciplines rather than providing an exhaustive survey of the pedestrian route choice literature.

This review is organised as follows. Section 2.2 consists of five parts. The first four each introduce one principle for the pedestrian route choice process and the last part discusses how pedestrian route choice depends on the context. Section 2.3 summarises all principles and discusses opportunities for future research.

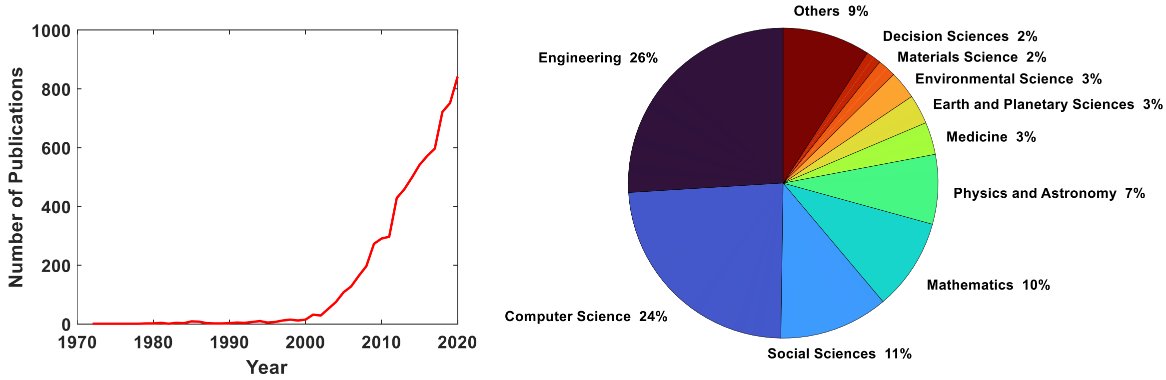


Figure 2.1: Visual illustration of analysis of research on pedestrian route choice. The line chart illustrates how the number of publications per year on this topic changes over time. The pie chart shows the frequency of the research based on the discipline. Data source: Scopus (accessed 5 November 2021).

2.2 Principles of pedestrian route choice

We argue that the essence of route choice in pedestrians can be distilled into four processes which we will discuss in the following: information perception, information integration, responses to information and decision-making mechanisms.

2.2.1 Information perception

Pedestrians can perceive information selectively and purposely, given the limited available information.

Information perception is the essential required first step for pedestrians to be able to represent the environment they are in when choosing a route to their destination. Two primary processes have been distinguished. First, acquiring sensations in which people gain experiences from the stimulation of a single sense organ, and second, perceptiveness in which people identify and interpret sensory information [118]. Selective attention has been identified as the dominant feature of these processes [104].

2.2.1.1 Selective attention

Previous research has established that people can choose information used for the representation of environments [209]. More specially, people centre their attention, purposely focusing on details and casting irrelevant information to the side-lines of their perception. For example, buildings offer too much spatial information for pedestrians to process, meaning that they are likely to only focus on landmarks or other memorable features that are useful for their route choice task. However, whether such information is selected at an early or late stage during information processing has been discussed extensively within the field of cognitive psychology [175]. The filter model of attention, proposed by Broadbent, based on dichotic listening tests, is a typical early selection model of attention [23]. It assumes that a selective filter is needed for information processing due to the limited capacity of attention, allowing only specific information to pass through for further processing and to filter unattended information out. By contrast, late selection models of attention suggest that both attended and unattended information are processed to the same deep level of analysis until the selection occurs [67]. Regardless of the specific mechanism, pedestrians perceive information selectively to allocate limited cognitive processing resources [4], which is often described as a bottleneck (Figure 2.2a).

In terms of selective attention, a key challenge is to determine which information should be attended to and which inputs should be ignored. The bottom-up (or stimulus-driven) attention and top-down attention (or goal-oriented attention) perspectives are commonly considered categories [106]. As shown in Figure 2.2b,c stimulus-driven attention is externally driven by salient features with inherent and distinct qualities that contrast with the surrounding environment. For example, pedestrians are reported to be distracted by billboards while crossing roads, even though the billboards are not relevant to their route choice task [213]. By contrast, goal-oriented attention is internally directed and allows people to allocate their attention voluntarily based on prior knowledge and current tasks [106]. In the process of wayfinding, pedestrians tend to focus on searching for signs to obtain directional clues, for example. While there are essential neurological differences between these two types of attention, they both result in the attended objects receiving preferential processing [106].

2.2.1.2 Limited available information in pedestrian route choice

Various types of information can be available to pedestrians. Information sources can be categorized into static, which do not change with time, and dynamic, which change over time [236]. Vision is the primary sense for most pedestrians to perceive information from the environment. Human brains use binocular disparity to extract depth information from the two-dimensional retinal images via stereopsis, allowing pedestrians to estimate the distance and size of an object [123]. In this way, pedestrians can detect spatial information, such as landmarks and signs, which help their navigation and orientation. Smell is another sense pedestrians rely on to perceive information. Pedestrians can extract spatial information by comparing the input across nostrils to assess the comfort of the street environment based on pleasant or unpleasant smells or to recognize the occurrence and origin of emergencies from olfactory cues, such as the smell of smoke in fires or the acrid smell of chemical gas leaks [176]. Similarly, for hearing, interaural cues facilitate the localization of auditory signals [232]. Environmental noise is an essential factor for the perceived quality and comfort of places, and alarms and other auditory messages can alert and guide pedestrians in evacuations [119]. Differences between individuals, illness, injury or disability influence how pedestrians use their senses and thus what spatial information is available to them.

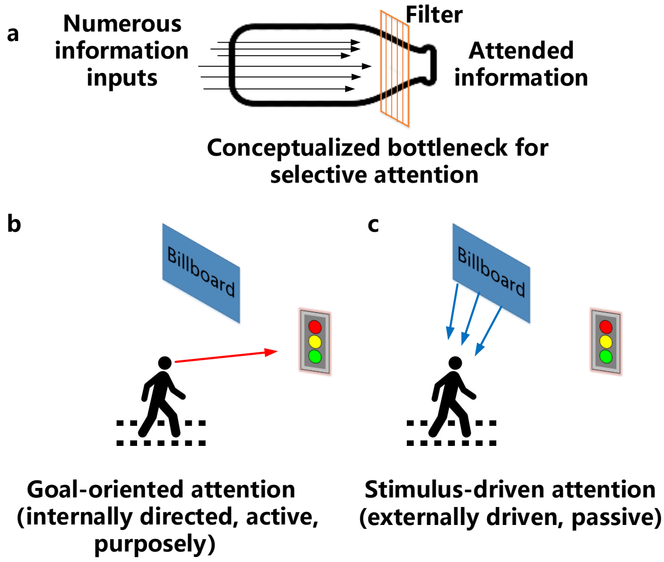


Figure 2.2: (a) Conceptualized bottleneck for selective attention. (b,c) Two different processes of attention.

While pedestrians can perceive information selectively and purposely, the available spatial information is still limited, which can present a challenge in route choices. For example, the spread of smoke in fires or power supply failures can mean there is little or even no visibility [99]. In such circumstances, pedestrians may struggle to detect emergency signs, walls, floors, doors and stairways. Instead of visual perception, pedestrians have to depend on haptic perception to avoid surrounding obstacles and to find a route to safety [59, 69].

2.2.2 Information integration

Pedestrians subjectively integrate environmental spatial information into mental representations.

After perceiving information, pedestrians need to integrate this information into mental representations of the environment surrounding them. There are many ways to represent spatial arrangements of environmental features, such as walls, rooms and signs (Figure 2.3). Some of these representations are adopted by researchers for convenience or computational benefits, whereas others try to describe or capture the cognitive processes of pedestrians. For example, in transportation, space is often represented as a network where each node represents an intersection point, and each edge that links nodes represents the streets in cities, paths in the countryside or corridors in buildings that pedestrians can travel on [10] (Figure 2.3e). Models predicting pedestrian route choice from an origin to a destination based on networks are generally developed in an algorithmic manner, such as Dijkstra's algorithm for finding the shortest route to a destination and the A-star algorithm, which determines a path to a given goal with the smallest cost [240].

Space syntax is another method for representing space, which focusses on the connectivity and integration between spatial components [9]. Three types of maps can be derived for different purposes. An Isovist map depicts the volume of space visible from any given position within the configured space (Figure 2.3b), which provides a mathematical basis for analysing visual information and can be used to investigate the visual stimulus of the arrangement of interior elements for improving architecture design [196]. A convex map is the minimal set of convex spaces that covers a layout (Figure 2.3c). It has been related to the social use of spaces [9]. An axial map is constructed by the least number of axial lines that cover all convex spaces of a layout (Figure 2.3d), which can describe the structure of movement in a spatial setting, making it a valuable tool for studying the dynamics of social life such as the selective distribution of a population and the range of choices determining their mobility in spaces [9].

Networks and maps generated using space syntax capture objective representations of spatial environments. By contrast, the mental representation pedestrians develop of external environments is based on cognitive processes that might affect route choice. Researchers have worked toward formalizing this process by suggesting cognitive maps that capture spatial relations among features and objects, as a method of describing mental spatial representation [61]. Five typical elements of cognitive maps have been suggested: paths, nodes, districts, edges and landmarks [38]. Paths refer to the corridors, edges are limiting or enclosing features, districts are larger spaces that may be categorized according to common characters, nodes are the intersections of major paths or places, and landmarks are distinctive features that people use as reference points for their location. The concept of cognitive maps was termed by Tolman based on evidence about rats possessing clues about specific objects and their spatial relation that they obtained from the experience of previously visiting other environments [216]. Research evidence from rats also suggests that the hippocampal formation is involved in the establishment of cognitive maps and that specific cells, such as place cells and grid cells [40], play a role in spatial information integration. Similar cells that provide environmental information have also been discovered in the human brain [50].

In the process of constructing cognitive maps, two different spatial reference frames are used to structure the environmental information. One is called the egocentric (self-to-object) frame, which refers to topographical relationships between a person and the environment he/she is in; the other is called the allocentric (object-to-object) frame and it records spatial information about the location of objects relative to each other in the environment [31]. Figure 2.3g,h shows examples for these two kinds of reference frames. The egocentric frame is self-centred meaning the perspective depends on the current location of an individual, while the allocentric frame is founded on world-based coordinates and encodes spatial information from a stationary perspective. Both reference frames are necessary for pedestrian navigation and pedestrians can switch between them or combine them if needed [151]. Previous research has demonstrated that there is no difference between the behavioural performance of participants who are provided with either allocentric or egocentric visualizations [165], but it has been suggested that the reference-frame preference of individuals is influenced by their age [183] and gender [28]. Thus, individual characteristics are likely to influence the cognitive maps constructed for environments, but it is not clear to what extent this also influences route choice.

Since pedestrians perceive spatial information selectively and purposely, they integrate different information and construct subjective cognitive maps for episodic activities that may depend on their beliefs, experiences or attitudes, even if they have access to the same information from the same environment [149]. Therefore, cognitive maps can be inaccurate, simplified, or even distorted when compared to objective representations of physical environments (Figure 2.3e,f) [155].

2.2.3 Response to information

Pedestrians tend to be attracted and repelled by specific attributes individually and this can lead to positive or negative feedback loops across many individuals.

Pedestrians respond to their environment based on the mental representation of it they have developed and because of their inherent response preferences to attributes of the environment. Previous research suggests attributes that characterize an environment, such as sidewalk condition, steep slopes, intersection density, distance and the number of directional changes, are relevant to pedestrian route choice [70, 93]. Pedestrians tend to be attracted or repelled by specific attributes and these individual-level responses can result in positive or negative feedback loops across many individuals.

2.2.3.1 Desirable and undesirable attributes

In general, attributes of the environment relevant to route choice can be categorized as being desirable or undesirable, reflecting the tendency or preference of choosing or avoiding a route that has a given attribute. These categories have alternatively been described as attractive and repulsive forces [85].

The exact response of pedestrians to specific attributes may depend on individual characteristics or previous experience and, importantly, the context. For example, some people prefer a less busy route to avoid others, while other people who are not familiar with a building may tend to follow the crowd because the movement of others is an important source of information. Other behaviours may be more stable across populations. One example of this is the side preference behaviour where pedestrians prefer to walk on the right-hand side or the left-hand side, to avoid conflicts in a bi-directional flow situation [233]. It has been shown that each pedestrian possesses an inherent side tendency, although this preference varies significantly with regions, suggesting it is related to cultural conventions [161]. We will discuss the importance of the context on the behavioural responses of a pedestrian to environmental attributes below.

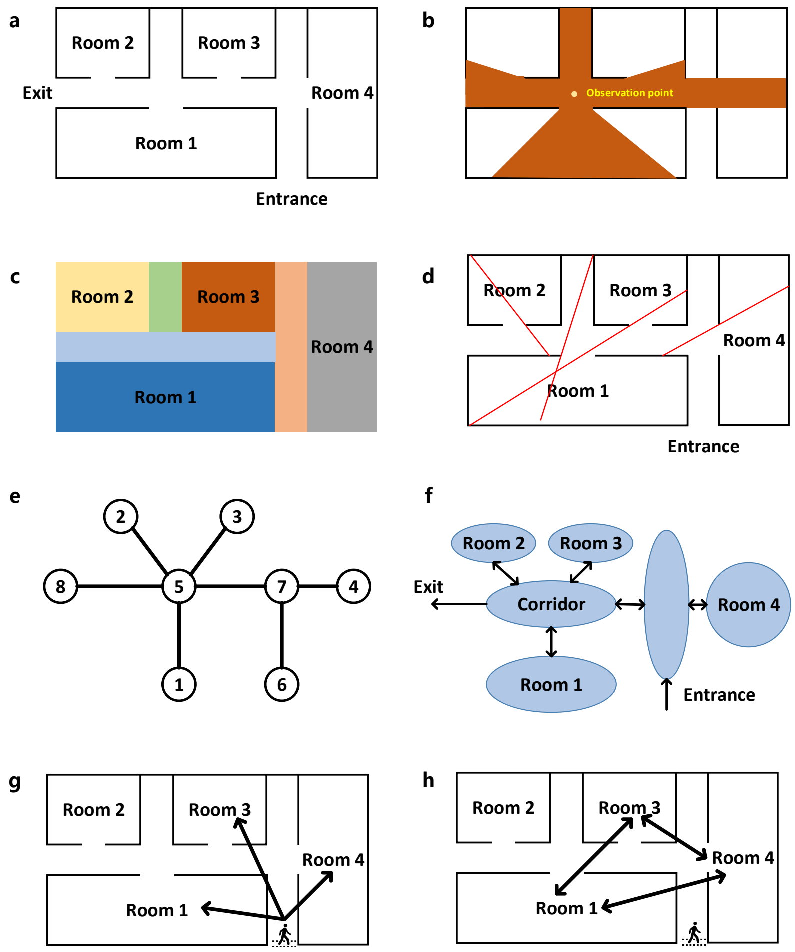


Figure 2.3: Different representations of space: (a) original floor plan, (b) isovist map, (c) convex map, (d) axial map, (e) network representation, and (f) one possible cognitive map. The remaining panels show spatial reference frames: (g) egocentric frame and (h) allocentric frame. See text for details.

2.2.3.2 Positive and negative feedback

Positive feedback is the amplification of events through recruitment or reinforcement. It is one of the paradigmatic features of collective behaviour, dynamics arising from the interaction between many individual agents [211]. A good example of pedestrian route choice is shown in Figure 2.4a. Consider a passageway where two pedestrian flows are moving in opposite directions. Pedestrians can use either of two doors. While pedestrians moving in opposite directions hinder the passage through a door, it is much easier to follow people moving in the same direction through a door. Thus, over time, a slight imbalance between the doors can accumulate with increased flows in one direction gradually blocking the flow in the opposite direction through a door. This can result in pedestrians walking in opposite directions using different doors. The mechanism for this process can be active in that pedestrian choose to use the door that allows them to pass more easily, or passive in that having to avoid others walking in the opposite direction hinder progress towards one of the doors. In either case, the positive feedback could mean two doors are much more efficient than one single door that is twice as wide, in this case [88].

Another example of positive feedback is the spontaneous formation of paths by pedestrians (Figure 2.4b) [87]. Some pedestrians occasionally forge a new path as a shortcut and if noticed or visible to others this new path may be attractive to subsequent pedestrians, who further reinforce the path. This positive feedback reduces the physical and cognitive costs for pedestrians [64]. While the preceding examples suggest beneficial outcomes of positive feedback loops, they can also lead to suboptimal solutions. As shown in Figure 2.4d, if individual pedestrians tend to follow others while escaping a smoky room through two exits that are partially concealed by smoke, which can be explained by the theory of affiliation which suggests pedestrians tend to seek out the company of others during evacuations [43], then the resulting positive feedback increases the number of the crowd moving in a specific direction and causes unbalanced and thus inefficient, or even overcrowded, exit usage [85].

By contrast, negative feedback is a process when the results of an action inhibit that action from continuing to occur. It generally promotes stability and reduces the effects of perturbations. Consider, for example, a simple network, as shown in Figure 2.4d, where pedestrians have to choose either a longer route or a shorter route to reach a destination. Suppose they are more likely to choose the less busy route to lower their individual travel cost, making this preferred route busier than the other route. However, as more people choose the shorter route, it becomes congested, which incurs a time delay, making the shorter route less and less attractive compared to the longer route. As a result, the process reaches an equilibrium where there is no longer an incentive to preferentially choose either of the routes (Figure 2.4e) [228]. Figure 2.4f illustrates another example where pedestrians are distributed unevenly in a room with four exits prior to the onset of egress from this room. If each pedestrian chooses an exit based on an objective estimation of the remaining travel time, then they will initially tend to choose the nearest exit. Over time, the increasing number of people clustered around exits will cause congestion and increase the estimated travel time for exits causing pedestrians to avoid exits, even if they are nearby. As a result, pedestrians will distribute approximately evenly across the available exits (Figure 2.4g) [122]. This process reduces the total and individual egress travel time and thus leads to an effective evacuation.

2.2.4 Decision-making mechanism

Pedestrians perform trade-offs based on the evidence provided by different attributes.

So far, we have discussed how pedestrians perceive information, how they integrate it into mental representations, and how some aspects of environments are desirable and others are

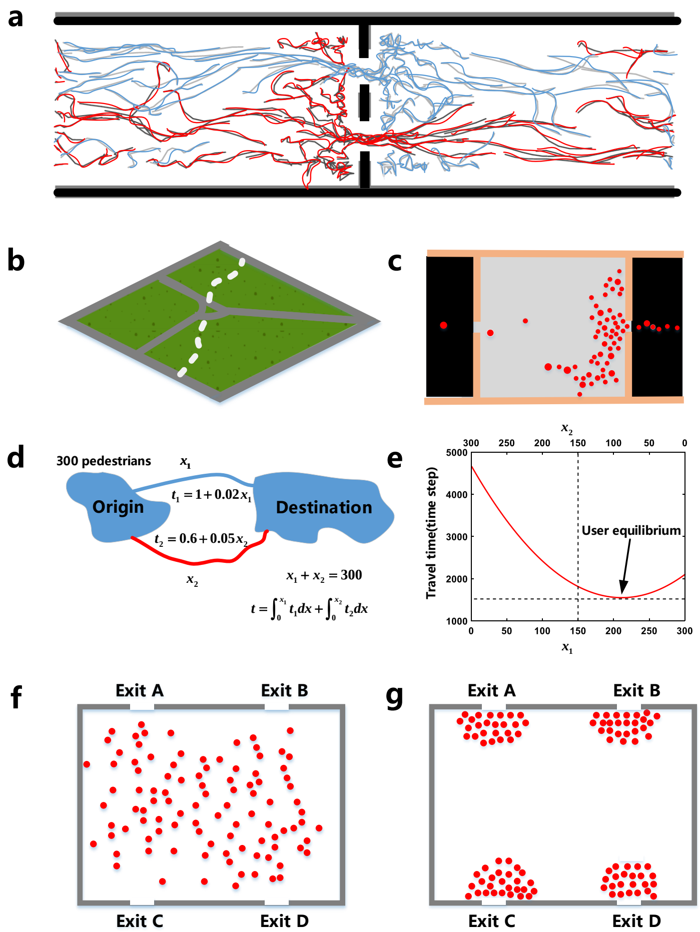


Figure 2.4: Examples of positive and negative feedback in pedestrian route choice. (a) Different door usage for pedestrian flows moving in opposite directions. (b) The spontaneous path. (c) Unbalanced exit usage caused by positive feedback. (d,e) User equilibrium caused by negative feedback in route choice. (f,g) Negative feedback of congestion can convert an initial inhomogeneous spatial distribution of pedestrians into a balanced distribution of pedestrians across exits during egress. (d,e) Examples given by the authors. (a–c,f) and (g) are redraw from [85, 87, 88] and [122], respectively.

undesirable in route choice. Now, we discuss the mechanisms by which pedestrians decide on their route. There is a consensus that if pedestrians are aware of several route options, they trade off the evidence provided by different environmental attributes associated with the alternatives when making their decision. The precise process for how this trade-off is arrived at is unknown. There are two broad theoretical paradigms that are both useful for understanding and predicting pedestrian route choice. The first can be described as utility theory. It assumes pedestrians assign a value to environmental characteristics and then choose the option with the best value, potentially subject to some uncertainty [60]. The second assumes that pedestrians do not perform such optimizations but instead rely on a repertoire of simple decision strategies or rules of thumb that are known as heuristics [62].

2.2.4.1 Utility theory

The applicability of utility theory is not solely dependent on one's understanding of utility, but also on the assumption of optimization [58]. Utility theory postulates that individuals are rational and select alternatives that maximize their expected utility. This assumption is based on the premise that individuals possess complete information and can effectively weigh the costs and benefits of different alternatives to identify the one that yields the highest expected utility. In utility models, the preference of a pedestrian for each option is assigned a quantitative value, known as a utility. The utility measures the degree to which the goals of an individual are achieved as a result of their decisions. Thus, the utility assigned to environmental features, such as exit signs, or properties of routes, such as their length, is crucial. The choice set contains all available mutually exclusive alternatives which in the context of pedestrian route choice is a finite number of options [58].

The general form of the utility function is shown in Equation 2.1.

$$U_n = V_n + \epsilon_n \tag{2.1}$$

and

$$V_n = \beta_1 X_1 + \beta_2 X_2 + ... + \beta_k X_k \tag{2.2}$$

For an alternative n, the utility U_n consists of a deterministic component V_n and a random component ϵ_n. The former is calculated by combining the utilities of separate attributes associated with alternative n. One example for this is given in Equation 2.2., where X_k is the vector of observed attribute values and V_n is expressed as a linear combination of the contribution of the k observed attributes, with a vector of utility parameters β_k that captures the relative weight of the corresponding attributes. The random component ϵ_n can be interpreted to describe lack of information or other cognitive processes in pedestrians, or it can reflect our incomplete knowledge of the decision-making processes in pedestrians, such as not knowing all factors that influence pedestrian route choice or differences between individuals. Different assumptions about the distributions of the random utility component result in different utility models. For example, in probit models, logit models and multinomial logit (MNL) models, the random components are assumed to follow a normal, logistic and extreme value (Type I) distribution, respectively [215]. Current research into pedestrian route choice using utility theory aims to establish the relative utility of route attributes via measurements or experimentally, or it develops novel models based on the concept of utility. For example, [78] conducted an experiment on stated and revealed pedestrian exit choices and estimated the utility parameters of several attributes using four mixed logit models. Their findings suggest that the spatial distance to exits, the level of congestion around exits, and the visibility of the exit contribute significantly to the exit choices of pedestrians. In a different approach, experiments are used to test the sensitivity of pedestrian route choice to changes in different attributes. For example, [19, 20] distinguish static information (time-independent), such as exit width or route length, from dynamic information (time-dependent), such as the level of congestion along different routes, and test the trade-off between these two kinds of information regarding pedestrian exit choice. An example for theoretical developments is the work by [93] who proposed a new model for pedestrian behaviour based on utility theory. In this model, pedestrians are assumed to schedule their activities, the activity areas, and the paths between the activities simultaneously to maximize the predicted utility of their efforts and walking.

Utility theory, while useful in some cases, has limitations when it comes to representing route choice decisions [36]. It often makes assumptions, such as aiming for optimal utility, that do not always align with real-world behaviour. Evidence has shown that travelers' stated-preference behaviour can violate expected utility theory in some cases, such as the Allais paradox (also known as the certainty effect) [8]. This effect is demonstrated by situations where the extreme underweighting of high probabilities makes certain (low) travel time outcomes more attractive than other options.

2.2.4.2 Heuristics

Despite their random component, utility models assume people hold knowledge of costs associated with all alternatives and perform an optimization across them. It has been suggested that this may not be an appropriate representation of the cognitive processes people perform [194, 202] called situations where people could have near-perfect knowledge 'small worlds', assuming they only occur in constrained circumstances, and argued that people are more likely to use rules of thumb or heuristics to make decisions in the 'large world' where information tends to be unknown and cannot be measured easily.

A heuristic is a decision rule that does not seek to optimize and may ignore part of the information with the goal of effort reduction. In other words, heuristics allow people to make decisions quicker and with less cognitive effort using simple rules and inferences. It has been suggested that this reflects how individuals use cognitive shortcuts to reach intuitively correct decisions [62].

A regular criticism of heuristics is that people save time and effort with a heuristic at the cost of accuracy. However, in some cases simple heuristics are more accurate than standard statistical methods that have the same or more information. When less information or computation leads to more accurate judgements than more information or computation, these results are known as

Table 2.1: Examples of heuristics identified in pedestrian route choice.

Types	Heuristics	Descriptions
	The least-decision-load heuristic	Pedestrians tend to choose the route with the least number of possible decision points.
One-reason heuristics	The least-angle heuristic	Pedestrians tend to choose the path at an intersection which is most in line with the target direction.
	The shortest distance heuristic	Pedestrians tend to choose the shortest path.
	The quickest path heuristic	Pedestrians tend to choose the quickest path.
	The least costly path heuristic	Pedestrians tend to choose the least costly path.
	The action continuation heuristic	Pedestrians tend to proceed with the current course of action, ignoring other alternatives.
Others	The initial segment heuristic	Pedestrians tend to choose the initial path with a later turn so that they don't have to turn for as long as possible along their route.
	The central point heuristic	Pedestrians tend to choose the well-known parts of a building, even if this requires detours.
	The hill-climbing heuristic	Pedestrians tend to complete easily obtainable subgoals that can be done immediately for reaching the destination.
	The fine-to-coarse planning heuristic	Pedestrians tend to divide the environment into different areas, making rough planning when navigating between areas and fine planning within a given area.

less-is-more effects [63].

Research has identified several heuristics pedestrians may use to make route choices (Table 2.1 and see [100] for a review). One type of heuristic can be described as one-reason heuristics that assume pedestrians only use one cue (principle, rule, criteria or strategy) to compare alternatives for decision making and focus on the characteristic of the route. Examples include: (1) the least-decision-load heuristic, (2) the least-angle heuristic, (3) the shortest distance heuristic, (4) the quickest path heuristic and (5) the least costly path heuristic. Other types of heuristics focus on the relationship between the route and the environment. Examples include (1) the action continuation heuristic, (2) the initial segment heuristic and (3) the central point heuristic, (4) the hill-climbing heuristic and (5) the fine-to-coarse planning heuristic.

2.2.5 Context dependency

How pedestrians perceive, integrate, respond to, and decide upon information is not fixed but varies with the context.

While the principles of pedestrian route choice we have introduced above are generally valid, the detailed mechanisms relating to each principle are not fixed but vary with the context. Differences in context can be across environments, consider typical behaviours at tourist sites and railway stations busy with commuters, or over time within environments, such as the onset of a fire alarm in an office building or students gradually becoming familiar with the building on their university campus after the start of term. In the following, we discuss the contextual factors that have received the most attention in previous research: motivational state, familiarity, social influence and individual characteristics.

2.2.5.1 Motivational state

Motivation is essential for human decision-making and motivational states are associated with different neurological mechanisms [108], which may lead to different choices when pedestrians select their route.

A good example is the route choice of tourists, commuters and shoppers. These three groups of pedestrians may consider route attributes in very different ways. Tourists for sightseeing purposes may emphasize the quality of visual attraction offered by routes that make the route entertaining or pleasant [35]. Commuters with the goal of reaching workplaces as easily as possible tend to choose the shortest possible route without inclines [72]. The route preference of shoppers varies with their motivation: hedonic shoppers like to stroll around in the shopping area while utilitarian shoppers prefer more efficient routes [107].

Another typical example is route choice in emergency evacuations where pedestrians are often under time pressure, which can give rise to a range of behavioural responses that are often described as stress. Even though stress can lead to a beneficial vigilance in information processing, higher stress levels may limit the capacity of individuals to process environmental information effectively and, therefore, ultimately lead to errors in decision making. For example, based on virtual experiments pedestrians may be more likely to select known routes and are less likely to adapt their choices, even if this leads to longer evacuation times. [17, 20, 86] considered extreme emergencies where pedestrians are assumed to transit from normal behaviour to behavioural states where they have a stronger tendency to follow others, resulting in the unbalanced usage of exits. [74] compared the attributes of pedestrian route choice in normal and emergencies, finding that under normal circumstances the distance to the exit is the dominant factor affecting pedestrian choice, while pedestrians place a much higher priority on avoiding crowded exits in an emergency.

2.2.5.2 Familiarity

Familiarity describes the spatial knowledge of pedestrians, which is acquired through experience. Human spatial memory can be distinguished into route knowledge and point and survey knowledge [6]. Route knowledge enables pedestrians to follow a sequence of connections between landmarks to reach their desired destinations without the knowledge of general interrelationships between building elements. By contrast, point and survey knowledge are related to a more general knowledge of the relative spatial positioning of elements in the environment, including awareness of their location relative to the current position of pedestrians.

Evidence from anecdotal observations and field studies reveals that pedestrians tend to follow exit routes they are familiar with and that they do not identify all available exits in fires [200] and other emergencies [13]. This preference for familiar routes can persist even when other available exits are closer [13] or others leave by a different exit [111], because pedestrians are not prepared to try an unknown route [180]. The preference of pedestrians for familiar places has been identified as an essential factor affecting pedestrian route choice [200]. One possible explanation is that people feel more comfortable in familiar spaces. The uncertainty in unfamiliar places may result in spatial anxiety, a type of anxiety about performing spatial tasks (e.g. navigation, wayfinding), which is a situation pedestrians try to avoid [174]. Furthermore, an alternative explanation is provided by prospect theory. This theory proposes that individuals tend to make decisions based on the perceived value of potential gains and losses, rather than absolute values. In the context of evacuation, this could mean that individuals may be more likely to choose familiar routes to reduce uncertainty and mitigate potential losses [164].

By contrast, when pedestrians are not familiar with an environment, they have to seek clues for their route choice. Landmarks [57], signs [184] and the movement of others [219] are specific clues, and their function in guiding pedestrians have been widely studied.

2.2.5.3 Social influence

Social influence in pedestrian route choice describes the ways in which pedestrians change their behaviours to meet the demands of a social environment. In terms of pedestrian route choice, social influence can involve the effects of social groups and strangers on the decisions of individuals.

A social group is a number of pedestrians that are connected via social relationships, such as family ties, friendship or work relationships [235]. The members of such groups tend to stay close to each other and will thus try to walk along the same route [94]. This has implications for route choice [20]. For example, groups may have to reach a consensus on which route to choose, or individuals may follow designated or emergent leaders. Such group decisions may take longer but could also help to avoid individual errors in route choice. By contrast, strangers are pedestrians that are not connected by social ties. Previous research has established that in normal situations, pedestrians who know an environment tend to avoid busy routes and thus other pedestrians. However, pedestrians tend to treat others as a source of directional information and imitate their choices to reach a destination when they lack spatial knowledge of the environment [219]. In addition, research in social psychology suggests that strangers can develop and share a social identity (sense of unity, psychological togetherness, groupness) with each other in disasters and emergencies [42]. Social identity can motivate solidarity with strangers and enables pedestrians to identify with each other as part of a psychological crowd and then help and cooperate with each other [43]. This suggests that the influence of social groups on individual route choice can extend to strangers. However, additional research is needed to support this notion.

In addition, emergent social groups can have a significant impact on individual decision-making and behaviour during an emergency. This phenomenon has been observed in real-life evacuation scenarios, such as during the world trade center attacks on 9/11, where individuals formed groups based on shared characteristics or goals, and this influenced their evacuation decisions [41]. It is also important to understand the relationships between different factors and their prevalence in specific scenarios. For instance, social influence can sometimes override the effects of other factors, such as proximity to exits or perceived safety [190].

2.2.5.4 Individual characteristics

In addition to contextual factors, individual characteristics are critical for determining which route pedestrians take. Previous studies have established that age and gender can affect the process of pedestrian route choice. Older adults have reduced wayfinding performance since spatial abilities (such as mental rotation and visualization) decline with age [39]. They tend to pick up environmental information with a higher level of saliency [127] and rely more heavily on egocentric reference frames compared to younger adults who use egocentric and allocentric reference frames equally [183]. Studies suggest that male participants prefer geometry cues related to the general shape of the environment and allocentric reference frames, while female participants use more landmark cues and prefer egocentric reference frames [28, 187]. Furthermore, pedestrians with disabilities may perform different route choice behaviours. Pedestrians with visual impairment or blindness face both physical difficulties and increased cognitive loads while navigating and cognitively mapping new surroundings. Although adept at making up for missed visual information by improving awareness of environmental cues and navigation equipment, they may have poorly organized and integrated mental representation of their surrounding [26] and may prefer to take a longer but safer route to their destination than the shortest route [94]. Mobility-impaired pedestrians may pay more attention to accessibility instead of the distance of the route from origin to destination and tend to choose the most accessible route [157].

The contextual factors listed above illustrate the diversity of contexts and their contribution to shaping pedestrian route choice behaviours. Pedestrian route choice involves the pedestrian and the context itself as well as the interactions between them. Although the principles we identified can capture the key mechanisms and cross-domain relationships in this process, the role of these scenario factors should be considered when we apply these principles to a certain situation.

