Crowd Dynamic Modelling and Simulation

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Abstract

The ability to accurately model and simulate the interactions between pedestrians and the natural environment is a matter of interest in the crowd dynamics field. A primary objective is to optimise the design of entry and exit points and thus provide safe passage in crowded venues such as schools, theatres, mosques, airports, railway stations, concert halls and football stadiums. Therefore, understanding the dynamics of crowd behaviour is important for improving the safety of crowds. People's movements are affected by interactions with other individuals and the environment. The interactions between humans and physical objects are of particular concern in crowd movement, especially during an emergency, and require further study.

Pedestrian simulation has been recognised as a tool that provides a robust framework for understanding crowd dynamics in a complex environment and for predicting crowd density during an extreme event. However, for pedestrian simulations to produce reliable numerical simulation outputs, they must be calibrated using reliable experimental data so that they can produce reasonable results. Therefore, investigating the effects of factors such as pedestrian competition levels (in normal and emergency conditions) and crowd density on the behaviour of pedestrians is an important topic. In this study, we performed experiments focusing on the interaction of crowds and their surrounding physical situation; specifically, we observed how pedestrians avoid obstructions in a compound indoor environment at different speed levels (low–high) and density levels (low–high).

This research aimed to study the effect of the various sizes of obstacles (1.2 m, 2.4 m, 3.6 m and 4.8 m) on human behaviour (walking and running) at particular density levels (or flow rates). Several factors that affect the movement of pedestrians around objects were studied using macro- and micro-level approaches. The results were then utilised to enhance a pedestrian simulation model developed at the University of Melbourne over the past 10 years. The outcome of this study was used to investigate the obstacles' positions, the exit locations, and the placement of obstacles around the exit to improve the movement of crowds under normal and emergency conditions.

Declaration

I declare that:

1- This thesis comprises only my original work towards the PhD except where stated in the preface;

2- I have made due acknowledgement in the text to all other material used;

3- This thesis is fewer than 100,000 words, exclusive of tables, maps, bibliographies and appendices.

Abdullah Alhawsawi

Preface

Papers published during the study:

1- Investigating pedestrians' obstacle avoidance behaviour
A Alhawsawi, M Sarvi, M Haghani, A Rajabifard
Collective Dynamics 5, 413-422-(2019)

AUTHOR CONTRIBUTIONS
Conception and design: MS, AA, MH and AR. Experiments: MS and AA. Data analysis: AA . Critical revision: AA, MS, MH, and AR. **Author: AA.**

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Abdullah Alhawsawi, Majid Sarvi, Milad Haghani, Abbas Rajabifard
Transportation Research Board 98th Annual Meeting Transportation Research Board (2020)

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3- Understanding pedestrian characteristics and collective movement under different obstacles size and flows rates: An experimental study
Abdullah Alhawsawi,Majid Sarvi,Abbas Rajabifard, Jianyu Wang
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Conference Presentations

1- The 3rd Saudi Scientific Symposium 2018, Crowd dynamic, modelling and simulation, Sydney, Australia

2- Crowd dynamic modelling and simulation
40th Australasian transport research forum, Auckland, Darwin, Australia

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1.1 Introduction

Panic in a crowd has been identified as a major hazard that can occur during public events [1]. One of the most disastrous forms of collective human behaviour is a stampede induced by panic. Panic usually results in fatalities as people are stamped on and crushed. From time to time, this behaviour results in life-threatening situations in crowded buildings. Stampedes can also be dangerous during various activities such as a rush for seats. In 1863 in Santiago, 2,000 people died in a church in such an event. In 1881 in Vienna, 570 died when a stampede occurred during a theatre performance. And in Bhavnath, India, in 2012, 7 people died and 12 were injured at a temple because of a stampede. Therefore, studying the dynamics of pedestrians in normal and panic situations will help us understand the unique characteristics of human behaviour under two different speed conditions [2].

In an emergency, it is very important to evacuate a crowd safely and efficiently. However, the number of disasters is still increasing all over the world. A list of such catastrophes can be found at the following URL: http://www.gkstill.com/ExpertWitness/CrowdDisasters.html. Improving the security of enormous crowds is a major challenge and an essential topic for research not only during emergency evacuations but also during other activities. The focus should be on maintaining the safety of large crowds when they are moving.

Previous studies have examined crowd disasters using crowd models and simulations [2-5], particularly in normal evacuation situations [6], evacuation during panic situations [2, 7] and escaping from a room during a panic situation in a complex environment [8]. All of these investigations attempted to assess the built environment and to predict hazards by investigating pedestrians' behaviour in various geometrical and network settings in order to develop crowd simulation tools.

In addition to these evacuation assessments, modelling and simulating pedestrian dynamics has recently attracted much attention [9, 10]. This field has been studied for over four decades [7]. Modelling and simulation have provided productive results that can be used to test evacuation facilities and conduct risk analyses. Many models have been developed to study the interactions between the physical environment [11] and pedestrians' movement at an individual level. These include, for example, cellular automation models [12-18] and social force models [5, 8, 19]. The study of individual movement has mostly been based on social force models, which according to Helbing and Molnar [5] suggest that pedestrians’ motions can be described as if they were subject to ‘social forces’. These forces are not directly exerted by the pedestrians' environment; they are a measure of the internal motivations of individuals to perform certain actions (movements). Thus, the social force model has become a well-accepted framework for describing the interactions between humans and the physical environment. However, this method sometimes leads to abnormal results because of the interaction force and the relative position of individuals. Certain factors affect how pedestrians respond to each other and the environment. According to Gao, Chen [20], more experiments and studies are needed to understand the environment and the pedestrians' behaviours in it and to investigate any effects of human interactions.

Many studies have been published on human interaction with the physical environment. Most of these analyses are empirical or theoretical, meaning they involve field observations or experimental studies. These studies have been presented to verify various behavioural phenomena, such as crossing and intersecting pedestrian movement flows [5], bidirectional [21] and T-junction pedestrian movement flows [22], turning angles and collective agreement on angled pathways [23, 24]. Other studies have examined walking through narrow bottlenecks [25], through angled corridors [26] and walking on stairs or escalators [27, 28]. Researchers have also used experiments to collect data. These observed data are critical for the calibration and validation of simulation tools, which are increasingly being used to improve and optimise the design of open or closed evacuation areas. These data expand the current knowledge of pedestrian dynamics and lead to improvements based on characteristic walking behaviour [29].

Understanding the walking characteristics of individuals might be beneficial for calibrating the parameter rules for microscopic pedestrian simulation models, in which individual agents are treated as separate entities with unique tendencies. This view is especially helpful in situations in which individuals interact with their physical surroundings in different indoor environments by, for example, avoiding obstacles or choosing between two exits. These simulations could involve various speed levels, varying density levels and other contextual elements. More studies are needed to comprehensively understand the characteristics of walking at different speed levels, which is associated with complex geometries and architectural features.

Several authors have addressed and discussed the issue of reliability in current dynamic simulation models. These models focus on developing pedestrian motion in several areas including evacuation situations and local interaction behaviours [8, 14, 27, 30-51]. Different types of models, such as physically based models, cell-based models, queuing network models and multi-agent-based models, have been used. These models have contributed to microscopic-level investigations of behaviour based on different assigned roles.

For example, physically based models are generally developed based on continuous space, and the optimal acceleration is related to the physical force. The equation of motion is related to the pedestrian's movement in each time step. The strongest element of this model is the ability to assign decision-making roles or capabilities so that pedestrians keep their distance from each other and demonstrate self-organisation phenomena. In addition, this model is well-suited to support the design of evacuation strategies. However, the weakness of this model is that the crowd does not completely follow the rules of physics at all times, and complex structures might be hard to simulate. These models may require validation based on visual observation of emergency conditions [32, 52, 53].

Cell-based models are generally developed based on discrete space, and the space is divided into several cells. Individuals move from cell to cell based on occupancy rules defined for the cells in each time step. The strongest elements of this model are that it is simple to develop and can be updated quickly, making it suitable for simulations of large, complex structures. However, some researchers have reported difficulties simulating crowd cross flow through concourses, and the movement pattern of people hopping on grid cells seems unrealistic [18, 54].

In queuing network models, the pedestrian facility is generally represented as a network of walkway sections, and pedestrian flow is modelled using a queuing network process-oriented discrete-event simulation. This type of model is simple to develop and computationally efficient. It is suitable for assessing the inflow of people during critical events (like congestion) in a building and also for assessing the effectiveness of evacuation. However, this model is heavily based on probabilistic assumptions, and visualisation of the actual movement patterns of each pedestrian is impossible [55].

Multi-agent-based models are process-oriented models in which each individual acts as an autonomous agent. The agents are characterised by certain conditions of mobility, such as following or leading other agents or avoiding congestion. The strength of this model is the ability to assign decision-making capabilities to agents, which makes it suitable for modelling large-scale evacuation scenarios and complex systems. However, the formal basis of the model is weaker than other modelling approaches, and the process takes longer because force effects, which are important in emergencies, are not considered [56]. Notably, Schadschneider, Klüpfel [37] stated that simulation is a powerful framework and tool when seeking to comprehend the movement behaviours of pedestrians, but it fails to accurately predict the evacuation process in a complex geometric environment. These issues lead to the following research questions:

1.2 Research questions

- Are the current simulation models able to accurately predict pedestrian crowd behaviours in a complex situation? Examples of complex situations include: (1) pedestrian crowd behaviours in a complex geometric environment under panic and normal conditions; (2) pedestrian behaviours while avoiding objects; (3) pedestrian exit choice behaviours, including decision-making points and herding behaviour.
- Are the current models able to calibrate the above situations under both walking and running speeds to support efficient evacuation?
- Do the current models need more development to generate more realistic outcomes?
- Are the current simulation models able to predict different crowd behaviour phenomena under any situation, i.e. panic, fire or flood?

To answer the above questions, we have to consider the reliability of the current widely used simulation model tools [5, 9, 17, 44, 51, 57, 58]. Then, these models should be modified so that they can provide better results for understanding the interactions of pedestrian crowds within complex geometrical settings, by testing different assumptions mentioned by Helbing, Farkas [2].

1.3 Problem statement

The reliability of current dynamic simulation models of human behaviours during an emergency has been investigated by several researchers [5, 10, 12, 31, 52, 59-62]. They have observed that simulation can be a powerful framework and tool to understand pedestrian behaviour during an emergency. However, accurate prediction of the evacuation process in a complex geometric environment is not possible with present simulation models [63], and the current simulation models cannot provide good replication of the interaction of the pedestrian crowd with complex geometries, especially during an emergency or panic situation. Therefore, we have tested several phenomena, factors and sub-factors related to pedestrian movements under two speeds regimes: (1) walking, which represents normal conditions, and (2) running, which represents emergency conditions.

1.4 Research aims

This study aims to investigate pedestrian behaviours within complex geometries under different speeds and density conditions. The study will be based on concrete empirical evidence from human experiments with a focus on the interactions of crowds with their physical surroundings. Interactions of interest include obstacle avoidance manoeuvres, decision-making points, pedestrians' speed while avoiding objects and herding behaviour in indoor environments under different speed and density levels.

1.5 Research objectives

The objectives of the proposed study are:

(1) To determine the impact of obstacle size on pedestrian behaviour under different speeds and densities;

(2) To apply the developed methodology to enhance crowd safety around obstacles;

(3) To increase the efficiency of crowd obstacle avoidance manoeuvres;

1.6 Scientific knowledge and gaps

I have conducted a detailed literature review in order to understand the accumulated scientific knowledge regarding crowd dynamics and to identify any remaining gaps. The gaps in this area are discussed below:

(1) There is a lack of experimental studies that describe pedestrians' evacuation characteristics around obstacles.

There are very few studies related to pedestrian movement during evacuation conditions [10, 52, 64-68]. These studies have mainly focused on exploring pedestrian interactions, the impact of different walking characteristics or characteristics that are unique to uncommon conditions. They discussed various fundamental features of pedestrian movement dynamics such as flow, density, speed, patterns, acceleration, deceleration, speed patterns and trajectory. Only a few studies evaluated pedestrian movement and behaviours during an emergency by examining obstacle avoidance through experimental studies.

(2) There is a lack of experimental scenarios relating to pathways and pedestrian movement patterns around obstacles during emergency conditions.

The lack of experimental data on human panic is a critical gap in the study of crowd dynamics that has limited the improvement and assessment of models. The limited amount of empirical data or case studies is a major reason that there are so few models focusing on panic situations. It is also the reason that most of the literature is restricted to the study of normal evacuation processes. Even the researchers who developed the current models of crowd panic have identified the need for more rigorous modelling contexts and improved approaches in order to increase the reliability of model predictions of movement patterns during emergencies. In this study, several factors related to pedestrian movement behaviour will be examined in both normal and emergency conditions to determine behaviour patterns and support future studies. As discussed and suggested by Smith, James [69], we need more realistic experimental data in order to design a crowd simulation model.

Chapter 2: Research Plan and Research Methodology

2.1 Research plan

The research aims are to understand how the design of obstacles affects crowd dynamics and to apply this understanding to create better environments for pedestrians and construct obstacles in the safest manner. We used the following research plan to accomplish these aims:

Stage 1: We conducted a comprehensive literature review on crowd dynamics and pedestrian behaviour, especially obstacle-evading behaviour, in order to fill a gap in the literature review.

Stage 2: We conducted a comprehensive human experiment.

Stage 3: We conducted data analysis to investigate how different designs affect crowd dynamics, in support of the first aim of this study.

Stage 4: Using models, we investigated collective escape behaviour with regard to direction choice by applying econometrics modelling concepts to enhance movement in the majority or minority direction, in support of the study's second aim.

Stage 5: We conducted a thorough calibration and validation by using the data to simulate scenarios with different obstacle designs, in support of the second and third objectives in this study.

Stage 6: We set up new experiments based on several new scenarios with different obstacle designs. We also stimulated these new scenarios using the software that was calibrated in Stage 3. Then, data collected from Stage 4 (real data) were compared to the simulated data, in support of the study's third aim.

Figure 2.1 shows a flowchart of the research plan.