2.3 Discussion

We identify principles that capture the essence of pedestrian route choice and are relevant across disciplines, and we give examples to demonstrate how these principles shape pedestrian choice behaviour. These principles are reiterated below:

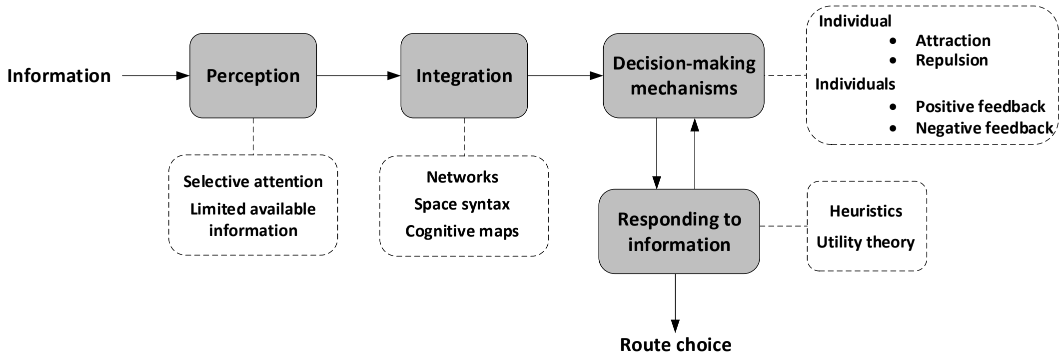


Figure 2.5: Framework for pedestrian route choice based on the principles identified here. Decision stages are shown as grey boxes. Arrows indicate the direction in which pedestrians process information, and boxes with dashed boundaries includes details on the principles we identified for each decision stage.

1. Pedestrians can perceive information selectively and purposely, given limited available information.
2. Pedestrians integrate environmental spatial information into mental representations with subjectivity.
3. Pedestrians tend to be attracted and repelled by specific attributes individually and this can lead to positive or negative feedback loops across many individuals.
4. Pedestrians perform trade-offs based on the evidence provided by different attributes.
5. How pedestrians perceive, integrate, respond to and decide upon information is not fixed but varies with the context.

Figure 2.5 illustrates a framework for the route choice decision-making process and it relates to the principles we identified here. The route choices of individual pedestrians involve behavioural and physiological mechanisms related to information perception, information integration, responding to information and making decisions. All stages and mechanisms involved in this process can be affected by the context. The four decision stages shown in Figure 2.5 and the processes associated with them can occur in sequence or simultaneously. For example, when pedestrians make decisions, they are still constantly perceiving new information and thus update their spatial mental representations. However, for a single route choice, pedestrians may process information according to the steps shown in Figure 2.5 in sequence, and each stage depends on the previous stage until this route decision is completed (except for interdependent decision-making mechanisms and responding to information). Processes and mechanisms relevant to each stage can be described using the principles identified here.

These proposed principles are reflected in models that researchers have developed. For example, the knowledge-based routing model in [30] constructs a personalized cognitive map for navigation by using individual spatial memory and provided environmental information. This process can be associated with the second principle. Suppose we apply concepts of selective information perception from the first principle to this model. In that case, individuals may only perceive part of the available information for the creation of cognitive maps. In this way, our framework provides a reference point for assessing which aspects of behaviour can be added to existing or new models. The protective action decision model, a multistage model that provides a structured approach for individuals to evaluate potential risks and benefits associated with different protective actions during emergency evacuations [136], can be further strengthened by integrating this framework and identified principles. Developing new models is one of the possible uses of our framework. However, we suggest its main usefulness is different and discuss this below.

Much research into pedestrian route choice focusses on specific settings and does not consider aspects that are not immediately relevant to the research question investigated. While this reductionist approach forms an important part of the knowledge generation process and may be entirely appropriate to describe behaviour in fixed settings, such as carefully controlled experiments where participants are exposed to different stimuli in the same scenario, it is important to acknowledge the limitations of this approach. For example, a utility model can have an excellent performance in pedestrian route prediction even if selective information perception or/and feedback, the first principle we discussed, is not included in the model. However, such a model may not be useful for scenarios where pedestrians can only perceive limited information. We do not suggest that the principles we identify here provide a route to establish a universal model for pedestrian route choice. Instead, we suggest that our contribution provides a framework for considering which aspects of pedestrian route choice are accounted for in a given model.

From the perspective of managing pedestrian facilities during events or emergencies, it is desirable to be able to predict or even control the route choice of pedestrians to minimize uncertainty and to maximize evacuation efficiency. Our principles provide a theoretical basis for developing route choice control or route guidance strategies. For example, taking the first principle as a starting point would suggest to selectively highlight information about particular routes. Alternatively, based on the third principle, routes could be made more attractive by changing their attributes, such as lighting or signage, or, based on the fifth principle, pedestrians could be made familiar with routes in a targeted way, as already happens on passenger airplanes. While many of these approaches are already being used or considered, we suggest that our principles provide a framework to structure and contrast strategies.

More generally, we suggest the usefulness of our principles is that they provide a frame of reference that can be used to catalogue, contrast and analyse existing and planned research on pedestrian route choice. The broad behavioural mechanisms we identify facilitate abstracting from the details of behaviours observed and contexts investigated in individual studies. As such, they provide an ideal basis for categorizing and comparing existing work and for researchers to examine to what extent their planned work is already covered in the existing literature. For example, a large body of research focuses on how pedestrians respond to specific types of information during evacuation, and if researchers categorize their work into the third principle of our framework, they can find other similar research to avoid duplication of work and find potential reasons to interpret differences in results by comparing to other work. Alternatively, as discussed above, in transportation research there are many studies that investigate the attractiveness of route characteristics in experiments or from observations, but much fewer studies investigate the second principle, subjective mental representations of environments, which possibly influences human route choice and is worth further investigation. Our principles also provide a structured theoretical starting point for interpreting or explaining observed behaviours. For example, if it is observed that pedestrians completely avoid an available route, we suggest it is useful to structure the search for an explanation by considering our principles in turn. For example, it is possible that, based on the first principle, participants selectively ignore the information provided by the researchers, or based on the fourth principle, they choose their route according to specific heuristics, disregarding other options. It may be that future research identifies principles in addition to the ones we discuss here. This would be a clear indication of how our understanding of pedestrian route choice extends.

Technological and methodological innovations will continue to facilitate research into pedestrian route choice. We suggest that four technologies in particular will shape this field of research in the coming years: virtual reality, wearable sensors, machine learning and theory-based approaches for large data. Separately, and in combination these tools will allow examining the principles of pedestrian route choice in unprecedented breadth and detail. In virtual reality experiments participants interact with a highly controlled immersive virtual environment [182]. The fact that experimenters can control precisely what information is available to participants who may be near-stationary (e.g. on a treadmill) opens up the possibility to investigate detailed questions on what environmental features pedestrians attend to, possibly linked to neurological activity, and how different route attributes are traded off. While this experimental paradigm is already widely used and accepted in pedestrian behaviour research, a drawback is that its ecological validity should be considered carefully [143]. By contrast, increasingly available wearable sensors can continuously record the position, as well as physiological and neurological activity of pedestrians [51], making it possible to examine route choice in field studies where behaviour can be observed outside of experimental settings. Both of these approaches result in large quantities of data that has to be examined for relevant patterns. Machine learning can consume and process unstructured data and automatically determine the features that distinguish different categories of data from one another [193]. Thus, in combination with the other tools we expect machine learning will help researchers discover pedestrian decision-making patterns and determine more principles that influence human behaviour. Theory-based approaches involve using theoretical frameworks to analyse and interpret large datasets, which can help identify patterns and relationships in data that might not be immediately apparent [148]. These approaches have numerous benefits for analysing large datasets, including the ability to make predictions based on identified patterns and relationships. This makes theory-based approaches particularly suitable for investigating pedestrian route choice, which involves numerous variables.

Pedestrian route choice is a highly interdisciplinary topic. Researchers from different disciplines are contributing to it by applying the methodologies and theoretical frameworks of their discipline. We argue our principles provide a general theoretical framework that facilitates bridging across disciplines.

CHAPTER 3

IMPACTS OF MOVEMENTS OF THE CROWD ON PEDESTRIANS ROUTE CHOICE

This chapter investigates how pedestrians respond to the movements of others, seeking to answer **RQ2** and its associated sub-questions in Section 2.1. This work starts with a general background of responses of pedestrians to environmental information (Section 3.1) and identifies spatial knowledge, crowd state and crowd split as essential contextual factors affecting the impact of crowd movements through a literature review (Section 3.2). Section 3.3 presents a virtual experiment to investigate how individuals respond to the movement of others in scenarios associated with identified contextual factors and the results are described in Section 3.4. These sections are linked to **RQ2.1** and **RQ2.2**. Additionally, Section 3.4 provides a simulation study that aims to explore the consequences of the findings obtained from the experiments. Finally, Section 3.5 discuss the main findings and opportunities for future research.

The work presented in this chapter has been published in Safety Science: Y. TONG AND N. W. BODE, *An investigation of how context affects the response of pedestrians to the movement of others*, Safety science, 157 (2023), p. 105919 [223]. A video of the virtual environment can be found in this paper. All data collected for this study is openly available at the University of Bristol data repository [1].

3.1 Introduction

Pedestrians are often faced with a choice between route alternatives in emergencies. Making efficient and effective spatial decisions is the key to protecting pedestrians from disasters. In order to make such a decision, pedestrians require to perceive all possible directional information,

[1] University of Bristol data repository: https://doi.org/10.5523/bris.3kn82h2aamsfw2eplor4v2ewk0

especially when they have little knowledge about their surrounding. Therefore, identifying the attributes affecting pedestrian decision-making and exploring their influence on human exit choice has become a central task for understanding human evacuation in buildings.

Research on pedestrian exit choice reveals the role of environmental attributes in the process of decision-making of pedestrians, especially what has been described as static information (e.g. building layout and placement of evacuation signs) [124, 141] and dynamic information (e.g. movements of the crowd) [168]. In emergencies individuals respond to the behaviour and in particular the movement of others, making crowd evacuations an example of social behaviour [40]. This social context influences pedestrian dynamics at different spatio-temporal scales, including, for example, both the tactical level (pedestrian decision on where to go) and the operational level (e.g. small-scale pedestrian decisions to avoid collisions) [195]. At the operational level, pedestrians may show competitive or cooperative behaviours [43]. For example, a pedestrian may try to overtake others or even push others in high-density situations [94]. In other cases, pedestrians may help others [18] or simply walk together [94]. In contrast to this work at the operational level, how pedestrians respond to others at the tactical level, the focus of this contribution, has not been investigated at the same level of detail.

Previous work on the responses of pedestrians to the movement of others has produced diverse results. In pedestrian dynamics models, pedestrians are often assumed to have a tendency to follow others [85, 145]. This can reduce pedestrian evacuation efficiency because the effectiveness of the exit is not fully utilised due to unbalanced exit usage caused by following behaviour [80]. Other modelling work suggests this tendency can be beneficial, as moderate degrees of following behaviour can help optimise the evacuation system and shorten evacuation times [117]. In contrast, some studies assume pedestrians display a behaviour opposite to following - they try to avoid others when making exit choices [138, 245]. In addition, in exit choice models that can describe heterogeneity among pedestrians, pedestrian exit choice is assumed to be influenced by individual characteristics such as demographic variables [205] and individual cognition [131], and thus whether the individual follow others or not varies among the crowd. For example, [212] employ the degree of rationality to determine the tendency of following others.

Similar to the various assumptions made in models, empirical findings on how pedestrians respond to the movement of others are diverse. Some studies found that the direction preferred by a majority does not have a significant effect on human exit exit choice in isolation but that it can be relevant combined with other factors [19, 77]. Other research found that pedestrians spontaneously tend to follow others [219] and it has been suggested that this tendency gets stronger as stress levels increase [163]. Following behaviour is also observed in pedestrian evacuations under zero visibility conditions [69]. However, other empirical evidence suggests that instead of following others, pedestrians prefer to search for an alternative exit and avoid smoke when faced with a fire [128]. It has also been suggested that pedestrians are more likely to follow the minority and that increased stress levels or crowding amplifies that behaviour [81].

[140] suggest that pedestrians follow the minority in order to minimise their evacuation time.

Most previous research considers the movement of others only as one factor amongst other attributes relevant to pedestrian exit choice. An exception is the study by [75] which centres on whether pedestrians follow or avoid a crowd in an emergency via a human crowd experiment. This work reveals whether participants follow the crowd or avoiding it depends significantly on their knowledge about the route chosen by the crowd. The experiment simulates a crowded condition and additional stress is only imposed on participants via the notification about an emergency. Therefore, this work can explain the influence of crowds on pedestrian exit choice in specific scenarios. However, how pedestrians respond to the crowd in other contexts, especially where the crowd has various conditions, as mentioned above, has not been examined comprehensively.

The preceding discussion highlights the importance of further empirical research on how people respond to the movement of others in various contexts. In this contribution, we use a virtual experiment to investigate the effects of contextual factors on pedestrians' response to the movement of others. Virtual experiments permit a highly controlled setting and this experimental paradigm has been used widely and is well-accepted in pedestrian behaviour research [115, 185], even though the ecological validity of such experiments should be considered carefully [143]. There are several virtual reality technologies with different characteristics for pedestrian exit choice, such as desktop VR, head-mounted display (HMD) and cave automatic virtual environment (CAVE) [55]. We use desktop VR in this work due to the following reasons. Firstly, it is a cost-effective solution for data collection. Secondly, participants can take part remotely, which increases accessibility and reduces logistical challenges. Additionally, desktop VR allows for the collection of large amounts of data in a controlled and repeatable environment, which is important for ensuring the validity and reliability of the results. Moreover, desktop VR enables researchers to simulate a wide range of scenarios and manipulate variables with precision, which may be difficult or impossible in real-world evacuation studies. This provides researchers with a unique opportunity to gather high-quality data. Previous research has consistently shown that pedestrians exhibit similar exit choices when presented with a set of alternative exits in virtual environments, regardless of the virtual reality method used to implement them, suggesting the validity of desktop VR [55, 129, 189]. While many contextual attributes may affect pedestrian behaviour, we select the three essential factors identified and discussed below and investigate their primary influence and interactions on pedestrian exit choice.

To further demonstrate the implications of our findings, we conduct simulations of a simple model for pedestrian dynamics in a facility with two exits. We propose a model in the framework of mathematical queuing theory [199]. It consists of arrival process which describes the properties of pedestrian arrival, exit choice process which illustrates pedestrian exit choice at the strategy level and service process which captures the interactions between pedestrians at the operational level by using the fundamental diagram for pedestrian dynamics.

The remained of this contribution is structured as follows. First, we review relevant work on how contextual factors affect pedestrian exit choice. Then, we describe our experiment and data collection. Finally, we present our empirical findings and introduce our model, before discussing our results.

3.2 Literature review

The discussion above suggests that how pedestrians respond to the movement of others when deciding where to go may depend strongly on the specific context. Based on the literature, we identify three essential contextual attributes: spatial information about the location of exits, the size of crowds in a given setting, and the distribution of individuals across exits. In the following, we discuss previous findings on these attributes. Moreover, we review the role of stress and socio-demographic factors in pedestrian exit choice.

In terms of spatial information, pedestrians are reported to prefer familiar exits [199]. Two examples from the literature suggest pedestrians prefer not to follow others when they have sufficient or informative spatial information about the environment they are in. In the first example, previous work found that most pedestrians treat other people as potential sources of congestion and additional delay and thus try to avoid crowds when there is little uncertainty about where exits are (e.g. when all exits are visible). However, if the uncertainty increases (e.g. either exit becomes invisible), pedestrians prefer the direction of the majority [75–77]. In the second example, experimental work suggests that pedestrians who tend to follow others in the absence of additional information are more likely to choose the direction indicated by exit signs when these are visible [219].

Considering the size of crowds in a given setting, this can directly affect congestion levels and associated queue shapes, such as approximately straight line queue [140], arched congestion around an exit [20], and no congestion near exits [219]. Such visible differences in queues may affect the exit choice of pedestrians and it has been suggested that pedestrians prefer faster-moving queues [20]. [116] found participants show different tendencies to follow others when the crowd size changes, indicating that the size of crowds may play an essential role in pedestrian exit choice. In terms of the distribution of individuals across exits, the uneven split of individuals across exits is commonly used for testing whether participants follow the majority or the minority [19, 133]. Some studies investigate the influences of different split levels of the crowd and have diverse results. [142] found that participants tend to choose less crowded exits, and the greater the difference in the number of simulated pedestrians between the two exits, the less likely participants are to follow the majority. In contrast, [116] find a non-linear relationship between crowd proportion and exit choice and suggest that whether pedestrians follow the majority is influenced by both crowd size and crowd proportion. Most importantly for this work [116, 142] found that when all people choose the same exit and leave the other exit unused, pedestrians are more likely to follow the crowd.

Previous work has established that individual characteristics are critical for determining which exit pedestrians choose (see [221] for a review). Socio-demographic factors are essential aspects of individual characteristics and have been extensively studied. For example, it has been suggested that female participants are more likely to follow the crowd than male participants [187]. Students are less predisposed to show following behaviour compared to other groups [142] and participants from different cultural backgrounds do not show significant differences regarding following behaviour [133]. Moreover, the influences of other socio-demographic factors such as age, income, ethnicity and occupation, have been investigated [11].

Time pressure or other factors that lead to behavioural or physiological responses commonly described as stress present additional important contextual factors that have been identified in previous work [17, 163]. Stress can increase the vigilance of pedestrians and may be beneficial for evacuations. For example, [82] found that compared to low urgency conditions, high urgency conditions can trigger a more instant response and faster rush to exits, resulting in shorter individual and total evacuation times. In contrast, other studies found that as the level of stress increases, it may impair pedestrian information processing ability and thus pedestrians may make decisions that are far from optimal at both the individual and group levels. For example, pedestrians tend to choose the familiar exit rather than the closer one under stress, which can be detrimental to their evacuation time [17]. However, in this work we have not investigated stress. A key problem in investigating this is the experimental difficulty of achieving consistent and desired participant responses or stress levels in virtual environments. In previous work, participants were informed of an emergency via a message [133, 140], or they were given an evacuation order or signal [75]. Some studies impose additional stress by imposing time limits [17], monetary penalties, or by implementing stress-inducing elements in the virtual environment, such as lower luminosity and flashing lights [163]. However, the validity of such methods to impose stress has been questioned, because participants are aware that they are moving and acting within a virtual environment, facing no real danger [53]. Therefore, we suggest further work should be done to investigate pedestrian exit choice in contexts with different stress levels, combined with data from a real-life environment where pedestrians have no or little knowledge of being tracked and are thus more likely to behave more naturally.

3.3 Experiment

3.3.1 Virtual environment

We conducted a virtual experiment with human participants to investigate whether pedestrians would follow other pedestrians when making exit choices in different contexts. Participants had a three-dimensional first-person view of a virtual environment and could control the movements of an avatar by using the arrow keys on the keyboard to move forward and backwards, turn left and right. The presence of the virtual pedestrian allowed participants to identify their position in the

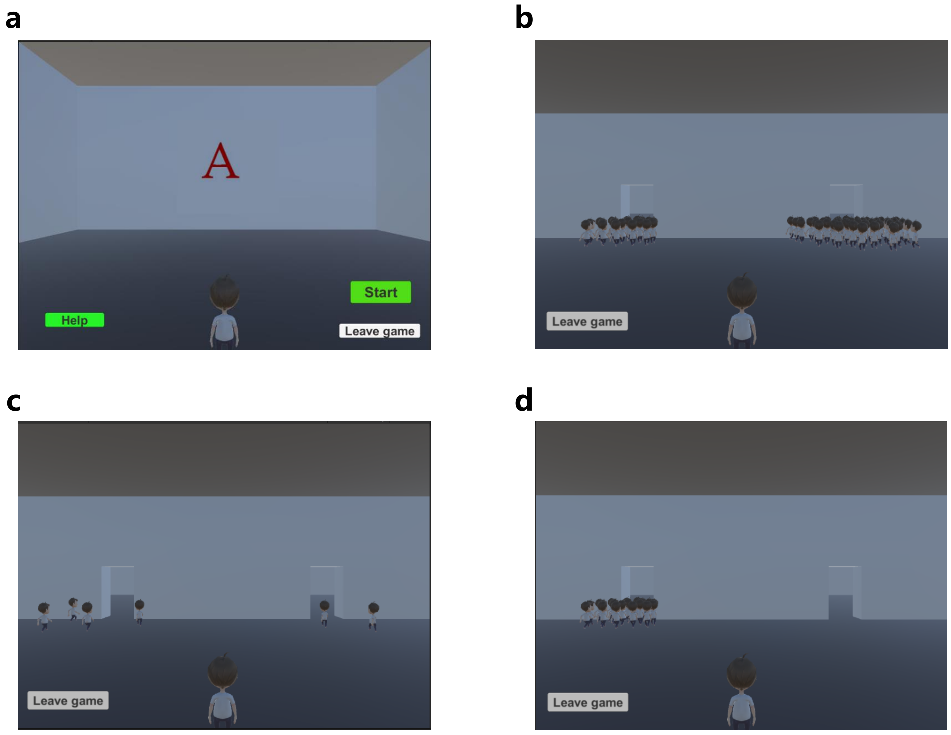


Figure 3.1: Still images of the virtual experiment as seen by participants on screen for the training phase (a) and for the exit choice phase (b)-(d). We show different experimental conditions: uneven split of the crowd in the busy state, where there is congestion in front of both exits (b), and the free state, where there is no congestion (c), and an example for a 0-1 split of pedestrians across exits, where one exit remains unused (d).

room and relative position to other pedestrians. Our experiment consisted of a training phase and a exit choice phase. In the training phase, participants could move freely within a room to familiarise themselves with how to control the movement of the avatar. In the exit choice phase, participants had to complete a simulated evacuation under one of the experimental conditions, which were designed to introduce different contextual factors, as discussed in detail below.

The virtual environment was implemented in Unity 3D (Version 2020.3.20f1). The avatar controlled by participants and the virtual pedestrians were animated using the same Unity Character Pack (sample Sam, Version 2.0.0) (Unity, 2020), to reduce the possible influence of virtual characters on participant exit choice. The walking and rotation speeds were set to 1.7m/s and 80 degrees per second, respectively. A video of the virtual environment can be found in Appendix.

In the training phase, participants received instructions on how to control the avatar by using the keyboard and could move freely inside a square room. Landmarks, letters from the Latin alphabet, were shown on the four walls of the room, so that participants had a clearer perception of controlling the avatar in terms of movement direction and speed (see Figure 3.1a). Participants

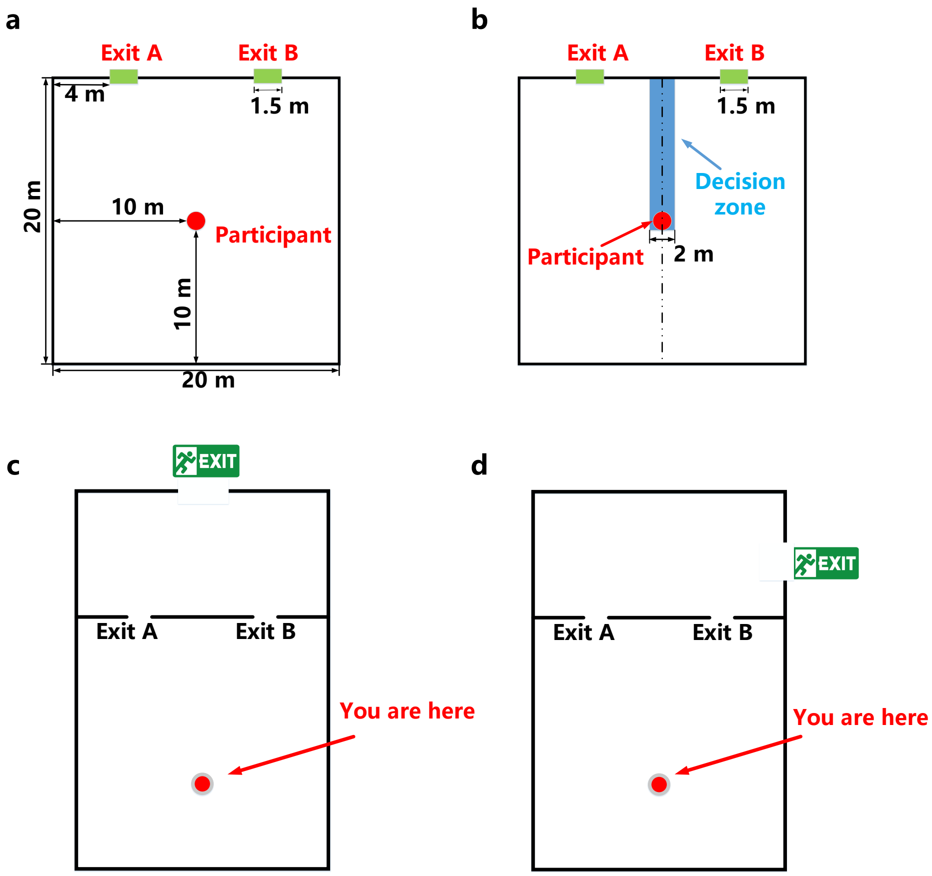


Figure 3.2: Map of the virtual environment for the exit choice phase (a). Map indicating the positioning and extent of the decision zone defined for this study (b). Maps shown to participants before the start of the simulated evacuation with equal exit utility (c) and biased exit utility where the right door has a higher utility, as it is closer to the indicated exit (d).

only moved on to the exit choice phase when they confirmed they were confident in being able to control the avatar movement. We did not record the movements of participants inside the virtual environment during this training phase.

In the exit choice phase, the avatar controlled by participants was situated inside a room with two exits and it was facing these exits. Figure 3.2a shows the starting point of the avatar and the layout of the room. Participant avatars were positioned equidistant from both exits and at a sufficient distance from exits to ensure participants could fully see both exits and the area immediately in front of the exits before they started to move (see Figure 3.1b-d for examples). Participants received the following instructions at the start of the exit choice phase and before they could start to move the avatar: “Suddenly, there is a fire alarm, please go to the exit as quickly as possible". Participants would see simulated pedestrians evacuating through the exits, as described below, and were thus faced with a choice between the two exits. Once participant

Table 3.1: The number of simulated pedestrians using each exit for each of the 36 experimental conditions (16 conditions with an uneven split of pedestrians between exits, 16 conditions that switch the imbalance between exits compared to the previous set, and 4 conditions with an even split of pedestrians across exits).

Variables				Original scenario		Mirror scenario	
Spatial information		Crowd state	Split level	Left exit	Right exit	Left exit	Right exit
No information		Busy	Uneven	20	40	40	20
			0-1 split	20	0	0	20
			Even	20	20	\	\
		Free	Uneven	2	4	4	2
			0-1 split	2	0	0	2
Map with equal exit utility		Busy	Uneven	20	40	40	20
			0-1 split	20	0	0	20
			Even	20	20	\	\
		Free	Uneven	2	4	4	2
			0-1 split	2	0	0	2
Map with biased exit utility	Left exit has a higher utility	Busy	Uneven	20	40	40	20
			0-1 split	20	0	0	20
			Even	20	20	\	\
		Free	Uneven	2	4	4	2
			0-1 split	2	0	0	2
	Right exit has a higher utility	Busy	Uneven	20	40	40	20
			0-1 split	20	0	0	20
			Even	20	20	\	\
		Free	Uneven	2	4	4	2
			0-1 split	2	0	0	2

avatars reached the outside of one of the exits, the exit choice phase and therefore the experiment ended. This phase was designed to investigate the influence of contextual factors on pedestrian exit choice. The movements and exit choices of participants in the virtual environment were recorded during this phase.

3.3.2 Experimental design

We adopted a factorial experimental design with three between-subjects variables that we refer to as: spatial information (what information participants have about the exit routes), crowd state (whether the size of the crowd causes congestion) and crowd split level (how simulated pedestrians are distributed across exits). Participants were randomly assigned to an experimental condition that represented one of three types spatial information, two crowd states and three crowd split scenarios. We employed a between-subject design to prevent potential learning effects that could arise in a within-subject design. When the same participants are exposed to different conditions or treatments, they may become more familiar with the experiment, leading to biased results.

For the variable of spatial information, participants were provided either with no spatial information or with information provided via a map indicating building exit locations before they started to move. If a map was provided, it showed the relative position of the exits of the room where the participant avatar was positioned to the final destination of participants, an exit marked with an exit sign. Participants saw one map out of a set of three maps that all suggested different room exit utilities: a map where both room exits were equidistant from the final exit (equal exit utility, see Figure 3.2c) and maps where the left exit or right exit was closer to final exit (biased exit utility, see Figure 3.2d for an example). The spatial information variable was thus used to establish how the existence of spatial information and exit utility influence pedestrians' response to the movement of others.

The crowd state variable indicated the congestion level of simulated pedestrians around the exits and could take the values referred to here as busy or free. In the busy state, the simulated crowd would cause congestion at the exits and participants were expected to wait before they could go through their preferred exit. In the free state, the simulated crowd was small and would thus not hinder the movement of the participant. We implemented the different states by changing the number of people around the exits. The crowd size chosen for our experiment needed to meet the following conditions: (1) The crowd should not completely obstruct participants' view of exits, especially when the crowd size is large. (2) The difference between two levels of crowd size in each state should allow participants easily and quickly to identify the exit used by the majority. After testing, we allocated 20 or 40 simulated pedestrians to exits in the busy state (see Figure 3.1b for an example), and 2 or 4 simulated pedestrians to the exits in the free state (see Figure 3.1c for an example). The movements of the simulated crowd were under the control of Unity's physics engine, which allowed them to move, react to collisions with each other and form congestion in a physically realistic way. The crowd state variable was used to test whether the response of pedestrians to the crowd is affected by congestion levels.

For the crowd split variable, we implemented three ways in which simulated pedestrians were distributed across exits: even or uneven split (see Figure 3.1b-c for examples), and what we refer to as 0-1 split, where all simulated pedestrians present used one exit (see Figure 3.1d for an example). An even split implied that the same number of pedestrians used either exit. An uneven split meant that different numbers of simulated pedestrians used the two exits (2 and 4 in the free crowd state or 20 and 40 pedestrians in the busy crowd state). The crowd split variable was designed to investigate how the distribution of other pedestrians across exits affects pedestrian exit choice.

To establish whether participants have an innate preference for choosing the left or right exit, we implemented mirror versions of all experimental conditions considering how simulated pedestrians were distributed across exits and the information provided about exits (see Table 2.1). Assuming that an even split of simulated pedestrians across exits was uninformative for exit choice, we only implemented a busy crowd state for this experimental condition but varied the spatial information. As a result, 36 experimental conditions were implemented, as shown in Table 2.1.

3.3.3 Data collection and analysis

We recruited participants using the online platform Prolific[2] between the 24th and the 28th of October 2021. Participants received a payment of £0.9 per person (equivalent to £7.5 per hour based on the estimated completion time). Participants had to download an executable file for the virtual experiment to their computer and submit an output file via Typeform [3], a website that provides online survey services. The experiment file could only be executed once. All participants were briefed on the broad purpose of the experiment. Ethical approval for our experiment was granted by the Ethics Committee of the Faculty of Engineering at the University.

A total of 1178 participants signed up for our experiment on Prolific. Six-hundred participants completed their submission, 507 participants decided to leave the experiment early, and 71 participants exceeded the maximum time allowed without completing their submission. Of the 600 participants who completed the experiment, 53 participants failed to upload the correct output file. Therefore, the data from 547 participants were analysed. Table A.1 in the appendix shows details on the sample size for each experimental condition. It has been observed that a significant proportion of participants who sign up for the experiment withdraw before its commencement. One potential reason for this could be that they realize it is not suitable for them after reading the detailed instructions, such as the requirement to use a Windows computer to complete the experiment.

Reported ages ranged from 18 to 35 years, with a median, average age and standard deviation age of 23 years, 24.6 years and 5.8 years, respectively (5 participants (0.9%) did not disclose their age). The gender distribution of participants included 234 female participants (56.75%), 307 male participants (43.25%) and 6 participants who either did not want to disclose gender information or did not subscribe to either of the aforementioned gender categories.

To assess participant behaviour quantitatively, we defined α as the ratio of decision time to the total finishing time of participants. The decision time was the time the participant spent in the decision zone where we assumed that the participant had not chosen an exit yet. The horizontal distance from the starting position of the participant to each exit was 4.5m, and we selected the band within 1m of the horizontal distance from central axis of two exits as the decision zone (see Figure 3.2b). We use a ratio for the decision time rather than a direct measurement to account for differences between pedestrians in terms of their speed of movement inside the virtual environment. For example, participants more used to this type of virtual environment may move faster on average both overall and whilst making their decision. We used generalised linear models (GLMs) for data analysis and confirmed the appropriateness of these models by examining residual plots.

[2]Prolific: Online participant recruitment for surveys and market research URL: https://prolific.co/, accessed 24 November 2021

[3]Typeform: People-Friendly Forms and Surveys. URL: https://www.typeform.com/, accessed 24 November 2021

3.4 Results

We first examined whether participants had an innate preference for choosing the left or right exit. Table A.2 in the appendix shows Chi-squared tests on differences in exit choice between mirrored scenarios. No significant differences were found. This suggests that participants did not show an innate left or right preference. We thus combined all data in the following analysis and did not account explicitly for whether left or right exits had higher utility or were used by larger numbers of simulated pedestrians.

3.4.1 Context determines following behaviour

Table 3.2: The effect of α (proportion of overall time in decision zone), gender, and contextual factors on whether pedestrians follow the majority of simulated pedestrians. Positive parameter estimates indicate that it is more likely that people choose the exit used by the majority. P-values less than 0.05 are shown in bold. The last entry, 'Crowd state : 0-1 split' indicates an interaction term.

Effect	Estimate	SE	F	P
Intercept	-1.4083	0.3286	-4.2855	$\mathbf{1.8232}\times10^{-5}$
Crowd state (busy)	-0.4203	0.3320	-1.2658	0.2056
0-1 split	1.1522	0.3037	3.7943	**0.0001**
No map	0.3967	0.3097	1.2809	0.2002
Map with a higher utility exit the majority choose	0.6176	0.3089	1.9992	**0.0456**
Map with a lower utility exit the majority choose	-0.6593	0.3464	-1.9035	0.0570
Gender (female)	0.5749	0.2004	2.868	**0.0041**
Crowd state (busy) : 0-1 split	-1.0350	0.4574	-2.2630	**0.0236**

We next investigated how contextual factors affect whether pedestrians follow the crowd. We used a generalised linear model with Binomial error structure and logit link function for our statistical analysis. The response variable was a Boolean indicating whether participants chose the exit more simulated pedestrians used (value 1) or not (value 0). The categorical explanatory variables included in the model were an intercept, the different levels of spatial information (with a map showing equal exit utility being the baseline absorbed in the intercept), and Boolean variables indicating the gender of the participants (0 for male, absorbed in the intercept; 1 for female), crowd state (0 for free, absorbed in the intercept; 1 for busy) and 0-1 split suggesting whether all simulated pedestrians chose to the same exit (0 for no, absorbed in the intercept; 1 for yes).

Our statistical analysis (see Table 3.2) shows that on average, in the absence of other factors, participants had the tendency to avoid the exit the majority selected (negative intercept estimate). However, when all simulated pedestrians chose the same exit, this trend was reversed (0-1 split parameter estimate). Considering the spatial information provided, we could not rule out that showing no map to participants had no effect, compared to a baseline of participants seeing a map suggesting equal exit utility (p-value for 'No map' parameter). This can be explained by the fact that not seeing a map may have increased the uncertainty of participants (see also below), but it did not provide them with directional information. When one exit had a higher utility, participants tended to follow this information, even when it meant they then had to follow the majority of simulated pedestrians. Depending on the significance threshold chosen, the case when the exit used by the majority of simulated pedestrians also had a lower utility may not have an effect ($p = 0.0631$). Nevertheless, these results suggest that exit utility is important in directing exit choice behaviour of pedestrians, as expected.

We found that an interaction term between crowd state and 0-1 crowd split improved model fit. This indicates that the effect of the crowd state and the 0-1 crowd split were linked. When all simulated pedestrians in the busy state selected the same exit, participants were less likely to choose the exit the crowd preferred. Considering the relative size of estimated parameters this suggests that the 0-1 split effect is substantially reduced if there is congestion. However, on its own, congestion did not have a clear effect on exit choice in our experiment (Crowd state, $p = 0.1712$). This suggests that when the crowd is unevenly split across exits and both exits are used, participants were affected by the relative split across exits rather than the number of simulated pedestrians or congestion levels in our experiment.

We found that gender had a statistically significant effect on the exit choice of participants. Female participants were more likely to follow the majority than male participants, an effect that has been observed in previous work[187]. We suggest that such gender effects need to be treated with caution, however, as we did not control for additional individual characteristics in our participant sample, such as training, professional or cultural background, which could also explain this finding.

3.4.2 Uncertainty increases decision times

Table 3.3: The effect of contextual factors on α, the proportion of time participants spend inside the decision zone. Positive parameter estimates indicate that people spend more time in the decision zone. P-values less than 0.05 are shown in bold.

Effect	Estimate	SE	F	P
Intercept	0.2799	0.0183	15.285	$\mathbf{4.2186}\times10^{-44}$
Crowd state (busy)	-0.0024	0.016	-0.1489	0.88174
0-1 split	0.0634	0.0158	4.0068	$\mathbf{7.0177}\times10^{-5}$
No map	0.0521	0.0199	2.623	**0.009**
Map with a higher utility exit the majority choose	0.0694	0.0221	3.1439	**0.0018**
Map with a lower utility exit the majority choose	0.0182	0.0216	0.8422	0.4

The quantity α is an approximate measure to indicate the length of time participants take to make their exit choice and it could thus give insights into the decision-making process. We used a generalised linear model with Normal error structure and identity link function to investigate how contextual factors affect pedestrian decision time ratio. The response variable was α, the ratio of decision time of participants to the total evacuation time in the experiment. Explanatory variables were an intercept, the different types of spatial information provided, crowd state, and 0-1 split, which were all implemented as previously described for the analysis of participants' exit choices.

We found that on average participants spent just under a third of the total time it took them to complete the evacuation task inside the decision zone (intercept= 0.2799, see Table 3.3). This time increased when all simulated pedestrians selected the same exit, when participants were not presented with a map, or when they were presented with a map suggesting higher exit utility for the busier exit (see Table 3.3). We suggest that a possible explanation for these findings is that each of these three factors is likely to increase the uncertainty of participants about the environment compared to the other scenarios. Faced with higher uncertainty, participants required more time to process the decision making, leading to a larger α in these cases.

3.4.3 Exploring implications of the findings via simulations

Our experiment reveals that participants had an innate preference to avoid the busier exit but also that this trend was reversed when one exit remained unused and there was no congestion (0-1 split and the crowd is in the free state). We refer to this change in following behaviour "split effect". To further explore the implications of this effect on pedestrian exit choice we propose a model based on queuing theory[199].

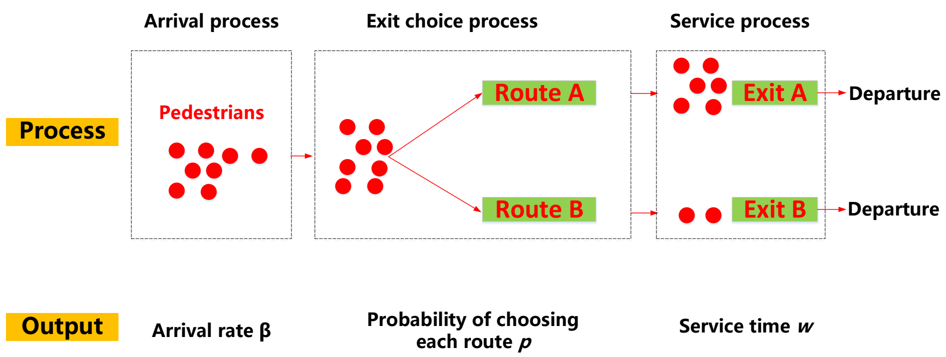


Figure 3.3: Description of the queuing model for pedestrian exit choice between two possible routes.

In this model, the journey of pedestrians from arrival to departure is described as a queuing system as shown in Figure 3.3. Pedestrians first arrive with a specified arrival rate (β), determined by the assumption of the arrival process, and then choose one of several routes according to the probability p in the exit choice process. If more than one pedestrian chooses the same route, the time it takes then to pass through the exits is modelled akin to the service process in queuing models, parameterised via the service time, w, that indicates the time cost incurred by pedestrians. We describe the arrival process, exit choice process and service process in detail below.

Arrival process We assume that the arrival of pedestrians can be described as a Poisson process, a common assumption in queuing theory [15]. The Poisson process implies that (1) pedestrians arrive one at a time (2) the probability that each pedestrian arrives at any time is independent of when other pedestrians arrived and (3) the probability that each pedestrian arrives at a given time is independent of the time. These assumption have been verified empirically to approximately represent many real unscheduled arrivals[68]. In terms of our application, these assumptions imply that pedestrians do not arrive in groups and that there is no underlying scheduling process for arrivals, such as the arrival of trains at stations of a perfectly synchronised departure following an alarm during emergencies. Equ.3.1 describes the probability of the number of arrivals in any given time period $N(t)$ which follows a Poisson distribution where β is the arrival rate representing the expected number of arrivals per unit time. In this work, we characterise the Poisson process by setting the time between consecutive arrivals, called the inter-arrival time (I) to have an exponential distribution [188], as shown in Equation 3.2.

$$Probability\{N(t)=n\} = \frac{e^{-\beta t}(\beta t)^n}{n!} \tag{3.1}$$

$$Probability\{I \leq t\} = 1 - e^{-\beta t}. \tag{3.2}$$

where n is the number of arrivals, I is the inter-arrival time of a Poisson process with rate β, and $1/\beta$ is the average time between arrivals.

Exit choice process To model the exit choice process, we directly use our experimental findings. We implement the exit choice process in the model with and without split effect, but do not consider different types of information provided to pedestrians. In the latter version of the model, pedestrians avoid following the majority and the probability of choosing a route is based on the frequency with which participants had chosen each route in the experiment. For example, the probability that pedestrians follow the majority when there are fewer than 20 pedestrians in total, is given by the proportion of people among all participants across all experimental conditions (except the 0-1 split) who decided to follow the crowd. This is based on the assumption that exit utilities tested in the experiment average our across experimental conditions. In the former version of the model (with split effect), pedestrians respond to the crowd differently as the distribution of the crowd across exits changes. More specifically, participants generally tend to avoid the crowd but prefer to follow the crowd if only one exit is used unless the state of the crowd became busy (the threshold for the number of pedestrians is 20) when they start to avoid the crowd. All the probabilities in the models are obtained directly from the experimental data, as described above. The first pedestrian to arrive is allocated a route, as the probabilities from our experiment do not describe this situation.

Service process After pedestrians have made their exit choice, they start to move along their chosen route. the service time (w) represents the time required for each pedestrian from arrival to departure and can be calculated by Equ.3.3. We incorporate Weidmann's fundamental diagram to describe the relationship between density k (pedestrian/m^2) and speed v [125, 239], as shown in Equ.3.4.

$$w = \frac{d}{v} \tag{3.3}$$

where d is the distance of the route, set to d=1m throughout.

$$v = \begin{cases} v_{max}(1 - e^{-1.913(\frac{1}{k} - \frac{1}{k_{max}})}), & k \le k_{max} \\ v_{min}, & k > k_{max} \end{cases} \tag{3.4}$$

where the maximum speed v_{max} is 1.34 m/s, the maximum density k_{max} is 5.4 pedestrian/m^2, and the minimum speed v_{min} is 0.04 m/s, as suggested in [125].

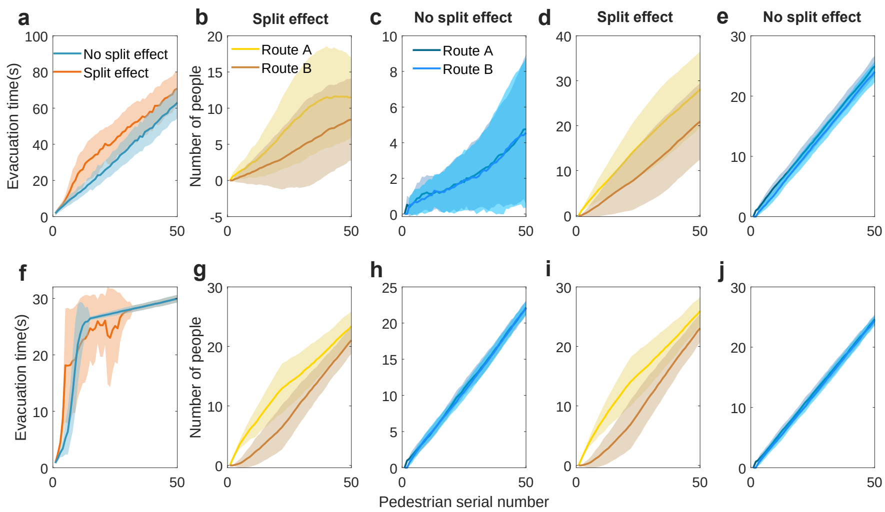


Figure 3.4: Simulations on the impact of the split effect on pedestrian flow when the arrival rate is low (a-e) or high (f-j). The abscissa, pedestrian serial number, describes the sequential order in which pedestrians arrive. Panels a and f show the time at which each pedestrian reaches their destination. Panels b,c,g and h show the number of pedestrians in routes A and B at the moment each pedestrian arrives when the split effect is present (b and g) or not present (c and h). Panels d,e,j and j show the accumulated number of pedestrians in routes A and B over the whole simulation when the split effect is present (d and i) or not present (e and j). We show the average value across 100 simulations and shaded regions indicate one standard deviation. Simulation parameters are $\beta = 1$ per second for the low arrival rate and $\beta = 10$ per second for the high arrival rate. In simulations, the first pedestrian is set to choose route A.

Using this model, we first investigated the implications of the split effect when the pedestrian arrival rate was low (see Figure 3.4a-e). We found that when the split effect was present, on

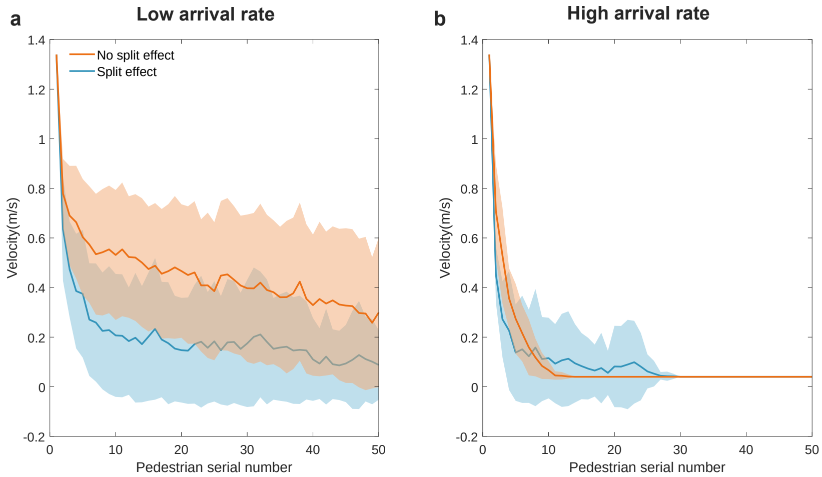


Figure 3.5: The speed of each simulated pedestrian when the arrival rate is low (a) or high (b). The abscissa, pedestrian serial number, describes the sequential order in which pedestrians arrive.

average pedestrians took longer to depart (see Figure 3.4a) and the usage of the two routes was unbalanced (see Figure 3.4b). In contrast, without the split effect the number of pedestrians on the two routes was almost the same over time (see Figure 3.4c). This unbalanced exit choice explained the longer departure times when the split effect was present, because pedestrians tended to choose the crowded exit, leaving the other route empty and thus reducing the average speed of the pedestrian flow. Moreover, overall more people chose the route selected by the first person and the exit choice process was more unpredictable when considering the split effect (compare the standard deviation in Figures 3.4d and 3.4e).

We next considered the implications of the split effect when the arrival rate was high (see Figure 3.4f-j). We found that the split effect still caused an imbalance in route usage (compare Figure 3.4b and g). However, it did not lead to a longer overall departure time as observed in the low arrival rate scenario, only the first few pedestrians needed more time to depart when the split effect was considered (see Figure 3.4f). The reason for this was under the high arrival rate both routes were congested quickly. This meant that with the exception of the first arrivals at the exits, most pedestrians in simulations evacuated at the minimum speed and thus the speed difference induced from the imbalance in the number of pedestrians was reduced. Figure 3.5 compares the average pedestrian speed over the course of simulations in the low and high arrival scenarios and provides evidence for this explanation. When the arrival rate was low, pedestrians maintained a higher speed when the split effect was not present. However, when the arrival rate was high, pedestrian speed both with and without the split effect dropped rapidly to the minimum value. In addition, we found that a higher arrival rate made pedestrian exit choice more predictable (compare the size of the standard deviations in Figures 3.4b-e with 3.4g-j, respectively). Figure A.1 provides more details on how the arrival rate can affect pedestrian dynamics. We found that as the arrival rate increased, pedestrians took less time to evacuate and the split effect had less of an influence on evacuation time. This was because when pedestrians arrived quickly, the whole crowd (50 pedestrians) could start to evacuate early, on average, leading to a shorter overall evacuation time. Meanwhile, in high arrival scenarios the number of pedestrians could reach the threshold for a busy state at one exit in a short time and thus the impact of the split effect gradually diminished. Furthermore, when the arrival rate was high, there was less variability in the summary statistics we recorded, indicating that a high arrival rate made pedestrian dynamics more predictable.

In summary, we found the split effect could result in unbalanced usage of routes. It could reduce the average speed of pedestrian flow when the arrival rate was low, but for higher arrival rates this reduction became small in size. A higher arrival rate also made pedestrian exit choice more predictable in our simulations.

3.5 Discussion

Our work has found evidence that the response of pedestrians to the movement of others during exit choice depends on the context. In agreement with previous work, participants in our experiment have an innate preference of avoiding busier exits [81, 138, 245]. However, additional spatial information can mean that exits with a higher utility are preferred, even when they are used by more pedestrians than alternative options. Our experiment also shows that this behaviour changes when one exit is not used at all suggesting the tendency of pedestrians to avoid empty exits which has been observed in previous work [142]. A possible explanation for this finding is that pedestrians may perceive exits that are not used by others as not viable or safe [142]. Our simulations show that this effect can lead to unbalanced route usage, but they also show that how this influences pedestrian flow depends on the context, such as the arrival rates of pedestrians. We suggest that more empirical data are needed for determining the size of this effect and its possible consequences in real-life situation.

We compare our work in detail with three previous relevant studies. One is the work by [116] where they investigate the effect of crowd proportion and size on pedestrian exit choice. They found pedestrians tend to follow the majority when the crowd size is small or the exit width is narrow but prefer the less-crowded exit if the crowd becomes larger or the exit is wider. In contrast, our experiments do not show a significant effect of crowd size on pedestrian exit choice. We can only speculate what causes the difference. A possible reason is that the trade-off between exit utility and estimated congestion caused by the crowd may influence their choice, which is not a consideration in our experiment. The previous work also found the tendency of pedestrians to avoid an empty exit because pedestrians tend to eschew unknown exits that no one chooses. A non-linear relationship between crowd proportion and exit choice is found. In contrast, our work only considers uneven and even crowd split, without implementing additional proportions of how the crowd is distributed across exits. Therefore, we cannot give more details on the influence of crowd proportion. The second is the work by [219] where they investigate following behaviour in sequences of consecutive pedestrian route choices. They assume pedestrians do not have prior knowledge about the building, so we only compare situations where participants are not presented with the map in our experiment. Our findings have two main consistent conclusions. First, compared to the information indicated by the crowd, pedestrians rely more on other directional information (exit signs in their work and maps in our experiment). Second, both this and our previous study found that when all pedestrians choose the same exit, pedestrians who have no spatial information tend to follow others. The third is the work by [80] where they found that following behaviour hinders the efficiency of crowd evacuation processes in simulations where pedestrians prefer to follow the crowd. In contrast, in our simulations pedestrians tend to follow the crowd due to the split effect when numbers are low, but start to avoid others when the number of pedestrians reaches the threshold. Our results show that following the crowd may cause unbalanced usage of exits and thus hinder pedestrian flow. However, this still depends on the context. For example, the split effect has little influence on pedestrian dynamic when the arrival rate is high. The comparison with these three studies suggests that even though the role of the crowd in pedestrian exit choice is highly context-dependent, we still can find some consistency across scenarios and make predictions based on appropriate contextual factors.

We have explored possible implications of our experimental findings through modelling. Our model assumes that the arrival of pedestrians can be described as a Poisson process. While only applicable in certain circumstances, we argue our model is still useful for investigating implications of the split effect for crowd dynamics.

Control over extraneous variables was essential in our experiment. Extraneous variability was unavoidable but could be reduced by appropriate measures. First, when we recruited participants we did not set any criteria for their socio-demographic factors, aiming to obtain a truly representative sample. Second, participants were assigned to a scenario randomly and could only take part in the experiment once, which helps to create a balanced participant pool regarding known and unknown individual characteristics. Third, except for the treatments, experimental settings for each participant remained identical (e.g., initial position, room size and exit properties), which could be easily implemented using desktop virtual reality, in order to standardize the experimental procedure for all participants.

In this work, we assume that the time pedestrians spend in a decision zone is relevant for capturing aspects of their decision-making process and measure the ratio α of the total time it takes participants to complete the experiment. We argue that while α is not a direct measure of the decision-making process, it can still capture and reflect pedestrian intentions in the exit choice process. Previous work describes pedestrian intentions by their movement direction, body orientation, or head turns [132]. The decision zone measures pedestrian intention based on the location, which is effective for situations where details of individuals' movement that are commonly used to determine their intentions are difficult to measure. More work and data is needed to establish the general validity of this measure but we argue that it is reasonable in our carefully controlled experiment where pedestrians start at the midpoint of the horizontal line of two geometrically identical exits.

There are limitations to our study that need to be pointed out here and resolved in future research. First, we investigate pedestrian exit choice in virtual environments. While some previous work has directly demonstrated the validity of the virtual experiment paradigm for pedestrian exit choice and decision making in some contexts [129], our experiment should not be interpreted as a direct test of pedestrian decision-making in real environments. Specifically for our experiment, the fact that participants have a third-person rather than first-person perspective, the fact that all simulated pedestrians appear to be male, the instructions given, the mouse and keyboard steering mechanisms, and the environmental features are examples of aspects that could influence the decision making of participants. For example, in using a keyboard to control the movements of virtual pedestrians, participants may find it less effortful to navigate through the environment, which could potentially lead to a reduced sensitivity to distance and ultimately affect their route choice behaviour. While these aspects do not affect the internal validity of our experiment, as they remain fixed within the experiment, further investigation using real-world data is therefore needed to establish if our findings extend to human exit choice in reality. We used a simple and less immersive virtual environment in our experiments. On one hand, it can eliminate the influence of irrelevant extra information, leading to a more focused study of pedestrian decision-making. This is particularly important when studying specific factors or when extraneous information may introduce biases in participant behaviour. On the other hand, the simplicity of the virtual environment may reduce the immersion of the participants, potentially affecting the realism of the experiment and the generalizability of the findings. Moreover, it is possible that the less immersive environment may not fully capture the complexity and dynamics of real-life emergency situations, limiting the study's validity. Third, there are several other factors that may potentially influence participant route choice, including the contextual information provided to them. Previous research has established how the delivery of evacuation messages can affect people's perception and evacuation behaviour [130]. To maintain internal consistency in our experiment, all participants were exposed to the same experiment, except for the treatments that we were investigating. Forth, we recruited participants on a dedicated scientific research platform and the experiment was conducted online. Although online recruitment allowed us to gather data in an effective, flexible and controlled way, this approach has limitations. For example, the self-selected group of participants may not represent the general population, because on average certain groups of people might be more likely to participate in online research than others. Research on online recruitment for research indicates that the data quality is reasonably high and compares well to laboratory research but important caveats remain [32].

Our work confirms the key role of contextual factors in explaining the response of pedestrians to the movement of others during exit choice. Therefore, when we attempt to explain the mechanism of following behaviour, we should consider the context and be cautious about generalising across contexts. In particular, when designing an experiment, we should carefully consider and control for the interference of other attributes that may affect pedestrian behaviour in addition to the factor we aim to investigate. For example, in a pedestrian exit choice experiment, displaying spatial information to participants may be more advisable than not displaying any spatial information, because participants who are not given spatial knowledge about an environment may have certain unknown expectations of the space, which may affect their choices.

CHAPTER 4

IMPACTS OF BUILDING LAYOUT PROPERTIES ON PEDESTRIANS ROUTE CHOICE

This chapter presents a virtual experiment to investigate the impacts of building layout on pedestrian route choice, which links to **RQ 3** in Section 1.2. Section 4.1 introduces the general background and a literature review on the role of building layout in pedestrian route choice. Section 4.2 describes a method for generating buildings with various layout properties in the forms of networks to answer **RQ 3.1**, identifies several measurements of route and layout properties for exploring **RQ 3.2**, and presents a virtual experiment to investigate the influences of building layout properties on different aspects of pedestrian route choice for addressing **RQ 3**. The results are presented in Section 4.3 and are discussed in Section 4.4.

The work presented in this chapter has been published in Transportmetrica A: Transport Science: Y. TONG AND N. W. BODE, *How building layout properties influence pedestrian route choice and route recall*, Transportmetrica A: Transport Science, (2022), pp. 1 [220]. Data are available at the University of Bristol data repository [1].

4.1 Introduction

Pedestrian route choice is one of the most interesting and challenging problems for research into pedestrian behaviour [93]. Route choice behaviour of pedestrians inside buildings, especially in complex facilities, such as airports and hospitals, is often directly relevant to building design, crowd management and evacuations in emergencies. It has long been a question of great interest in a wide range of fields including engineering, mathematics, psychology, and safety science.

[1]University of Bristol data repository: https://data.bris.ac.uk/data/dataset/14zfc07k0co9c2f2rho04ex9uw

In general, pedestrians are assumed to perceive and process environmental spatial information through a subjective cognitive process and then choose routes based on preferences, such as the shortest distance and the fewest turns [6]. This process can depend on individual characteristics. Previous studies have established that age, gender, culture and vision ability can affect how pedestrians choose a route [14, 83, 126]. However, the factors deemed to be most important in route choice behaviour are environmental factors. Static information (time-independent), such as signs and building layout, has been distinguished from dynamic information (time-dependent), such as the level of congestion along different routes [19]. The influence of both types of information on route choice has been widely investigated using experiments and simulations [78, 139]. The effect of dynamic information is often tested by updating the information shown to participants in well-controlled experiments or by setting simulated rules based on assumptions in simulations. For example, [133] investigate how pedestrians choose their routes when presented with different split levels of crowd flow via an immersive virtual metro station experiment. In contrast, static information is more likely to be tested by comparing the route choice of pedestrians in different pre-designed buildings with specific structures. For example, [244] investigated how likely pedestrians were to follow signs with different designs during evacuations. Furthermore, different information use strategies influence pedestrian route choice. For example, [134] identified reactive pedestrians who only rely on current information to make decisions and predictive pedestrians who choose routes based on the predictive travel cost.

In addition to individual characteristics, previous research has established that pedestrian route choice depends on the context. Motivations, social influence and familiarity have been identified as essential factors affecting pedestrian route choice. Motivation indicate the travel purposes of pedestrians and affect their route choice strategies. For example, compared to commuters who prefer the shortest possible route without inclines [192], tourists are more likely to choose routes with more pleasant visual attractions [35]. Social influence describes how pedestrians change their route choice in a social environment [166]. For example, some studies found pedestrians in a social group that are connected via social relationships such as friendship or work relationships, prefer to stay close to each other and share the same destination [94, 235]. Familiarity reflects the spatial knowledge of pedestrians about the environment surrounding them [6]. Some work reveals that pedestrians are more likely to choose familiar exits even when other available exits are closer [13] . In contrast, pedestrians who are not familiar with the environment have to seek other information for their route choices such as the movements of others [219] or signs [184].

A crucial but understudied aspect of pedestrian environments is the layout of buildings, that is to say the spatial arrangement of rooms, corridors, doors, and walls. Previous work already provides evidence that building layout properties, such as curved and angled corridors, influence pedestrian movement characteristics [103]. Two types of research can be distinguished: first research that considers only part of the building layout and second research that considers the entire building layout. The former type of research has received much attention and focuses on specific structures, such as obstacles in front of doors, the number of doors, and exit widths [129]. In contrast, the latter type of research is concerned with investigating the influence of the entire building layout on pedestrian route choice. It has received much less attention and is the focus of our work presented here.

One of the essential concepts of investigating the influence of building layout on pedestrian route choice can be described as building layout complexity. This term reflects the condition of the geometric elements in a building and the forms of relationships among these elements. As it is a broad concept, different approaches to quantifying it exist [96, 207]. An important measure is the Inter Connection Density (ICD), defined by [170] as the total number of choices at decision points divided by the number of decision points in the building. ICD measures the density of available paths between places in an environment, such as a building. Findings suggest that as the average ICD of buildings increases, individuals construct less accurate cognitive maps of buildings and their wayfinding performance, measured by the number of wrong turns and backtracking events, decreases [170]. Other work also found that people spend more time and have higher errors in wayfinding tasks in environments with higher ICD values [203]. Going beyond the ICD, the effect of other building layout measures, such as geometrical misalignment [231], a spatial relation that measures whether the current perspective is parallel to the perspective of pedestrians when they obtain map information, and intersections of corridors with various angles [101] have been investigated but no statistically significant results were found. The theory of affordances can help us understand how different elements of the environment (such as walls, doors, and stairs) offer affordances for movement and navigation [169]. For example, a layout with multiple paths and exits may provide more affordances for movement and evacuation (higher ICD), whereas a layout with dead-end corridors and narrow passages may limit affordances and impede movement, which could potentially impact pedestrian route choice.

While the influence of ICD on pedestrian route choice has been confirmed in several studies, [231] argue that many buildings may have the same ICD values but different other geometrical attributes and pedestrians perform differently in these cases. Thus, there might be some other factors affecting pedestrian behaviour. Importantly, most previous research has only considered a limited number of manually constructed building layouts (fewer than 10). Therefore, more empirical data that involves a large number of building layouts is needed to ensure a broader range of possible layout properties is investigated. In addition, examining Inter Connection Density (ICD) in building design can yield insights into creating effective evacuation routes. Research could identify common ICD values across building types and their impact on evacuation. This can guide architects and engineers to design buildings with optimal ICD values for evacuation. It would also be useful to study the relationship between ICD and optimal route choices. For example, it would be intriguing to examine if buildings that require frequent evacuations, such as hospitals or high-rise buildings, tend to have distinct ICD values compared to buildings with fewer evacuation events. This inquiry can inform designing buildings with optimal ICD values for their intended use and evacuation needs. However, a multidisciplinary approach is necessary to conduct this research.

Previous research indicates that how pedestrians interpret route information from their own subjective perspective is essential for pedestrian route choice [197]. Cognitive maps, the mental representations of external environments constructed by pedestrians, can capture the cognitive factors that might affect pedestrian route choice. This concept is termed by Tolman who found evidence that rats possess a clue about specific objects and their spatial relation obtained from previous visiting experiences, and that hippocampal formation is involved in the establishment of such a cognitive map [216]. They found that Specific cells, such as grid cells [160] and border cells [204], play a role in spatial information perception. Similar cells that provide environmental information have also been discovered in the human brain [50]. Five elements of cognitive maps are identified: paths, nodes, districts, edges and landmarks [147]. Paths refer to the shared corridors, edges are limiting or enclosing features, districts are larger spaces sharing some common characters, nodes are the intersections of major paths or places, and landmarks distinctive features that people use to reference locate themselves.

Network theory is a convenient and successful approach to represent the relations between discrete objects and has been widely used [173]. Networks can be used to represent spatial relations. When representing building layouts via networks, each node represents an intersection point, and each edge that links nodes represents the space pedestrians can walk through, such as corridors [10]. Measures, such as the average path length (average length of connections between intersection points), have been developed to characterise properties of networks. For example, the ICD discussed above is exactly the concept of average degree – the average number of edges per node in a network. This suggests concepts in network theory are suitable for measuring building layout properties.

Previous studies have adopted various measures to create different levels of simulated stress for participants in experiments, such as imposing time pressure, giving financial incentives and presenting motivational instructions. However, studies on the effect of stress have produced diverse results. The work by [82] shows stress may increase the vigilance of participants and thus decrease their reaction time, leading to a short evacuation time. In contrast, the work by [17] found stress may impair pedestrian information processing ability and leads participants to choose routes that are far from optimal. Moreover, it is difficult to achieve consistent and desired participant responses or stress levels in virtual experiments. Therefore, in this work, we only present participants with motivational messages and argue that this is sufficient to test participants' responses to different building layouts.

Pedestrian route choice can be regarded as a decision-making process in terms of spatial navigation in psychological research. [221] identify four processes of pedestrian route choice: "information perception" considers how pedestrians perceive information in a selective and purposeful way, “information integration" deals with how pedestrians subjectively integrate environmental spatial information into mental representations, “responding to information" describes how pedestrians tend to respond to information individually and collectively and “decision-making mechanisms" are concerned with how pedestrians trade-off the evidence and make final route choice. In each process, pedestrian behaviours change across contexts. It is almost impossible to consider all potential factors that will result in the subjectivity of pedestrian route choice. Therefore, we focus on the processes of “responding to information" and “decision-making mechanisms" in this work. We abstract complex buildings into networks and investigate the relationship between properties of building layouts and pedestrian route choice without considering heterogeneous cognitive maps in data analysis.

In this contribution, we first develop a method for automatically generating building layouts and then investigate the influence of building layout properties on pedestrian route recall and route choice behaviour in a virtual experiment that involves over 200 human participants. Using a virtual experiment means we can easily expose participants to a wide variety of buildings with different layout features. The paradigm of virtual experiments is established and widely used in research on pedestrian decision-making [43, 114], as they are safe, cheap and allow exposing participants to carefully controlled environments [143]. Different types of virtual reality technologies can be classified: desktop VR, head-mounted display, and cave automatic virtual environment [52]. In this work, we use desktop VR because it is cheaper and allow participants to attend remotely. While desktop VR provides a less immersive environment, previous work has established participants make similar route choices in different types of virtual environments [52, 189], which indicates the validity of desktop VR. While it has not yet been determined to what extent human decisions in virtual environments extend to the real world, they nevertheless provide an ideal starting point to explore what characterises building complexity and how it affects route choice. In our experiment, participants can navigate a virtual avatar to complete several route choice tasks in a large number of automatically generated buildings with different layout properties. We analyse the route choice strategies of participants and the effects of the building layout properties on pedestrian route choice behaviour.

The key novelty of this work lies in two aspects. On the one hand, the method we developed allows us to automatically generate building layouts whose properties (e.g. the average degree of their network representations) can be controlled by a few variables. This research method can be applied in other research into building design and pedestrian behaviour. On the other hand, we use large numbers of automatically generated buildings with different layout properties to test pedestrian route choice mechanisms. Our research greatly expands the available data on pedestrian behaviour in buildings with different layouts, compared to previous research that normally considers a limited number of manually constructed building layouts.

4.2 Experiment

4.2.1 Generation of spatial networks representing building layouts

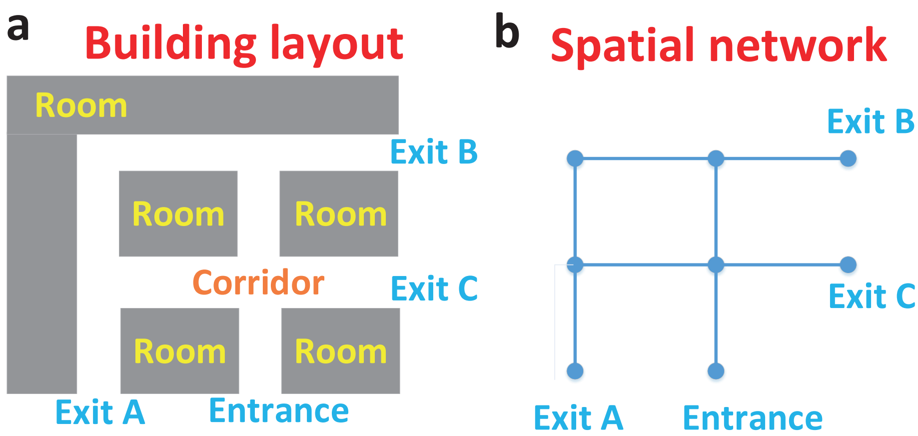


Figure 4.1: An example of how a building layout is represented as a spatial network.

The layout of a building can be represented as a spatial network composed of nodes representing intersections and lines representing paths that connect nodes (see Figure 4.1 for an example). There are many methods to generate complex networks with selected properties for experiments or simulations (see [179] for a review). In this work, we refer to previous work [159] to construct network generation algorithms but make some modifications to meet the following requirements: (1) The generated networks should be planar graphs, meaning their edges only meet at nodes. (2) The generated networks should have a wide range of properties, such as the average number of connections between nodes, to ensure the possible variability in building layouts is captured. (3) The generated networks should be comparable in spatial extent, seeing that we want to compare the route choice behaviour of people across networks.

Taking these criteria into consideration, we generate spatial networks stochastically using the following three steps. First, we generate a grid of nodes. Second, we adjust the regularity of the grid of nodes, and third, we generate two networks based on the nodes with different average degrees: Gabriel graphs and reduced Gabriel graphs, as shown in Figure 4.2.