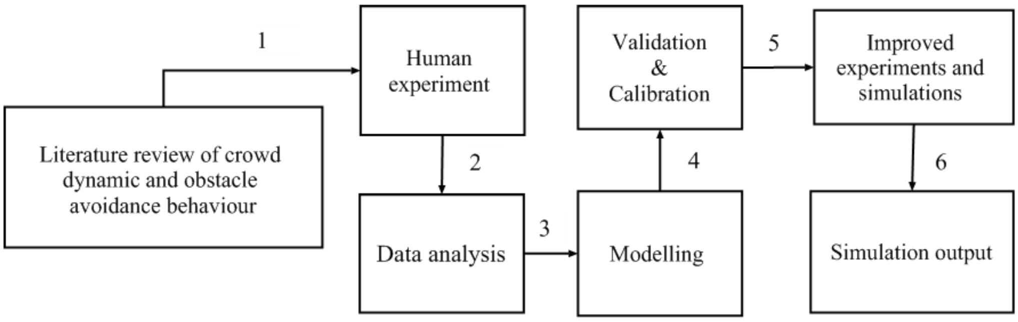

Figure 2.1: Flowchart illustrating the research plan

2.2 Research methodology and thesis structure

To meet the study aims, I applied quantitative and qualitative methodologies in this research, as detailed in the research plan (see **Figure 2.1**). I designed this methodology to provide a clear framework for realising the objectives of this study. Both methods were used to analyse pedestrian behaviour based on human experiments and to compare the experimental behaviour with the behaviour of simulated agents. The research approach and the methodology are presented in detail in **Figure 2.2** and **Figure 2.3**, respectively.

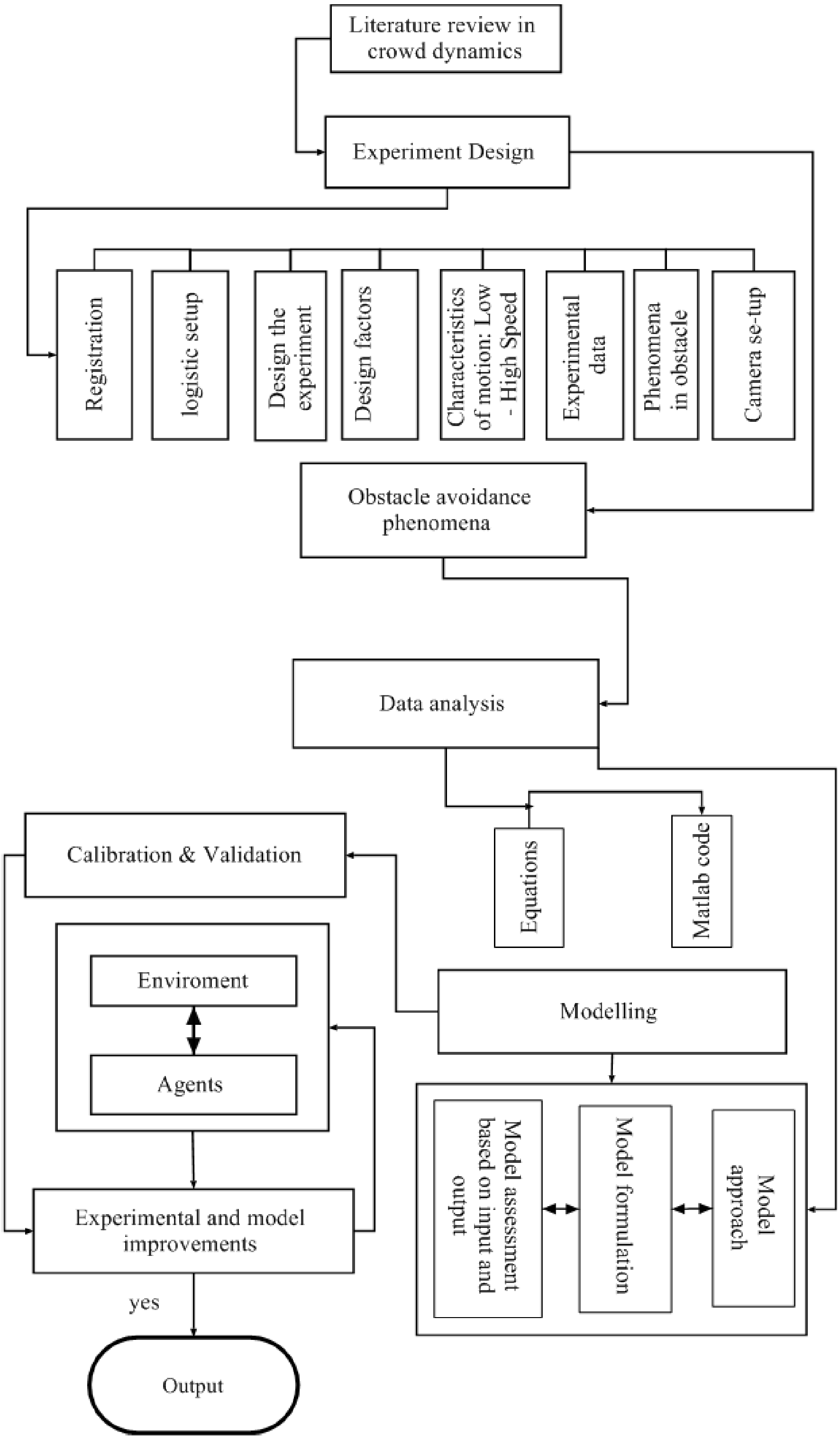

Figure 2.2: Flowchart illustrating the research approach and methodology

In Chapter 3, a detailed literature review is conducted on the topic of pedestrian obstacle avoidance behaviour in crowds. The chapter also provides an introduction to crowd modelling techniques and describes the various types of models that have been used to study crowd dynamics. Different approaches to crowd modelling are also discussed, including socio-psychological studies, experimental studies with humans and mathematical modelling and simulation. Mathematical modelling provides two types of models that can extract the level of detail we seek. The first is the microscopic level, focusing on individual interactions among pedestrians in order to study their behaviours as trajectories. The second is the macroscopic level, assessing pedestrian movement in a crowd through other variables such as speed, flow and density.

Following this, in Chapter 4, the set-up and execution of the human experiment are presented. We performed an experimental study using two different speed conditions – walking and running. We focused on exploring how pedestrian movement is affected by three phenomena: speed, density and obstacle size.

These components are described in Chapter 5, which presents micro- and macro-level data analysis. We applied quantitative and qualitative methodologies to investigate pedestrian behaviour. At the micro-level, we focused on three characteristics to determine their impact on pedestrian movement: (1) speed, (2) obstacles and (3) deviation behaviour based on pedestrians moving to the left or right. Each of these characteristics contains several factors that describe pedestrian movement behaviours at different speeds. In the macro-level analysis, we examined the pedestrians' speed, density and accumulative flow. We explored these behaviours based on crowd movement in each scenario, and by doing so, we achieved the first objective in this study.

Chapter 6 presents the models that were designed to simulate crowd and pedestrian behaviours and represent the phenomena explained in Chapter 5. We predicted which factors are associated with human decision-making and modelled these factors using an approach based on econometrics modelling. We also used the model to investigate the effects of several subs-factors such as the number of people in front of each target pedestrian, the number of people in the area and the interpersonal distance between the agent and their neighbours.

The calibration and validation of the models are explained in Chapter 7. To calibrate our results, we used the social force model as a base and applied the results from the sub-factor trials at the strategic level. Simulations were used to calibrate the design factors (i.e. speed, flow and density) based on the results of different scenarios and to design improvements for these scenarios, which helped us to achieve the study's second objective. To validate our results, we compared two different data sets, the simulation data and the empirical data, at two different speed levels, walking and running, using micro- and macro-level analysis. This was done in order to explore the differences between the movements of an agent in a simulation and a human in an actual situation. We explored the characteristics of several factors, such as average trajectory, in order to describe collision avoidance behaviours, speed, travel time, travel distance and lateral distance. By doing so, we achieved the study's third objective.

Chapter 8 summarises the study, presents the conclusions and offers suggestions for future research. **Figure 2.3** illustrates the thesis structure.

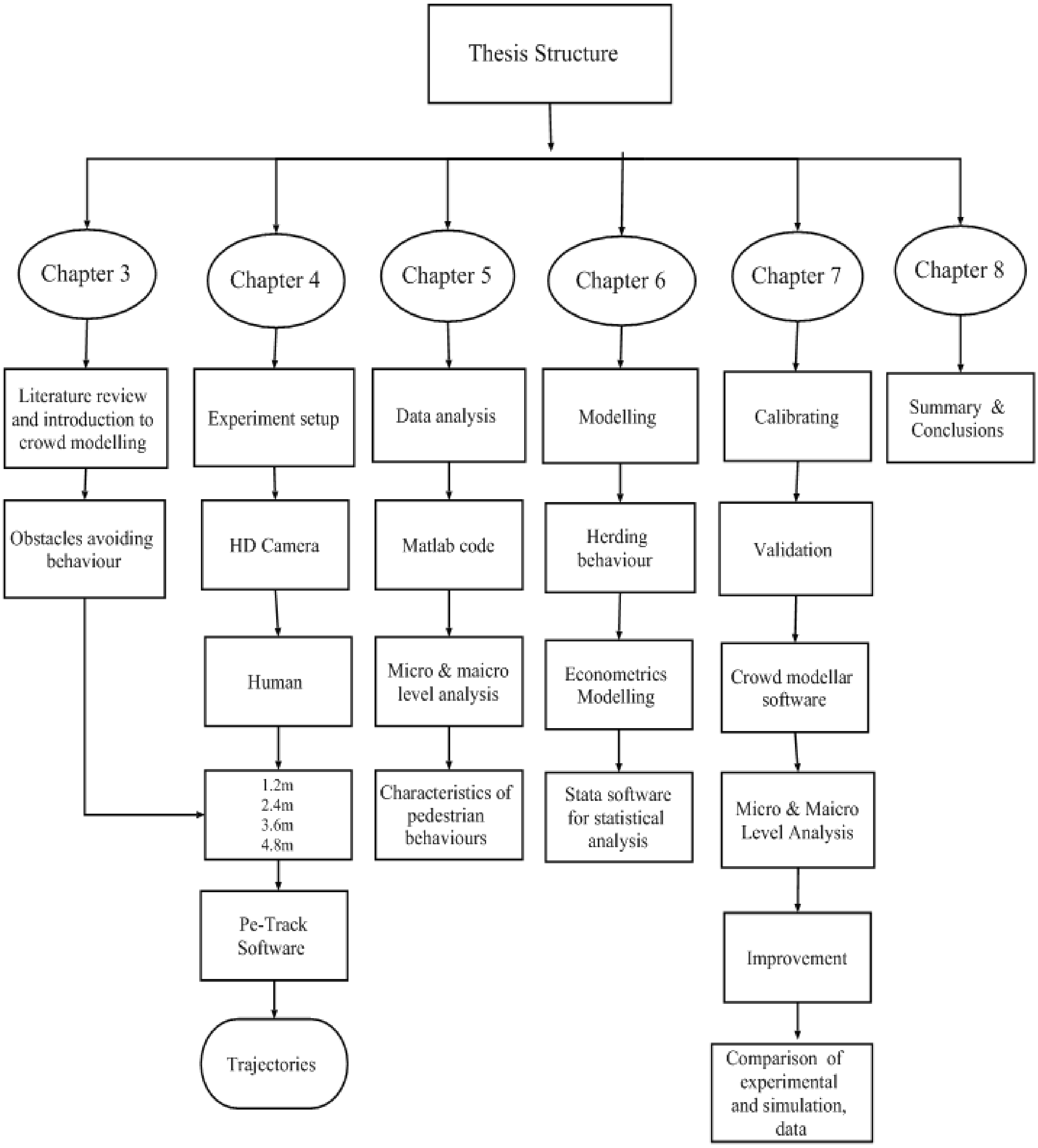

Figure 2.3: Flowchart illustrating the thesis structure

Chapter 3: Literature Review of Obstacle Avoidance Behaviour

Pedestrian behaviour has attracted the attention of many researchers in recent decades [26, 28, 70-76], including various investigations of pedestrians' responses to common obstacles (e.g. walls, pillars, barriers, etc.) in outdoor and indoor areas such as footpaths and corridors at railway stations and airports [66, 77, 78]. The effects of obstacles on pedestrian movement have been studied by many scholars [16, 23, 27, 32, 79-84]. Chen, Fu [85] studied the effects of obstacle layout on pedestrian flow in corridors, showing that pedestrians will change direction to avoid collisions with different objects. These authors suggested that the distance a pedestrian moves to avoid an obstacle is related to their direction of movement as well as their distance from the obstacle and the obstacle's relative location. Several researchers Moussaïd, Helbing [86] found that avoidance behaviour occurs at 0.8–1.5 m, while Jia, Feliciani [87] observed it at 2.0–2.64 m. The estimates vary substantially, and determining the distance of deviation is still poorly understood. These studies were performed with only small numbers of participants, and each study represented a different culture. More work is needed to better understand and model obstacle avoidance behaviour in pedestrians, as only a few studies have been completed to date. For instance, Jia, Feliciani [87] explored the impact of different obstacles, determining that when pedestrians encounter an obstacle, they walk a certain distance and then change direction. The results vary based on the experimental set-up and the shape and location of the obstacles. In addition, the seriousness of the obstacle may also influence a pedestrian's behaviour. In a recent study, Li, Zhang [88] compared the route-choice behaviour of pedestrians moving around obstacles in a virtual experiment and a field study:

One crucial component of pedestrian behaviour is the decisions individuals make on which route to use to reach their intended destinations. These decisions can cover different spatial scales. On the one hand, pedestrians may decide on routes over long distances, such as their commute to work, or a shopping or sightseeing trip. Pedestrians also have to decide on much smaller spatial scales. For example, pedestrians can choose between two routes to walk around a freestanding obstacle (left or right toward movement) and in confined indoor spaces, pedestrians can often choose between several exits.

Based on this description, there is a need to continue investigating the factors that can influence route-choice events, such as the decision-making point for going left or right, the distance to exits and the directness of routes. In addition, we need to better understand the cognitive behaviour of individuals and pedestrians when avoiding stationary obstacles.