4.2.1.1 Randomising the node-set

We generate a regular grid of 25 nodes arranged equally spaced in a 5×5 grid (see Figure 4.2a) to avoid the influence of different aspect ratios of building layouts on pedestrian route choice. The distance between any two nodes is given by d units. To reduce the regularity of the grid, we implement the parameter "randomness", which is defined as the maximum ratio of the coordinate offset of each node to the original coordinate and d. For example, if $d = 1$ unit and $randomness = 0.02$, for each node in the grid, its horizontal and vertical coordinates will

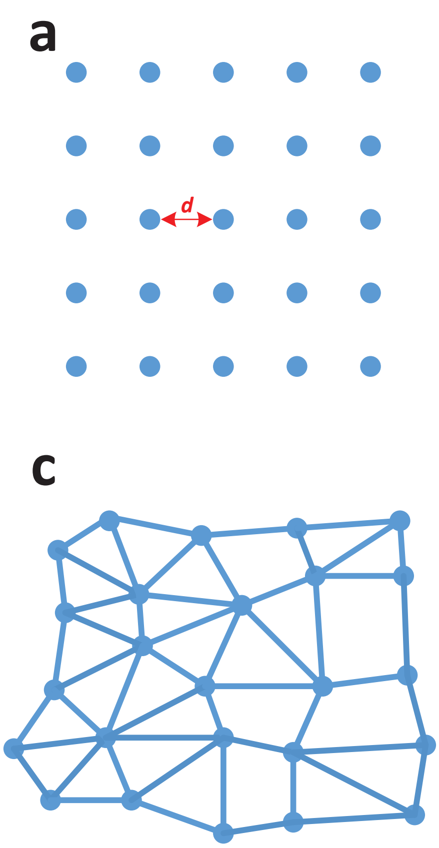


Figure 4.2: Generation of spatial networks: (a) a regular grid with 25 nodes arranged; (b) adjusting the regularity of the grid of nodes; (c) the Gabriel graph based on the nodes; (d) reduced Gabriel graphs with a lower average degree.

randomly increase or decrease by no more than 0.02 units (see Figure 4.2b for an example). As the randomness increases, the regularity of the network decreases and overlaps of nodes may occur. To avoid this from happening, we set the randomness to be between 16% and 32% of d.

4.2.1.2 Generation of Gabriel graphs

We generate Gabriel graphs based on the grid of nodes generated in the previous step. In Gabriel graphs two nodes are linked if a circle centred on their midpoint with diameter equal to the distance between the nodes contains no other nodes (see Figure 4.2c). We use a well-established algorithm to construct Gabriel graphs for a given set of nodes [102].

4.2.1.3 Generation of reduced Gabriel graphs

As the average degree of Gabriel graphs has a narrow distribution, we select some generated Gabriel graphs to reduce their average degree by randomly deleting the links between some nodes (see Figure 4.2c). By doing this, we can obtain a certain number of networks with similar randomness but a wide range of average degrees.

The algorithm is as follows:

1. Calculate the average degree of the spatial network.

2. Calculate the degree of each node.

3. For each node, if its degree is greater than the average degree and no less than 2 randomly remove one of the links to other nodes.

4. Repeat steps 2 to 3 until no link meets the above conditions (i.e. the original average degree is used throughout).

The steps described above define the process for how one spatial network representing a building layout is generated. To obtain a wide range of network and therefore layout properties, the “randomness" parameters is uniformly randomly selected from the interval [0.16,0.32], and each generated Gabriel graph has a 50% probability of being reduced (see section 4.2.1.3). Using this methodology, we generate 1,200 building layouts. The distribution of selected network/layout properties is shown in Figure 4.3.

4.2.2 Virtual experiment

4.2.2.1 Overview

To investigate the influence of building layout properties on pedestrian route choice, we conduct a virtual experiment with human participants. Participants could move on building layouts that were randomly selected from the 1,200 networks we generated and they were asked to complete two different tasks twice. The first task was designed to test route recall and the second task was designed to test route choice behaviour. The experiment takes approximately 5 minutes to complete and is described in detail below.

In our experiment, participants were shown a top-down view of a virtual environment in which a building is displayed in the form of a network (see Figure 4.4). Participants could control an avatar represented by a red circle in two ways: by using the arrow keys on the keyboard to move forward and backwards, turn left and right, or by selecting the position they wanted the avatar to move to with the mouse, ensuring that participants who have different preferences of computer input habits can control the virtual pedestrian in their preferred way. In each task, participants were asked to move the avatar to a designated or preferred destination. We did not record any identifying information about participants. We only recorded the movements of participants inside the experiment and (optionally) the age and gender of participants. The virtual environment was implemented in Unity 3D (Version 2019.3). Ethical approval for our

Table 4.1: Summary of the measures of building layout and route properties.

Measurement	Factor	Definition	Purpose
	Randomness	The maximum ratio of the coordinate offset for each node compared to the original coordinate and the default distance between any two nodes(d)	To measure the regularity of the network
Building layout measurements	Average degree	The average number of edges per node in the network	To measure the connection between nodes
	Average path length	The average number of steps along the shortest paths for all possible pairs of network nodes	To measure the efficiency of transport on a network
	Relative distance	The ratio of the length of the chosen route and the shortest route among all possible routes	To measure how close the selected route is to the optimal route in terms of distance
	Relative number of turns	The ratio of the number of turns in the chosen route and the smallest possible number of turns across all possible routes	To measure how close the selected route is to the optimal route in terms of the number of turns
Route measurements	Relative accumulated angle change	The ratio of the accumulated angle change between consecutive links in the chosen route and smallest possible value for this measure across all possible routes	To measure how close the selected route is to the optimal route in terms of the accumulated angle change
	Proportion of the path on the edge (edges are the outside limit of the building and contain all periphery nodes of the grid)	The number of periphery nodes passed by a route divided by the total number of nodes included in this route	To measure the tendency of people to follow the linear physical heterogeneities of the environment
	Large turn preference	The number of turn angles between consecutive links on a route that are greater than 45° or 90°	To measure the preference of people choosing the turn with greater angle

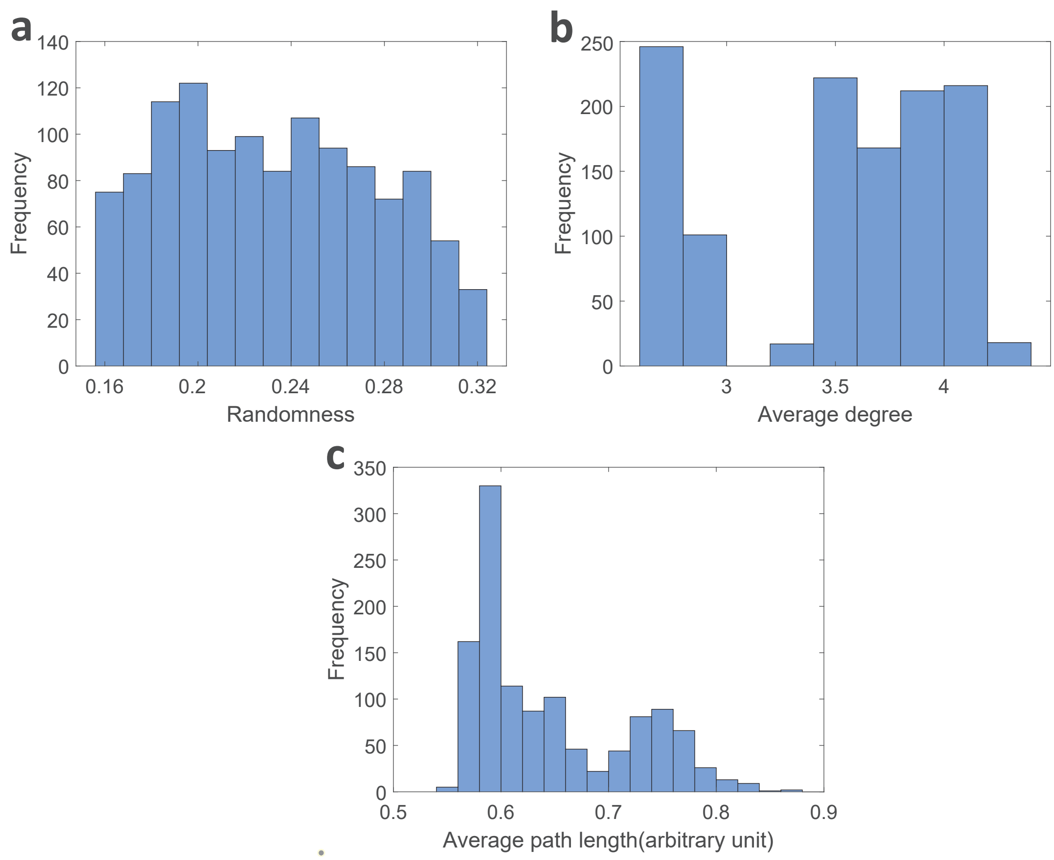


Figure 4.3: Distributions of building layout properties (the definition of properties can be found in Table 4.1 below).

experiment was granted by the Ethics Committee of the Faculty of Engineering at the University of Bristol.

At the start of the experiment, participants were shown a building floor plan and the corresponding network used to represent it to demonstrate the link between networks and buildings and to introduce the experiment (see Figure A.2 in appendix). In addition to this introduction, participants received the information that “In each task, task information will be shown at the bottom right of the screen. You are a person (represented by a red circle) in a building. There is no correct answer to the route choice, so please decide according to how you think you would choose in reality."

In the first task of the experiment, participants were asked to move to a designated destination via a route of their choice (see Figure 4.4a). The instructions for this part were “Please move to the destination at the top right as soon as possible." Once they reached the destination, they were asked to retrace their route to return to the starting point: “Please try to go back to where you started through the same route you came in." The task was completed once participants reached the starting point. This task was designed to test the influence of building layout properties on route choice strategy and route recall.

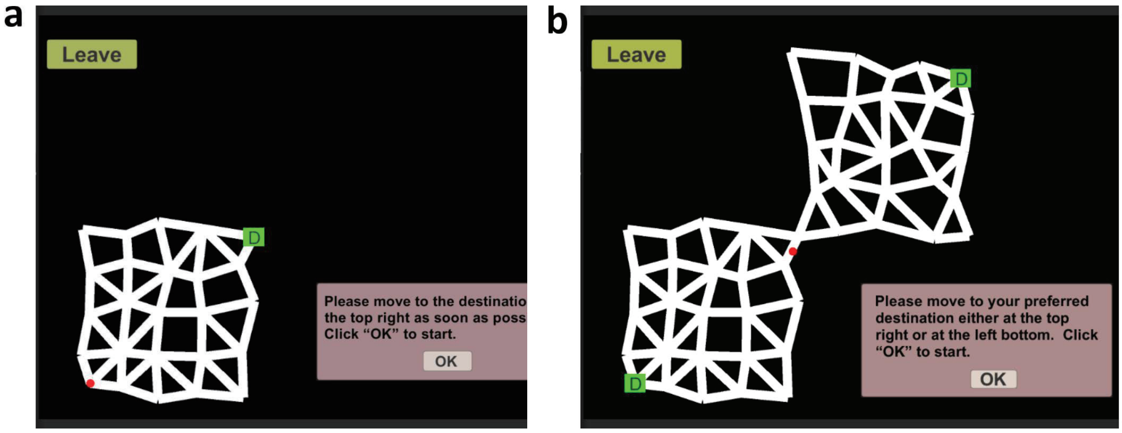


Figure 4.4: Still images of the virtual experiment as seen by participants on screen for the first task (a) and the second task (b).

In the second task, participants were asked to a designated destination in the same way as in the first task. However, when they reached the destination, another building layout was displayed (see Figure 4.4b). Participants were at the intersection of these two buildings, equidistant from their starting point and a new alternative destination. They were asked to move to either of these destinations via a route of their choice. The instructions were: "Please move to your preferred destination either at the top right or the left bottom." The task was completed once participants reached their preferred destination. This task was designed to test the influence of building layout properties on route and destination choice.

In our experiment, participants were asked to complete a total of four tasks, two replicates each of the two tasks described above. The tasks were placed in a randomised order, ensuring that the first two tasks were different and thus making participants not do the same task in succession. To investigate learning or habituation effects arising from participants completing the same task more than once, we tested for an effect of task order on the behaviour shown by participants. For each participant, we selected six different networks at random from the 1,200 networks we generated: two networks for the first task and four networks for the second task. We recorded all movements of participants inside the virtual environment.

4.2.2.2 Data collection

We recruited participants on the online platform Prolific [2] between the 22nd and the 23rd of July 2021. Participants were paid an amount equivalent to £7.5 per hour based on the estimated time to completion (this equated to £1.7 per person). All participants were briefed on the broad purpose of the experiment and were asked to only take part once. Participants had to download

[2] Prolific: Online participant recruitment for surveys and market research URL: https://prolific.co/, accessed 25 September 2021

an executable file for the virtual experiment onto their computer and return an output file via email upon completion of the experiment. The experiment file could only be executed once.

A total of 506 participants signed up for our experiment on Prolific: 272 participants completed their submission, 216 participants decided to leave the experiment early and 18 participants exceeded the maximum time allowed without completing their submission. Of the 272 participants who completed the experiment, 6 participants uploaded incorrect data files, 10 participants took part in the experiment twice and 55 participants failed to submit the output file. Therefore, the data from 201 participants were analysed.

Reported ages ranged from 18 to 64, with a median and average age of 23 years and 25 years, respectively (5 participants did not disclose their age). The gender distribution included 77 female participants (39.5%), 118 male participants (60.5%) and 6 participants (3%) not identifying with either of these categories or choosing not to disclose a gender. In terms of how participants moved the avatar inside the virtual experiment, 88 participants (43.78%) used the keyboard, 70 participants used the mouse (34.83%) and 43 participants (21.39%) used a mix of both controls.

4.2.2.3 Data analysis

We summarise the properties of routes and building layouts used in our data analysis in Table 4.1. For the first task, in which participants were asked to retrace their route, we used a measure for spatial similarity between two routes [1].

For route A(R_a)and route B(R_b), the spatial similarity between them ($sim(R_a, R_b)$) can be described as the ratio of common nodes and the total of nodes across both routes, as shown in Equation 4.1.

$$sim(R_a, R_b) = \frac{\text{Number of nodes common to } R_a \text{ and } R_b}{\text{Total Number of nodes in } R_a \text{ and } R_b} \tag{4.1}$$

Thus, $0 \leq sim(R_a, R_b) \leq 1$ and $sim(R_a, R_b) = sim(R_b, R_a)$.

For our statistical analysis, we use generalised linear models (GLMs) with a Binomial error structure and a logit link function. We provide details on the model structure below and we confirmed the appropriateness of these models by examining residual plots. All data analysis was conducted in Matlab R2021a [152].

4.3 Results

4.3.1 Pedestrian route choice strategies

We first investigate factors influencing the route choice of participants in the experiment. At the start of each task, participants were asked to choose their preferred route to a designated destination. Only when they reached the destination, they were informed of the following tasks. Therefore, we use their route choice data from this part of the experiment. Figure 4.5 shows the

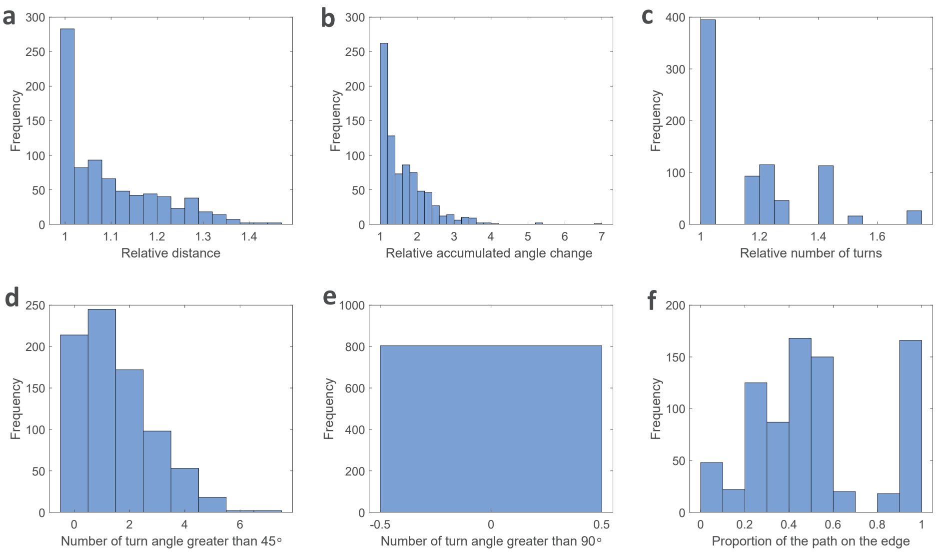


Figure 4.5: Distributions of route properties as shown in Table 4.1.

distributions of the route properties introduced in Table 4.1. We find that distance, the number of turns and accumulated angle changes of routes were important factors influencing the route preferences of participants. Many participants selected the shortest routes with the smallest accumulated angle change and the smallest number of turns (see Figures 4.5a-c). Although overall participants were not inclined to routes with many turns greater than 45°, there were still more people choosing routes with only one big turn than those without big turns (see Figure 4.5d). No one selected a route with a turn greater than 90° (see Figure 4.5e).

We found a large number of participants preferred a route with many nodes on the periphery of the network (see Figure 4.5f). It could be expected that using the keyboard to steer the avatar in the experiment may affect this preference. Walking in straight lines is the least effort in this case and the routes around the periphery of the network are mostly along straight lines with one big turn in a corner of the network (compare to Figure 4.4). However, we found no evidence for an effect of the steering mechanism participants used on their edge-seeking behaviour (χ_1^2 =1.4769, p=0.2243) by comparing the proportion of the path on the edge of data from participants using different steering mechanism. Our statistical analysis suggests that on average, participants tended towards walking far away from the edge of the building (intercept in Table 4.2). One possible explanation for this is that many participants preferred both the shortest route and the route with the least accumulated angle change. These routes track the leading diagonal through the network and are thus not close to the periphery of the network. For increased randomness or the average degree of the building layout, participants became more likely to select a route along the periphery of the network (parameter estimate in Table 4.2). This implies that when participants were faced with more uncertainty caused by a less regular layout or a higher number of connections in the network leading to more possible route choices, they preferred the route

Table 4.2: Statistical analysis of the behaviour of pedestrians walking along the periphery of spatial networks. To distinguish participants completely following the periphery of the network, the response variable is a Boolean indicating whether the participants choose the path that is all on the edge of the building or not (1 for yes, 0 for no). Explanatory variables were the building layout properties randomness and average degree. Average path length was excluded from the model because of its high correlation with average degree (R=-0.6746, p=0.00). P-values less than 0.05 are shown in bold. Positive parameter estimates correspond to it being more likely that participants choose to walk along the edge of the building.

Effect	Estimate	SE	F	P
Intercept	-13.72	3.167	-4.3323	1.4759×10^{-5}
Randomness	38.462	14.395	-2.6719	**0.007543**
Average degree	3.3221	0.87171	3.811	**0.00013838**

on the edge of the building, even though other routes are optimal in terms of distance and accumulated angle change.

4.3.2 Route recall

As shown in Figure 4.6a, most participants could retrace their route accurately in the first task of our experiment (route similarity=1). We test what factors influence the similarity between the original and retraced route of participants. We use our measure for route similarity which indicates the proportion of common nodes between the two routes. Importantly, we find no evidence for a difference in results between the two replicates of this experimental task using the Wilcoxon Test (p=0.9218) and we thus combine the data from two repeated tasks in the following analysis. As explanatory variables for route similarity, we consider the factors in Table 4.1 and assess if they help explain our data using likelihood ratio tests. Based on this analysis, we exclude the randomness (Likelihood-ratio test, χ^2_1 =0.6825, p=0.4087) and the proportion of the path on the periphery of the network (Likelihood-ratio test, χ^2_1=0.4541, p=0.5004). In addition, the correlation between the average path length and the average degree (R=-0.7019, p=6.57×10^{-61}), between the relative number of turns and the relative distance (R=0.7943, p=1.29×10^{-88}), and between the number of large turns over 45° and the relative accumulated angle change (R=0.5593, p=1.86×10^{-34}), suggest one factor of each of these pairs of factors should be included into our statistical analysis to avoid multicollinearity. Therefore, the explanatory variables included in our statistical analysis are average degree, relative distance, and relative accumulated angle change, as shown in Table 4.3.

Our statistical analysis shows that on average, participants tend to select a similar route to return their starting point (large positive intercept in Table 4.3 implying a route similarity close to one). The average degree, relative distance and angle change all have a non-zero effect on route similarity. As all three parameter estimates were negative, the route similarity score decreases both when the building layout has a larger average degree and when the initial route

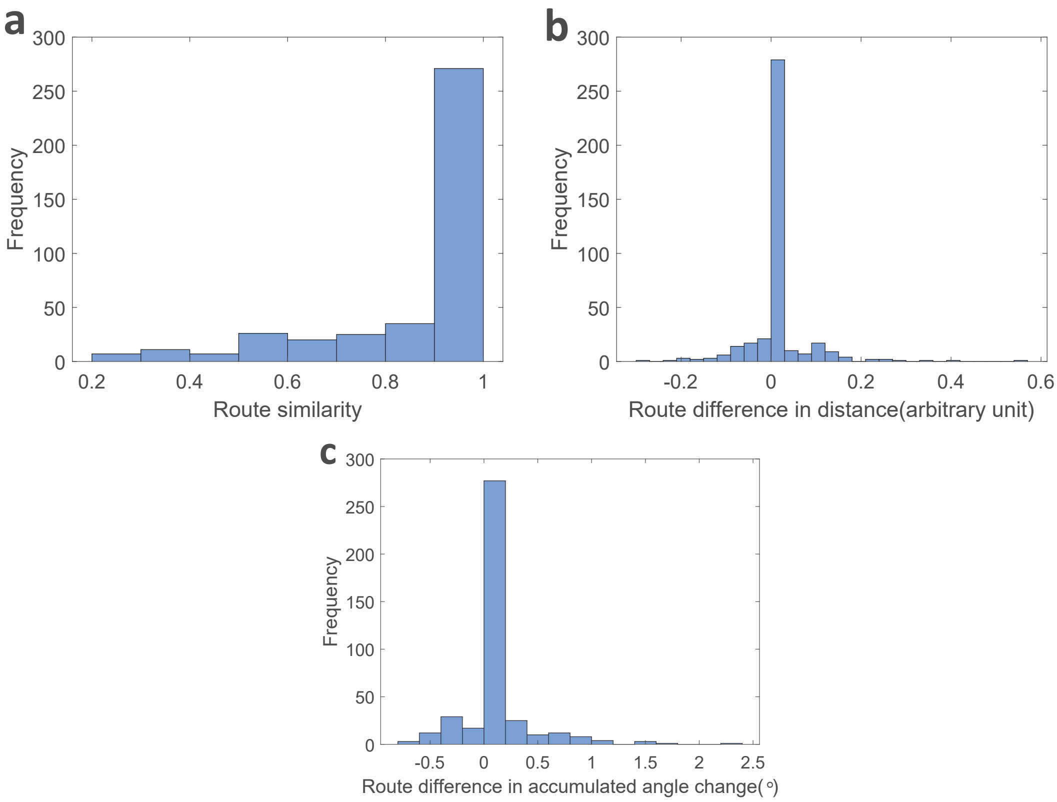


Figure 4.6: Distributions of measures for route recall in the first task of the experiment. Panel (a) shows the route similarity measure, (b) the difference in length, and (c) shows the difference in accumulated angle change between the initial route and the recalled route. Negative values in (b) and (c) indicate that the initial route was longer or had a higher value of the accumulated angle change, respectively.

Table 4.3: Statistical analysis of route similarity. P-values less than 0.05 are shown in bold. Positive parameter estimates indicate it is more likely that participants select a route that is similar to the route they used to reach the destination and vice-versa. We fit a Generalised Linear Model with binomial errors and a logit link function.

Effect	Estimate	SE	F	P
Intercept	11.386	3.0509	3.7321	0.00019
Average degree	-1.421	0.6035	-2.3545	**0.018548**
Relative distance	-2.889	1.4528	-1.9886	**0.046741**
Relative accumulated angle change	-0.41698	0.21033	-1.9825	**0.047425**

Table 4.4: Statistical analysis of distance using a standard linear model. The response variable is the difference in distance between the initial and the recalled route. It is positive if the recalled route is longer and vice versa. The explanatory variable was the relative distance of the initial route participants chose compared to the shortest possible route. P-values < 0.05 are shown in bold.

Effect	Estimate	SE	F	P
Intercept	0.20063	0.058337	3.4391	0.00064525
Average degree	0.0078684	0.01058	0.7437	0.45749
Relative distance	-0.19653	0.032982	-5.9588	$\mathbf{5.5988}\times10^{-9}$
Relative accumulated angle change	-0.0046288	0.00495	-0.93511	0.3503

chosen by participants is longer or has more turns compared to the optimal route in the network (larger relative distance and accumulated angle change, respectively; Table 4.3). As discussed above, participants prefer the shortest route with the smallest accumulated direction changes. For many building layouts only one or very few routes that are optimal according to these factors are available. So, participants may choose this most direct route consistently. However, as the average degree of the building layout increases, the number of the possible routes also increases, which might make it more difficult for participants to choose the same route, even if they are looking for the most direct route. This could explain why increasing average degrees of building layouts had a negative effect on the route recall of participants.

In addition to route similarity, we investigate two further measures for the difference between the two routes chosen by participants: the difference in length and the difference in accumulated changes in direction between the two routes. We consider the same predictors for these measures as for route similarity but use Linear Models, to capture the positive and negative values we find. Most retraced routes are similar to the initial route participants choose (see Figures 4.6 b-c). This is also reflected in our statistical analysis (see low values for intercepts in Tables 4.4 and 4.5). When participants select a longer route than the shortest route to come in, they are more likely to choose a shorter retraced route (see parameter estimate for relative distance in Table 4.4). Similarly, when participants choose a less direct route, they are more likely to choose a more direct route subsequently (see parameter estimate of accumulated angle change in Table 4.5).

4.3.3 Building layout preference

In the second task, participants are asked to move to a designated destination and another building layout is displayed when they reach the destination. Therefore, participants are faced with a choice: either choose the destination in the building they have walked through or select the destination in the new alternative building. We study how properties of the building layout influence participant preference by comparing the layouts of these two buildings. We find that on average, participants prefer the destination in the first building that they are already familiar with (positive intercept in Table 4.6). It can be explained by the theory of affiliation, which

Table 4.5: Statistical analysis of the accumulated angle change. The response variable is the difference in accumulated angle change between the initial and the recalled route. It is positive if the recalled route has a higher value of the accumulated angle change and vice versa. The explanatory variables were the average degree of the building layout, the relative distance and the relative accumulated angle change of the initial route participants chose compared to the shortest possible route and the route with the smallest accumulated angle change. P-values < 0.05 are shown in bold.

Effect	Estimate	SE	F	P
Intercept	0.30917	0.278	1.1121	0.26676
Average degree	0.060017	0.050418	1.1904	0.23461
Relative distance	-0.24322	0.15717	-1.5475	0.12255
Relative accumulated angle change	-0.12759	0.023589	-5.4089	**1.0968**$\times 10^{-7}$

Table 4.6: Statistical analysis of building layout preference. The response variable is a Boolean variable indicating whether participants choose the destination in the building they entered (0 for no and 1 for yes). Explanatory variables are the difference in the randomness parameter and the average degree between the first building and the second building. P-values < 0.05 are shown in bold.

Effect	Estimate	SE	F	P
Intercept	1.1173	0.2036	5.4878	4.07 $\times 10^{-8}$
Difference in randomness	-0.5049	0.2254	-2.2401	**0.02508**
Difference in average degree	0.1050	0.2256	0.4658	0.6414

suggests that people have a natural tendency to seek out and form connections with places, groups, and individuals that provide them with a sense of belonging and social support [43]. Therefore, individuals may feel more comfortable and confident navigating towards familiar destinations, as they provide a sense of familiarity and affiliation [112]. In addition, participants are more likely to choose the destination in the building with a smaller randomness parameter (negative parameter estimate for the difference in Table 4.6). In other words, participants prefer more regular building layouts. We find no evidence for an influence of average degree on destination selection (p=0.6414). The average path length is not considered, as it is highly correlated with the average degree.

For participants who chose the destination in the new alternative building, they may make this decision because they found a preferred route in the new alternative building rather than because they preferred the building layout. To clarify this, we compare the properties of the two routes: one is the participants' previous preferred route in the first building and the other is chosen route in the new alternative building. We find that the two routes are similar in terms of relative distance and relative accumulated angle change (see Figure A.3 in the Appendix). This suggests that the preference of participants for a building layout depends on the properties of the building layout itself rather than on whether they can choose a better route in either building layout.

4.4 Discussion

We develop a method to generate buildings with random layout properties, conduct a virtual experiment with over 200 participants and use statistical models to explore the influence of building layout properties on pedestrian route choice behaviour. We find that increases in the average degree of building layouts represented as networks negatively affects the route recall of participants. Participants prefer the destination they are familiar with and more regular building layouts. We also observe edge-seeking behaviour of participants in that they follow the periphery of the networks representing buildings. Similar behaviour has previously been found in buildings with low or limited visibility where people walk along walls to evacuate, because it is a safe way to avoid the obstacles and find the exit when there is no visible directional information [69, 101] . There is also considerable evidence for edge-seeking behaviour in animals such as ants [48] and mice [191]. The causes and mechanisms for this behaviour are likely to differ across contexts but a common aspect is that edges can be used as structural guidelines to orient and navigate in an environment. In our experiment, edge-seeking behaviour occurs more frequently with decreases in regularity and increases in average degree of building layouts. One possible explanation for this is that in the experimental environment, participants only control the movement of the virtual pedestrian, in a way that is far less labour-intensive than in reality, so they are less sensitive to distance differences between routes and thus tend to follow a specific heuristic for route choice. Another possible reason is that it presents a simple, repeatable, and low-risk route choice or even heuristic for pedestrians that avoids the effort or need to carefully evaluate alternative routes in less regular environments with many options. Although the reasons for pedestrians walking along edges may differ across a low-visibility context and abstracted route choice, for example, the fact that it occurs repeatedly suggests it may be a fundamental behaviour that may be worthy of further research.

Our findings reveal pedestrian route preferences in buildings: participants tend to select the shortest routes with the smallest accumulated direction change and number of turns. This preference for the most direct route has also been found in previous work [92, 210]. Building layouts are generated automatically in our research, which means we cannot disentangle the relative effects of route length and direction changes, as the smallest values for these factors may coincide in many buildings. Nevertheless, our experiment helps to establish a general understanding of pedestrian strategies through the data and expands the empirical database on the role of building layout in pedestrian route choice.

In the first task of our experiment, we find that as the average degree of the building layout increases, participants retrace their route less accurately. As discussed in the introduction, the average degree has also been described as Inter Connection Density (ICD) and our work confirms the role of this measure on pedestrian route recall and route choice. The consistency between this work and the results of previous studies suggests the potential and feasibility of the network method in how building layout affects pedestrian route choice. The network method allows not only to generate building layouts with controlled properties effectively but also to apply the well-established knowledge in the field of network science to explore how to capture building layout properties that have immediate relevance to pedestrian spatial decisions. For example, while the average degree in this work can measure the connections between nodes in a network, the degree distribution, the probability distribution of these degrees over the whole network, can measure the connections in another way [238]. Pedestrians may have more predictable route choices in a network that follows a power-law degree distribution, because in this type of network only a few nodes have many more connections than others [229], probably making them have a high probability of being on the path of pedestrians. Therefore, other network summary statistics may also help to explain pedestrian route choice strategies and this could be an interesting topic for further investigation.

In the second task of our experiment, we find that participants tend to choose the route in the original building they are familiar with. The preference of pedestrians for familiar places has been suggested to be an essential factor in pedestrian route choice [200]. One possible explanation for this is that the uncertainty in unfamiliar places may result in spatial anxiety, which is a situation pedestrians try to avoid [174]. In addition, participants in our experiment prefer the more regular building layout (generated with a smaller randomness value). This is an entirely novel finding, the mechanism for which are yet to be studied. One explanation for this could centre on the perceptual fluency, the subjective feeling of ease or difficulty while processing perceptual information [181], which has been widely studied in the field of cognitive psychology [154]. Compared with disorganized information, people prefer regular information that leads to a higher perceptual fluency [16]. A limitation of this task in our experiment is that the difference in the layout properties of two buildings is limited to a range due to the constraints imposed in the layout generation. Therefore, the conclusion we draw about pedestrians choosing destinations based on layout properties rather than route properties is only valid within the range of layouts we studied and it may not be valid when there are extreme differences between building layouts. A new building generation method that can generate a wider range of layout properties that are still meaningful would be useful to explore the trade-offs between the layout and route preferences.

There are many other building layout properties (e.g., network orientation or direction) and potential factors that affect pedestrian route choice (e.g., movements of other pedestrians). However, we argue that our work is not an exhaustive examination and still can provide a starting point for future investigations.

Control over extraneous variables is essential in our experiments. We have investigated the influences of several variables on experiment results. First, we provided two types of steering mechanism participants could use to control the movements of the virtual avatar and tested whether the steering mechanism affected their behaviours. Although, the locomotion setup employed in this study may have influenced participants' route choice due to the restricted steering behaviour enabled by mouse and keyboard. It could have led to less natural and less efficient steering behaviour compared to real-life movement. However, the use of a VR environment still allowed us to manipulate key factors related to the layout design and investigate their effects on pedestrian route choice. Second, participants were asked to complete several tasks in their experiment, so we randomly assigned the task order and investigated the effect of task order on participant route choice. However, there were other factors that possibly affected pedestrian route choice but were not considered. For example, the orientation of the 2D maps shown to participants implies the main movement direction is along the diagonal from bottom left to top right. This might potentially play a role in pedestrian route choice, especially for participants who had a specific orientation preference. Therefore, more empirical work on factors affecting pedestrian route choice remains to be done.

The method of generating building layouts we use is primarily controlled by three parameters: the randomness (related to the regularity of the grid of nodes), the distance between nodes and the minimum degree of nodes when generating reduced Gabriel graphs. This method allows us to automatically create a large number of networks representing buildings with different layout properties but cannot ensure the authenticity of the generated buildings, because the building layout is not abstracted from real building floor plans. We suggest that our approach is sufficient for a preliminary investigation on the role of building layout properties on pedestrian route choice. Our approach can help identify relevant factors that can then be compared with real or planned building layouts, and with pedestrian behaviour in the real world. To ensure the practical application of such designs, it is essential that future work focuses on validating them against real-world design regulations, such as building codes. By doing so, we can ensure that the generated designs meet the necessary safety and structural requirements.

One of the limitations of our study comes from the method we used. We conduct our experiment in a virtual environment and participants interact with abstracted building layouts for decision-making, raising questions of the extent to which our findings extend to pedestrian behaviour [143]. Our experiment also presents participants with a top-down view of an entire building layout. This could be compared to choosing a route on a map and the difference between this situation and human visual cognition in real-world settings, as well as effects of human-computer interaction, could influence our findings. There is work that directly demonstrates the validity of the virtual experiment paradigm for pedestrian route choice and decision making [129] and the route choice of participants in abstracted buildings can still capture their preferences [54, 56]. Moreover, the discussion above shows that elements of our findings on route choice confirm the findings of previous research, suggesting our approach is valid. Moreover, the 2D representation of the building allows participants to have global knowledge about the building simply and quickly. This could produce new features affecting pedestrian spatial perception such as the orientation of maps. Therefore, further research on how spatial representations can affect pedestrian route choice would be useful (e.g., comparison of pedestrian route choice in 2D and 3D virtual environments).

Participants for our experiment were recruited using a dedicated platform for scientific research and the experiment was conducted online. While online recruitment allows us to collect data cheaply, effectively and flexibly, there are may be issues with this type of data collection. For example, the self-selected pool of participants may not be representative for the general population and participants who are not directly supervised by researchers may show different behaviours. Research on this issue has suggested that in principle this data collection paradigm is valid, but caution is warranted [32]. A possible measure that can address this issue is to conduct online and offline experiments simultaneously, aiming to obtain a truly representative sample.

Chapter 5

Pedestrian behaviour in sequences of route choices

This chapter explores pedestrian behaviours in sequences of route choices to address **RQ2** and **RQ4** in Section 1.2. Section 5.1 describe the formation of the hypothesis that the sensitivity of pedestrians to environmental information diminishes the more decisions they make in sequence by reviewing relevant literature. Section 5.2 proposes a mathematical model that can formalise the hypothesis and Section 5.3 presents a virtual experiment to validate the model. In Section 5.4, the experiment results are analysed, an additional case study is conducted to test the model and the consequences of diminishing sensitivity to environmental information are explored. Finally, Section 5.5 discusses the main findings and suggests potential avenues for future work.

The work presented in this chapter has been published in Transportation research part C: emerging technologies: Y. TONG AND N. W. BODE, *The value pedestrians attribute to environmental information diminishes in route choice sequences*, Transportation research part C: emerging technolo, 124 (2021), p. 102909 [219]. Two videos of the virtual environment can be found in this paper. Data are available at the University of Bristol data repository [1].

5.1 Introduction

The decision making process individuals use to get from one location to another location is fundamental to research into pedestrian dynamics. This process of wayfinding or routing [2] controls how pedestrians distribute over available routes and is therefore important for determining pedestrian densities and flows in available infrastructure. For all but the simplest routes, two extremes for how pedestrians make these decisions can be distinguished. On the one hand,

[1] University of Bristol data repository: https://doi.org/10.5523/bris.2vu5reaqiwjt72n4yrapjq1i6l

pedestrians may pre-plan their route and subsequently follow this route from start to finish. This process relies on pedestrians having some form of global knowledge of their environment, and it has received wide attention in research (see e.g. [110] for an overview). On the other hand, the route pedestrians take may emerge from a sequence of decisions, each of which is taken at a junction of roads. This process is particularly relevant for situations when pedestrians have no knowledge of the environment they are in. It is this second process that we investigate here.

The route choices pedestrians make at junctions of roads can be regarded as their integration and subsequent response to environmental information, such as signs and the movement of others, and internal information, such as prior knowledge, innate preferences or psychological state. These decisions have been studied in detail (e.g. see [79] for a review of empirical work). Due to their ubiquity and relevance to pedestrian route choice, we focus on two sources of environmental information: signs and the movement of others.

It is generally accepted that signs are an important factor in the movement decision of pedestrians [22, 167]. Previous work has investigated different aspects of signage, such as its positioning, dynamic lighting, observation angle, its colour scheme and the format it is displayed in, to give a few examples [60, 184, 186, 227, 234]. Among this research there is consensus that the direction indicated by signs has a high likelihood of determining the movement decisions of pedestrians.

The movement of other pedestrians is a type of social information that is often studied with a focus on whether pedestrians follow each other. Following behaviour can be defined as imitation behaviour or the act of following others, and it has been studied widely in simulations and experiments on crowd evacuations [73]. In contrast to the effect of signs on route choice, the evidence on following behaviour is contradictory and suggests it depends strongly on the context(for a comprehensive review, see [73]). For example, early work suggests heightened stress levels result in individuals copying each other [85]. Later work takes the more nuanced view on movement initiation that the more people someone sees leaving, the more likely they are to leave themselves and that people are less likely to move towards an emergency exit if others move in the opposite direction [113]. Other work suggests that pedestrians prefer to exit through familiar doors even if others leave by a different door [111]. Research into crowd psychology indicates that individuals with close psychological ties will attempt to escape together during evacuations [200, 201]. In contrast, recent experiments conducted using crowds of volunteers found that the dominant behavior of pedestrians is to avoid others and greater stress or crowding amplifies this behavior [81]. Following behaviour can lead to an imbalanced use of exits, but some findings suggest that an imbalanced exit use actually results in pedestrians avoiding busier routes [17]. Some work suggests that signs outweigh following tendencies [19] but this notion should not be over-interpreted, as it is likely to also depend on the context. Here, we focus on the route choice of pedestrians who are not familiar with the building they are in. Therefore, the movement of others is an important source of information and we assume individuals are more likely to follow others.

While single instances of route decisions have been investigated in detail, as discussed above, the properties of sequences consisting of many such decisions have to date not been studied. Decision making sequences are likely to occur in large and complex buildings, such as transportation hubs or shopping malls, that contain many different and long thoroughfares or evacuation routes which can force pedestrians to not only make one but many route choices.

A larger number and more complex route decisions along a path increase the cognitive load of pedestrians during the navigational process [158]. Research in psychology has found that the quality of decisions made by an individual deteriorates after a long session involving many decisions [24, 98]. This phenomenon is sometimes called decision fatigue, a term coined by the social psychologist Roy F. Baumeister [226]. Examples for when it has been observed to occur include purchases decision of customers[226] and parole board's decisions [34]. Considering route choice decisions in pedestrians, long routes that force people to not only make one but many decisions could potentially cause decision fatigue in pedestrians. Uncertainty over long sequences of decisions in a complex environment could increase the stress levels of pedestrians which could in turn affect their ability to perceive and process information. It has been suggested that individuals under stress are more likely to have a narrowed focuses of attention [121, 208], meaning they may either fail to gather the right kind of information or, alternatively, eliminate nonessential information and focus on what is most relevant. The preceding discussion of previous work in other fields of research thus suggests that the decision making process of pedestrians may change as the number of decisions they have to make consecutively increases. Establishing the existence, nature and consequences of such effects are the key research questions of our work presented here.

In this contribution, we first present a novel model for pedestrian route decisions. Informed by the work in psychology discussed above, the central hypothesis of this model is that the sensitivity of pedestrians to environmental information diminishes as the number of decisions they have to make consecutively increases. While many types of environmental information could be relevant for pedestrian route choices, we focus on signs and the movement of others. Based on previous findings for single route choices, we assume that following tendencies become stronger, the more people use a given route [114]. The mathematical structure of our model resembles previous work in theoretical biology [7].

We then test our central hypothesis and validate our model, via a virtual experiment that was designed to allow for long sequences of route decisions. Virtual experiments are a widely used and accepted experimental paradigm in pedestrian dynamics research, as they are cheap, safe, flexible and they permit a highly controlled setting, even though their ecological validity should be considered carefully [143]. We test the effect of landmarks to aid orientation in our virtual building in addition to the effect of signs and information provided by the movement of others. Landmarks act as reference points that have been suggested to aid pedestrian wayfinding by identifying features in an environment and facilitating the monitoring of progress during navigation [109, 206]. Although landmarks did affect the behaviour of participants in our experiment, we disregard this effect in our subsequent model calibration and validation, as discussed below.

Finally, we present a case study that is inspired by the real-world setting of a metro station. We compare simulations of our model to previously published data on this setting [133] and explore the consequences diminishing sensitivity to environmental information has on the predictability of evacuation dynamics in this setting.

5.2 Model

Our model describes the probability of pedestrians to choose either of two possible routes, denoted x and y and we focus on situations where individuals have to make several such decisions in sequence. We assume decisions are influenced by the innate preference of individuals for either option (e.g. based on familiarity with the building) and by environmental information. As discussed in the introduction, many environmental factors can influence pedestrians' route choice. Here, we select two types of environmental information, namely signs and the movement of other pedestrians, which are generally accepted as important factors influencing the route choice of pedestrians. Extensions to include further information sources,such as the relative distance of routes, are possible but we only model such influences implicitly via the innate preferences. Aspects of the structure of our model are based on previous work on decision-making in animal groups [7]. The key novelty of our model is that we allow individuals to become less sensitive to environmental information, the more decisions they have to make.

The probability for a pedestrian to choose option x, denoted as P_x, is computed as the ratio of the evidences for the two options, D_x and D_y (the probability P_y is computed analogously):

$$P_x = \frac{D_x}{D_x + D_y} \tag{5.1}$$

The evidence for option x is computed as a weighted sum of the information sources and the innate preference of individuals. It is given by (analogous for y):

$$D_x = f(k_c C_x + k_s S_x) + k_\sigma \sigma_x \tag{5.2}$$

where σ_x quantifies the innate preference of individuals, C_x quantifies the information obtained from the movement of others and S_x indicates the presence of a sign for a route. The model parameters k_c, k_s and k_σ capture the relative weight of the corresponding information source and $f()$ is a function that implements the change in sensitivity of individuals to environmental information for consecutive decisions. We now explain each of these terms in more detail.

C_x captures the preference of pedestrians for option x, depending on how many other pedestrians have already chosen each of the options, assuming that individuals have a tendency to follow others. We implement a simple mechanism for this following tendency that is unlikely to be appropriate for all contexts but serves as an approximation of pedestrian behavior over short time intervals for low pedestrian numbers or when sightlines are uninterrupted. We do not consider issues, such as occlusion where only pedestrians visible to others are influential for route choice.Let n_x and n_y represent the number of people who have chosen options x and y, respectively. Then we define:

$$C_x = \frac{n_x}{n_x + n_y} \tag{5.3}$$

such that $C_x + C_y = 1$. Thus, the higher the difference in the number of pedestrians between the two options, the larger is the probability of pedestrians to choose the more popular option.

S_x is a binary variable indicating if there is a sign, such as an emergency exit sign, pointing in the direction of option x:

$$S_x = \begin{cases} 1, & \text{if there is a sign} \\ 0, & \text{otherwise} \end{cases} \tag{5.4}$$

The innate preference of individuals for an option is a constant and $\sigma_x + \sigma_y = 1$ across the two options. Thus, $\sigma_x = \sigma_y = 0.5$ implies individuals have no preference for either option.

For the model parameters k_σ,k_c and k_s, we require $k_c + k_s + k_\sigma = 1$, to implement the weighting of environmental information sources and innate preference. As these parameters are fixed during subsequent decisions, the function $f()$ affects the balance between the innate preference and environmental information from the other pedestrians and signs.

As discussed in the introduction, we hypothesise that the more decisions pedestrians make in sequence, the less sensitive they become to environmental information. Let $k_f \geq 0$ be a parameter measuring the strength of this effect and N the number of decisions a pedestrian has already made (i.e. $N = 0, 1, 2, ...$). Then we define the decrease in sensitivity to environmental information as follows:

$$f(a) = \frac{a}{exp(k_f N)} \tag{5.5}$$

While alternative functional forms for $f()$ are possible, we suggest Equation 5.5 provides a sufficiently general starting point.

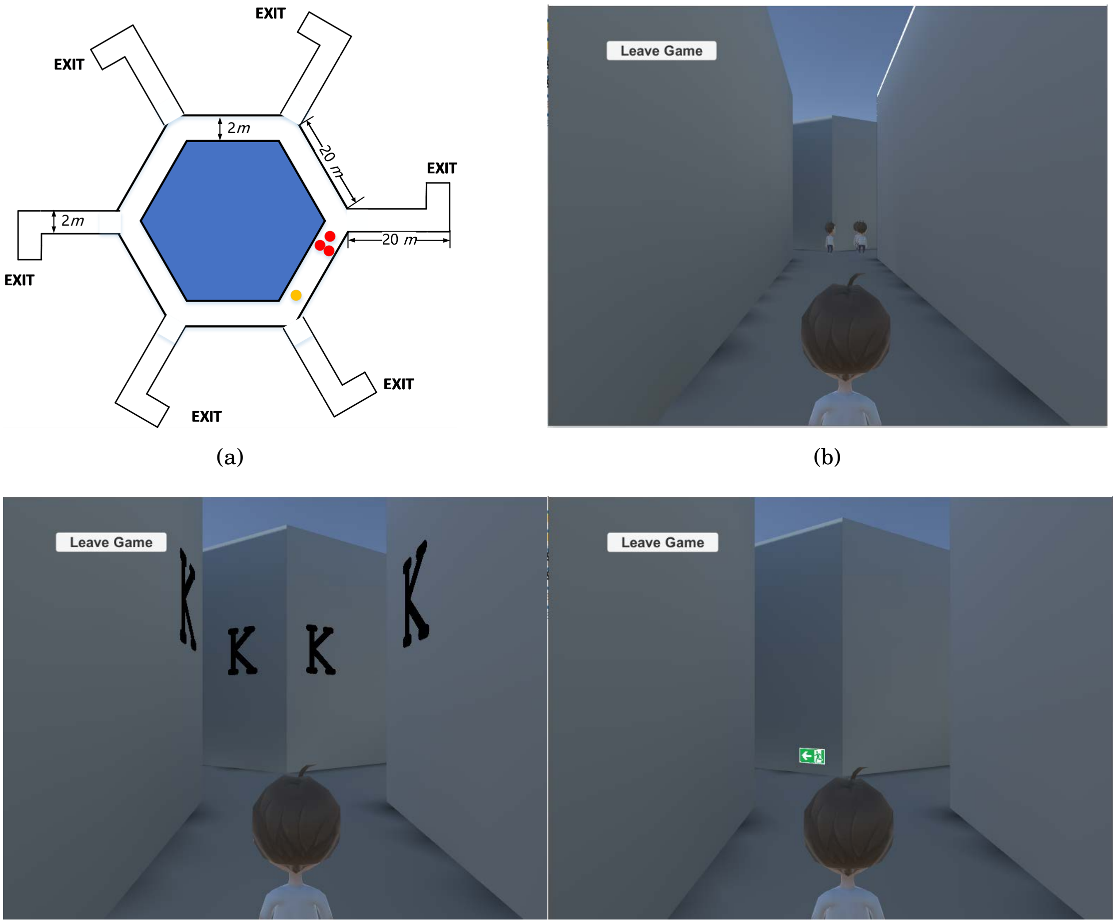
Combining all elements of the model, P_x can be described by the following equation:

$$P_x = \frac{k_\sigma \sigma_x exp(k_f N) + k_c \frac{n_x}{n_x + n_y} + k_s S_x}{k_\sigma exp(k_f N) + k_c + k_s S_x + k_s S_y} \tag{5.6}$$

This expression can be simplified substantially and conveniently for model calibration if only a subset of information sources is relevant, as discussed below.

5.3 Experiments

5.3.1 Virtual environment



(a) (b)

(c) (d)

Figure 5.1: Map of the virtual environment for the main experiment (a) and still images of the virtual experiment as seen by participants on screen for the control treatment (b), the landmark treatment (c) and the sign treatment (d).

5.3.2 Experimental treatments

In our experiment, we tested the influence of two sources of information that are immediately relevant for the route choice of pedestrians in addition to following behaviour: landmarks and signs. A landmark is an object or feature with distinct qualities contrasting with the surrounding environment. It can be used as a reference to help pedestrians memorise or recognise routes and locate themselves relative to their ultimate destination [206]. We have already discussed the relevance of signs to the route choice of pedestrians in the introduction.

Each participant was only allowed to take part in the experiment once and was exposed to one randomly selected treatment out of five separate treatments in the second part of the experiment. Figure 5.1 shows the different treatments from the perspective of participants. In the control treatment, the computer-controlled pedestrians walked in the clockwise direction around the hexagonal corridor, turning right at every junction. There were no features that distinguished different parts of the building. This treatment was designed to establish the baseline behaviour of participants in the experiment (i.e. tendency to follow others). In the anticlockwise treatment, the computer-controlled pedestrians walked in the anticlockwise direction around the hexagonal corridor. This treatment was designed to establish if participants had an innate preference for turning left or right at junctions. In the landmark and sign treatments, computer-controlled pedestrians walked in the clockwise direction, and we added features to the virtual building. Landmarks consisted of letters displayed on the walls at junctions (Figure 5.1c). We used the six letters (K, H, E, X, B, M) in the non-alphabetical order shown (clockwise). The sign treatment consisted of small commonly used emergency exit signs that pointed in the direction of the exit at the junctions of the hexagonal corridor (see Figure 5.1d). The fifth treatment, referred to as "both" for simplicity, included both signs and landmarks and computer-controlled pedestrians walked in the clockwise direction.

5.3.3 Data collection and analysis

We recruited participants on the campus of the University of Bristol, UK, between the 6th of February and the 12th of March 2020. Participants were not paid and only took part once. Before the experiment, participants were informed about the broad topic of the experiment and were told that they could quit the experiment at any time. No questions asked by participants were answered during the experiment to avoid providing different information across participants that might affect their decisions. To collect data from multiple participants simultaneously, we used three different laptop computers during data collection. We noticed no difference in participant experience across the different machines. The laptop models used are listed in Table.A.3 in the Appendix for completeness.

A total of 205 participants took part in our experiment. The data from seven participants had to be excluded from our analysis: one participant did not complete the questionnaire after the experiment, three lost interest and quit the experiment, and three talked with someone else during the experiment, which could have affected their decision-making. Thus the data from 198 participants were analysed, distributed across the treatments as follows: 40 participants for control, 40 participants for anticlockwise, 40 participants for landmarks, 40 participants for signs, and 38 participants for both signs and landmarks. Reported ages ranged from 18 to 45, and the median age was 21 years (12 (6%) participants did not disclose their ages). The gender distribution was approximately balanced with 99 female participants (50%), 95 male participants (48%) and 4 participants (2%) not disclosing their gender. Most participants came

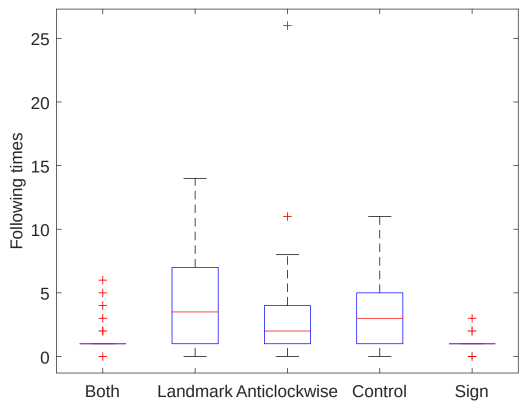


Figure 5.2: Following times for each treatment. Box and whisker plots show the median, the 25th and 75th percentiles (box) and 1.5 times the interquartile range or the maximal values in the data (whiskers). Observations beyond the whisker length are shown as outliers.

from English-speaking countries (142 or 71.7%). Amongst the participants who did not come from an English-speaking country, we could not discern any noticeable difficulties with understanding the meaning of instructions and concepts in this experiment.

To assess participant following behaviour quantitatively, we defined following times as the number of times a participant followed the computer-controlled pedestrians at junctions, including the initial decision before the first junction is reached. Thus, if a participant follows the computer-controlled pedestrians to the first junction and then exits, this count equals 1. For our statistical analysis of the effect of our experimental treatments and other factors on this count data, we used generalised linear models (GLMs) with a Poisson error structure and a log link function. We confirmed the appropriateness of these models by examining residual plots.

Details on how our model for sequential route choices was calibrated on this experimental data are provided after the findings of the experiment.

5.4 Results

5.4.1 Experimental evidence for information use

We first established what information affected the route choices of participants in our experiment, before studying our model. Figure 5.2 shows the following times of participants for each experimental treatment. Across all treatments, the largest number of following times we observed was 25 in the anticlockwise treatment, and some participants did not follow the computer-controlled pedestrians at all. For the sign treatment and the treatment including both signs and landmarks, most participants had following times of less than five, which was noticeably less than in other treatments. Differences between the control and anticlockwise treatment were small.

Our statistical analysis confirmed these observations (Table.5.1). We found that on average, participants had a tendency to follow others (non-zero intercept in Table 5.1), but altering the movement direction of the computer-controlled pedestrians did not reveal an inherent bias of participants to turn left or right (no effect of anticlockwise treatment, Table 5.1). Participants were substantially less likely to follow others when signs were present (significant negative effect of sign, Table 5.1). This confirms the findings from previous work on the importance of signs when compared to other sources of information in directing pedestrian route choice. Interestingly, our treatment displaying landmarks had the opposite effect to what we expected as it led to an increase in following times compared to the baseline (positive effect of landmark in Table 5.1). This would suggest that as different parts of the building became more distinguishable, participants followed the computer-controlled pedestrians more. As the comments by participants did not provide any qualitative explanations for this behaviour (see Table A.4 in the Appendix), we can only speculate as to why this behaviour occurred. Perhaps the different landmarks made participants curious meaning they wanted to see more of the building, or participants saw the changing landmarks as confirmation that they were following other pedestrians to new places and were thus on the right route, as there was no other information available. When landmarks and signs were present conjointly, the behaviour of participants was indistinguishable to the situation when only signs were present (Figure 5.2) and we found no evidence for an interaction in the effect of the two sources of information (Likelihood-ratio test, $\chi_1^2 = 0.0332$, $p = 0.8555$). We suggest that while our findings on landmarks are interesting, further work is needed on their role in pedestrian route choice sequences. Based on these findings, we decided to not include information from landmarks into our theoretical model.

In addition to the experimental treatments, data from our personality test also helped to explain the number of times participants followed the computer-controlled pedestrians (Likelihood-ratio test, $\chi_5^2 = 22.5970$, $p = 4.0301 \times 10^{-4}$). We found that conscientiousness, the personality trait of being careful or diligent, and emotional stability, a person's ability to remain stable and balanced, both reduced the number of following times (See Table A.5 in the Appendix). None of the remaining three dimensions of personality had an effect on participant route choice. It is possible that participants with high conscientiousness scores tended to notice information that might initially be missed by others (e.g. signs), and that participants with high emotional stability scores could handle negative emotions during the experiment such as decision fatigue and make rational choices. We suggest that these findings could provide a starting point for future investigations.

In summary, we found evidence that participants followed the computer-controlled pedestrians on average more than once (many times, in some cases) and that signs were a more influential source of information than following others.

Table 5.1: Statistical analysis of following times using a generalised linear model with Poisson error structure and log link function(see Appendix A.3 for details). The response variable is the following time, a count for how many times participants followed others in the experiment. Explanatory variables are an intercept and Boolean variables indicating the presence of signs, landmarks and anticlockwise movement of computer-controlled pedestrians. P-values ≤ 0.05 are shown in bold.

Effect	Estimate	SE	F	P
Intercept	1.16327	0.088388	13.16	**1.4998** $\times 10^{-39}$
sign	-1.1882	0.11501	-10.331	**5.0984** $\times 10^{-25}$
landmark	0.28856	0.097493	2.9598	**0.0030782**
anticlockwise	0.10229	0.11807	0.86636	0.38629

5.4.2 Evidence for the diminishing sensitivity to environmental information

Having established that sequences of route choices occurred frequently in our experiment, we next calibrated our model on the experimental data and used this to test our key hypothesis on the diminishing sensitivity of pedestrians to environmental information. We used our theoretical model instead of further statistical analysis, as it easily extends to other contexts, as demonstrated below in the following section.

As we found no difference between the control and the anticlockwise treatment, we did not distinguish between these two treatments, combined their data and refer to the route taken by the computer-controlled pedestrians as option x in the following. In the absence of signs ($S_x = S_y = 0$), Equation 5.6 for the probability of individuals to choose option x can be simplified to:

$$P_x = \frac{k_\sigma \sigma_x exp(k_f N) + k_c}{k_\sigma exp(k_f N) + k_c} \tag{5.7}$$

Making use of the requirement that the weights for different information sources add to 1 (i.e. here $k_\sigma + k_c = 1$), equation 5.7 can be written as:

$$P_x = \frac{(1-k_c)\sigma_x exp(k_f N) + k_c}{(1-k_c) exp(k_f N) + k_c} \tag{5.8}$$

Similarly, for the sign treatment P_x in our experiment, we have $S_x = 0$ (signs always indicate the alternative option y), Equation 5.6 can be simplified as follows (making use of $k_\sigma + k_c + k_s = 1$):

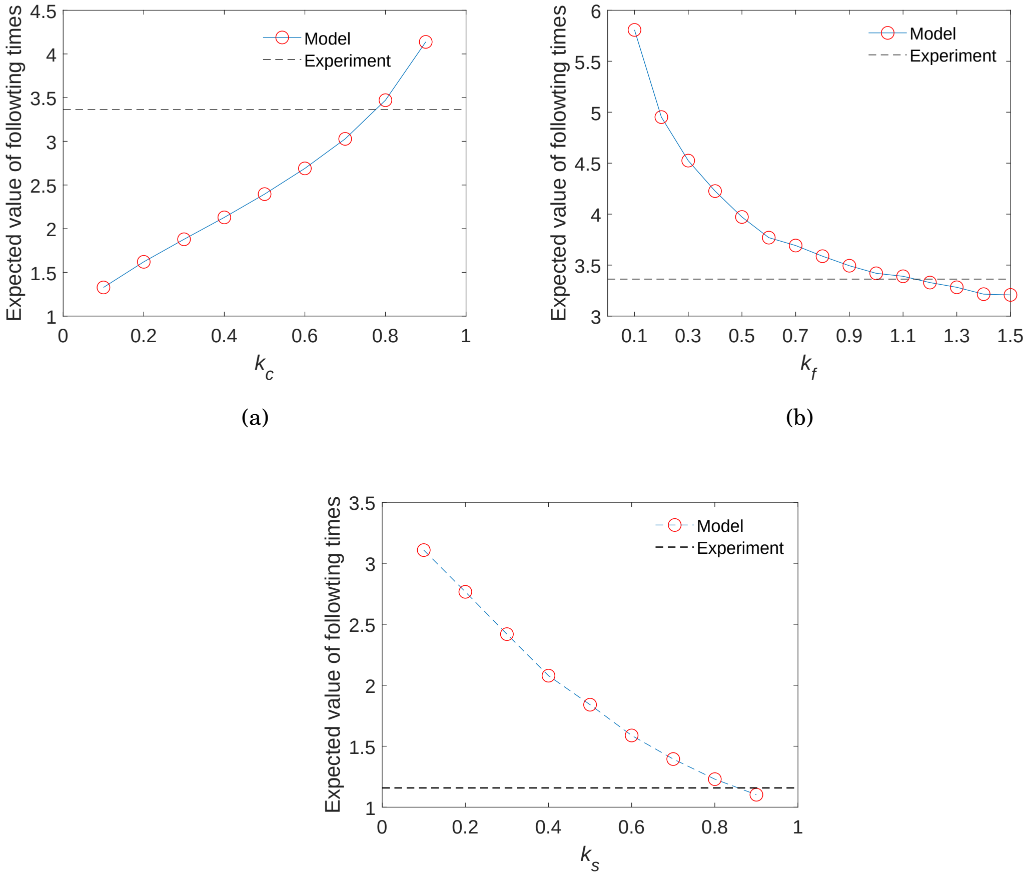
$$P_x = \frac{k_\sigma \sigma_x exp(k_f N) + k_c}{k_\sigma exp(k_f N) + k_c + k_s} \tag{5.9}$$

$$P_x = \frac{(1-k_c-k_s)\sigma_x exp(k_f N) + k_c}{(1-k_c-k_s) exp(k_f N) + k_c + k_s} \tag{5.10}$$

Before calibrating our model on the experimental data, we used equations 5.8 and 5.10 to gain an understanding of the behaviour suggested by our model in the experiment for different parameter values. As we had no information on innate preferences for either option, we assumed $\sigma_x = \sigma_y = 0.5$ throughout. To calculate following times, we simulated individuals who made a sequence of choices between two options based on our model until they chose not to follow the computer-controlled pedestrians. We first considered the situation in the absence of signs (see Equation 5.8). Figure 5.3(a) and (b) show the effect of the two relevant parameters k_c (weighting for information to follow others) and k_f (rate of decrease in sensitivity to information) on the expected value of following times. As k_c increases, the expected value of following times increases capturing the fact that larger k_c values imply a higher weighting for adhering to information provided by the three computer-controlled pedestrians in our experiment. In contrast, as k_f increases the expected value of following times decreases, because the following behaviour diminishes faster over consecutive decisions for larger k_f. Considering the sign treatment, Equation 5.10 shows that k_s additionally determines the route choice of individuals (weighting for information indicated by signs). Figure 5.3(c) shows the trade-off between the different sources of environmental information. As k_s increases relative to k_c, the expected value of following times decreases.

To calibrate our model, we assumed that the model parameters remain unchanged across experimental treatments, that is to say that any changes in participant behaviour arose from changes in the environmental information provided. Thus, we first fitted the parameters present in Equation 5.8 (absence of signs). For the first decision, $N = 0$, which means we could determine k_c directly from the proportion of participants who chose to follow the computer-controlled pedestrians, finding $k_c = 0.78$. To determine the value of k_f, we used the data from subsequent decisions. We found that for $k_f = 1.1$ model simulations closely matched the number of following times observed in experiments (calculated as the value of k_f for which the linear interpolation between neighbouring values covered by our parameter scan in Figure 5.3(b) was equal to the experimentally observed average following times). For the sign treatment, we then assumed that k_f remained unchanged and that the ratio between k_σ, and k_c also remained unchanged which allowed us to determine k_s in a similar way to the other parameters (i.e. the ratio $\alpha = k_\sigma/k_c$ is fixed, such that $k_s + k_c + \alpha k_c = 1$).

To validate our calibrated model and to examine our hypothesis on the diminishing sensitivity of participants to environmental information, we ran further model simulations. Figure 5.4(a) and (b) show the cumulative distribution function of following times for the experiment and an example simulation. These plots show a broadly similar shape, but also indicate substantial variability across simulations. Comparing the expected value (mean) of following times for model simulations with and without diminishing information in the situation without signs showed clear evidence for participants becoming less sensitive to environmental information over consecutive route decisions (Figure 5.4(c); the model without diminishing information fails to capture the



(a) (b) (c)

Figure 5.3: The effect of the model parameters k_c (a),k_f (b) and k_s (c) on the expected value of following times (k_c and k_s determine the weighting of information from other pedestrians and signs, respectively; k_f determines the rate at which the sensitivity of individuals to environmental information diminishes). We show the mean following times for 1,0000 model simulations. See main text for details on model calibration. In (a) and (b), $k_f = 1.1$,$k_c = 0.78$ and $k_\sigma = 0.22$ whenever the parameters are not varied. In (c) $k_f = 1.1$ and the relation between k_c and k_σ is fixed (see main text).

experimental data). In contrast, when signs were present, we could not determine if diminishing sensitivity to environmental information was important, because most participants followed the direction indicated by the sign at the first opportunity. Note that while it may be possible to adjust k_c in the model without diminishing information sensitivity to achieve a better fit, this would compromise the model fit for the first decision ($N = 0$).

We also compared our model simulations to our experimental data by counting the number of participants who followed the computer-controlled pedestrians above a threshold number of times (more than six times and more than once for the situations without and with signs, respectively). As for the number of following times, we found that for the situation without signs, including

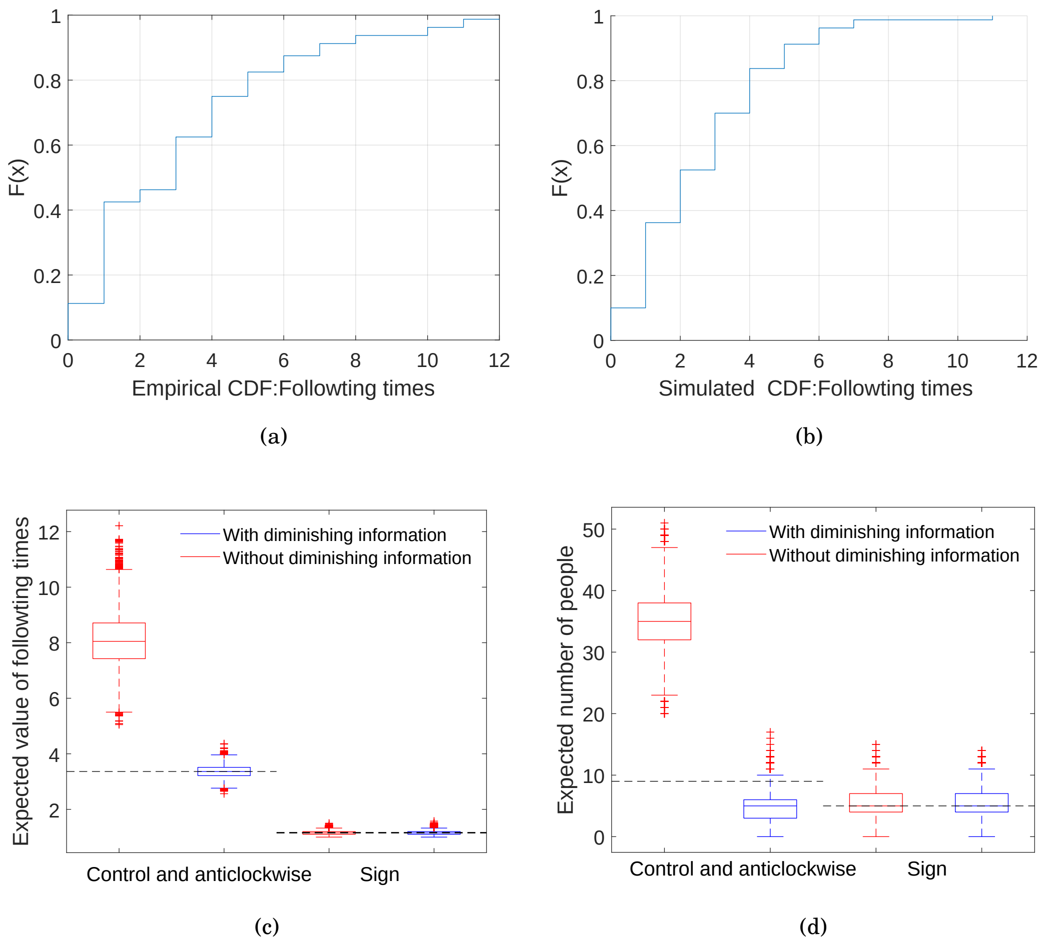


Figure 5.4: Comparison of following behaviour between experiment and model simulations with or without considering diminishing information. (a) Empirical cumulative distribution function for following times for the control and anticlockwise treatments. (b) Example of a simulated cumulative distribution function for the model calibrated on the control and anticlockwise treatments. (c) Expected value of following times from simulations for the situation without and with signs and including or excluding diminishing sensitivity to environmental information. (d) Expected number of people with a following time larger than six in the absence of signs, and a following time larger than one when signs are present. The dashed horizontal lines show the experimental data. Parameters are $k_\sigma = 0.22$, $k_c = 0.78$ for (c) and $k_s = 0.85$ and $k_\sigma / k_c = 0.28$ for (d). $k_f = 1.1$ and $k_f = 0$ for the simulations with or without diminishing information, respectively. We performed the same number of model simulations as the number of participants in our experiment (control and anticlockwise treatments: 70 participants; sign treatments: 40 participants.).

diminishing sensitivity to information into our model was necessary to achieve a good fit to the experimental data (Figure 5.4(d)). The distinction for the situation with signs was similarly inconclusive as for the following times.