Several agent-based models have described the characteristics of collision avoidance [20, 89], collective behaviour [32] and pedestrian response to different obstacles [42, 66, 77, 78]. These include several microscopic pedestrian simulation models [40], social force models [5], network-based representations [90] and cellular automaton models [54]. According to [2], researchers opt for models because they promise results and are well accepted. This is in spite of the fact that they sometimes generate unrealistic results due to interaction forces or environmental geometries, particularly with regard to the relative position of individuals (such as agent route choice) in the built environment [9].

In the previous works [84], researchers investigated the movement characteristics of individuals using several obstacle sizes to test the impact of an obstacle on human speed while walking and running. Their results suggested that speed was not significantly affected when participants walked towards an obstacle of any size, but the obstacle did have a more significant impact when subjects were running. Based on this concept, we suggest further investigation of human behaviour, particularly the route-choice behaviour of pedestrians moving around obstacles at different speeds, which is important for traffic management. Several methodologies exist for studying the behavioural dynamics of pedestrians and the issues that arise in built environments [2, 5, 90]. To simulate collision avoidance behaviour, more than one model should be combined (e.g. agent-based simulation and discrete choice models or agent-based simulation and network-network-based representation) so that the model can capture the different behaviours of individual agents. According to Bierlaire, Antonini [90], agent-based simulation and discrete choice models provide a great deal of flexibility and the ability to capture complex interactions, since the behaviour of each element in the system can be modelled independently. Each agent's behaviour can be modelled as a sequence of specific choices such as distance, itinerary and direction that determine where the agent will step next. Muramatsu, Irie [91] defined pedestrian route choice as follows:

"Their route choice is lane-based. Addressing the destination and/or route choice problems in a pedestrian behaviour context stems from previous research activities, namely in the Intelligent Transportation System context. Among the route choice literature, [32, 49, 92-96], several new models capturing driver behaviour and traveller behaviour, and traffic simulators, have been extended to the pedestrian behaviour and way-finding problems" [91].

In another study [97], the authors proposed an approach that framed waypoint selection as a choice between two competing goals. This method improves path selection and minimises the global path curvature as explained by Gérin-Lajoie and Warren [98]. The authors used the smaller distance (d) and the deviation angle (β) to test the determinants of route selection, and their "Research Question: How does route selection in barrier avoidance depend on the local distance (d) and deviation angle (β) of each end, and on global path length (P) and curvature (C)? Methods: Participants (Exp1 N = 19; Exp2 N = 15) walked around a barrier to a visible goal in a virtual environment. Barrier orientation and lateral position were manipulated to vary the difference in distance (Δd) and in deviation angle (Δβ) between the left and right ends of the barrier". The authors observed that 'participants select a route that minimizes the local distance (d) and deviation angle (β) of the waypoint, rather than the global path length (P) or path curvature".

All of these studies require verification from empirical data regarding the avoidance behaviour of pedestrian crowds in different geometrical settings. This kind of experiment has been done under normal walking conditions, but more studies are needed to better understand avoidance behaviour during an evacuation.

3.1 Introduction to crowd modelling approaches

As can be seen in the previous review of crowd modelling studies, only some of these studies used experiments to observe the interactions of humans with their physical environment. Various factors influence the basic dynamics of crowd activity such as crowd movement, speed and interactions within a location. Therefore, the design and layout of a study should be determined based on a variety of situations and factors. For example, social, physical and psychological factors may all influence crowd activity [24] in an unfamiliar environment. The physical aspects of an individual are the most important attributes in the simulation process. Simulation models must incorporate these factors in order to establish human behaviour and patterns. It has been observed that many models lack specific detail and information about human behaviour. For example, movement characteristics have not been well studied at different speed levels, and investigations are in progress to develop better ways to simulate realistic human behaviour in different situations [7, 28], especially with regard to obstacle avoidance and turning area. For this purpose, Shiwakoti, Sarvi [62] developed a classification system for studies of crowd dynamics (**Figure 3.1**) using the categories of socio-psychological approaches, experimental approaches and mathematical modelling and simulations.

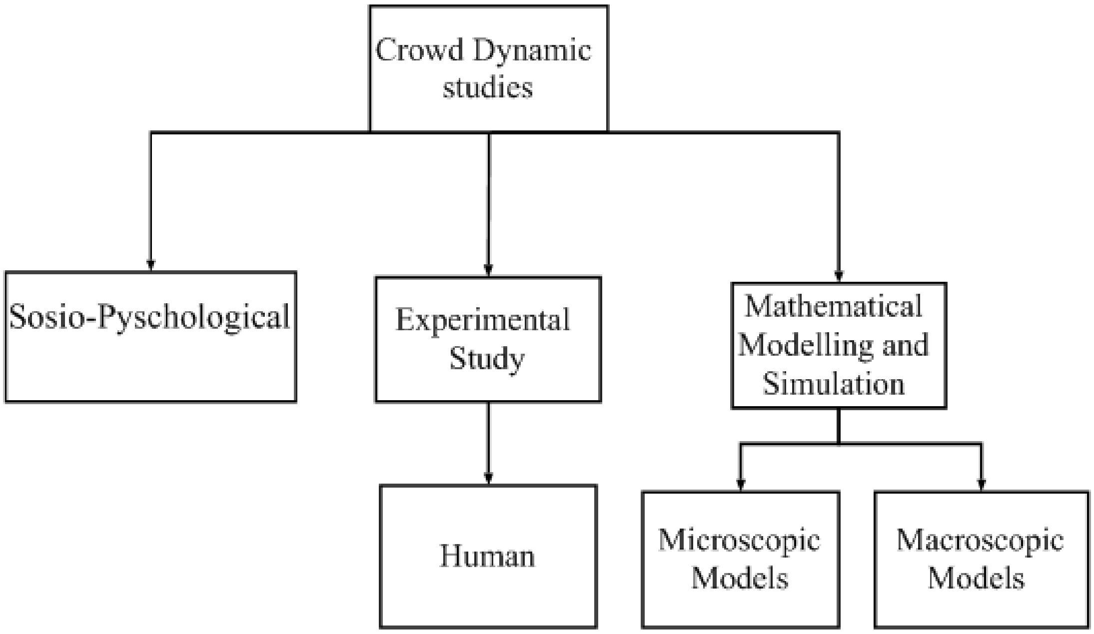

Figure 3.1: Flowchart illustrating classifications for crowd dynamic studies

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3.2 Psychological perspectives

Environmental changes influence pedestrians to adjust their state of motion. Pedestrians move to a destination with the premise of keeping a safe and psychologically comfortable distance from obstacles and objects to reduce the risk of getting hurt. If the distance between a pedestrian and another pedestrian or any object decreases to a certain level, the pedestrian feels uncomfortable [99]. Therefore, further studies are required to comprehensively understand the characteristics of distinct movement to extract different psychological rules that will be beneficial for calibrating parameter rules for microscopic pedestrian simulation models.

3.3 Mathematical modelling and simulation

Mathematical models of crowd dynamics can be classified as either microscopic or macroscopic according to the level of detail that the model extracts. Most of these are theoretical and mathematical models that focus on specific evacuation conditions including normal, panic and emergency conditions. According to Shiwakoti [62], however, these models need more development, and more research is required to make them realistic and efficient. Therefore, more studies are also needed to validate the models and identify the ones that are most accurate [62].

3.4 Experiments with humans

There are two methods for investigating crowd dynamics: mathematical modelling and simulation [77] and experiments with real people [23, 26, 61]. Many studies [64, 66, 99-101] have been conducted to study aspects of obstacle avoidance, including room evacuation in the presence of an obstruction [100], strategies for changing direction and for going over obstacles [66], changes in pedestrian tracking during obstacle avoidance [20] and avoidance of pedestrian collisions [99]. Other researchers have investigated human behaviour in situations involving pedestrians trying to escape from rooms during panic situations. In some experiments, placing an obstacle near the exit improved the evacuation time [2], but these results depended on the layout of the room. Other studies found that the greatest improvement in evacuation time could be achieved by specific adjustments to the obstacle's size and distance from the exit; however, this was valid for self-driven particles and gravity-driven fragments only [99]. Some studies were able to increase pedestrian flow by 30%–100% above the flow with no obstacle. Of course, all of these results were related to the environment used during the experiment.

3.5 Macroscopic models

Macroscopic models focus on the aggregation of pedestrian movement in a crowd using different variables related to speed, flow and density. Macroscopic models have revealed that the average speed levels of pedestrians decrease as density levels increase. A better way to describe density is the area model (M), which considers the factors affecting pedestrian flow in terms of human movement

Bellomo and Dogbe [60], for example, considered macroscopic models, but these models did not satisfy the classical continuum assumption, making them approximate and irrelevant to the study of low-density systems. Another drawback that has been pointed out by researchers is the assumption that all individuals will behave in the same way, an assertion that overlooks the heterogeneousness of systems. Conversely, macroscopic models are characterised by lower computational complexity, which allows their almost immediate application. Corbett [102] considered physical analysis, modelling and applications of multi-scale crowd dynamics. This author, in particular, encouraged fellow researchers to estimate uncertainties related to crowd dynamics that were influenced by traffic. Therefore, the researcher expressed the need to, first, fit statistical models with experimental measurements of the incoming density and, second, evaluate the impact of the traffic with the help of simulation [102].

3.6 Microscopic models

Microscopic models treat each pedestrian in a crowd as an individual agent occupying a certain area at a particular instant in time. These models can provide valuable insights across a wide range of behavioural inputs. Microscopic models address all of the factors that take pedestrians towards their goal or ultimate destination including the interactions between pedestrians and the other components around them, and therefore they provide realistic descriptions of pedestrian movements. But many problems demand high analytical and computational effort [62]. For this study, these models can be classified into four groups: physically based models, agent or multi-agent models, social force models and cell-based models (**Figure 3.2**). The following sections will review these approaches:

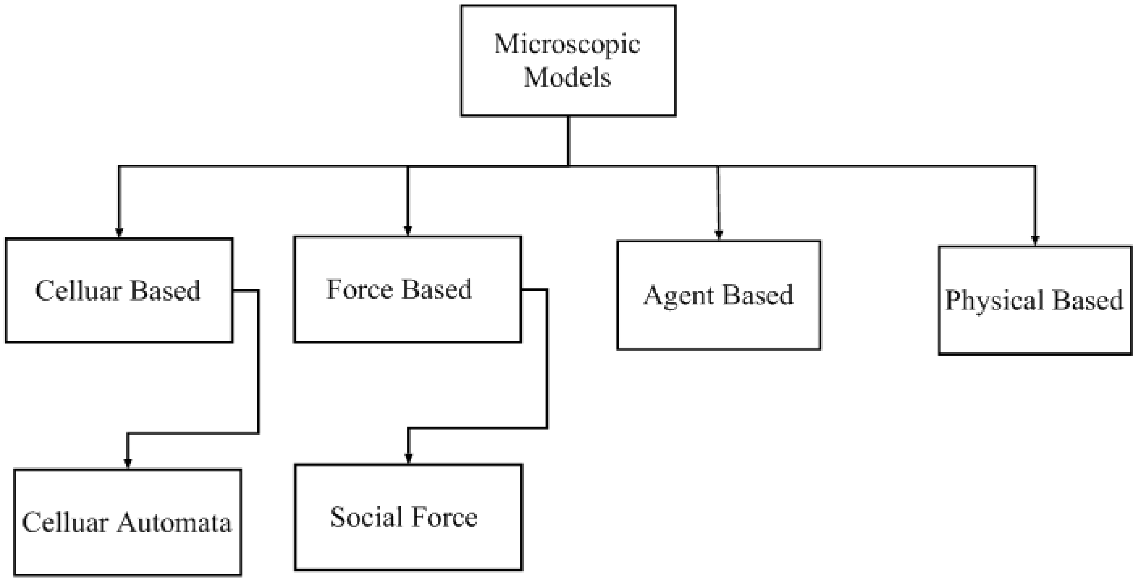


Figure 3.2: Flowchart illustrating approaches to microscopic modelling

3.6.1 Physically based models

Physically-based models had used recently by [103, 104]. These models have been widely used in indoor environments, especially in emergency and panic conditions [2]. Accordingly, they are useful for evaluating pedestrian movement in indoor environments and designing strategic plans for evacuation. In the models, optimal acceleration is determined based on different physical forces that are used to create equations to describe movement; the simulation is updated from time to time based on distinct steps that are also applied in social force models [2, 62].

3.6.2 Agent-based models or multi-agent systems

Agent-based models or multi-agent systems are also known as Situated Cellular Agents (SCA) [12]. This tool combines the benefits of multi-agent systems, specifically their ability to model heterogeneous systems, with principles of cellular automata that are useful for examining complex special dynamics. The basic rationale of the SCA approach is that crowds are systems of situated agents whose movements may be affected by attraction or repulsion to stimuli in the environment, which in turn may be perceived or ignored by different pedestrians depending on their inner states or behaviours. The main interaction occurs between the agent and the environment and may trigger the agent to change his/her route or speed. The interaction between pedestrians has lesser weightage; agents are believed to influence only neighbouring agents.

3.6.3 Cell-based models

Cell-based models are also called cellular automata or matrix-based systems. In this model, the floor space is divided into cells. Every cell in the model represents either independent floor space, an obstacle, or a space occupied by a human, a physical object or the individual. Individuals travel from one cell to another based on occupancy [16].

3.6.4 Social force models

According to Teknomo, Takeyama [57], Helbing and Molnar developed social force models [5]. The basic concept of this model is that pedestrians are motivated to reach their destinations. The model explores crowd movement when each agent has a goal of reaching a certain point at the target time, described in the following equation, dv/dt, as:

(3-1)

$$m\frac{d\underset{v_i}{\rightarrow}(t)}{dt} = m\frac{v_{o\underset{e\ i}{\rightarrow}} - v_{i\ (t)} + \mathcal{E}_i(t)}{t}$$

$$+\sum_{j(\neq i)} f \rightarrow ij((x \underset{i}{\rightarrow}(t)).x \rightarrow j(t)$$

$$+f_b(x \underset{i}{\rightarrow}(t))$$

These functions will be explained in the calibration section in Chapter 6. Therefore, the following chapter will explain the experimental set-up used in this study.