In summary, we found clear evidence for a diminishing sensitivity of participants to some environmental information in sequences of consecutive route choices.

5.4.3 Case Study

To demonstrate the flexibility of our model in applications to different contexts and to further investigate the role of diminishing sensitivity to environmental information in route choices, we compared our model to a previously published experiment [133]. In this experiment, individual human participants had to exit an immersive virtual metro station via one of five available routes in the presence of computer-controlled pedestrians (see 5.5(a) for a diagram of routes). Crucially, the proportion of computer-controlled pedestrians using different routes was varied according to three different patterns, in which all computer-controlled pedestrians chose the same route (pattern 1), the majority of them chose the same route (pattern 2) and they split evenly across options at each decision point (pattern 3). The three patterns are shown in Figure A.3 in the Appendix. We used our model from Equation 5.6 to simulate participant behaviour for this setting considering the three patterns of crowd flow. The original study included signs pointing to all exits and for simplicity we therefore did not include any signs in our comparison, which is equivalent in our model.

We calibrated our model using Maximum Likelihood Estimation (MLE) on data from patterns 1 to 3 (for data and parameter estimates, see Table A.6 in the Appendix). Parameters k_c ($k_\sigma = 1 - k_c$) and k_f were constrained to be between 0 and 1 and non-negative, respectively. Figure 5.5(a) shows that route options in the experiment included staircases and hallways, and we therefore allowed for an innate preference σ_x for hallways in our calibration. The choice between two staircases of identical length and look was implemented as $\sigma_x = \sigma_y = 0.5$. We did not include additional information about the relative distance of route in our model, as the previous analysis had shown that participants did not select the shortest route, suggesting that other information sources were more important [133]. However, for other contexts it may be necessary to include such information in our model. MLE suggested that $k_f \approx 0$. We used the Akaike Information Criterion (AIC) to compare the support of the data for our models for different values of k_f, finding $AIC = 351.5$, 386.0 and 532.7 when $k_f = 0.0$, 1.1 and 3, respectively. These results suggest that diminishing sensitivity to environmental information was not important for the data from [133].

Figure 5.5 (b) and (c) show that under patterns 1 and 2 in which the computer-controlled pedestrians split unevenly between two available routes at decision points, simulations without diminishing sensitivity to information ($k_f = 0$) produced a closer match to the experimental data, especially considering participants choosing route 1, the route used by most participants. One possible explanation for this finding could be that the length of the sequences of decisions (at most three decisions) was too short for the sensitivity to environmental information to diminish noticeably. However, without further data, this explanation remains speculative. In contrast to our findings for patterns 1 and 2, under pattern 3 in which the computer-controlled pedestrians

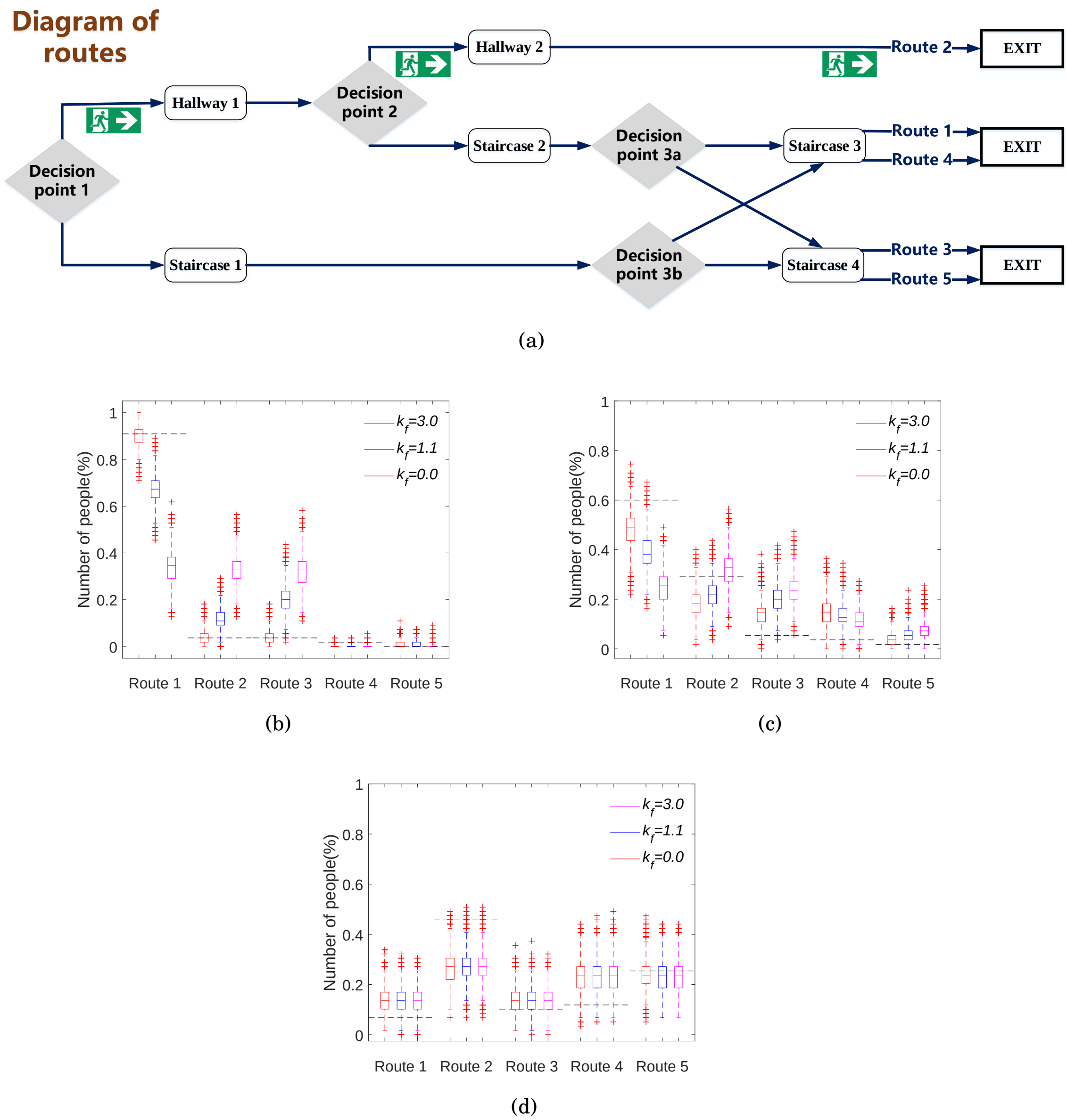


Figure 5.5: Comparison of route choices between an experiment [133] and our model for a metro station. In the experiment a single human participant had to exit the station in the presence of computer-controlled pedestrians. (a) Diagram of the possible exit routes from the starting point. The original study included signs pointing to all options. Signs are therefore not included in the simulations presented in this figure. The signs shown in (a) are considered in Figure 5.6. (b)-(d) The proportion of individuals selecting available routes for different scenarios that vary how computer-controlled pedestrians split at the decision points. In these patterns all computer-controlled pedestrians chose the same option, route 1 (100-0 split; pattern 1), split unevenly between options favouring route 1 (80-20 split; pattern 2), or they split evenly (50-50 split; pattern 3). See main text and Figrue A.3 in the Appendix for details. We simulated the same number of participants as the experiment, which was 55 under pattern 1, 55 under pattern 2 and 59 under pattern 3. Dashed horizontal lines show the empirical data. Parameters used: $k_s = 0$, $k_\sigma = 0.0891$ and $k_c = 0.9109$. Values of k_f are shown in the figure.

split evenly at every decision point, diminishing information sensitivity had no substantial effect on simulations, as information from computer-controlled pedestrians did not indicate a preference for any direction and signs were not considered, see Figure 5.5(d).

In simulations, we additionally investigated the variability in observed behaviour depending on the trade-off between different sources of environmental information and on the speed at which the sensitivity of individuals to this information diminished over consecutive decisions. We considered the same metro station scenario with two changes. First we included signs pointing exclusively along the shortest route (route 2) to an exit from the starting point, as shown in Figure 5.5(a). Second, instead of including directional information in the form of some individuals always walking certain routes, as in the previous experiment [133], we simulated the full route choice process for 100 participants in the building who started one after the other from the same starting point. Thus, each simulated pedestrian would consider the route choices of all previous pedestrians in their decisions. We compared the proportion of pedestrians choosing route 2, the shortest route, for different values of k_s, k_c and k_f.

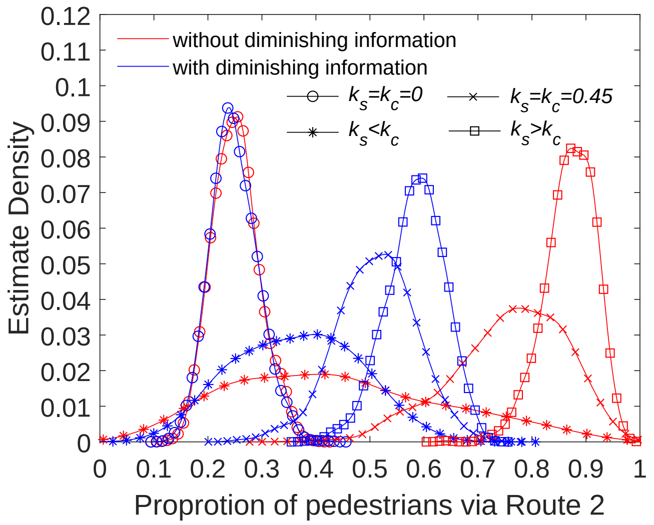


Figure 5.6: The proportion of pedestrians choosing the shortest route, route 2, in the metro station scenario, as predicted by model simulations, when diminishing sensitivity to environmental information is present or absent. Signs point in the direction of route 2. The blue and red lines represent the route choice of pedestrians with (k_f=3) or without diminishing sensitivity to information (k_f=0), respectively. The line with circle markers indicates the baseline in which the crowd and signs have no effect on pedestrians' directional choices (k_s=0, k_c=0 and k_σ=1); the line with asterisk markers shows the situation when the movement of the crowd is highly influential(k_s=0.2,k_c=0.7 and k_σ=0.1), the line with cross markers indicates the situation when signs and crowd have an equally strong influence (k_s=0.45, k_c=0.45 and k_σ=0.1) and the line with square makers shows the situations when signs strongly influence pedestrians' route choice (k_s=0.7, k_c=0.2 and k_σ=0.1).

Figure 5.6 shows the distribution of these proportions over 1000 replicate simulations, each with 100 pedestrians. We consider the full distribution over replicate simulations, as the variance in global route choice outcomes is informative. The smaller the variance, the more predictable is the dynamics for a given scenario. We found that for $k_s = k_c = k_f = 0$ when pedestrians had no preferences, the proportion of pedestrians choosing route 2 was around 0.25, as expected from an approximately even distribution of pedestrians over routes at each decision point. When pedestrians followed others more closely than signs ($k_s = 0.2$, $k_c = 0.7$, $k_f = 0$), the proportion of pedestrians choosing route 2 increased on average but also became substantially less predictable (notice the large variance in proportions observed in Figure 5.6 for these parameter values). As k_s was increased further relative to k_c, the proportion of pedestrians choosing route 2 increased further and the variability in simulation outcomes was reduced. For $k_s = 0.7$, more than 85% of pedestrians chose route 2, on average.

When introducing diminishing sensitivity to environmental information ($k_f = 3$), we found a qualitatively similar trend as the balance between k_s and k_c was altered. However, with the exception of the case $k_s = k_c = 0$, when including diminishing information, a smaller proportion of pedestrians chose route 2. This can be explained by the fact that when $k_f > 0$ in our model, the information about this exit route was considered less and less by pedestrians after each decision point. While this could be considered as detrimental to finding the shortest exit route, interestingly $k_f > 0$ also reduced the variance across simulation outcomes. This suggests that diminishing sensitivity to environmental information could in some circumstances make crowd dynamics more predictable.

5.5 Discussion

We have formalised in a mathematical model the hypothesis that pedestrians become less sensitive to environmental information as the number of consecutive route decisions they make increases. Comparison of our model to data from a virtual experiment suggests that sensitivity to information diminishes for the case when only social information was available to pedestrians. Comparison to data from the sign treatment in our experiment and the case study [133] suggests that this effect cannot be detected in short sequences of route decisions that contain three or fewer decision points. We can only speculate on what causes this effect, taking research in Psychology and Neuroscience as starting points. One explanation could centre on the neurological processing of repetitive patterns in the hippocampus of the human brain, which has been shown to be responsible for storing a cognitive map for navigation [33]. Another explanation could take "decision fatigue" demonstrated in psychological experiments as a starting point [24, 98]. Regardless of the precise mechanism, it is likely that the psychological state of pedestrians, such as increased stress levels, could also impact this behaviour [121, 208]. An alternative mechanism also leading to diminishing sensitivity to environmental information over time could be increasing smoke levels in fires that limit the visual field of pedestrians.

Exactly how the sensitivity of pedestrians to environmental information changes in the course of completing a trip between two locations is therefore likely to depend on the setting and context. We have shown that the effect exists in the somewhat idealised but nevertheless plausible setting of our virtual experiment. Moreover, our simulations of the metro station demonstrate the possible implications of diminishing sensitivity to information in consecutive route decisions. On the one hand, fewer pedestrians may follow the route indicated by signs but on the other hand, following behaviour can be suppressed leading to more predictable movement patterns (following behaviour can cause unbalanced route usage based on the initial decisions of few individuals which may be subject to substantial variability).

In agreement with previous work [19], participants in our experiment were more likely to follow the direction indicated by signs than by the simulated pedestrians. Previous work suggests that the location, colour scheme, and display of signs influences the response of pedestrians to them [184, 186, 227]. We use a commonly used exit sign design and positioned signs in prominent positions in our virtual environment which may have enhanced their effect on pedestrians. Based on previous work, our model assumes that pedestrians are more likely to follow the majority of other pedestrians at junctions of roads [114] and our successful model calibration and validation using previously published data [133] suggests this assumption is correct in the contexts we considered. This suggests a positive feedback mechanism in following behaviour in the absence of other environmental information that can lead to popular routes becoming more and more busy. However, we did not explicitly consider high pedestrian densities and resulting blockages which could deter pedestrians from following others, as previously indicated [17].

Our model achieves a good match to data from two separate experiments suggesting it can successfully capture pedestrian route choice across contexts. Extensions to our model that consider additional sources of information, such as light levels, pedestrian densities or road surface are possible, if needed. However, we acknowledge that our model is only suitable for certain scenarios where people are not familiar with the building and the building has a limited number of potential routes, and participants only need to make a choice between two available alternatives at each junction.

The two virtual experiments we consider in this study differ substantially. The first has a simplified setting that uses symmetry to limit directional information to the signs, landmarks and crowd movement we implement. The second scenario is based on a real metro station with open spaces. We argue that it is appropriate to use the same model to explain the route choice of pedestrians in these different settings. In both experiments participants had no prior knowledge of the building and the route information shown to them was precisely controlled (i.e. signs, crowds, landmarks). Therefore, the response of pedestrians to different types of information can be investigated and our proposed model, which integrates these different information sources, can be applied in these two contexts as an approximation of the route choice mechanisms of pedestrians. More generally, the difference between the two experimental settings we consider raises the question of ecological validity, of how applicable we can expect our findings to be to real-world contexts. On the one hand, our experiment is highly controlled and abstracted and further evidence is thus needed to test if our findings generalize to real-world contexts. On the other hand, because our experiment carefully controls the information available to participant and removes extraneous information or effects, we can be certain that we have detected diminishing sensitivity to directional information, as we set out to do. We do not wish to claim that our experiment completely answers the question we pose. More work and data with higher ecological validity is needed. However, we suggest our work is a useful starting point that provides a proof of existence for the effect we investigate and, via our model, a way of making quantitative predictions that can be tested in other contexts.

The importance of landmarks for pedestrian navigation has been highlighted before [109, 206]. In our experiment, the presence of landmarks increased the likelihood of pedestrians to continue following others and to remain inside the building. It might be the tendency for participants to explore the virtual environment more extensively than they would in real-life scenarios, possibly due to the absence of physical limitations, such as fatigue, associated with movement in virtual reality. While this issue is discussed in the thesis, it is worth emphasizing its potential impact on the validity of the experimental results. It is a limitation of our work that we cannot provide insights into the causes of this effect. Testing different types of landmarks (e.g. ones more recognisable from real buildings) and controlling the motivation of participants more carefully to avoid curiosity-driven exploration (e.g. via monetary incentives) could be informative.

We have compared our model to data from experiments in virtual environments. This experimental paradigm facilitates highly controlled data collection in large and complex buildings, which presents logistical challenges in real physical spaces. While experiments in virtual experiments present opportunities and advantages, it is essential to carefully consider their ecological validity [143]. In our experiment, participants were presented with an on-screen, three-dimensional environment that they could interact with via the computer keyboard. It has previously been suggested that for the type of route choices we consider here, lower levels of immersiveness than we use are adequate [129]. However, until more empirical evidence becomes available, there is no guarantee that this is the case. The virtual experiment we conducted has a simplified setting with limited elements, which is different from real-life scenarios that are more complex. This simplistic setting allowed us to focus on the specific factors we were investigating without the influence of extraneous information. However, it also raises potential issues, such as the possibility that pedestrians may become disengaged or bored with the limited environment, which could affect their behaviour. We suggest that for our goal of demonstrating the existence of diminishing sensitivity to environmental information in sequences of route decision, experiments in virtual environments are a useful and adequate starting point.

One possible source of behavioural heterogeneity in pedestrian crowds are the different personality traits of individuals. Therefore, there is an interest to map personality traits to behaviours [47]. For example, in crowd simulation models traits described as 'psychoticism' and 'neuroticism' are implemented as pedestrians moving past others closely in order to avoid detours and taking indirect paths to keep their distance from others, respectively [71]. Similarly, in another model [46], the parameters controlling the movement of individuals were varied based on an assumed mapping to the Big Five personality traits [65]. We have found that participants in our experiment who reported high conscientiousness and emotional stability tended to follow the computer-controlled pedestrians less. Thus, our research provides empirical data to inform future work and to calibrate the parameter of models that investigate how personality traits influence pedestrian behaviour.

CHAPTER 6

CONCLUSIONS

6.1 Conclusions

The overall aims of this thesis are to establish a theoretical framework for pedestrian route choice and explore how pedestrians respond to various sources of environmental information and pedestrian behaviour in sequences of consecutive route choices.

RQ1: How can we develop a systematic framework for pedestrian route choice that can capture the essence of pedestrian route choice across disciplines? - A systematic theoretical framework for pedestrian route choice can be established based on general processes of human decision-making. In each process, the principles can be identified according to the key mechanism of pedestrian route choice. The framework can serve as a common process of pedestrian route choice across disciplines and scenarios but the principle for each process depends on the context. Thus, a systematic theoretical framework for pedestrian route choice is possible, but it requires contextual characterises to be applicable to certain scenarios.

RQ1.1: **Where does the complexity of pedestrian route choice come from?** - The complexity of pedestrian route choice lies in two aspects: first, pedestrian route choice involves a variety of disciplines and is being investigated with different emphasis and techniques, making it a strong interdisciplinary topic, as shown in Figure 2.1 in Section 2.1. Second, pedestrians can make route choices in different temporal and spatial scales, ranging from city exploration to building evacuation. Due to its complexity, the establishment of a theoretical framework across disciplines is essential and possible based on our work in Chapter 2.

RQ1.2: **What processes can be identified to describe pedestrian route choice across contexts?** - The process of pedestrian route choice can be described in various ways. In this thesis, information perception, integration, responding to information and decision-making mechanisms are classified based on the process of how people handle information and make decisions. It is a common process in human decision-making and thus can describe how pedestrians choose routes across contexts.

RQ1.3: **What are the principles of pedestrian route choice in each identified process?** - The principles of pedestrian route choice of each process are: (1) In the process of information perception, pedestrians can perceive information selectively and purposely, given the limited available information. (2) In the process of information integration, pedestrians integrate environmental spatial information into mental representations with subjectivity. (3) In the process of responding to information, pedestrians tend to be attracted and repelled by specific attributes individually and this can lead to positive or negative feedback loops across many individuals and (4) In the process of decision-making mechanisms, pedestrians perform trade-offs based on the evidence provided by different attributes. More importantly, how pedestrians perceive, integrate, respond to and decide upon information is not fixed but varies with the context.

RQ2: How do various sources of directional information (e.g., signs and movements of others) impart pedestrian route choice in buildings? - There are many available sources for directional information during the process of pedestrian route choice. In this thesis, the role of signs, landmarks and movements of others in directing pedestrian route choice has been investigated via virtual experiments where participants are asked to make route choices based on given information. Apart from landmarks that do not have a significant effect on participant decision-making, signs and movements of others are found to influence how pedestrians choose routes in buildings. Further details are discussed below.

RQ2.1: **How do pedestrians trade off various sources of environmental information?** - Chapter 5 presents a model to measure different weightings of environmental information for individual route choices in buildings. Results indicate that pedestrians tend to follow a sign for escape even if the sign and movements of others indicate different directions, which is consistent with previous research [17], suggesting the dominant influence of signs on pedestrian decision-making in virtual experiments. Chapter 3 explores the impacts of contextual factors on pedestrian route choice via a virtual experiment. Results show when available, spatial information shown in a map influences pedestrian route choice more than the movement of others. Thus, pedestrians tend to rely more on signs and maps than the movement of others to make route choices. However, the trade-offs between signs and maps have not been examined in this work, which can be investigated in future work.

RQ2.2: **Are responses of pedestrians to experimental information consistent in different contexts? If not, what contextual factors can be important?** - Chapter 3 investigates how pedestrians respond to the movement of the crowd in different contexts. The result shows whether pedestrians follow others significantly depends on contextual factors. Spatial information (what information participants have about the exit routes), crowd state (whether the size of the crowd causes congestion) and crowd split level (how simulated pedestrians are distributed across exits) are identified as essential factors. Participants are more likely to avoid the crowd but tend to choose the exit with shorter escape routes even if these routes are chosen by a majority of the crowd. Furthermore, participants tend to avoid empty exits regardless of their higher utility. Therefore, pedestrians are more likely to make different route choices in different contexts and spatial information and conditions of the crowd are important factors. However, there are many other aspects of contexts such as stress levels and building types that can be important but have not been investigated in detail.

RQ3: **How can building layout properties influence pedestrian route choice in buildings?** - In this thesis, a virtual experiment is conducted to investigate how building layout properties can affect pedestrian route preference and route recall that measures how well participants can remember their previously chosen routes. Results show that increases in the average degree of building layouts have a negative impact on the route recall of participants. Pedestrians are more likely to choose the destination they are familiar with and more regular building layouts and tend to walk along the edges of the building layout. Although the findings are applicable for certain scenarios, for example, where participants have a top-view of the building and thus have global spatial knowledge about the environment, they can still help establish a general understanding of pedestrian strategies and expand the empirical database on the role of building layouts in pedestrian route choice.

RQ3.1: **How to develop a method that can create buildings with different layout properties?** - Section 4.2 in Chapter 4 describes a method to generate buildings with various layout properties in the forms of networks based on network theory through which the building layout can be represented as a spatial network with nodes and edges. The network can be controlled by "randomness" that measures the regularity of the network, defined as the maximum ratio of the coordinate offset of each node to the original coordinate and nodes distance, and "average degree" that measures the connections between nodes, calculated by the average number of edges each node in the network. This technique can automatically generate a large number of networks covering a wide range of possible layout properties. While there are many other possible options, this proposed method can be served as a starting point and suggests the potential and feasibility of network methods.

- **RQ3.2**: **What are some factors that can measure different aspects of building layout properties?** - Several measurements are identified including "randomness", "average degree" and "average path length" to capture the properties of the entire network. In addition, several factors are used to measure the properties of the route chosen by participants (a part of the building): "relative distance" and "relative number of turns", "relative accumulated angle change", "the proportion of the path on the edge" and "large turn preference". The full list can be found in Section 5.1. However, among these measurements, only randomness, average degree, relative distance and relative accumulated angle change and found to have a significant impact on pedestrian route choice behaviours in the experiment.

RQ4: **Do pedestrians behave the same in single decisions and sequences of consecutive route choices? If not, how to establish the existence, nature and consequences of such changes?** - Chapter 5 presents a mathematical model that formalises the hypothesis that the sensitivity of pedestrians to environmental information diminishes as pedestrians make more decisions in sequence. This model has been validated via a virtual experiment and a comparison with previously published work [133]. Results suggest that compared to single decisions, pedestrian behaviour in sequences of consecutive route choices may be different because the cognitive process of pedestrians changes as they make more than one route choice. The nature of such effect can be associated with decision fatigue which indicates individuals tend to make worse decisions after a long session involving many decisions [24, 98]. A simulation study is conducted to explore the consequences of such effects and results indicate that the diminishing sensitivity to environmental information may suppress pedestrian following behaviour and make crowd egress more predictable. In the virtual experiment presented in Chapter 5, the participants are not shown any spatial knowledge about the building and thus whether the findings obtained from this scenario can be extended to other contexts requires more empirical research.

In summary, this thesis has established a systematic theoretical framework across disciplines for pedestrian route choice which can provide general processes of human decision-making and principles that capture the essence of pedestrian route choice. This work has also gained insights into the impacts of environmental information (e.g., signs and movements of others) and building layout properties on pedestrian route choice in buildings via virtual experiments, and explored how pedestrians choose routes in sequences of consecutive route choices.

The experimental data collection were conducted using desktop VR, which may have limitations on the generalizability of the study findings. Given that desktop VR systems differ from immersive VR setups in terms of the level of immersion, visual fidelity, and interaction capabilities, it may not be feasible to extend the study's conclusions to real-world situations. Therefore, future research should consider conducting experiments in real-world settings to increase the generalizability of the findings. Furthermore, there are other methodological limitations that may affect the validity of the results, such as steering mechanisms and participant characteristics.

It should be noted that the building layouts used in the study may not align with current or future real-world designs. While the study's findings can provide valuable insights into designing more effective evacuation routes, further research is needed to evaluate the generalizability of the findings to real-world settings. This can involve comparing the building layouts used in the study to existing building designs or developing new building designs based on the study's findings and assessing their feasibility and effectiveness in real-world scenarios.

Furthermore, the experiments were conducted prior to the COVID-19 pandemic, and it is unclear whether the pandemic has had any impact on the observed crowd-following behaviour. It is possible that the pandemic may have prompted people to engage in more crowd-following behaviour, as the theory of affiliation suggests that people may seek out social support in times of crisis and uncertainty. However, further research would be needed to investigate the potential impact of the pandemic on the study's findings.

6.2 Future work

This section summarises issues that arise immediately from this thesis, provides possible solutions to each problem and additionally suggests potential avenues for future work in the field of pedestrian route choice.

Several virtual experiments are conducted to explore how participants make spatial decisions in various contexts. While this experimental paradigm presents unique advantages especially in terms of highly controlled data collection, and has been well-accepted in pedestrian behaviour research [115, 185], its ecological validity should be carefully considered. Some studies provide evidence for the validity of virtual experiments by comparing pedestrian route choice behaviour in virtual and physical environments [55, 129, 189]. However, the empirical data is still far from sufficient to establish the broad validity of this paradigm across contexts. However, our research has demonstrated unique advantages of desktop VR in conducting certain experiments. In comparison to other VR methods, desktop VR allows us to collect data from a large number of participants in a well-controlled experiment, which is particularly suitable for experiments that require a large sample size, such as our experiment on building layout. In the near future, it is possible to collect such numerous data on pedestrian route choice in a metaverse where users can interact simultaneously and independently in remote physical locations and pedestrian route choice is inevitably involved. For example, various contexts for users to explore can be constructed in a metaverse, and the recorded data associated with the scenario and user activity can be used for model calibration and validation. Furthermore, some key questions on virtual experiments remain unanswered such as how to measure the quality of virtual experiments, what levels of immersiveness should be to derive effective participant behavioural feedback and to what extent human-computer interactions influence participant behaviour. The solution to these issues could be to establish a framework for quantitatively evaluating virtual experiments, which can measure how well the experiment can be extended to the real worlds based on various aspects of the experiment and their corresponding weights. However, the establishment of this framework requires not only the joint efforts of multidisciplinary researchers but also requires a large amount of data for calibration, which can be the focus of future work.

One of the research questions of this thesis is to explore pedestrian decision-making in sequences of consecutive route choices. The findings in Chapter 5 provide evidence for the hypothesis that pedestrians tend to have less sensitivity to environmental directional information as they make more spatial decisions. However, Chapter 5 only considers certain aspects of the route choice in specific scenarios where pedestrians have no prior knowledge of their surrounding environment and thus how pedestrians make sequences of route choices in other contexts remains unclear. Therefore, further investigations can be done to fill the gap in research on pedestrian behaviour in route choice sequences. One of the main challenges for empirical studies on this topic is the difficulty in collecting data from pedestrians who make more than one decision because in natural experiments the digital sensor systems can hardly identify and track specific pedestrians in complex environments and the data collection is time-consuming and has low controllability in well-controlled laboratory experiments. To address this issue, wearable sensors that can continuously record the position, as well as the physiological activity of pedestrians, can be used for data collection [237]. Therefore, future work can focus on using wearable sensors to investigate sequences of pedestrian route choices in buildings.

The work presented here investigates pedestrian route choice when various source of information is present in buildings and many observed pedestrian behaviours can be explained by psychological theory. For example, the tendency of pedestrians to avoid the unused exit observed in Chapter 3 may be relevant to social isolation avoidance, the edge-seeking behaviour in Chapter 4 is possibly associated with cognitive effort avoidance and the diminishing sensitivity to environmental information in Chapter 5 may be concerned with decision fatigue in human decision-making. These psychological theories provide a possible explanation for pedestrian behaviour in virtual experiments, but it is difficult to examine their validity based on the results in this thesis because no relevant treatments are implemented in the experiments. Therefore, further research is needed to explore the psychological mechanisms behind pedestrian behaviours observed in this thesis that can be useful for interpreting pedestrian behaviours in buildings. To achieve this, collaborations across disciplines are needed. For example, cognitive psychologists working on fundamental processes of human decision-making can apply their knowledge and techniques to investigate the cognitive processes underlying route choice behaviour in buildings.

Chapter 3 and Chapter 5 present virtual experiments to investigate how participants respond to the movement of others, which is a manifestation of social influence. In the experiments, other pedestrians are simulated by virtual avatars and the information participant perceive about the crowd is only their movements. However, in reality, the social interactions between pedestrians include more forms such as eye contact and body language. While the effects of various social interactions on social behaviour has been extensively studied in psychological research, little is known about the influences of social interactions on pedestrian route choice behaviour. A challenge is how to implement valid social interactions in experiments and formalise social influence in models, which can be one focus of future study.

This thesis has made significant progress towards understanding how pedestrians make route choices in buildings, though more empirical work is needed to extend the findings to a general context. However, how to apply the knowledge obtained from this thesis to improve pedestrian safety is another essential but challenging topic. For example, from the standpoint of managing pedestrian facilities during emergencies, how to forecast and even control pedestrian route choice to minimise uncertainty and maximise evacuation efficiency would be worth further investigation. Additionally, while this thesis focuses on pedestrian route choice in buildings, understanding pedestrian behaviour at large spatial scales and long-distance navigation and wayfinding are important as well, which in turn generate fresh insight into human spatial decision-making in buildings.

This thesis primarily focuses on the tactical level of pedestrian route choice, although some of the findings could be applicable to the operational level of decision-making. For instance, the tendency of participants to avoid crowded exits may be relevant to collision avoidance in real-world scenarios. Future research could explore this further and investigate how the findings on route choices could be translated to operational decision-making. Furthermore, it is crucial for future research to examine the connections between the methods and outcomes proposed in this thesis and real-world design practices. For instance, the building layout measure developed in Chapter 4 could be combined with building codes and safety regulations to assess the layouts of actual buildings and conduct experiments to investigate route choice and identify problematic areas. The findings may assist in identifying areas where enhancements can be made to improve pedestrian safety and efficiency. The outcomes of this thesis have the potential to impact real-world building designs in numerous ways. For example, the tendency of pedestrians to move to the periphery of the network suggests that architects and designers should pay more attention to these areas to aid navigation. The huge influence of signage on pedestrian exit choice indicates that designers should create clearer exit signage in emergencies. Additionally, the following behaviour of pedestrians indicates that wider walkways and exits can be integrated into building designs to promote smoother pedestrian flow and reduce the likelihood of congestion.

Across this thesis, it seems that research on pedestrian route choice has a bright future, not only for solid and deep insights but also for applications in various contexts. The dream research paradigm can be that researchers gain knowledge from data-driven models and examine findings via normative virtual experiments that are pre-designed and rigorously calibrated for exploring a large variety of aspects of pedestrian behaviour. For example, researchers found that pedestrians tend to follow others by exploring numerous real-world data. The normative virtual experiments covering typical scenarios (e.g., crowded museums and less busy streets) and various treatments (e.g., presence/absence of other pedestrians), enable researchers to test, in a standard and flexible way, whether the observed pedestrian following behaviour can be extended to other contexts and how it is altered by various factors. To achieve this, the methodology that makes data useful is essential, which probably flourish and be applicable to pedestrian behaviour interpretation within the next decade.

Appendix A

Appendix

A.1 Supplementary Tables

Table A.1: Sample size for each experimental condition described in Table 3.1.

Variables				Original scenario	Mirror scenario	Age	Male(%)
Spatial information		Crowd state	Split level	Sample size	Sample size		
No information		Busy	Uneven	15	13	23.2	60.7
			0-1 split	14	14	23.1	50.0
			Even	26		24.3	50.0
		Free	Uneven	13	16	23.9	41.4
			0-1 split	16	12	23.8	53.6
Map with equal exit utility		Busy	Uneven	14	14	25.3	60.7
			0-1 split	13	16	24.2	44.9
			Even	29		25.8	48.3
		Free	Uneven	12	12	22.7	58.3
			0-1 split	13	13	24.6	53.9
Map with biased exit utility	Left exit has a higher utility	Busy	Uneven	15	11	24.9	53.9
			0-1 split	15	13	24.4	53.6
			Even	29		24.7	50.0
		Free	Uneven	13	15	28.3	50.0
			0-1 split	14	15	26.6	55.1
	Right exit has a higher utility	Busy	Uneven	11	13	24.0	33.3
			0-1 split	15	12	23.7	55.6
			Even	28		23.4	50.0
		Free	Uneven	14	13	22.9	37.0
			0-1 split	12	14	24.2	42.3

Table A.2: Chi-squared statistic for tests on differences in exit choice between mirror versions of otherwise identical experimental conditions to test for innate preferences for the left or right exit.