3.7 Summary

A literature review was conducted on the topic of obstacle avoidance behaviour in order to understand how humans' interactions with nearby physical objects such as obstacles affect their movement characteristics. In the problem statement section, we have mention that the current simulation models cannot provide good replication of the interaction of the pedestrian crowd with complex geometries, especially during an emergency or panic situation. Therefore, we are going to teste several phenomena, factors and sub-factors related to pedestrian movements under two speeds regimes: (1) walking, which represents normal conditions, and (2) running, which represents emergency conditions. The aims of this study are to investigate pedestrian behaviours within complex geometries under different speeds and density conditions. The study was based on concrete empirical evidence from human experiments with a focus on the interactions of crowds with their physical surroundings. Interactions of interest include obstacle avoidance manoeuvres, decision-making points, pedestrians' speed while avoiding objects and herding behaviour in indoor environments. The research objectives in this study are, to find the impact of obstacle on pedestrian crowd considering: (1) obstacle size, (2) speed of pedestrian, (3) density/flow of pedestrian, (4) and to apply the developed methodology to enhance the safety of crowd around obstacle. Finally, the scientific knowledge in crowd dynamics and the gaps as mentioned on above: (1) there was a lack of experimental studies that describe pedestrians' evacuation characteristics around obstacles and, (2) there was a lack of experimental scenarios relating to pathways and pedestrian movement patterns around obstacles during emergency conditions. The results of this study are a contribution to the modelling and simulation field, which can validate and support various simulation systems, such as a crowd simulation model under walking and running conditions.

Chapter 4: Experimental Set-up

4.1 Experimental objectives

The objective of this study is to examine the characteristics of individuals moving past obstacles of various sizes in order to test the impact of obstacles on human moving speed and on individual movement behaviours at high and low speeds and different flow rates. Experiments were conducted to gather data from actual human subjects. The experiments involved a group of people moving around obstacles of different sizes at different speeds. Participants were told to enter a doorway that was either 0.5 m, 1 m or 1.5 m wide and travel to the opposite aspect, bypassing obstacles with widths of 1.2 m, 2.4 m, 3.6 m or 4.8 m.

4.2 Experiment execution

On 6 March 2017, 20 trials were performed to gain an understanding of the characteristics of collective motion when moving around obstacles of various sizes on the basketball court at the Melbourne University sports centre. The investigations were supported by the Engineering Human Research Ethics Advisory Group. They involved over 110 students of both genders moving in a 120 m^2 area with a square shape (x-axis = 12 m, y-axis is free). The participants were between 21–25 years old, and they were all university graduates. The participants had to self-register their information through a website that was designed for this task. Each participant was paid around 80 AUD per day in a purchase voucher that they could use later. To determine the specific characteristics of collective motion for pedestrians avoiding obstacles, we asked the participants to move past different obstacles (1.2 m, 2.4 m, 3.6 m and 4.8 m) at two different speeds: walking/low speed (LS) and running/high speed (HS). Three different entrance sizes (0.5 m, 1 m and 1.5 m) were used to control the flow rates: low-flow (LF) scenarios had an entrance width of 0.5 m; medium-flow (MF) scenarios had a width of 1 m and finally, high-flow (HF) scenarios had a width of 1.5 m. **Figure 4.1** presents snapshots from the field experiment in which the interface of the tracking program shows the pedestrians passing obstacles of different sizes (1.2 m, 2.4 m, 3.6 m and 4.8 m). These snapshots were taken from the raw footage of the four trials in low-flow (LF) scenarios: (a) a scenario in which the pedestrians passed a 1.2 m obstacle; (b) a scenario in which the pedestrians passed a 2.4 m obstacle; (c) a scenario in which the pedestrians passed a 3.6 m obstacle and (d) a scenario in which the pedestrians passed a 4.8 m obstacle. **Figure 4.2** shows the measurement region. The starting point (SP) was used to control flow rates via different entrance widths (0.5 m, 1 m and 1.5 m), the middle point (MP) was the location of the obstacle (MP = 7 m) and the end point (EP) marked the end of the measurement region. **Table 4.1** lists the experiments we conducted arranged from 1 to 20.

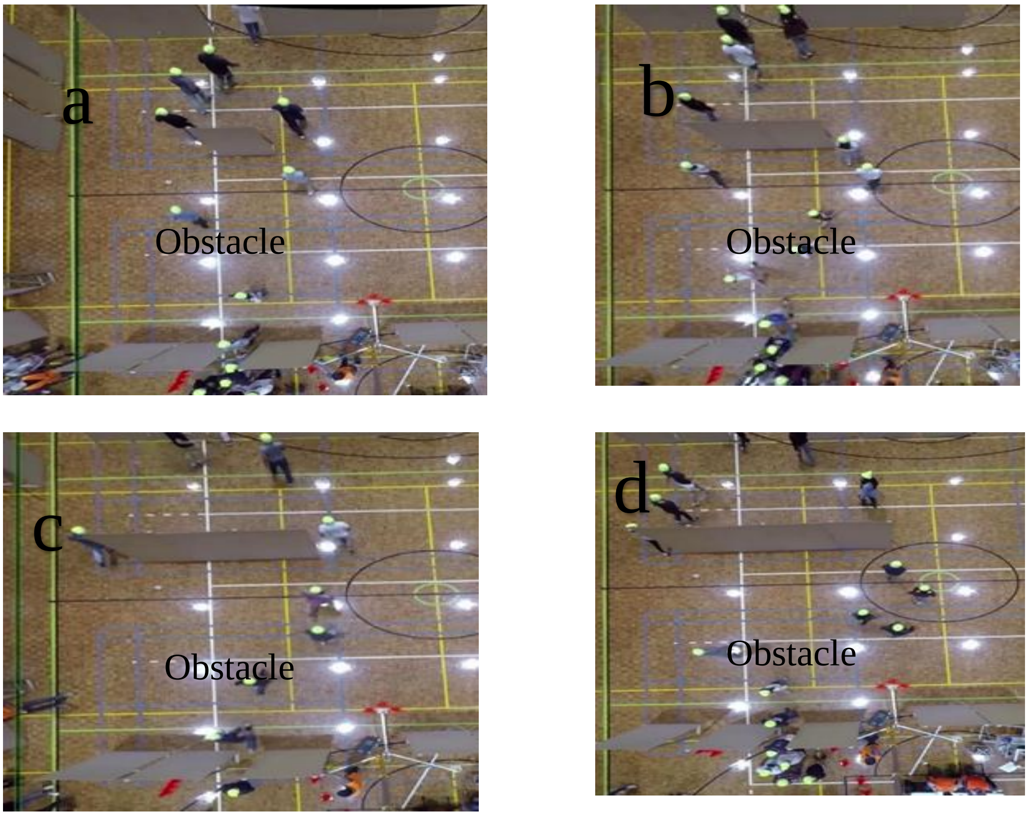


Figure 4.1: Snapshots from the raw footage of the four trials in low-flow (LF) scenarios: (a) a scenario in which the pedestrians passed a 1.2 m obstacle; (b) a scenario in which the pedestrians passed a 2.4 m obstacle; (c) a scenario in which the pedestrians passed a 3.6 m obstacle; (d) a scenario in which the pedestrians passed a 4.8 m obstacle

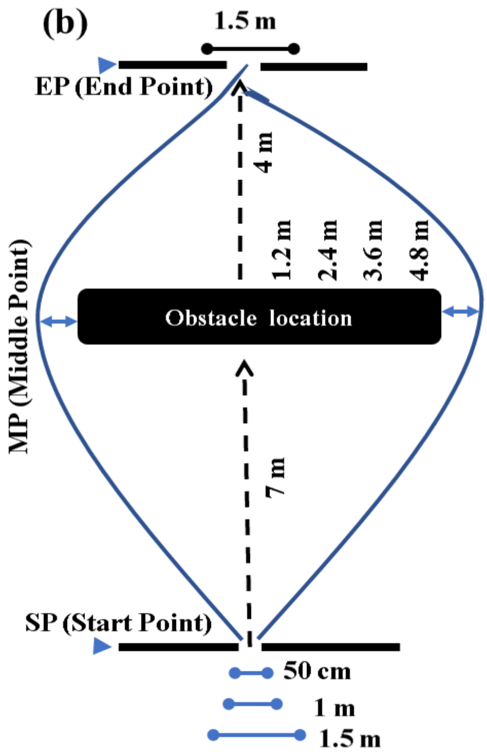


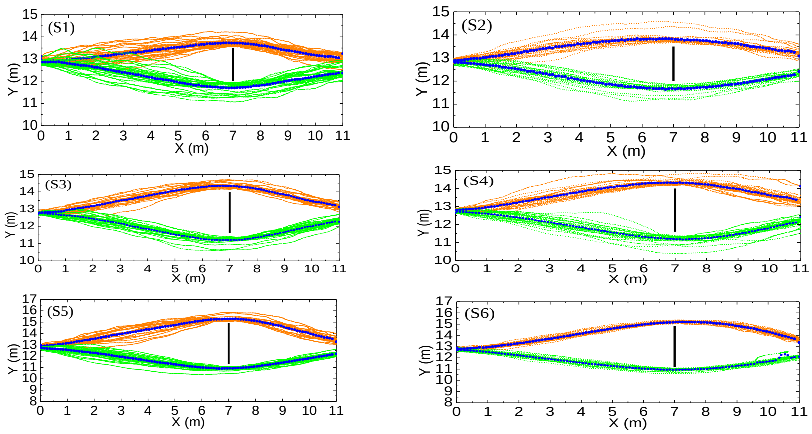
Figure 4.2: Schema for the measurement region

Table 4.1: Experiment scenarios

Experiment #		Flow Rate	Entrance 'Door' Width	Speed Regime	Obstacle size	Number of Participants
S1	LF&1.2m	Low- flow	0.5 m	Low-Speed	1.2 m	55
S2	LF&1.2m		0.5 m	High-Speed	1.2 m	55
S3	LF&2.4m		0.5 m	Low-Speed	2.4 m	55
S4	LF&2.4m		0.5 m	High-Speed	2.4 m	55
S5	LF&3.6m		0.5 m	Low-Speed	3.6 m	55
S6	LF&3.6m		0.5 m	High-Speed	3.6 m	55
S7	LF&4.8m		0.5 m	Low-Speed	4.8 m	55
S8	LF&4.8m		0.5 m	High-Speed	4.8 m	55
S9	MF&1.2m	Medium- flow	1 m	Low-Speed	1.2 m	55
S10	MF&1.2m		1 m	High-Speed	1.2 m	55
S11	MF&2.4m		1 m	Low-Speed	2.4 m	55
S12	MF&2.4m		1 m	High-Speed	2.4 m	55
S13	MF&3.6m		1 m	Low-Speed	3.6 m	55
S14	MF&3.6m		1 m	High-Speed	3.6 m	55
S15	MF&4.8m		1 m	Low-Speed	4.8 m	55
S16	MF&4.8m		1 m	High-Speed	4.8 m	55
S17	HF&3.6m	High- flow	1.5 m	Low-Speed	3.6 m	110
S18	HF&3.6m		1.5 m	High-Speed	3.6 m	110
S19	HF&4.8m		1.5 m	Low-Speed	4.8 m	110
S20	HF&4.8m		1.5 m	High-Speed	4.8 m	110

4.3 Methods for extracting trajectories

A high-definition camera with advanced image processing was used to record and extract the trajectories of the subjects in order to better understand individual behaviour. Pe-Track software: is "Automatic Extraction of Pedestrian Trajectories from Video Recordings" URL:https://www.fzjuelich.de/ias/ias7/EN/Expertise/Software/PeTrack/petrackNode.html;jsessionid=38D948DF9B14B6FBB98E836262DD5C9B. The software used for image processing techniques. The software is able to measure the quality of videos and to extract the coordinate positions for all participants and save it in a text file. The software also has an ability to deal with a wide angel lenses based on high density of pedestrian. The software also has different procedure such as calibration, recognition, tracking and height detection. Not only that but also, the system can help to "different kinds of markers (e.g. with height information, head direction) are implemented. With a special stereo camera also marker less tracking is possible". The Pe-Track [105] software was used to track the participants' positions in this study. The program parameters were calibrated according to the experimental environments in the field. The program had a colour-match-up mode, and participants in distinct groups were instructed to wear yellow or green beanies [106]. The movement of the participants was recorded at 50 frames per second. The software provided a mass trajectory file for each experiment as the raw output data, which was used for subsequent analyses. **Figure 4.3** displays a snapshot from the field experiment in which the interface of the tracking program shows the trajectories of people passing different obstacles.



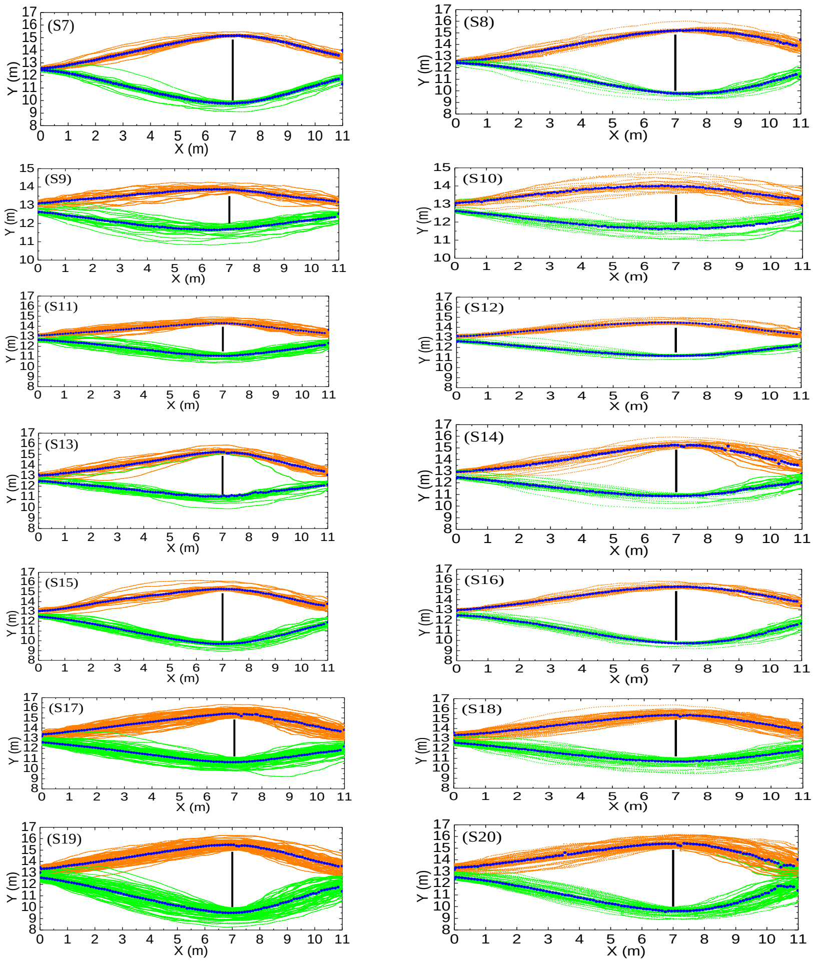


Figure 4.3: Average trajectories for all of the participants while passing (1.2 m, 2.4 m, 3.6 m and 4.8 m) obstacles in LF, MF, and HF in LS and HS experiments.

4.4 Summary

Experiments were performed in the sports centre at the University of Melbourne on 6 March 2017 to gain a better understanding of the behaviour of pedestrians moving around obstacles. The experimental procedure was approved by the Engineering Human Research Ethics Advisory Group. The experiment involved over 110 students of both genders moving in a 120 m^2 area with a square shape. The age group was limited to participants between 21–25 years old. The objectives of this experiment were to undertake an obstacle avoidance task at two levels of speed (low and high) using different flow rates (low, medium and high). After analysing the participants' extracted trajectories, we applied several methods to measure movement characteristics (i.e. speed, density, flow, distance and angle) and to investigate pedestrian behaviour, as elaborated in the following sections.

Chapter 5: Data Analysis (Introduction to Pedestrian Behaviour Around Obstacles, Micro- and Macro-Level Analysis)

Drawing on the previous literature review, two techniques were used to investigate the data and achieve the aims of this study. The first technique was microscopic analysis, which focuses on many minor details that describe pedestrian behaviours and the factors that affect pedestrian motion. The second was macroscopic analysis, which focuses on only some factors (e.g. density) in order to explore aggregation spots or other critical spots based on the different colour ranges. Both types of analysis will be explained in the following sections.

5.1 Pedestrian behaviour around obstacles

The investigation of pedestrian behaviour has attracted the attention of many researchers in recent decades [26, 28, 90, 107]. To investigate pedestrian movement behaviour, several experiments have been conducted involving obstacle avoidance [42, 66, 77, 78]. Obstructions are commonly used in outdoor and indoor environments such as sidewalks or corridors in public facilities like subway and railway stations or airports. These obstacles may have a variety of shapes, such as walls, pillars or barriers, and could affect many aspects of pedestrian movement. For example, they could delay pedestrian movement in built environments. Therefore, knowing how obstacles affect human behaviour is critical for enhancing the architecture of these environments.

In addition, accurately understanding the effects created by obstacles has direct relevance for future crowd models and simulations [2-5], and experiments could validate the findings of previous simulations, as is argued by Haghani, Sarvi [47]. Because of the difficulty of conducting experiments with humans and the challenges of data collection, many researchers have used mice, sheep and ants [32, 108, 109] to validate their models. These studies aimed at determining dependencies among different obstacles and the fundamental characteristics of pedestrian movements in various sorts of interactions between flows. For example, researchers have investigated whether setting an obstruction in front of the exit helps to control crowd flows and pedestrian evacuation. Some studies have noted the effect of architectural changes on pedestrians [110-112], and they have used different sizes of obstacles to explore this concept and also have investigated scenarios such as whether a corner exit is more efficient than a central exit given the same size of obstacle [33]. Other scholars have found that pedestrian speed changes based on the obstacle and the architecture. Changing the layout (parallel vs non-parallel) led to a 19% reduction in speed. They also found a 17% change in average passing time, according to Chen, Fu [85]. Therefore, to achieve the most improvement in evacuation time, we should optimise the size of the obstacle and its distance from the exit [83]. This approach has been validated for both self-driven and gravity-driven particles. Some studies have suggested that this method could increase pedestrian outflow by up to 30% or even double the flow that would have occurred without the obstacle at the exit. However, these studies have not yet explored pedestrian behaviour in all possible layouts [110].

A few studies have focused on people's avoidance behaviour when encountering different obstacles. Jia, Feliciani [87] explored the impact of various obstructions and found that when pedestrians encountered an obstacle, they walked a certain distance and then changed their walking direction. However, the results varied due to different experimental set-ups and scenarios, including changes in the shape and location of the obstacles. It is also possible that the position of the obstruction might affect its influence on pedestrian behaviour. The abovementioned factors might be part of the reason that there is a growing interest in studying the factors that affect how pedestrians respond to the environment in many walking facilities. Researchers are also exploring the use of two different obstacles, but this work is in its early stages and the effects are not yet fully understood. Chen, Fu [85] investigated the effect of obstacle layout on pedestrian flow in corridors and found that pedestrians change their waking direction to avoid collision with different objects such as obstacles. According to him, the distance travelled to avoid an obstacle is related to various characteristics such as the distance from the pedestrian to the obstacle, the walking distance, the angle or direction of deviation and, finally, the point at which the pedestrian begins to evade the obstruction. Therefore, ambiguity remains as to the expected distance, time or location at which pedestrians decide to avoid objects. Moussaïd, Helbing [86] found that, on average, walking pedestrians begin to deviate at a distance of between 0.8 m and 1.5 m from an obstacle, while Jia, Feliciani [87] found the distance to be between 2.0 m and 2.64 m. These authors regarded evading behaviour as a form of collision avoiding behaviour. They found that pedestrians began to evade an obstacle when they were 4.40 m away from it and they finished eluding it 4.85 m past the obstacle's location. However, an accurate method for finding the exact location of deviation has not yet been developed. Moreover, each of these studies were carried out with a small number of participants using only walking scenarios, and each experiment represented a different culture. Therefore, more studies are needed to explore pedestrian movement while passing various obstacles. The other problem is the determination of lateral distance. Lateral distance was defined in [87] as either the distance between the edge of the obstruction and the pedestrian while the pedestrian was passing the obstacle or the space between the obstacle's edge and the wall. This distance was determined to be a static value by Jia, Feliciani [87], who calculated it to be only 0.4 m after considering the average shoulder breadth of the participants. However, this value is a matter of concern requiring further investigation, which we carried out in this study.

According to [87], some studies have found that pedestrian trajectories contain two kinds of information: body sway and walking direction. As Hoogendoorn and Daamen [113] explained, 'pedestrians require space in both the longitudinal direction and in the lateral direction. The latter encompasses the shoulder width of the pedestrian, the shy-away distance from obstructions and other pedestrians directly beside him or her, but also the distance taken up by swaying'. Therefore, we can determine the relation between body sway and the lateral space in the movement direction by investigating the pedestrian trajectories in this study. The lateral range was found to be 0.45 m [113]. The body sway amplitude for the pedestrian crowd while heading to the bottleneck was between 0.04 m and 0.06 m and showed a negative correlation when associated with velocity ranges from 0.5 m/s to 1.5 m/s [114]. The amplitude ranged from 0.024 m to 0.034 m, and the body sways ranged from 0.28 m to 1.6 m [115]. Another study [116] measured the length of the step and sway amplitudes to calculate the space required for each pedestrian in a walking condition. That measurement was critical for determining the level of service and thus was a factor for walking facility design. Therefore, there is another ambiguity with regard to body sway, which is how the body movements will respond to other objects.

Understanding pedestrian walking characteristics and object avoidance behaviours might be supportive for calibrating the parameter rules for microscopic pedestrian simulation models in which individual agents are treated as separate entities with unique characteristics. This understanding is especially important for modelling individual's behaviours in response to their physical surroundings, such as avoiding obstacles, engaging in turning manoeuvres or choosing between a stairway or an escalator in an indoor environment. These models could involve different speed levels, varying density levels and other contextual elements. Several simulation models, such as agent-based models [11], social force models [5] and cellar automaton [54], offer technologically advanced descriptions of the characteristics of pedestrian motion, collision or obstacle avoidance and collective behaviours [89]. Several researchers have used these models because of their promising results and because they are well accepted. However, these models have produced some unrealistic results related to the relative position of individuals in the built environment and the ways pedestrians evade objects due to interaction forces or environmental geometries.

5.2 Micro-level analysis

In the micro-level investigation, we focused mainly on quantitative analysis by comparing different factors under different speed levels. To do so, we used the data that we extracted from the participants' trajectories in the experiments. At the microscopic level, we separated our analysis into three main parts: speed investigation, analysis of the influence of obstacles on pedestrian behaviours and characteristics, and deviation behaviour analysis based on pedestrians going left or right. To address the research questions posed in the introduction and to gain a better understanding of the avoidance behaviours of pedestrian crowds within different geometrical settings, we analysed pedestrian behaviour while passing different obstacles. (1) In our investigation of the impact of speed on pedestrian movement, I report our findings for the instantaneous speed, the speed in the movement direction (defined in this study as speed on the x-axis), the speed in the lateral direction (y-axis) and a comparison of the maximum, minimum and mean speed values for all of the experiments. (2) In our analysis of the influence of obstacles on pedestrian behaviours and characteristics, we examined avoidance behaviour by comparing travel times to assess the influence of obstacles on pedestrian movements, observed the impact of speed on pedestrian movement in terms of overall speed with a focus on the average speed and, finally, explored the effect of obstacles on body sway (slope) and deviation angles by observing lateral movement and measuring the lateral distances at the edges of the obstacles. (3) In our analysis of deviation behaviour based on pedestrians going left or right, we determined the decision-making point for going left or right, observed collision-avoidance behaviours on the left and right paths and explored pedestrian velocity on the left and right paths, including scenarios with different flow rates and speed conditions. In this way, we hope to improve the database related to pedestrian avoidance behaviour and contribute to a better understanding of collective pedestrian movement around different sizes of obstacles and at different flow rates. Therefore, we began with a flow rate factor comparison, which was crucial for determining pedestrian behaviour at each speed level. Our results are presented in the following section.

5.2.1 Flow rate investigation

To determine flow rate, we estimated the average flow rate (ped/s) for each experiment using the number of individuals (*N*) passing 'SP' **(Figure 4.2.)** and the location within time (*T*), as presented in **Equation (5-1)**. The average flow rate for each experiment was included in **Table 2**. As clearly indicated in **Table 5.1**, and **(Figure 5.1)** pedestrian ingress was greatest under high-flow conditions, followed by medium-flow conditions and then low-flow conditions, indicating a significant impact between low vs high-speed experiments with a 99% confidence level.

$$Flow\_rate = \frac{N}{T} \tag{5-1}$$

Table 5.1: Comparison of the flow rates for all scenarios

Speed Level	Low-Speed Experiments (LS)			High-Speed Experiments (HS)		
Obstacle Size	Low-Flow (Ped/s)	Medium-Flow (Ped/s)	High-Flow (Ped/s)	Low-Flow (Ped/s)	Medium-Flow (Ped/s)	High-Flow (Ped/s)
1.2 m	1.17±0.02	2.17±0.04	-	1.69±0.01	3.21±0.19	-
2.4 m	1.26±0.01	2.37±0.10	-	1.52±0.06	3.19±0.33	-
3.6 m	1.05±0.01	2.46±0.13	3.42±0.54	1.68± 0.07	2.94 ±0.14	4.78±0.67
4.8 m	1.27±0.03	2.13±0.10	3.54±0.23	1.48±0.03	3.27 ±0.08	4.84±1.10

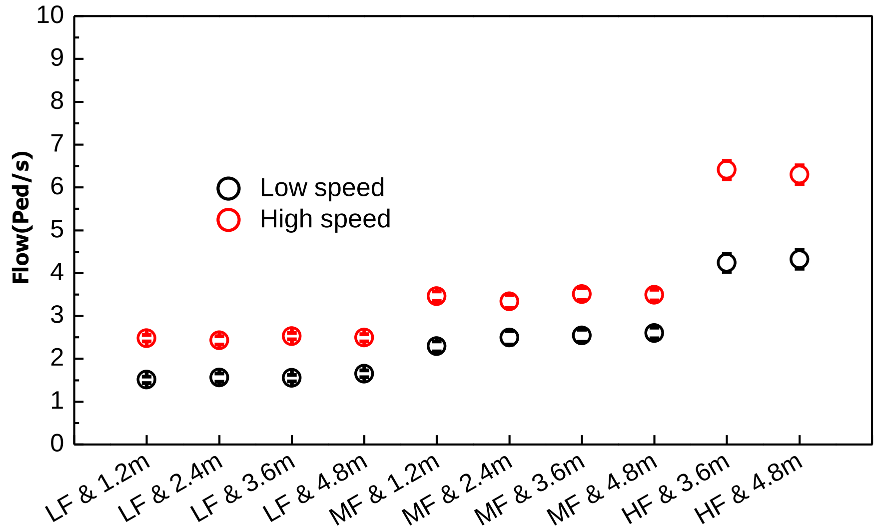


Figure 5.1: Comparison of the flow rates for all scenarios

5.2.2 Speed investigation

This section describes our investigation of the impact of obstacles on human movement. To study this, we found the impact of speed on pedestrians' movement (instantaneous speed), the speed in the movement direction (speed on the x-axis), the speed of lateral movement (y-axis) and a comparison of the maximum, minimum and mean speeds for all experiments. The following sections will provide more detail.