Spatial information	Crowd state	Split level	Statistic	P
No information	Busy	Uneven	0.4308	0.5116
		0-1 split	0.1905	0.6625
	Free	Uneven	0.6073	0.4358
		0-1 split	2.0538	0.1518
Map with equal exit utility	Busy	Uneven	0.2435	0.6217
		0-1 split	0.7375	0.3904
	Free	Uneven	1.8151	0.1779
		0-1 split	0.6190	0.4314
Map with biased exit utility	Busy	Uneven(the majority in higher utility exit)	1.1966	0.2740
		Uneven(the majority in lower utility exit)	0.6977	0.4036
		0-1 split (the majority in higher utility exit)	0.5197	0.4710
		0-1 split (the majority in lower utility exit)	0.0967	0.7558
	Free	Uneven(the majority in higher utility exit)	0.3453	0.5568
		Uneven(the majority in lower utility exit)	0.7778	0.3778
		0-1 split (the majority in higher utility exit)	0.1603	0.6889
		0-1 split (the majority in lower utility exit)	3.2833	0.0700

Table A.3: Details about the laptop computers used to collect data for the virtual reality experiment.

Item	Number of participants	Details
1	65	Intel(R) Core(TM) i5-7300HQ CPU 2.50 GHz, 8.0 GB RAM
2	60	Intel(R) Core(TM) i5-7500 CPU 2.50 GHz, 8.0 GB RAM
3	58	Intel(R) Core(TM) i5-6600 CPU 2.50 GHz, 8.0 GB RAM
4	22	Intel(R) Core(TM) i7-6700 CPU 3.40 GHz, 16.0 GB RAM

Table A.4: Optional free-text answers recorded from participants alongside their following time. The question posed was "What did you focus on in the last part of the experiment".

Followtimes	Comments
0	'The letters on the walls and that there were not any by the exit'
1	'To not follow the majority '
1	'the purpose of this game'
1	'Follow the sign'
1	'Keep turning right'
1	'Strategy of mazes, e.g. stick left + exit signs'
1	'The exit sign on the wall'
1	'Turning left'
1	'Turn left'
1	'Understand the purpose of the introduction of people to the environment.'
1	'Go opposite direction to group'
1	'The exit sign'
1	'Tricking the system. I thought that the game wanted me to follow everyone so I did not'
1	'Not follow the group'
2	'Try to think of a bird eye view of map'
2	'Doing opposite of the group '
3	'I thought following the people might lead me to the exit, but after a couple turns, I decided maybe it was a trick, so I chose a different pathway that did not follow the other people'
3	'Followed the group for the first couple of turns but when it became clear that they were running in a circle I took my own path.'
4	'Look out for traps'
5	'At first it was to leave the group, but when I could not see a visible door I followed'
7	'I followed other players as they might also know the way out.When they looped, I explored for the exit and found it.'
9	'Memorise the letter pattern'
9	'Reading the letters on the wall/ following the group'

Table A.5: Statistical analysis of following times using a generalised linear model with Poisson error structure and log link function (see Appendix A.3 for details). The response variable is the following time, a count for how many times participants followed others in the experiment. Explanatory variables are an intercept, Boolean variables indicating the presence of signs, landmarks and anticlockwise movement of computer-controlled pedestrians and scores for personality traits from our personality questionnaire (see Figure A.2. Personality trait scores are computed according to [65]. The data from two questions on "Emotional stability" and "Openness to experiences" was not collected successfully. We used scores from only one question for each personality trait, namely "Anxious, easily upset(reverse)" and "Open to new experiences, complex",to represent these aspects of personality traits. P-values less than or very close to 0.05 are shown in bold.

Effect	Estimate	SE	F	P
Intercept	1.0288	0.19037	5.4045	**6.498** $\times 10^{-8}$
sign	-1.1711	0.11519	-10.167	**2.79** $\times 10^{-24}$
landmark	0.30395	0.098463	3.0869	**0.0020223**
anticlockwise	0.11555	0.1186	0.97434	0.32989
extroversion	0.0049603	0.016266	0.30494	0.76041
agreeableness	0.030828	0.022181	1.3898	0.16458
conscientiousness	-0.047719	0.016155	-2.9539	**0.0031381**
anxious, easily upset(reverse)	-0.071251	0.025554	-2.7882	**0.052994**
open to new experiences,complex	-0.012659	0.036239	-0.34931	0.72686

Table A.6: Data for calibration of our model on previously published data. We show the route decisions of participants at each decision point from [133]. The last column shows the parameter values of σ_x obtained from this calibration using data from all three patterns. This innate preference is only calibrated when one option is a stairway and the other a hallway (decision points 1 and 2) and set to 0.5 otherwise. We find $k_c = 0.9109$ and $k_f \approx 0$ and use maximum likelihood fitting.

Decision point	Alternative directions	Number of participants	Descriptions
Pattern 1			
Decision point 2	Hallway 2	2	0.9153
	Staircase 2	52	0.0847
Decision point 3(a)	Staircase 3	50	0.5
	Staircase 4	2	0.5
Decision point 3(b)	Staircase 3	1	0.5
	Staircase 4	0	0.5
Pattern 2			
Decision point 1	Hallway 1	52	0.9153
	Staircase 1	3	0.0847
Decision point 2	Hallway 2	16	0.9153
	Staircase 2	36	0.0847
Decision point 3(a)	Staircase 3	33	0.5
	Staircase 4	3	0.5
Decision point 3(b)	Staircase 3	2	0.5
	Staircase 4	1	0.5
Pattern 3			
Decision point 1	Hallway 1	37	0.9153
	Staircase 1	22	0.0847
Decision point 2	Hallway 2	27	0.9153
	Staircase 2	10	0.0847
Decision point 3(a)	Staircase 3	4	0.5
	Staircase 4	6	0.5
Decision point 3(b)	Staircase 3	7	0.5
	Staircase 4	15	0.5

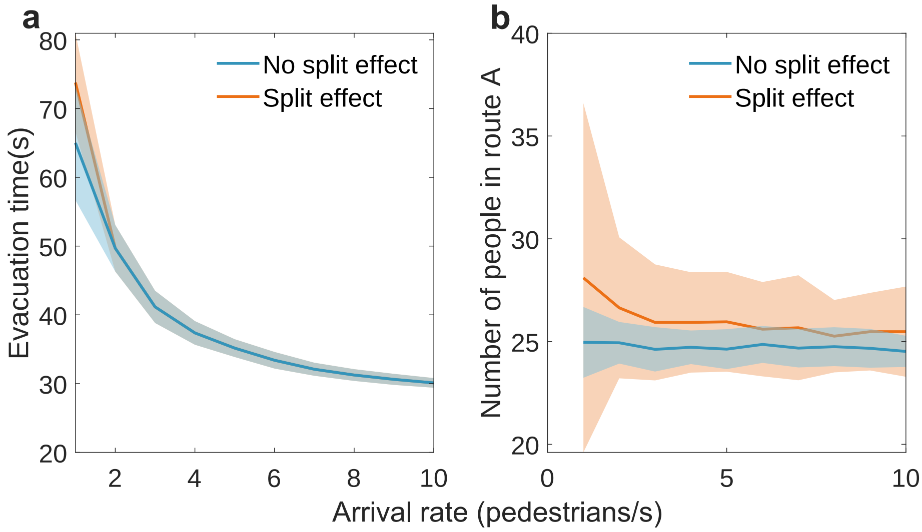


Figure A.1: Simulations on the impacts of the split effect on evacuation time (a) and the number of pedestrians in route A (b) as the arrival rate changes.

A.2 Supplementary Figures

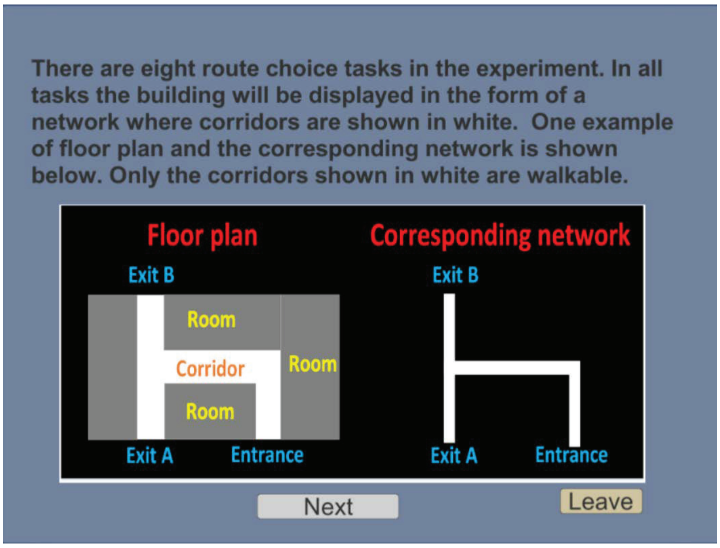


Figure A.2: Still image of the virtual experiment as seen by participants on screen before route choice tasks start.

A.3 Details of statistical models

The statistical models used in Tables 4.2 - 4.6 and Tables 5.1 and A.5 are Generalized Linear Models (GLMs). GLMs is a standard tool in statistics [38], which aim to explain variability

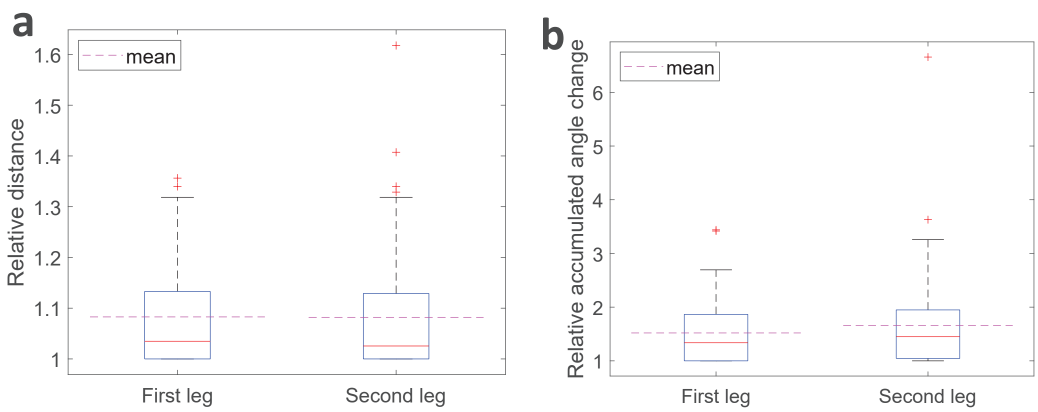
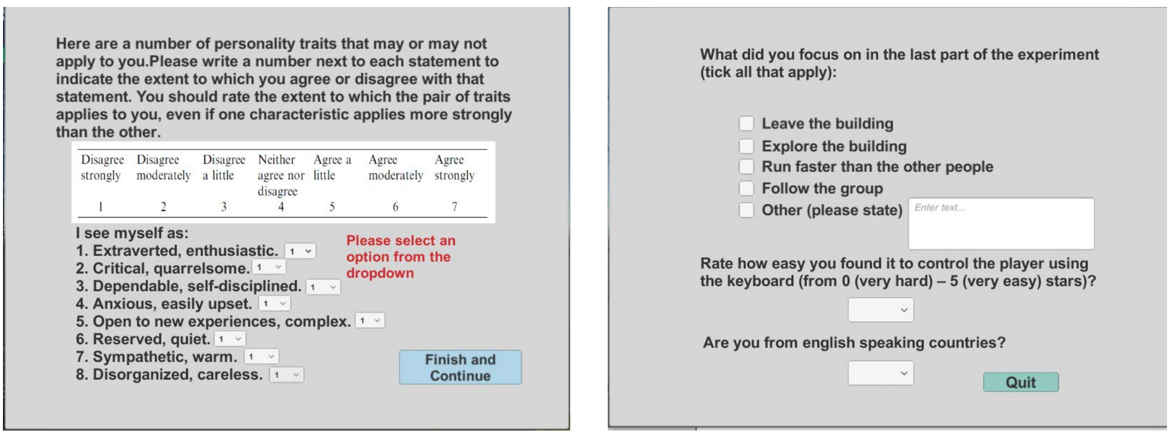


Figure A.3: Route comparison of the first and second leg for the participants who selected different destinations in the second task of the experiment. Dashed horizontal lines show the mean of the data.



(a) (b)

Figure A.4: Screenshot of the questionnaire section at the end of the experiment.

in a response variable y in terms of explanatory variables, x_i (where $i = 1,2,3,\ldots$). For our models, we assume y follows a Binomial distribution and we also assume that the expectation of y, $E(y)$, satisfies the following relationship: $logit(y) = k_0 + k_1x_1 + k_2x_2 + k_3x_3 + \ldots$, where k_0 is the intercept and $k_1, k_2, k_3, \ldots$ are the regression coefficients corresponding to the explanatory variables.

A.4 Navigation System in Unity

In Unity 3D (Version 2019.3), the computer-controlled pedestrians ('agents') are described as cylinders that can move within accessible areas within the virtual environment. The accessible areas are represented as a fine mesh composed of convex polygons. A path navigation algorithm

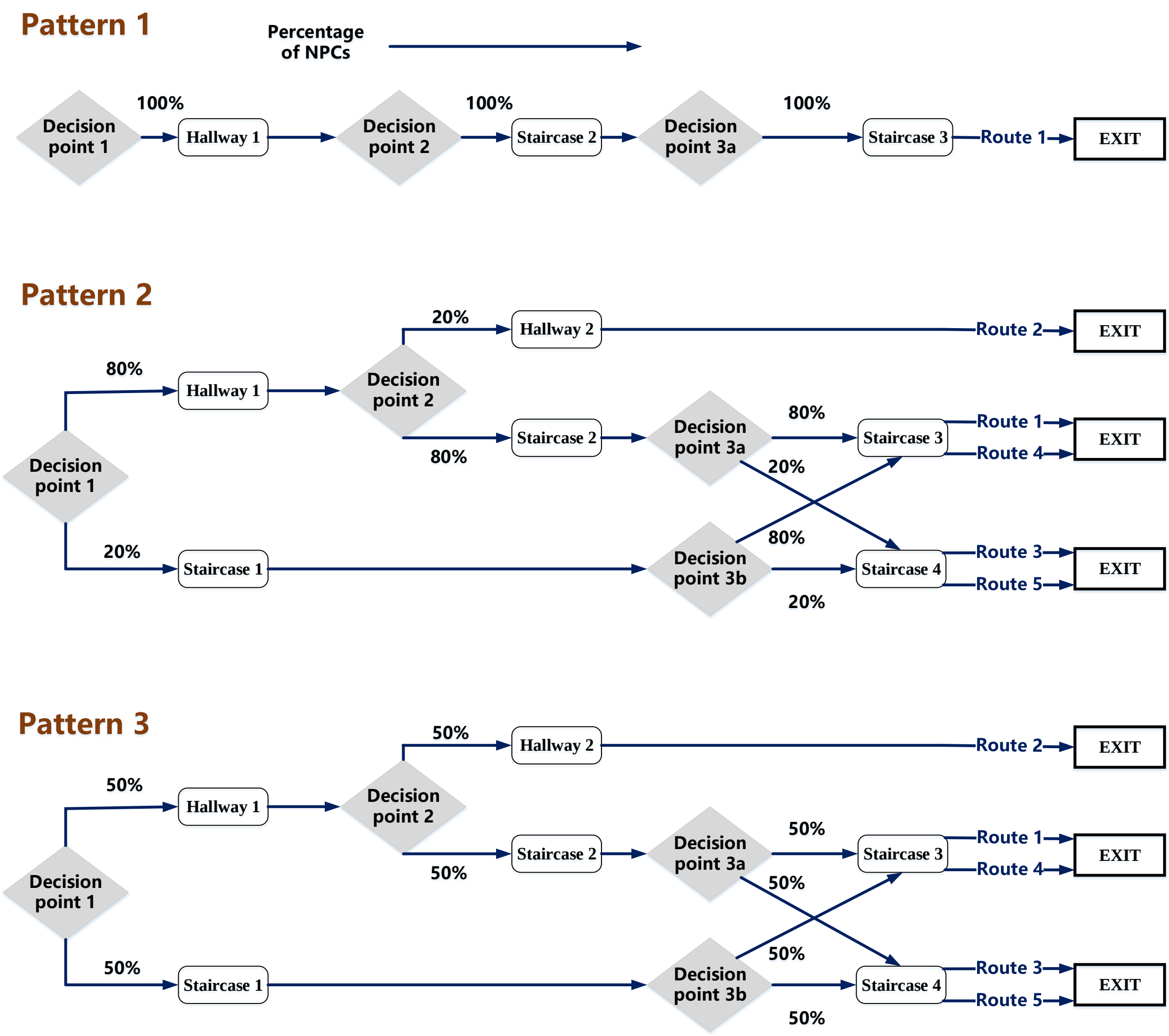


Figure A.5: Three patterns of routes taken by computer-controlled pedestrians, redrawn from [133]. The percentages shown on arrows indicate the proportion of computer-controlled pedestrians that choose this direction at the preceding decision point.

controls the movement of agents on this mesh. In the algorithm, the start point and destinations of the agents are mapped to their nearest mesh polygons. Agents then compute a path on the mesh between these polygons by considering all available (i.e. unfilled) polygons. Once a path is computed, agents follow it to reach their destination. Obstacles in the path (stationary or other moving agents) are avoided by dynamically computing new paths deviating from the original path to prevent collisions. Details of this navigation system in Unity can be found online [214] (accessed 15 May 2020).

BIBLIOGRAPHY

[1] S. ABRAHAM AND P. SOJAN LAL, *Spatio-temporal similarity of network-constrained moving object trajectories using sequence alignment of travel locations*, Transportation Research Part C: Emerging Technologies, 23 (2012), pp. 109–123.

[2] J. ADRIAN, M. AMOS, M. BARATCHI, M. BEERMANN, N. BODE, M. BOLTES, A. CORBETTA, G. DEZECACHE, J. DRURY, Z. FU, AND OTHERS, *A glossary for research on human crowd dynamics*, Collective Dynamics, 4 (2019), pp. 1–13.

[3] M. ALEKSANDROV, A. RAJABIFARD, M. KALANTARI, R. LOVREGLIO, AND V. A. GONZÁLEZ, *People Choice Modelling for Evacuation of Tall Buildings*, Fire Technology, 54 (2018), pp. 1171–1193.

[4] J. R. ANDERSON, *Cognitive Psychology and Its Implications*, Duffield, United Kingdom: Worth Publishers, 2005.

[5] E. ANDRESEN, *Wayfinding and Perception Abilities for Pedestrian Simulations*, PhD thesis, Universität Wuppertal, Verlag Jülich, Germany, 2018.

[6] E. ANDRESEN, M. CHRAIBI, AND A. SEYFRIED, *A representation of partial spatial knowledge: a cognitive map approach for evacuation simulations*, Transportmetrica A: Transport Science, 14 (2018), pp. 433–467.

[7] S. ARGANDA, A. PEREZ-ESCUDERO, AND G. G. DE POLAVIEJA, *A common rule for decision making in animal collectives across species*, Proceedings of the National Academy of Sciences, 109 (2012), pp. 20508–20513.

[8] E. AVINERI AND J. N. PRASHKER, *Violations of expected utility theory in route-choice stated preferences: Certainty effect and inflation of small probabilities*, Transportation Research Record, 1894 (2004), pp. 222–229.

[9] S. BAFNA, *Space syntax: A brief introduction to its logic and analytical techniques*, Environment and Behavior, 35 (2003), pp. 17–29.

[10] M. BARTHÉLEMY, *Spatial networks*, Physics Reports, 499 (2011), pp. 1–101.

[11] N. Basu, M. M. Haque, M. King, M. Kamruzzaman, and O. Oviedo-Trespalacios, *A systematic review of the factors associated with pedestrian route choice*, Transport Reviews, (2021), pp. 1–23.

[12] E. Ben-Elia and E. Avineri, *Response to Travel Information: A Behavioural Review*, Transport Reviews, 35 (2015), pp. 352–377.

[13] L. Benthorn and H. Frantzich, *Fire alarm in a public building: How do people evaluate information and choose an evacuation exit?*, Fire and Materials, 23 (1999), pp. 311–315.

[14] I. M. Bernhoft and G. Carstensen, *Preferences and behaviour of pedestrians and cyclists by age and gender*, Transportation Research Part F: Traffic Psychology and Behaviour, 11 (2008), pp. 83–95.

[15] U. N. Bhat, *An introduction to queueing theory: modeling and analysis in applications*, vol. 36, Berlin, Germany: Springer, 2008.

[16] P. H. Bloch, *Seeking the ideal form: Product design and consumer response*, Journal of Marketing, 59 (1995), pp. 16–29.

[17] N. W. Bode and E. A. Codling, *Human exit route choice in virtual crowd evacuations*, Animal Behaviour, 86 (2013), pp. 347–358.

[18] N. W. Bode, J. Miller, R. O'Gorman, and E. A. Codling, *Increased costs reduce reciprocal helping behaviour of humans in a virtual evacuation experiment*, Scientific Reports, 5 (2015), pp. 1–13.

[19] N. W. F. Bode, A. U. Kemloh Wagoum, and E. A. Codling, *Human responses to multiple sources of directional information in virtual crowd evacuations*, Journal of the Royal Society Interface, 11 (2014), p. 20130904.

[20] ——, *Information use by humans during dynamic route choice in virtual crowd evacuations*, Royal Society Open Science, 2 (2015), p. 140410.

[21] A. Borgers and H. Timmermans, *A model of pedestrian route choice and demand for retail facilities within inner-city shopping areas*, Geographical analysis, 18 (1986), pp. 115–128.

[22] A. Borowsky, D. Shinar, and Y. Parmet, *Sign location, sign recognition, and driver expectancies*, Transportation Research Part F: Traffic Psychology and Behaviour, 11 (2008), pp. 459–465.

[23] D. Broadbent, *Perception and Communication*, Amsterdam, Netherlands: Elsevier Science, 2013.

[24] I. Brocas and J. D. Carrillo, *The psychology of economic decisions*, Oxford, United Kingdom: Oxford University Press, 2003.

[25] E. Cascetta, *Transportation systems engineering: theory and methods*, vol. 49, Berlin, Germany: Springer Science & Business Media, 2013.

[26] S. M. Casey, *Cognitive Mapping by the Blind*, Journal of Visual Impairment & Blindness, 72 (1978), pp. 297–301.

[27] M. Cattan, M. White, J. Bond, and A. Learmouth, *Preventing social isolation and loneliness among older people: a systematic review of health promotion interventions*, Ageing & society, 25 (2005), pp. 41–67.

[28] C. Chen, W. Chang, and W. Chang, *Gender differences in relation to wayfinding strategies, navigational support design, and wayfinding task difficulty*, Journal of Environmental Psychology, 29 (2009), pp. 220–226.

[29] H. Cherni, N. Métayer, and N. Souliman, *Literature review of locomotion techniques in virtual reality.*, International Journal of Virtual Reality, (2020).

[30] M. Chraibi and D. Haensel, *Cognitive map routing*, in International Conference on Cellular Automata, Berlin, Germany: Springer, 2016, pp. 210–218.

[31] D. Colombo, S. Serino, C. Tuena, E. Pedroli, A. Dakanalis, P. Cipresso, and G. Riva, *Egocentric and allocentric spatial reference frames in aging: A systematic review*, Neuroscience & Biobehavioral Reviews, 80 (2017), pp. 605–621.

[32] M. J. C. Crump, J. V. McDonnell, and T. M. Gureckis, *Evaluating Amazon's Mechanical Turk as a Tool for Experimental Behavioral Research*, PLOS One, 8 (2013), p. e57410.

[33] R. Dalton, C. Hölscher, and H. Spiers, *Navigating Complex Buildings: Cognition, Neuroscience and Architectural Design*, in Studying Visual and Spatial Reasoning for Design Creativity, J. S. Gero, ed., Dordrecht, Netherlands: Springer Netherlands, 2015, pp. 3–22.

[34] S. Danziger, J. Levav, and L. AvnaimPesso, *Extraneous factors in judicial decisions*, Proceedings of the National Academy of Sciences of the United States of America, 108 (2011), pp. 6889–6892.

[35] N. Davies, *Who walks, where and why? Practitioners' observations and perspectives on recreational walkers at UK tourist destinations*, Annals of Leisure Research, 21 (2018), pp. 553–574.

[36] G. de Moraes Ramos, W. Daamen, and S. Hoogendoorn, *Expected utility theory, prospect theory, and regret theory compared for prediction of route choice behavior*, Transportation Research Record, 2230 (2011), pp. 19–28.

[37] N. Ding, T. Chen, Y. Zhu, and Y. Lu, *State-of-the-art high-rise building emergency evacuation behavior*, Physica A: Statistical Mechanics and its Applications, 561 (2021), p. 125168.

[38] A. J. Dobson and A. G. Barnett, *An introduction to generalized linear models*, London, United Kingdom: Chapman and Hall/CRC, 2018.

[39] S. H. Dobson, K. C. Kirasic, and G. L. Allen, *Age-related differences in adults' spatial task performance: Influences of task complexity and perceptual speed*, Aging, Neuropsychology, and Cognition, 2 (1995), pp. 19–38.

[40] J. Drury, *Social identity as a source of strength in mass emergencies and other crowd events*, International Journal of Mental Health, 32 (2003), pp. 77–93.

[41] ——, *The role of social identity processes in mass emergency behaviour: An integrative review*, European review of social psychology, 29 (2018), pp. 38–81.

[42] J. Drury and C. Cocking, *The mass psychology of disasters and emergency evacuations: A research report and implications for practice*, Brighton, United Kingdom: University of Sussex, 2007.

[43] J. Drury, C. Cocking, S. Reicher, A. Burton, D. Schofield, A. Hardwick, D. Graham, and P. Langston, *Cooperation versus competition in a mass emergency evacuation: a new laboratory simulation and a new theoretical model*, Behavior research methods, 41 (2009), pp. 957–970.

[44] E. Duarte, F. Rebelo, J. Teles, and M. S. Wogalter, *Behavioral compliance for dynamic versus static signs in an immersive virtual environment*, Applied Ergonomics, 45 (2014), pp. 1367–1375.

[45] D. C. Duives, W. Daamen, and S. P. Hoogendoorn, *State-of-the-art crowd motion simulation models*, Transportation Research Part C: Emerging Technologies, 37 (2013), pp. 193–209.

[46] F. Durupinar, J. Allbeck, N. Pelechano, and N. Badler, *Creating Crowd Variation with the OCEAN Personality Model*, in Proceedings of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems - Volume 3, AAMAS '08, International Foundation for Autonomous Agents and Multiagent Systems, Richland, United States, 2008, pp. 1217–1220.

[47] F. DURUPINAR, N. PELECHANO, J. ALLBECK, U. GÜDÜKBAY, AND N. I. BADLER, *How the Ocean Personality Model Affects the Perception of Crowds*, IEEE Computer Graphics and Applications, 31 (2011), pp. 22–31.

[48] A. DUSSUTOUR, J. DENEUBOURG, AND V. FOURCASSIÉ, *Amplification of individual preferences in a social context: the case of wall-following in ants*, Proceedings of the Royal Society B: Biological Sciences, 272 (2005), pp. 705–714.

[49] A. EDRISI, B. LAHOORPOOR, AND R. LOVREGLIO, *Simulating metro station evacuation using three agent-based exit choice models*, Case studies on transport policy, 9 (2021), pp. 1261–1272.

[50] A. D. EKSTROM, M. J. KAHANA, J. B. CAPLAN, T. A. FIELDS, E. A. ISHAM, E. L. NEWMAN, AND I. FRIED, *Cellular networks underlying human spatial navigation*, Nature, 425 (2003), pp. 184–188.

[51] A. ENGELNIEDERHAMMER, G. PAPASTEFANOU, AND L. XIANG, *Crowding density in urban environment and its effects on emotional responding of pedestrians: Using wearable device technology with sensors capturing proximity and psychophysiological emotion responses while walking in the street*, Journal of Human Behavior in the Social Environment, 29 (2019), pp. 630–646.

[52] Y. FENG, *Do different types of VR influence pedestrian route choice behaviour? A comparison study of Desktop VR and HMD VR*, in Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems, 2021, pp. 1–7.

[53] Y. FENG, D. DUIVES, W. DAAMEN, AND S. HOOGENDOORN, *Data collection methods for studying pedestrian behaviour: A systematic review*, Building and Environment, 187 (2021), p. 107329.

[54] Y. FENG, D. C. DUIVES, AND S. P. HOOGENDOORN, *Using virtual reality to study pedestrian exit choice behaviour during evacuations*, Safety Science, 137 (2021), p. 105158.

[55] Y. FENG, D. C. DUIVES, AND S. P. HOOGENDOORN, *Wayfinding behaviour in a multi-level building: A comparative study of HMD VR and Desktop VR*, Advanced Engineering Informatics, 51 (2022), p. 101475.

[56] Z. FENG, V. A. GONZÁLEZ, R. AMOR, R. LOVREGLIO, AND G. CABRERAGUERRERO, *Immersive virtual reality serious games for evacuation training and research: A systematic literature review*, Computers & Education, 127 (2018), pp. 252–266.

[57] G. FILOMENA AND J. A. VERSTEGEN, *Modelling the effect of landmarks on pedestrian dynamics in urban environments*, Computers, Environment and Urban Systems, 86 (2021), p. 101573.

[58] P. C. FISHBURN, *Utility Theory*, Management Science, 14 (1968), pp. 335–378.

[59] K. FRIDOLF, E. RONCHI, D. NILSSON, AND H. FRANTZICH, *Movement speed and exit choice in smoke-filled rail tunnels*, Fire safety journal, 59 (2013), pp. 8–21.

[60] L. FU, S. CAO, W. SONG, AND J. FANG, *The influence of emergency signage on building evacuation behavior: An experimental study*, Fire and Materials, 43 (2019), pp. 22–33.

[61] R. G.GOLLEDGE, R. D. JACOBSON, R. KITCHIN, AND M. BLADES, *Cognitive Maps, Spatial Abilities, and Human Wayfinding*, Geographical Review of Japan, Series B, 73 (2000), pp. 93–104.

[62] G. GIGERENZER AND W. GAISSMAIER, *Heuristic Decision Making*, Annual Review of Psychology, 62 (2011), pp. 451–482.

[63] D. G. GOLDSTEIN AND G. GIGERENZER, *The recognition heuristic and the less-is-more effect*, Handbook of experimental economics results, 1 (2008), pp. 987–992.

[64] R. L. GOLDSTONE AND M. E. ROBERTS, *Self-organized trail systems in groups of humans*, Complexity, 11 (2006), pp. 43–50.

[65] S. D. GOSLING, P. J. RENTFROW, AND W. B. SWANN, *A very brief measure of the Big-Five personality domains*, Journal of Research in Personality, 37 (2003), pp. 504–528.

[66] J. GOTTLIEB, *From thought to action: the parietal cortex as a bridge between perception, action, and cognition*, Neuron, 53 (2007), pp. 9–16.

[67] J. A. GRAY AND A. A. I. WEDDERBURN, *Grouping strategies with simultaneous stimuli*, The Quarterly Journal of Experimental Psychology, 12 (1960), pp. 180–184.

[68] L. V. GREEN, J. SOARES, J. F. GIGLIO, AND R. A. GREEN, *Using queueing theory to increase the effectiveness of emergency department provider staffing*, Academic Emergency Medicine, 13 (2006), pp. 61–68.

[69] R. GUO, H. HUANG, AND S. C. WONG, *Route choice in pedestrian evacuation under conditions of good and zero visibility: Experimental and simulation results*, Transportation Research Part B: Methodological, 46 (2012), pp. 669–686.

[70] Z. GUO AND B. P. LOO, *Pedestrian environment and route choice: evidence from New York City and Hong Kong*, Journal of Transport Geography, 28 (2013), pp. 124–136.

[71] S. J. GUY, S. KIM, M. C. LIN, AND D. MANOCHA, *Simulating heterogeneous crowd behaviors using personality trait theory*, in Proceedings of the 2011 ACM SIGGRAPH/Eurographics Symposium on Computer Animation - SCA '11, New York, United States: ACM Press, 2011, p. 43.

[72] M. HAGHANI, *Empirical methods in pedestrian, crowd and evacuation dynamics: Part I. Experimental methods and emerging topics*, Safety Science, 129 (2020), p. 104743.

[73] M. HAGHANI, E. CRISTIANI, N. W. F. BODE, M. BOLTES, AND A. CORBETTA, *Panic, Irrationality, and Herding: Three Ambiguous Terms in Crowd Dynamics Research*, Journal of Advanced Transportation, 2019 (2019), pp. 1–58.

[74] M. HAGHANI AND M. SARVI, *Human exit choice in crowded built environments: Investigating underlying behavioural differences between normal egress and emergency evacuations*, Fire Safety Journal, 85 (2016), pp. 1–9.

[75] ——, *Following the crowd or avoiding it? Empirical investigation of imitative behaviour in emergency escape of human crowds*, Animal Behaviour, 124 (2017), pp. 47–56.

[76] ——, *How perception of peer behaviour influences escape decision making: The role of individual differences*, Journal of Environmental Psychology, 51 (2017), pp. 141–157.

[77] ——, *Social dynamics in emergency evacuations: Disentangling crowd's attraction and repulsion effects*, Physica A: Statistical Mechanics and its Applications, 475 (2017), pp. 24–34.

[78] ——, *Stated and revealed exit choices of pedestrian crowd evacuees*, Transportation Research Part B: Methodological, 95 (2017), pp. 238–259.

[79] ——, *Crowd behaviour and motion: Empirical methods*, Transportation Research Part B: Methodological, 107 (2018), pp. 253–294.

[80] ——, *Imitative (herd) behaviour in direction decision-making hinders efficiency of crowd evacuation processes*, Safety Science, 114 (2019), pp. 49–60.

[81] ——, *'Herding' in direction choice-making during collective escape of crowds: How likely is it and what moderates it?*, Safety Science, 115 (2019), pp. 362–375.

[82] M. HAGHANI, M. SARVI, AND Z. SHAHHOSEINI, *Evacuation behaviour of crowds under high and low levels of urgency: Experiments of reaction time, exit choice and exit-choice adaptation*, Safety Science, 126 (2020), p. 104679.

[83] Y. HAN, H. LIU, AND L. LI, *An evacuation guidance model for pedestrians with limited vision*, Transportmetrica A: transport science, (2021), pp. 1–22.