5.2.2.1 Comparison of the instantaneous speed

After analysing the participants' extracted trajectories, we applied a method to measure pedestrian speed in the direction with minimal scatter [117]. To find the average speed of all individuals, we first calculated the speed in the movement direction (x-axis) and lateral direction (y-axis), as shown in **Equations (5-2)** and **(5-3)**:

$$v_x = \frac{\sqrt{(x_{i+\Delta t} - x_i)^2}}{t_{i+\Delta t} - t_i} \tag{5-2}$$

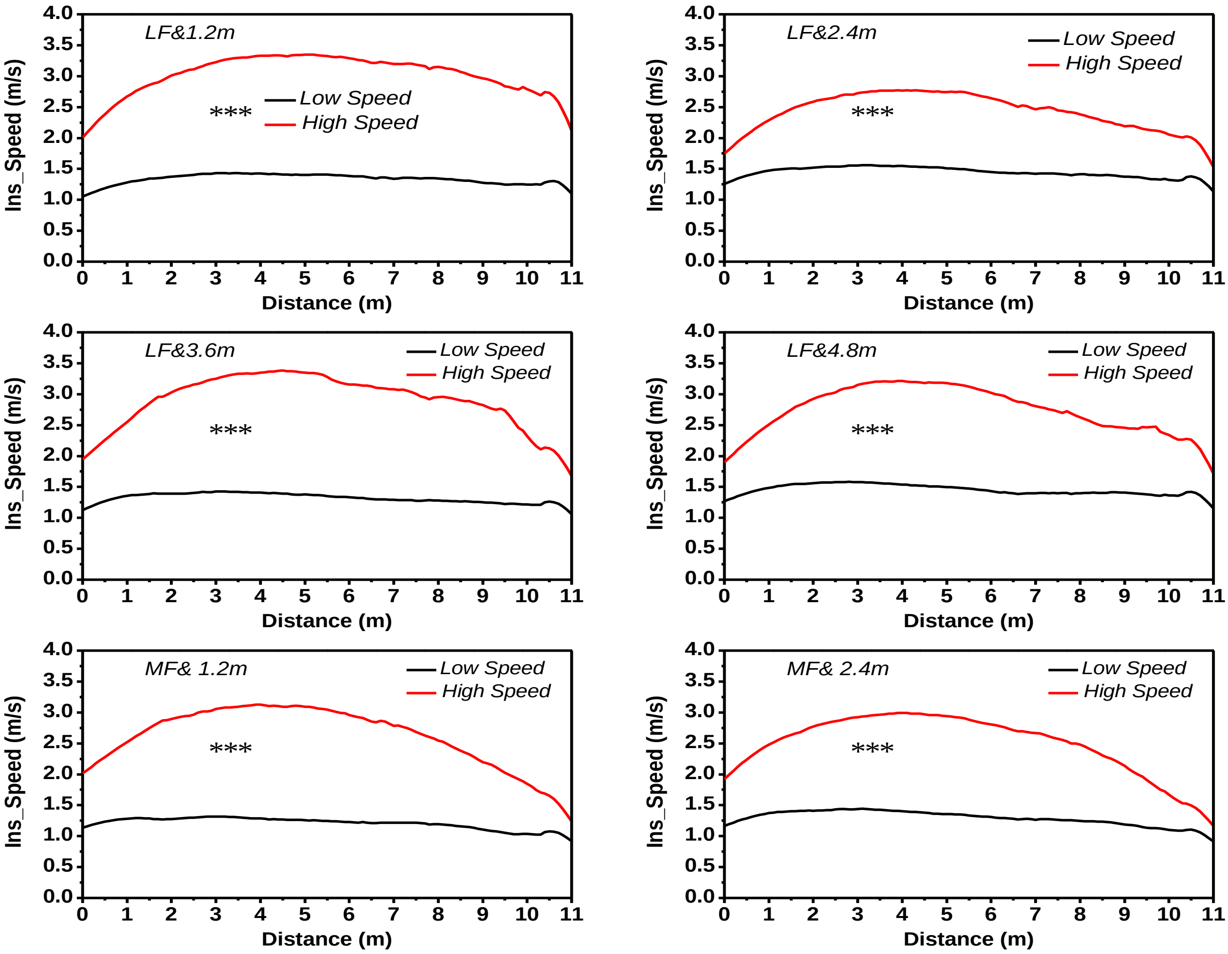
$$v_y = \frac{\sqrt{(y_{i+\Delta t} - y_i)^2}}{t_{i+\Delta t} - t_i} \tag{5-3}$$

From here, it is straightforward to calculate the instantaneous speed $v_{instantaneous}$, as shown in **Equation (5-4)**:

$$v_{instantaneous} = \sqrt{v_x^2 + v_y^2} \quad (5\text{-}4)$$

We then averaged the area at every 10 cm to calculate measurements for the total area [117].

Figure 5.2 presents a comparison of the instantaneous speeds in low-flow (LF & 1.2 m, LF & 2.4 m, LF & 3.6 m and LF & 4.8 m), medium-flow (MF & 1.2 m, MF & 2.4 m, MF & 3.6 m and MF & 4.8 m) and high-flow conditions (HF & 3.6 m and HF & 4.8 m). We have calculated instantaneous speed for all of the experiments, and the graphs are arranged in order from the smallest obstacle to the largest. Our results show that the range of instantaneous speeds was smaller in low-speed experiments compared to high-speed experiments. Because of that difference in the speed levels, our results were statistically significant for both experiments ($p < 0.0001$) at all three flow rates.



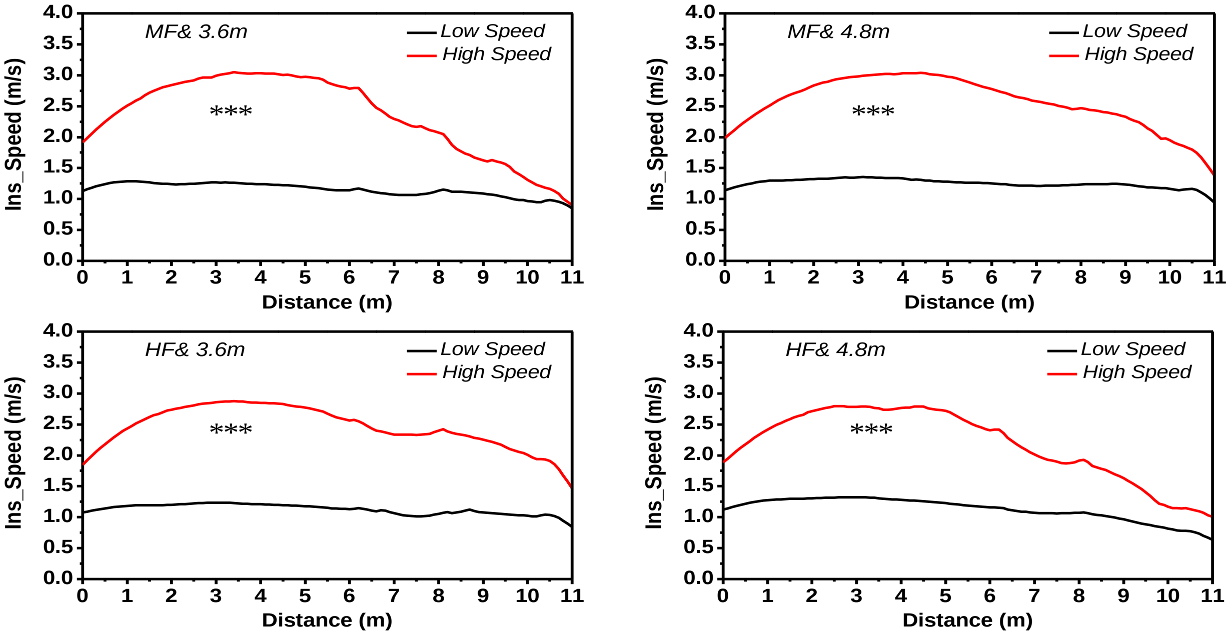
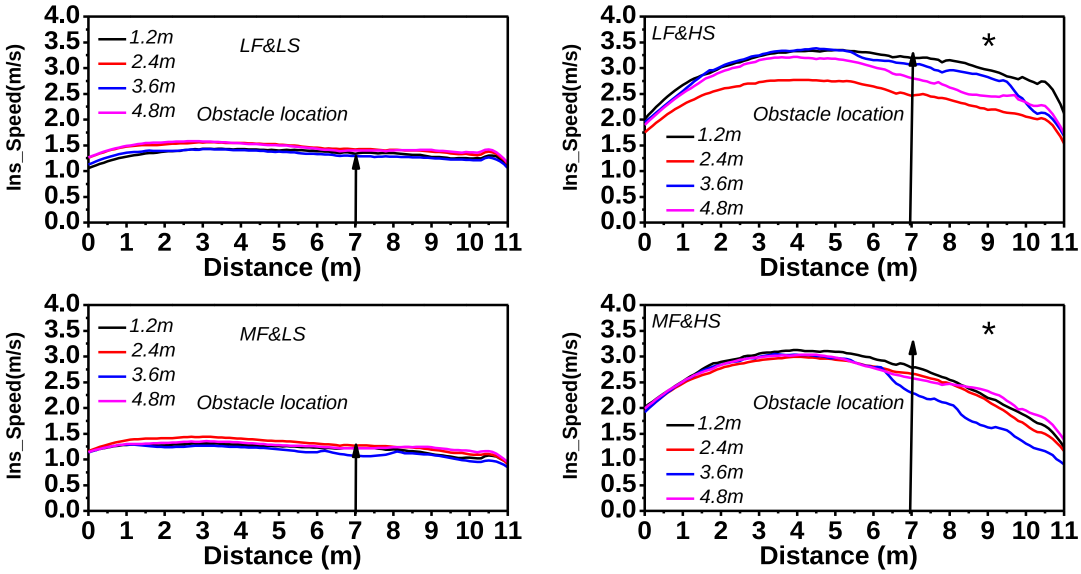


Figure 5.2: Comparison of instantaneous speeds at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m). The (***) indicates statistical significance at a 99% confidence level.

In addition, **Figure. 5.3** presents a comparison of the impact of obstacle size in low- and high-speed experiments at different flow rates. Our results found no significant impact in any of the low-speed experiments ($p > 0.05$). Meanwhile, our results did find a significant impact on the instantaneous speed ($p < 0.01$) at all three flow rates in high-speed experiments, indicating that the size of the obstacle had more impact on pedestrians moving at high speeds.



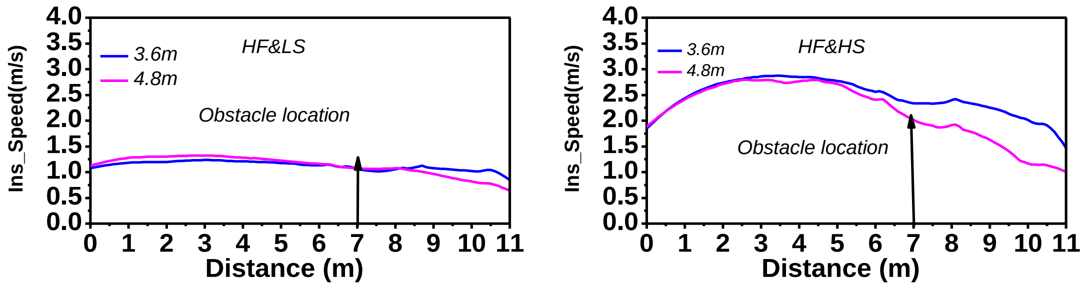
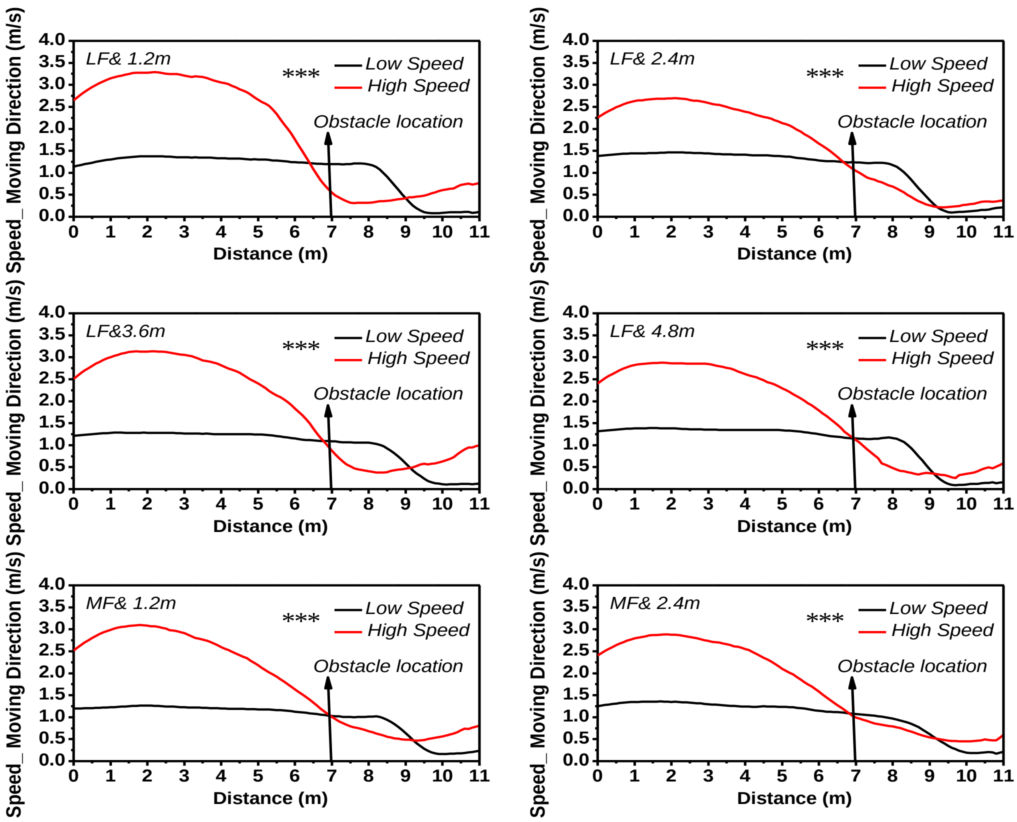


Figure 5.3: Comparison of instantaneous speeds for different obstacle sizes (1.2 m, 2.4 m, 3.6 m and 4.8 m) in LS and HS experiments at different flow rates (LF&LS, MF&LS, HF&LS, LF&HS, MF&HS and HF&HS). The (*) indicates statistical significance at a 90% confidence level.

5.2.2.2 Comparison of speeds in the movement direction

In **Figure 5.4**, we additionally compare the various speeds in the x-direction. It was found that the range of speeds in the movement direction was smaller in low-speed experiments compared to high-speed experiments. Also, participants reduced their speed before reaching the obstacle in high-speed experiments, while in low-speed experiments their speed dropped after they had passed the obstacle. Because of that difference in the speed levels, our results were statistically significant for both speed conditions ($p < 0.0001$) in all three flow rates.



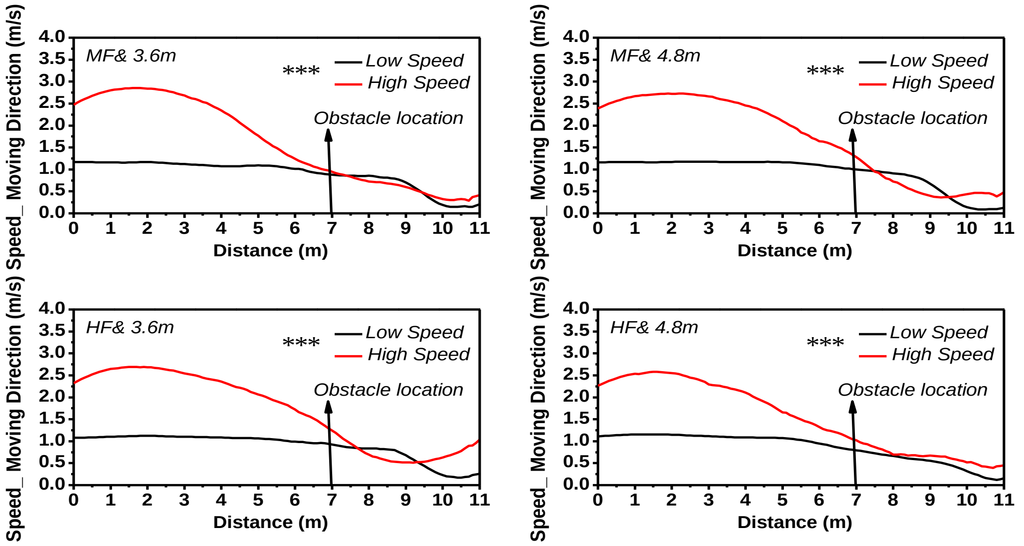
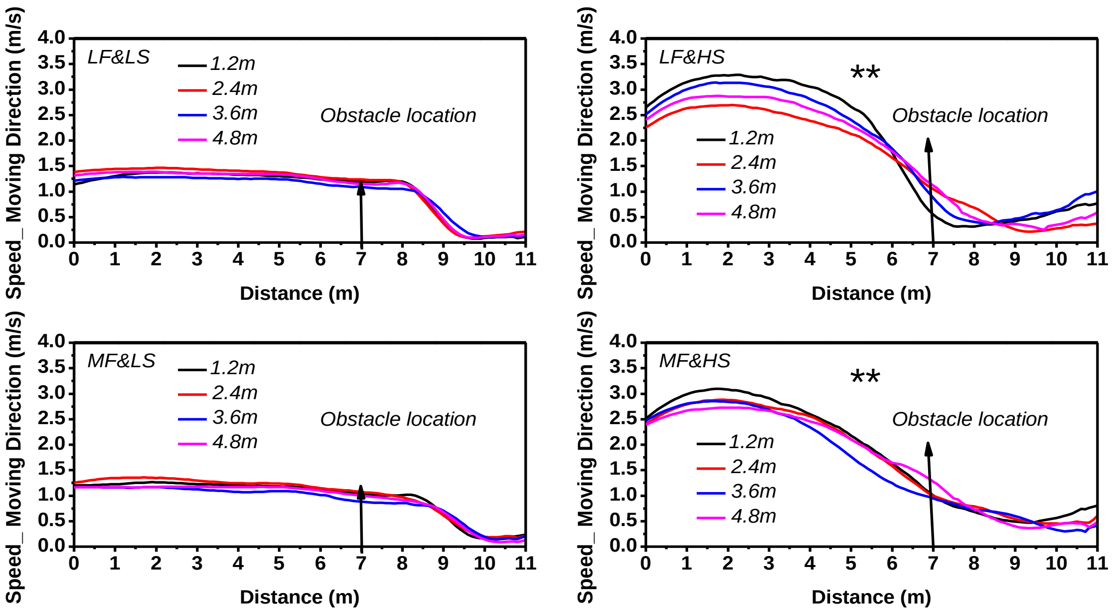


Figure 5.4: Comparison of speed in the movement direction at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m, and HF&4.8m). The (***) indicates statistical significance at a 99% confidence level.

In **Figure 5.5,** we additionally compare the impact of the size of the obstacle on speed in the movement direction in low- and high-speed experiments. Our results found no significant impact for any low-speed experiment ($p > 0.05$). Meanwhile, in high-speed experiments, our results indicated a significant impact on the speed in the movement direction ($p < 0.001$ and $p < 0.01$) at all three flow rates, indicating that the size of the obstacle had more impact on pedestrians in high-speed experiments.



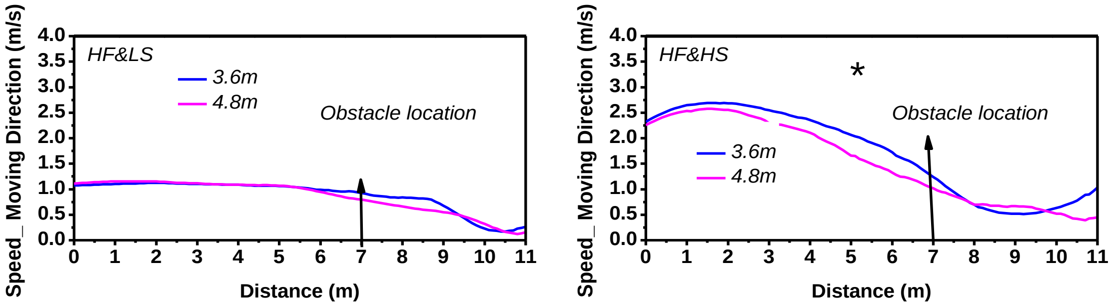
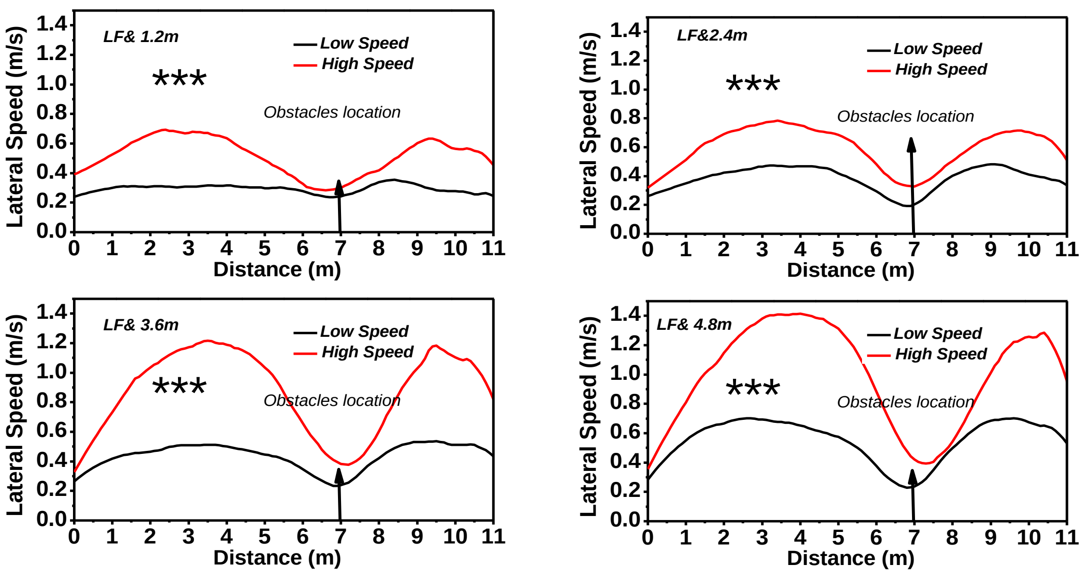


Figure 5.5: Comparison of speed in the movement direction for different obstacle sizes (1.2 m, 2.4 m, 3.6 m and 4.8 m) in LS and HS experiments at different flow rates (LF&LS, MF&LS, HF&LS, LF&HS, MF&HS and HF&HS). The (**) indicates statistical significance at a 90% to 95% confidence level.

5.2.2.3 Comparison of lateral speeds

Figure 5.6 shows a comparison of speeds in the lateral direction in low- vs high-speed experiments. Obstacles affected both cases. Approaching the obstacle impacted participants' movement in the lateral direction (y-axis) at both low- and high-speed velocities. However, our results indicated that the range of lateral speeds was smaller in low-speed experiments compared to high-speed experiments. Because of that difference, our results were statistically significant for both experiments ($p < 0.0001$) in all three flow rates. In both low- and high-speed experiments, the initial velocities have the same trends and patterns: they increase, then the speed drops at the location of the obstacle and then increases again. Our interpretation for that drop is that people anticipate a collision point at the obstacle location; hence, they try to avoid collision by dropping their speed.



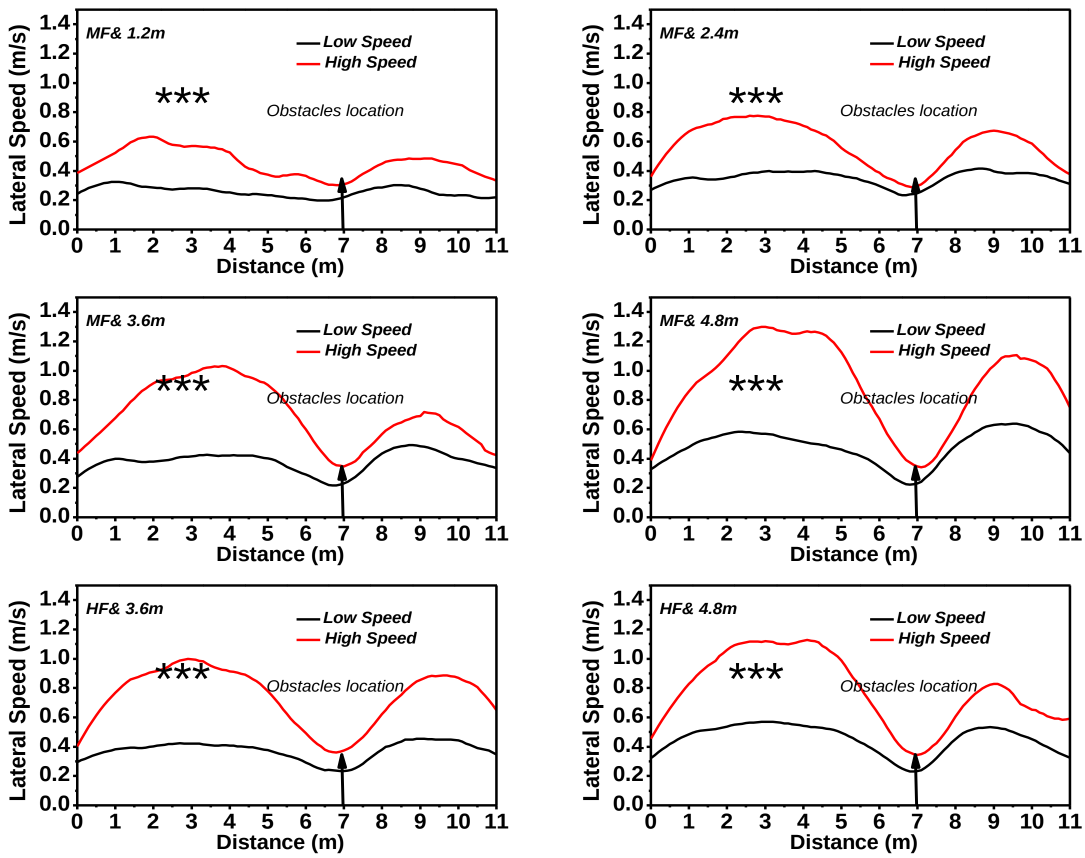
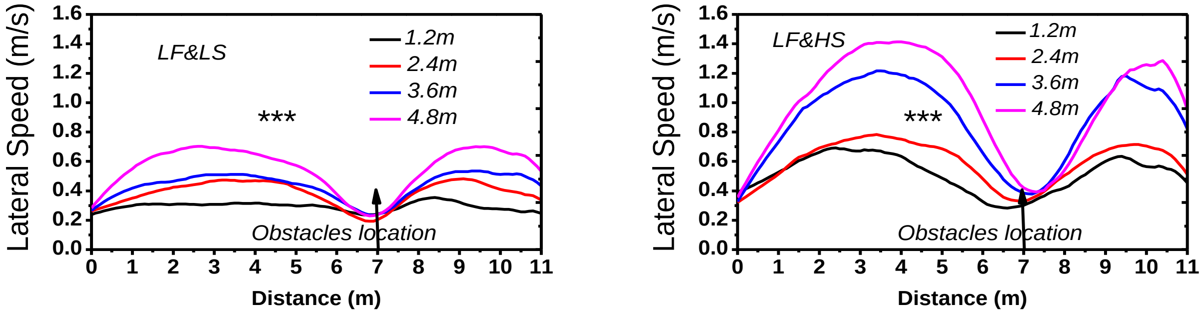


Figure 5.6: Comparison of lateral speeds at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m). The (***) indicates statistical significance at a 99% confidence level.

We also compared the impact of the size of the obstacle in each of the low- and high-speed experiments to further investigate the reduction of speed at the location of the obstacle. The results indicated that walking velocities were equally affected when participants moved toward different obstacles. This means that the reduced velocities all occurred at the same point as shown in **Figure 5.7**. In the running experiments, the point of lowest velocity differed based on the size of the obstacle as shown in **Figure 5.7**.