[84] R. HARTSON, *Cognitive, physical, sensory, and functional affordances in interaction design*, Behaviour & information technology, 22 (2003), pp. 315–338.

[85] D. HELBING, I. FARKAS, AND T. VICSEK, *Simulating dynamical features of escape panic*, Nature, 407 (2000), pp. 487–490.

[86] D. HELBING, I. J. FARKAS, P. MOLNAR, AND T. VICSEK, *Simulation of pedestrian crowds in normal and evacuation situations*, Pedestrian and evacuation dynamics, 21 (2002), pp. 21–58.

[87] D. HELBING, J. KELTSCH, AND P. MOLNÁR, *Modelling the evolution of human trail systems*, Nature, 388 (1997), pp. 47–50.

[88] D. HELBING, P. MOLNÁR, I. J. FARKAS, AND K. BOLAY, *Self-Organizing Pedestrian Movement*, Environment and Planning B: Planning and Design, 28 (2001), pp. 361–383.

[89] M. G. HERRMANNLUNECKE, R. MORA, AND L. SAGARIS, *Persistence of walking in chile: lessons for urban sustainability*, Transport reviews, 40 (2020), pp. 135–159.

[90] C. HEWAWASAM, S. BANDARA, AND S. WIRASINGHE, *Analysis of factors affecting pedestrian route choice*, Journal of Chemical Information and Modeling, 53 (2013), pp. 1689–1699.

[91] C. A. HILL, *Affiliation motivation: people who need people... but in different ways.*, Journal of personality and social psychology, 52 (1987), p. 1008.

[92] H. HOCHMAIR AND A. U. FRANK, *Influence of estimation errors on wayfinding-decisions in unknown street networks – analyzing the least-angle strategy*, Spatial Cognition and Computation, 2 (2000), pp. 283–313.

[93] S. P. HOOGENDOORN AND P. H. L. BOVY, *Pedestrian route-choice and activity scheduling theory and models*, Transportation Research Part B: Methodological, 38 (2004), pp. 169–190.

[94] Y. HU, J. ZHANG, H. XIAO, S. CAO, X. REN, X. LIANG, H. LI, AND W. SONG, *Experimental study and analysis on behaviours and strategies of social groups and individuals*, Safety Science, 127 (2020), p. 104736.

[95] H. HUANG AND R. GUO, *Static floor field and exit choice for pedestrian evacuation in rooms with internal obstacles and multiple exits*, Physical Review E, 78 (2008), p. 021131.

[96] C. HÖLSCHER AND R. C. DALTON, *Comprehension of Layout Complexity: Effects of Architectural Expertise and Mode of Presentation*, in Design Computing and Cognition '08, J. S. Gero and A. K. Goel, eds., Dordrecht, Netherlands: Springer Netherlands, 2008, pp. 159–178.

[97] H. IFTIKHAR, P. SHAH, AND Y. LUXIMON, *Human wayfinding behaviour and metrics in complex environments: a systematic literature review*, Architectural Science Review, 64 (2020), pp. 452–463.

[98] M. Inzlicht and B. J. Schmeichel, *What is ego depletion? Toward a mechanistic revision of the resource model of self-control*, Perspectives on Psychological Science, 7 (2012), pp. 450–463.

[99] M. Isobe, D. Helbing, and T. Nagatani, *Experiment, theory, and simulation of the evacuation of a room without visibility*, Physical Review E, 69 (2004), p. 066132.

[100] S. Jamshidi, M. Ensafi, and D. Pati, *Wayfinding in Interior Environments: An Integrative Review*, Frontiers in Psychology, 11 (2020).

[101] P. JansenOsmann, J. Schmid, and M. Heil, *Wayfinding Behavior and Spatial Knowledge of Adults and Children in a Virtual Environment: The Role of the Environmental Structure*, Swiss Journal of Psychology, 66 (2007), pp. 41–50.

[102] J. W. Jaromczyk and G. T. Toussaint, *Relative neighborhood graphs and their relatives*, Proceedings of the IEEE, 80 (1992), pp. 1502–1517.

[103] K. Jiang, J. Zhang, S. Cao, L. Xia, X. Ren, H. Li, X. Li, H. Xu, and W. Song, *Experimental study on the movement characteristics of individuals through angled corridors with different speeds and directions*, Transportmetrica A: Transport Science, (2022), pp. 1–34.

[104] W. A. Johnston and V. J. Dark, *Selective attention*, Annual Review of Psychology, 37 (1986), pp. 43–75.

[105] W. Karwowski, *Human factors of wayfinding in navigation*, in International Encyclopedia of Ergonomics and Human Factors-3 Volume Set, Florida, United States: CRC Press, 2006, pp. 2051–2056.

[106] F. Katsuki and C. Constantinidis, *Bottom-up and top-down attention: different processes and overlapping neural systems*, The Neuroscientist: A Review Journal Bringing Neurobiology, Neurology and Psychiatry, 20 (2014), pp. 509–521.

[107] A. D. A. M. Kemperman, A. W. J. Borgers, and H. J. P. Timmermans, *Tourist shopping behavior in a historic downtown area*, Tourism Management, 30 (2009), pp. 208–218.

[108] P. J. Kennedy and M. L. Shapiro, *Motivational states activate distinct hippocampal representations to guide goal-directed behaviors*, Proceedings of the National Academy of Sciences, 106 (2009), pp. 10805–10810.

[109] P. Kettunen, K. Irvankoski, C. M. Krause, and L. T. Sarjakoski, *Landmarks in nature to support wayfinding: the effects of seasons and experimental methods*, Cognitive Processing, 14 (2013), pp. 245–253.

[110] P. M. KIELAR, D. H. BIEDERMANN, A. KNEIDL, AND A. BORRMANN, *A unified pedestrian routing model for graph-based wayfinding built on cognitive principles*, Transportmetrica A: Transport Science, 14 (2018), pp. 406–432.

[111] M. KINATEDER, B. COMUNALE, AND W. H. WARREN, *Exit choice in an emergency evacuation scenario is influenced by exit familiarity and neighbor behavior*, Safety Science, 106 (2018), pp. 170–175.

[112] M. KINATEDER, B. COMUNALE, AND W. H. WARREN, *Exit choice in an emergency evacuation scenario is influenced by exit familiarity and neighbor behavior*, Safety science, 106 (2018), pp. 170–175.

[113] M. KINATEDER, M. MÜLLER, M. JOST, A. MÜHLBERGER, AND P. PAULI, *Social influence in a virtual tunnel fire – Influence of conflicting information on evacuation behavior*, Applied Ergonomics, 45 (2014), pp. 1649–1659.

[114] M. KINATEDER, E. RONCHI, D. GROMER, M. MÜLLER, M. JOST, M. NEHFISCHER, A. MÜHLBERGER, AND P. PAULI, *Social influence on route choice in a virtual reality tunnel fire*, Transportation Research Part F: Traffic Psychology and Behaviour, 26 (2014), pp. 116–125.

[115] M. KINATEDER, E. RONCHI, D. NILSSON, M. KOBES, M. MÜLLER, P. PAULI, AND A. MÜHLBERGER, *Virtual reality for fire evacuation research*, in 2014 federated conference on computer science and information systems, New Jersey, United States: IEEE, 2014, pp. 313–321.

[116] M. KINATEDER AND W. H. WARREN, *Exit choice during evacuation is influenced by both the size and proportion of the egressing crowd*, Physica A: Statistical Mechanics and its Applications, 569 (2021), p. 125746.

[117] A. KIRCHNER AND A. SCHADSCHNEIDER, *Simulation of evacuation processes using a bionics-inspired cellular automaton model for pedestrian dynamics*, Physica A: Statistical Mechanics and its Applications, 312 (2002), pp. 260–276.

[118] A. KLASIK, M. JANAS-KOZIK, I. KRUPKA-MATUSZCZYK, AND E. AUGUSTYNIAK, *Cognitive functions, their development and modern diagnostic methods*, Przeglad lekarski, 63 (2006), pp. 29–34.

[119] I. KNEZ, J. WILLANDER, A. BUTLER, A. O. SANG, I. SARLOV-HERLIN, AND A. AKERSKOG, *I can still see, hear and smell the fire: Cognitive, emotional and personal consequences of a natural disaster, and the impact of evacuation*, Journal of Environmental Psychology, 74 (2021), p. 101554.

[120] G. Kouskoulis, I. Spyropoulou, and C. Antoniou, *Pedestrian simulation: Theoretical models vs. data driven techniques*, International Journal of Transportation Science and Technology, 7 (2018), pp. 241–253.

[121] K. M. KowalskiTrakofler, C. Vaught, and T. Scharf, *Judgment and decision making under stress: an overview for emergency managers*, International Journal of Educational Management, 1 (2003), p. 278.

[122] T. Kretz and A. Grosse, *From unbalanced initial occupant distribution to balanced exit usage in a simulation model of pedestrian dynamics*, arXiv preprint, (2012), p. 6.

[123] A. Krishna, *Spatial perception research: An integrative review of length, area, volume, and number perception*, in Visual marketing: From attention to action, Oxfordshire, United Kingdom: Taylor & Francis, 2008, pp. 167–192.

[124] J. Kubota, T. Sano, and E. Ronchi, *Assessing the compliance with the direction indicated by emergency evacuation signage*, Safety Science, 138 (2021), p. 105210.

[125] B. Kunwar, F. Simini, and A. Johansson, *Evacuation time estimate for total pedestrian evacuation using a queuing network model and volunteered geographic information*, Physical Review E, 93 (2016), p. 032311.

[126] C. A. Lawton and J. Kallai, *Gender Differences in Wayfinding Strategies and Anxiety About Wayfinding: A Cross-Cultural Comparison*, Sex Roles, 47 (2002), pp. 389–401.

[127] S. Lee and R. Kline, *Wayfinding study in virtual environments: The elderly vs. the younger-aged groups*, International Journal of Architectural Research, 5 (2011), p. 63.

[128] H. Li, L. Huang, Y. Zhang, and S. Ni, *Effects of intuition and deliberation on escape judgment and decision-making under different complexities of crisis situations*, Safety Science, 89 (2016), pp. 106–113.

[129] H. Li, J. Zhang, L. Xia, W. Song, and N. W. F. Bode, *Comparing the route-choice behavior of pedestrians around obstacles in a virtual experiment and a field study*, Transportation Research Part C: Emerging Technologies, 107 (2019), pp. 120–136.

[130] X. Li, Z. Huang, Z. Fang, Y. Huang, W. Lv, R. Ye, and S. Cao, *An experimental study on the effectiveness of fire warnings on evacuation from a metro train: The response phase*, International Journal of Disaster Risk Reduction, 76 (2022), p. 103019.

[131] Z. Li, *An emergency exits choice preference model based on characteristics of individual diversity*, Advances in Mechanical Engineering, 9 (2017), p. 1687814017693541.

[132] W. LIAO, A. U. KEMLOH WAGOUM, AND N. W. F. BODE, *Route choice in pedestrians: determinants for initial choices and revising decisions*, Journal of the Royal Society Interface, 14 (2017), p. 20160684.

[133] J. LIN, R. ZHU, N. LI, AND B. BECERIKGERBER, *Do people follow the crowd in building emergency evacuation? A cross-cultural immersive virtual reality-based study*, Advanced Engineering Informatics, 43 (2020), p. 101040.

[134] Z. LIN, P. ZHANG, AND H. HANG, *A dynamic continuum route choice model for pedestrian flow with mixed crowds*, Transportmetrica A: Transport Science, (2022), pp. 1–26.

[135] M. K. LINDELL, J.-C. LU, AND C. S. PRATER, *Household Decision Making and Evacuation in Response to Hurricane Lili*, Natural Hazards Review, 6 (2005), pp. 171–179.

[136] M. K. LINDELL AND R. W. PERRY, *The protective action decision model: Theoretical modifications and additional evidence*, Risk Analysis: An International Journal, 32 (2012), pp. 616–632.

[137] L. LIU, R. VAN LIERE, C. NIEUWENHUIZEN, AND J.-B. MARTENS, *Comparing aimed movements in the real world and in virtual reality*, in 2009 IEEE Virtual Reality Conference, IEEE, 2009, pp. 219–222.

[138] S. LIU, L. YANG, T. FANG, AND J. LI, *Evacuation from a classroom considering the occupant density around exits*, Physica A: Statistical Mechanics and its Applications, 388 (2009), pp. 1921–1928.

[139] R. LOVREGLIO, D. BORRI, L. DELL'OLIO, AND A. IBEAS, *A discrete choice model based on random utilities for exit choice in emergency evacuations*, Safety Science, 62 (2014), pp. 418–426.

[140] R. LOVREGLIO, A. FONZONE, L. DELL' OLIO, AND D. BORRI, *A study of herding behaviour in exit choice during emergencies based on random utility theory*, Safety Science, 82 (2016), pp. 421–431.

[141] R. LOVREGLIO, A. FONZONE, AND L. DELL'OLIO, *A mixed logit model for predicting exit choice during building evacuations*, Transportation Research Part A: Policy and Practice, 92 (2016), pp. 59–75.

[142] R. LOVREGLIO, A. FONZONE, L. DELL'OLIO, D. BORRI, AND A. IBEAS, *The role of herding behaviour in exit choice during evacuation*, Procedia-Social and Behavioral Sciences, 160 (2014), pp. 390–399.

[143] R. LOVREGLIO AND M. KINATEDER, *Augmented reality for pedestrian evacuation research: Promises and limitations*, Safety Science, 128 (2020), p. 104750.

[144] R. LOVREGLIO, E. RONCHI, AND M. J. KINSEY, *An online survey of pedestrian evacuation model usage and users*, Fire technology, 56 (2020), pp. 1133–1153.

[145] D. J. LOW, *Following the crowd*, Nature, 407 (2000), pp. 465–466.

[146] L. LU, C. CHAN, J. WANG, AND W. WANG, *A study of pedestrian group behaviors in crowd evacuation based on an extended floor field cellular automaton model*, Transportation Research Part C: Emerging Technologies, 81 (2017), pp. 317–329.

[147] K. LYNCH AND OTHERS, *The image of the city (Vol. 11)*, Massachusetts, United States: MIT press Cambridge, 1960.

[148] W. MAASS, J. PARSONS, S. PURAO, V. C. STOREY, AND C. WOO, *Data-driven meets theory-driven research in the era of big data: Opportunities and challenges for information systems research*, Journal of the Association for Information Systems, 19 (2018), p. 1.

[149] A. M. MACEACHREN, *Application of environmental learning theory to spatial knowledge acquisition from maps*, Annals of the Association of American Geographers, 82 (1992), pp. 245–274.

[150] M. MANLEY, Y. S. KIM, K. CHRISTENSEN, AND A. CHEN, *Airport emergency evacuation planning: An agent-based simulation study of dirty bomb scenarios*, IEEE Transactions on Systems, Man, and Cybernetics: Systems, 46 (2015), pp. 1390–1403.

[151] S. A. MARCHETTE, A. BAKKER, AND A. L. SHELTON, *Cognitive mappers to creatures of habit: differential engagement of place and response learning mechanisms predicts human navigational behavior*, Journal of Neuroscience, 31 (2011), pp. 15264–15268.

[152] MATLAB, *MATLAB version 9.10.0.1602886 (R2021a)*, California, United States: The MathWorks Inc., 2021.

[153] M. S. MAYZNER, *Perceiving, acting, and knowing: Toward an ecological psychology*, 1978.

[154] B. MCKEAN, J. C. FLAVELL, H. OVER, AND S. P. TIPPER, *Three minutes to change preferences: perceptual fluency and response inhibition*, Royal Society Open Science, 7 (2020), p. 200766.

[155] J. MCKENNA, R. J. QUINN, D. J. DONNELLY, AND J. A. G. COOPER, *Accurate Mental Maps as an Aspect of Local Ecological Knowledge (LEK) a Case Study from Lough Neagh, Northern Ireland*, Ecology and Society, 13 (2008).

[156] M. G. MCNALLY, *The four-step model*, Bingley, United Kingdom: Emerald Group Publishing Limited, 2007.

[157] A. R. MEYERS, J. J. ANDERSON, D. R. MILLER, K. SHIPP, AND H. HOENIG, *Barriers, facilitators, and access for wheelchair users: sbstantive and methodologic lessons from a pilot study of environmental effects*, Social Science & Medicine, 55 (2002), pp. 1435–1446.

[158] A. MILLONIG AND K. SCHECHTNER, *Decision Loads and Route Qualities for Pedestrians — Key Requirements for the Design of Pedestrian Navigation Services*, in Pedestrian and Evacuation Dynamics 2005, N. Waldau, P. Gattermann, H. Knoflacher, and M. Schreckenberg, eds., Berlin, Germany: Springer, 2007, pp. 109–118.

[159] A. E. MIRELES DE VILLAFRANCA, R. D. CONNORS, AND R. E. WILSON, *Static traffic assignment on ensembles of synthetic road networks*, in International Conference on Traffic and Granular Flow, Berlin, Germany: Springer, 2017, pp. 29–36.

[160] E. I. MOSER, E. KROPFF, M.-B. MOSER, AND OTHERS, *Place cells, grid cells, and the brain's spatial representation system*, Annual Review of Neuroscience, 31 (2008), pp. 69–89.

[161] M. MOUSSAID, S. GARNIER, G. THERAULAZ, AND D. HELBING, *Collective Information Processing and Pattern Formation in Swarms, Flocks, and Crowds*, Topics in Cognitive Science, 1 (2009), pp. 469–497.

[162] M. MOUSSAÏD, V. R. SCHINAZI, M. KAPADIA, AND T. THRASH, *Virtual sensing and virtual reality: how new technologies can boost research on crowd dynamics*, Frontiers in Robotics and AI, 5 (2018), p. 82.

[163] M. MOUSSAÏD, M. KAPADIA, T. THRASH, R. W. SUMNER, M. GROSS, D. HELBING, AND C. HÖLSCHER, *Crowd behaviour during high-stress evacuations in an immersive virtual environment*, Journal of The Royal Society Interface, 13 (2016), p. 20160414.

[164] H. MU, J. WANG, Z. MAO, J. SUN, S. LO, AND Q. WANG, *Pre-evacuation human reactions in fires: An attribution analysis considering psychological process*, Procedia Engineering, 52 (2013), pp. 290–296.

[165] S. MÜNZER AND C. STAHL, *Learning Routes from Visualizations for Indoor Wayfinding: Presentation Modes and Individual Differences*, Spatial Cognition & Computation, 11 (2011), pp. 281–312.

[166] A. NICOLAS AND F. H. HASSAN, *Social groups in pedestrian crowds: review of their influence on the dynamics and their modelling*, Transportmetrica A: Transport Science, (2021), pp. 1–26.

[167] D. NILSSON, M. JOHANSSON, AND H. FRANTZICH, *Evacuation experiment in a road tunnel: A study of human behaviour and technical installations*, Fire Safety Journal, 44 (2009), pp. 458–468.

[168] M. OKAYA, M. SOUTHERN, AND T. TAKAHASHI, *Dynamic information transfer and sharing model in agent based evacuation simulations*, in Proceedings of the 2013 international conference on Autonomous agents and multi-agent systems, 2013, pp. 1295–1296.

[169] J. OLANDER, E. RONCHI, R. LOVREGLIO, AND D. NILSSON, *Dissuasive exit signage for building fire evacuation*, Applied ergonomics, 59 (2017), pp. 84–93.

[170] M. J. O'NEILL, *Evaluation of a conceptual model of architectural legibility*, Environment and Behavior, 23 (1991), pp. 259–284.

[171] X. PAN, C. S. HAN, K. DAUBER, AND K. H. LAW, *Human and social behavior in computational modeling and analysis of egress*, Automation in construction, 15 (2006), pp. 448–461.

[172] S. PAPADIMITRIOU, M. KAMITSIOS, K. CHRYSAFIADI, AND M. VIRVOU, *Learn-and-play personalised reasoning from point-and-click to virtual reality mobile educational games*, Intelligent Decision Technologies, 15 (2021), pp. 321–332.

[173] A. PARKHE, S. WASSERMAN, AND D. A. RALSTON, *New frontiers in network theory development*, Academy of Management Review, 31 (2006), pp. 560–568.

[174] J. PHILLIPS, N. WALFORD, A. HOCKEY, N. FOREMAN, AND M. LEWIS, *Older people and outdoor environments: Pedestrian anxieties and barriers in the use of familiar and unfamiliar spaces*, Geoforum, 47 (2013), pp. 113–124.

[175] C. POHL, A. KIESEL, W. KUNDE, AND J. HOFFMANN, *Early and late selection in unconscious information processing.*, Journal of Experimental Psychology: Human Perception and Performance, 36 (2010), p. 268.

[176] J. PORTER, T. ANAND, B. JOHNSON, R. M. KHAN, AND N. SOBEL, *Brain Mechanisms for Extracting Spatial Information from Smell*, Neuron, 47 (2005), pp. 581–592.

[177] J. N. PRASHKER AND S. BEKHOR, *Route choice models used in the stochastic user equilibrium problem: a review*, Transport reviews, 24 (2004), pp. 437–463.

[178] C. G. PRATO, *Route choice modeling: past, present and future research directions*, Journal of Choice Modelling, 2 (2009), pp. 65–100.

[179] B. J. PRETTEJOHN, M. J. BERRYMAN, AND M. D. MCDONNELL, *Methods for generating complex networks with selected structural properties for simulations: a review and tutorial for neuroscientists*, Frontiers in Computational Neuroscience, (2011), p. 11.

[180] G. PROULX, *Occupant behaviour and evacuation*, in Proceedings of the 9th International Fire Protection Symposium, Citeseer, 2001, pp. 219–232.

[181] R. Reber, P. Winkielman, and N. Schwarz, *Effects of perceptual fluency on affective judgments*, Psychological Science, 9 (1998), pp. 45–48.

[182] D. Reid, *Virtual reality and the person–environment experience*, CyberPsychology & Behavior, 5 (2002), pp. 559–564.

[183] M. K. Rodgers, J. A. Sindone, and S. D. Moffat, *Effects of age on navigation strategy*, Neurobiology of Aging, 33 (2012), pp. 202.e15–202.e22.

[184] E. Ronchi, D. Nilsson, and S. Gwynne, *Modelling the impact of emergency exit signs in tunnels*, Fire Technology, 48 (2012), pp. 961–988.

[185] E. Ronchi, D. Nilsson, S. Kojić, J. Eriksson, R. Lovreglio, H. Modig, and A. L. Walter, *A Virtual Reality Experiment on Flashing Lights at Emergency Exit Portals for Road Tunnel Evacuation*, Fire Technology, 52 (2016), pp. 623–647.

[186] E. Ronchi, D. Nilsson, H. Modig, and A. L. Walter, *Variable Message Signs for road tunnel emergency evacuations*, Applied Ergonomics, 52 (2016), pp. 253–264.

[187] H. E. Rosenthal, L. Norman, S. P. Smith, and A. McGregor, *Gender-based navigation stereotype improves men's search for a hidden goal*, Sex Roles, 67 (2012), pp. 682–695.

[188] S. M. Ross, *The exponential distribution and the poisson process*, Introduction to Probability Models. San Diego, CA: Academic, (2000), pp. 239–243.

[189] R. A. Ruddle and P. Péruch, *Effects of proprioceptive feedback and environmental characteristics on spatial learning in virtual environments*, International Journal of Human-Computer Studies, 60 (2004), pp. 299–326.

[190] A. M. Sadri, S. V. Ukkusuri, and M. A. Ahmed, *Review of social influence in crisis communications and evacuation decision-making*, Transportation research interdisciplinary perspectives, 9 (2021), p. 100325.

[191] C. Saloma, G. J. Perez, G. Tapang, M. Lim, and C. Palmes-Saloma, *Self-organized queuing and scale-free behavior in real escape panic*, Proceedings of the National Academy of Sciences, 100 (2003), pp. 11947–11952.

[192] S. Sarjala, *Built environment determinants of pedestrians' and bicyclists' route choices on commute trips: Applying a new grid-based method for measuring the built environment along the route*, Journal of Transport Geography, 78 (2019), pp. 56–69.

[193] I. H. Sarker, *Machine Learning: Algorithms, Real-World Applications and Research Directions*, SN Computer Science, 2 (2021), p. 160.

[194] L. J. SAVAGE, *The foundations of statistics*, Massachusetts, United States, 1972.

[195] A. SCHADSCHNEIDER, W. KLINGSCH, H. KLUEPFEL, T. KRETZ, C. ROGSCH, AND A. SEYFRIED, *Evacuation Dynamics: Empirical Results, Modeling and Applications*, Safety Science, 50 (2012), pp. 1253–1260.

[196] M. SENGKE AND P. ATMODIWIRJO, *Using isovist application to explore visibility area of hospital inpatient ward*, in IOP Conference Series: Materials Science and Engineering, vol. 185, Bristol, United Kingdom: IOP Publishing, 2017, p. 012008.

[197] F. SHATU, T. YIGITCANLAR, AND J. BUNKER, *Objective vs. subjective measures of street environments in pedestrian route choice behaviour: Discrepancy and correlates of non-concordance*, Transportation Research Part A: Policy and Practice, 126 (2019), pp. 1–23.

[198] X. SHI, S. XUE, N. SHIWAKOTI, D. LI, AND Z. YE, *Examining the effects of exit layout designs on children pedestrians' exit choice*, Physica A: Statistical Mechanics and its Applications, 602 (2022), p. 127654.

[199] J. F. SHORTLE, J. M. THOMPSON, D. GROSS, AND C. M. HARRIS, *Fundamentals of queueing theory*, vol. 399, New Jersey, United States: John Wiley & Sons, 2018.

[200] J. D. SIME, *Affiliative behaviour during escape to building exits*, Journal of Environmental Psychology, 3 (1983), pp. 21–41.

[201] J. D. SIME, *Crowd psychology and engineering*, Safety Science, 21 (1995), pp. 1–14.

[202] H. A. SIMON, *Rational decision making in business organizations*, The American economic review, 69 (1979), pp. 493–513.

[203] E. SLONE, F. BURLES, K. ROBINSON, R. M. LEVY, AND G. IARIA, *Floor Plan Connectivity Influences Wayfinding Performance in Virtual Environments*, Environment and Behavior, 47 (2015), pp. 1024–1053.

[204] T. SOLSTAD, C. N. BOCCARA, E. KROPFF, M.-B. MOSER, AND E. I. MOSER, *Representation of geometric borders in the entorhinal cortex*, Science, 322 (2008), pp. 1865–1868.

[205] X. B. SONG AND R. LOVREGLIO, *Investigating personalized exit choice behavior in fire accidents using the hierarchical Bayes estimator of the random coefficient logit model*, Analytic Methods in Accident Research, 29 (2021), p. 100140.

[206] M. E. SORROWS AND S. C. HIRTLE, *The Nature of Landmarks for Real and Electronic Spaces*, in Spatial Information Theory. Cognitive and Computational Foundations of Geographic Information Science, G. Goos, J. Hartmanis, J. van Leeuwen, C. Freksa, and D. M. Mark, eds., vol. 1661, Berlin, Germany: Springer Berlin Heidelberg, 1999, pp. 37–50.

[207] B. J. STANKIEWICZ, G. E. LEGGE, AND E. SCHLICHT, *The effect of layout complexity on human and ideal navigation performance*, Journal of Vision, 1 (2001), p. 189.

[208] K. STARCKE AND M. BRAND, *Decision making under stress: A selective review*, Neuroscience & Biobehavioral Reviews, 36 (2012), pp. 1228–1248.

[209] D. STEA, *Image and environment: Cognitive mapping and spatial behavior*, Oxfordshire, United Kingdom: Routledge, 2017.

[210] E. STIGELL AND P. SCHANTZ, *Methods for determining route distances in active commuting – Their validity and reproducibility*, Journal of Transport Geography, 19 (2011), pp. 563–574.

[211] D. J. T. SUMPTER, *The principles of collective animal behaviour*, Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences, 361 (2006), pp. 5–22.

[212] T. TANG, L. CHEN, R. GUO, AND H. SHANG, *An evacuation model accounting for elementary students' individual properties*, Physica A: Statistical Mechanics and its Applications, 440 (2015), pp. 49–56.

[213] H. TAPIRO, T. ORON-GILAD, AND Y. PARMET, *Pedestrian distraction: The effects of road environment complexity and age on pedestrian's visual attention and crossing behavior*, Journal of Safety Research, 72 (2020), pp. 101–109.

[214] U. TECHNOLOGIES, *Unity - Manual: Navigation System in Unity*, California, United States: Unity Technologies., 2020.

[215] H. J. P. TIMMERMANS, *Spatial Choice Models*, in International Encyclopedia of the Social & Behavioral Sciences, N. J. Smelser, J. Wright, and P. B. Baltes, eds., Amsterdam, Netherlands: Elsevier, 2001, pp. 14768–14771.

[216] E. TOLMAN, *Cognitive maps in man and animals*, Psychological Review, 55 (1948), pp. 189–208.

[217] Y. TONG, *My writing journey*, Science, 375 (2022), pp. 1062–1062.

[218] Y. TONG AND N. W. BODE, *Higher investment levels into pre-planned routes increase the adherence of pedestrians to them*, Transportation Research Part F: Traffic Psychology and Behaviour, 82 (2021), pp. 297–315.

[219] ——, *The value pedestrians attribute to environmental information diminishes in route choice sequences*, Transportation Research Part C: Emerging Technologies, 124 (2021), p. 102909.

[220] ——, *How building layout properties influence pedestrian route choice and route recall*, Transportmetrica A: Transport Science, (2022), pp. 1–23.

[221] ——, *The principles of pedestrian route choice*, Journal of the Royal Society Interface, 19 (2022), p. 20220061.

[222] ——, *Simulation investigation on crowd evacuation strategies for helping vulnerable pedestrians at different stages of egress*, International Journal of Disaster Risk Reduction, (2022), p. 103479.

[223] ——, *An investigation of how context affects the response of pedestrians to the movement of others*, Safety Science, 157 (2023), p. 105919.

[224] Y. Tong, C. King, and Y. Hu, *Using agent-based simulation to assess disease prevention measures during pandemics*, Chinese Physics B, 30 (2021), p. 098903.

[225] A. Tucker, K. L. Marsh, T. Gifford, X. Lu, P. B. Luh, and R. S. Astur, *The effects of information and hazard on evacuee behavior in virtual reality*, Fire Safety Journal, 99 (2018), pp. 1–11.

[226] K. D. Vohs, R. F. Baumeister, J. M. Twenge, B. J. Schmeichel, D. M. Tice, and J. Crocker, *Decision fatigue exhausts self-regulatory resources—But so does accommodating to unchosen alternatives*, Manuscript submitted for publication, (2005).

[227] J. Wang, C. E. Collyer, and C. Yang, *Enhancing motorist understanding of variable message signs*, Providence, United States: Rhode Island Department of Transportation, 2006.

[228] J. G. Wardrop and J. I. Whitehead, *Correspondence. some theoretical aspects of road traffic research.*, Proceedings of the Institution of Civil Engineers, 1 (1952), pp. 767–768.

[229] C. P. Warren, L. M. Sander, and I. M. Sokolov, *Geography in a scale-free network model*, Physical Review E, 66 (2002), p. 056105.

[230] L.-O. Wehden, F. Reer, R. Janzik, W. Y. Tang, and T. Quandt, *The slippery path to total presence: How omnidirectional virtual reality treadmills influence the gaming experience*, Media and Communication, 9 (2021), pp. 5–16.

[231] S. Werner and L. E. Schindler, *The Role of Spatial Reference Frames in Architecture: Misalignment Impairs Way-Finding Performance*, Environment and Behavior, 36 (2004), pp. 461–482.

[232] F. L. Wightman and D. J. Kistler, *Hearing in three dimensions: Sound localization*, in Audio Engineering Society Conference: 8th International Conference: The Sound of Audio, New York, United States: Audio Engineering Society, 1990.

[233] Y. XIAO, Z. GAO, R. JIANG, Q. HUANG, AND H. YANG, *Exploration of pedestrian side preference behavior with circle antipode experiments: analysis, simulation and implication*, Transportmetrica B: Transport Dynamics, 9 (2021), pp. 266–282.

[234] H. XIE, L. FILIPPIDIS, S. GWYNNE, E. R. GALEA, D. BLACKSHIELDS, AND P. J. LAWRENCE, *Signage legibility distances as a function of observation angle*, Journal of fire protection engineering, 17 (2007), pp. 41–64.

[235] K. YAMAGUCHI, A. C. BERG, L. E. ORTIZ, AND T. L. BERG, *Who are you with and where are you going?*, in CVPR 2011, New Jersey, United States: IEEE, 2011, pp. 1345–1352.

[236] L. YANG, S. LIU, J. LI, K. ZHU, AND T. FANG, *Information-based evacuation experiment and its cellular automaton simulation*, International Journal of Modern Physics C, 20 (2009), pp. 1583–1596.

[237] J. YOON, J. CHUN, AND H. KIM, *Investigating the relation between walkability and the changes in pedestrian policy through wearable sensing*, Sustainability, 12 (2020), p. 10447.

[238] X. YUAN, S. SHAO, H. E. STANLEY, AND S. HAVLIN, *How breadth of degree distribution influences network robustness: comparing localized and random attacks*, Physical Review E, 92 (2015), p. 032122.

[239] J. ZHANG AND A. SEYFRIED, *Empirical characteristics of different types of pedestrian streams*, Procedia Engineering, 62 (2013), pp. 655–662.

[240] Z. ZHANG AND Z. ZHAO, *A multiple mobile robots path planning algorithm based on a-star and dijkstra algorithm*, International Journal of Smart Home, 8 (2014), pp. 75–86.

[241] H. ZHAO AND Z. GAO, *Reserve capacity and exit choosing in pedestrian evacuation dynamics*, Journal of Physics A: Mathematical and Theoretical, 43 (2010), p. 105001.

[242] X. ZHENG, T. ZHONG, AND M. LIU, *Modeling crowd evacuation of a building based on seven methodological approaches*, Building and Environment, 44 (2009), pp. 437–445.

[243] F. ZHIMING, X. XINGPENG, J. LIXUE, L. XIAOLIAN, AND H. NAN, *Study on the exit-selecting behavior in underground indoor space with fire using a virtual experiment*, Tunnelling and Underground Space Technology, 112 (2021), p. 103936.

[244] Y. ZHU, T. CHEN, N. DING, M. CHRAIBI, AND W.-C. FAN, *Follow the evacuation signs or surrounding people during building evacuation, an experimental study*, Physica A: Statistical Mechanics and its Applications, 560 (2020), p. 125156.

[245] K. ZIA AND A. FERSCHA, *A simulation study of exit choice based on effective throughput of an exit area in a multi-exit evacuation situation*, in 2009 13th IEEE/ACM International Symposium on Distributed Simulation and Real Time Applications, New Jersey, United States: IEEE, 2009, pp. 235–238.