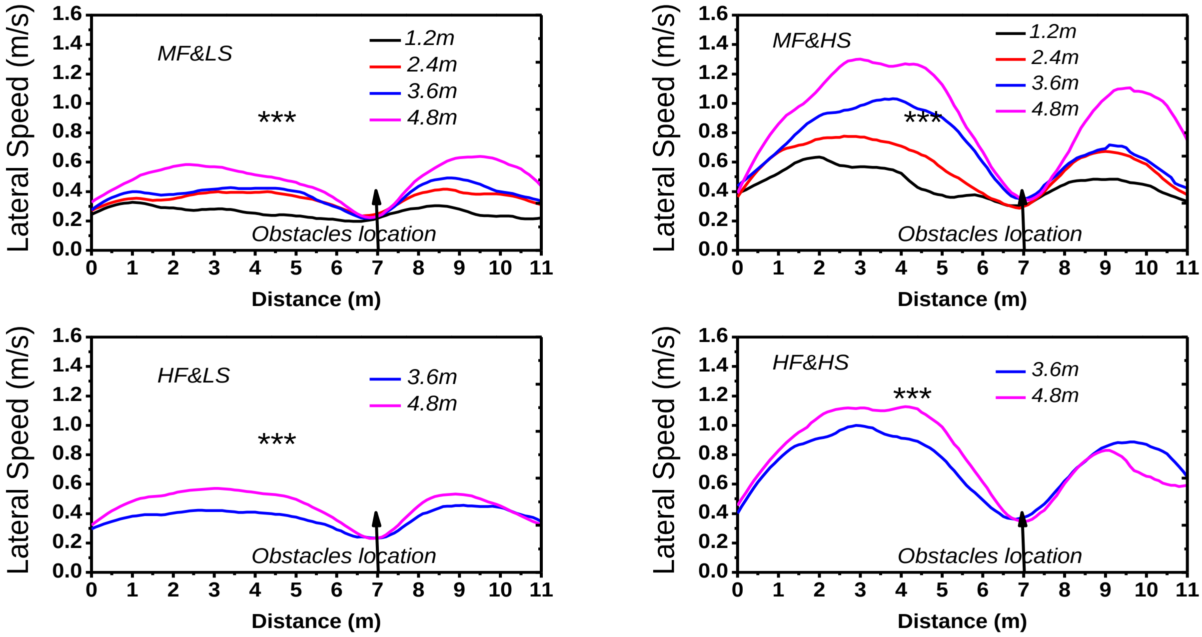


Figure 5.7: Comparison of lateral speeds for different obstacle sizes (1.2 m, 2.4 m, 3.6 m and 4.8 m) in LS and HS experiments with different flow rates (LF&LS, MF&LS, HF&LS, LF&HS, MF&HS and HF&HS) The (***) indicates statistical significance at a 99% confidence level.

In **Figure 5.8**, we investigate the reduction in speed by comparing the average speeds within the lateral direction. Our results show that the average speed increased linearly with increasing obstacle size in both low- and high-speed experiments. This result was statistically significant for all experiments ($p < 0.001$ for low-speed experiments and $p < 0.0001$ for high-speed experiments) in all three flow rates.

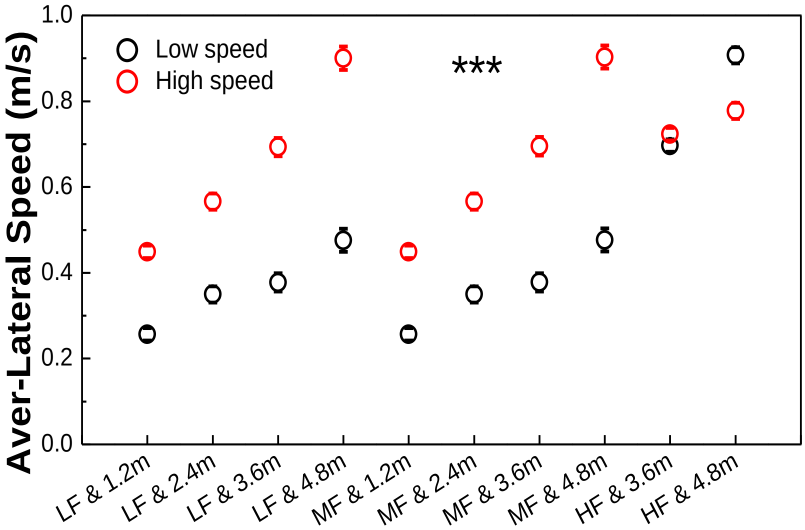


Figure 5.8: Comparison of the average lateral speeds at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m). The (***) indicates statistical significance at a 99% confidence level.

5.2.2.4 Comparison of the maximum speed for all experiments

Using empirical analysis, we compared the maximum velocity for all experiments, as shown in **Table 5.2**. The maximum velocity value for the 4.8 m obstacle was 1.65 m/s in experiments with low speed and low flow. The lowest speed (1.26 m/s) occurred with a 3.6 m obstacle at low speed and high flow. The maximum velocity value (3.52 m/s) occurred with a 3.6 m obstacle at high speed and low flow.

Table 5.2: Comparison of the maximum speed for all experiments

Flow levels		*Low flow (LF)*		*Medium flow (MF),*		*High flow (HF),*	
Speed		LS	HS	LS	HS	LS	HS
Obstacle size	1.2 m	1.61 m/s	3.71 m/s	1.36 m/s	3.38 m/s		
	2.4 m	1.59 m/s	3.04 m/s	1.53 m/s	3.04 m/s		
	3.6 m	1.53 m/s	3.52 m/s	1.53 m/s	3.09 m/s	1.26 m/s	2.92 m/s
	4.8 m	1.65 m/s	3.49 m/s	1.42 m/s	3.13 m/s	1.34 m/s	3.00 m/s

5.2.2.5 Comparison of the minimum speed for all experiments

We then compared the minimum velocity for all experiments, as shown in **Table 5.3**. At low speed, the highest minimum velocity value (1.28 m/s) occurred with a 4.8 m obstacle and high flow, and the lowest value (1.05 m/s) occurred with a 1.2 m obstacle and low flow. In the high-speed experiments, the highest minimum velocity value (2.58 m/s) occurred with a 4.8 m obstacle and high flow, and the lowest value (2.09 m/s) occurred with a 1.2 m obstacle and low flow.

Table 5.3: Comparison of the minimum speed for all experiments

flow levels		*Low flow (LF)*		*Medium flow (MF),*		*High flow (HF),*	
Speed		LS	HS	LS	HS	LS	HS
Obstacle size	1.2 m	1.05 m/s	2.09 m/s	1.25 m/s	2.29 m/s		
	2.4 m	1.10 m/s	2.16 m/s	1.25 m/s	2.32 m/s		
	3.6 m	1.09 m/s	2.23 m/s	1.25 m/s	2.32 m/s	1.12 m/s	2.34 m/s
	4.8 m	1.14 m/s	2.22 m/s	1.15 m/s	2.24 m/s	1.28 m/s	2.58 m/s

5.2.2.6 Comparison of the mean speed for all experiments

We also compared the mean velocity for all experiments, as shown in **Table 5.4**. The mean velocity value for the 4.8 m obstacle in low-speed and low-flow experiments was 1.31 m/s. The lowest mean value (1.01 m/s) was recorded in a low-speed experiment with a 4.8 m obstacle and high flow. The highest mean velocity value (2.66m/s) occurred with a 1.2 m obstacle at high speed and low flow.

Table 5.4: Comparison of the mean speed for all experiments

flow levels		*Low flow (LF)*		*Medium flow (MF),*		*High flow (HF),*	
Speed		LS	HS	LS	HS	LS	HS
Obstacle size	1.2 m	1.25 m/s	2.66 m/s	1.12 m/s	2.36 m/s		
	2.4 m	1.30 m/s	2.16 m/s	1.18 m/s	2.24 m/s		
	3.6 m	1.18 m/s	2.55 m/s	1.18 m/s	2.24 m/s	1.05 m/s	2.23 m/s
	4.8 m	1.31 m/s	2.41 m/s	1.14 m/s	2.18 m/s	1.01 m/s	1.89 m/s

5.2.3 Determining the influence of obstacles on pedestrian behaviours and their characteristics

5.2.3.1 Avoidance behaviour

To analyse obstacle avoidance behaviour, we assumed that the participants followed the experiment trajectories, which showed the participants' movements in the field. In order to better understand the chosen route, we calculated the average trajectory for each path (left and right) in each experiment and at low and high speeds using the binning method [118] and MATLAB, which helped us explore obstacle avoidance behaviours. This assumption could be represented as a linear path that increases with an increase in the obstacle size. This linear path can also be used to indicate the SP (see **Figure 4.2**), where the participants enter the experiment field, and the MP, where the edges of the obstacle are, as can be seen in the following figures indicating the average trajectories for each experiment. In this way, we can observe the general features of the obstacle avoidance behaviour from SP to EP for the 20 scenarios. Based on the left and right trajectories, which can be represented as upper = left trajectory (y > value) and lower = right trajectory (y < value), we calculated the average trajectory of each scenario by reversing all the trajectories from the right or the lower case by the y-axis and y-coordinate of EP and then applying a binning method. **Figure 5.9** presents a comparison of the average trajectory at low speed and high speed for all experiments. The participants responded to the obstacle early in the experiment and began trying to avoid a collision at the SP.

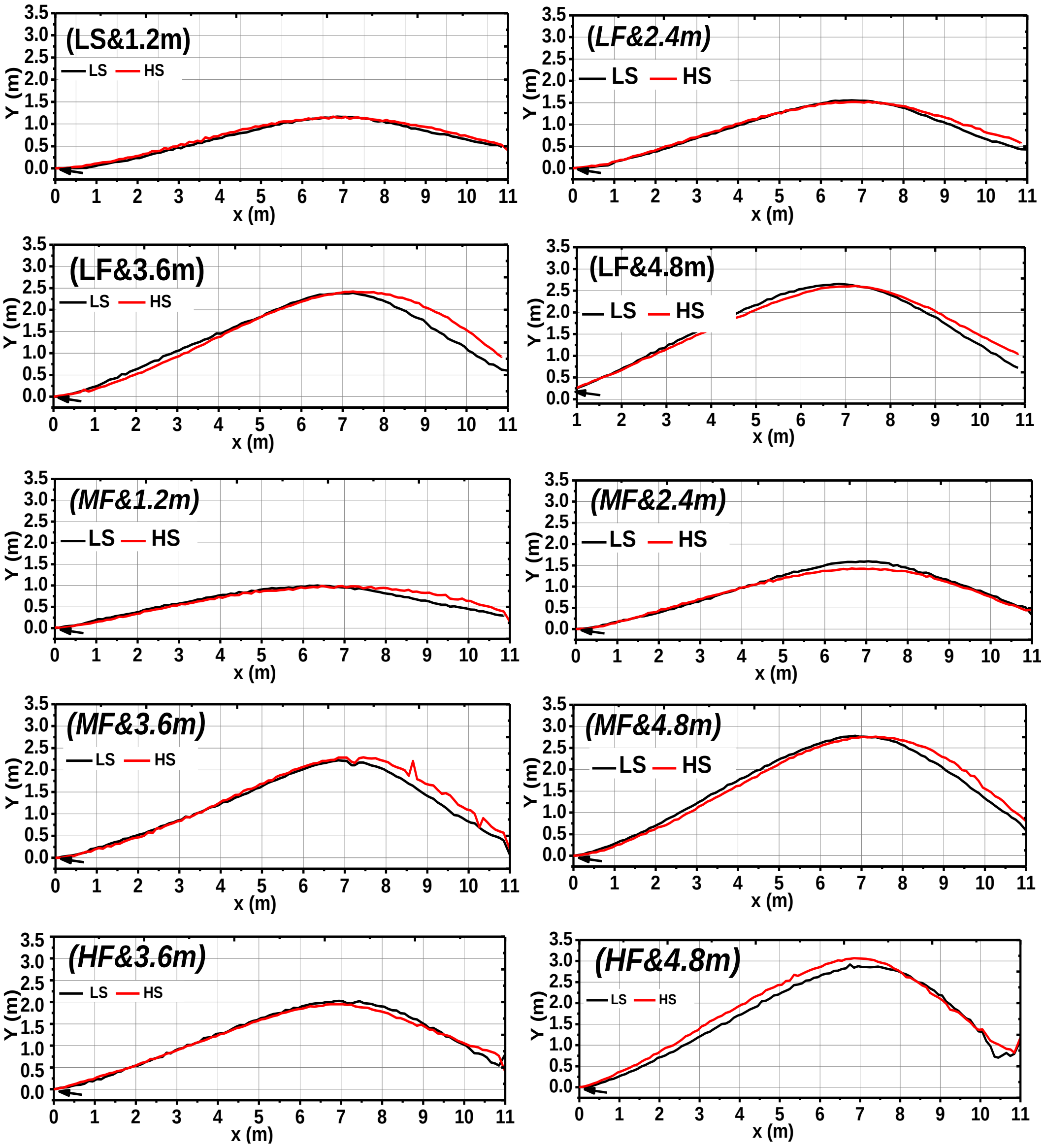


Figure 5.9: Comparison of the average trajectories at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m).

5.2.3.2 Pedestrian travel behaviour

5.2.3.2.1 Comparison of travel time

To determine the impact of the architectural adjustments on the influence of obstacles, we investigated the average travel time from SP to EP (see **Figure 4.2**) in each experiment under two speed regimes (LS and HS). Based on the trajectory data presented in **Figure 4.3**, it was possible to directly calculate the average travel time for each of the pedestrian speed regimes and obstacle set-ups, as presented in **Figure 5.10**.

The first observation that can be drawn from the data in **Figure 5.10** is that the total travel time was less in the high-speed experiments than in the low-speed experiments. Second, the effect of obstacle size on average pedestrian travel time seems unclear in that the average travel time did not display a constant upward or downward trend with different obstacle sizes. For example, the direction of change in average travel time in low-flow experiments with obstacles sized from 1.2 m to 4.8 m was reversed between the two speed regimes. Likewise, the graph for medium-flow experiments is U-shaped for the low-speed experiments while it increases linearly for the high-speed experiments. The third observation to be drawn from **Figure 5.10** is that the pedestrian inflow rate appears to impact the average time. The fastest travel time was found with medium inflow rates, followed by high inflow rates and finally low inflow rates. The reason for this could be related to the pedestrian's choice of direction (left or right) when an obstacle is located in front of them.

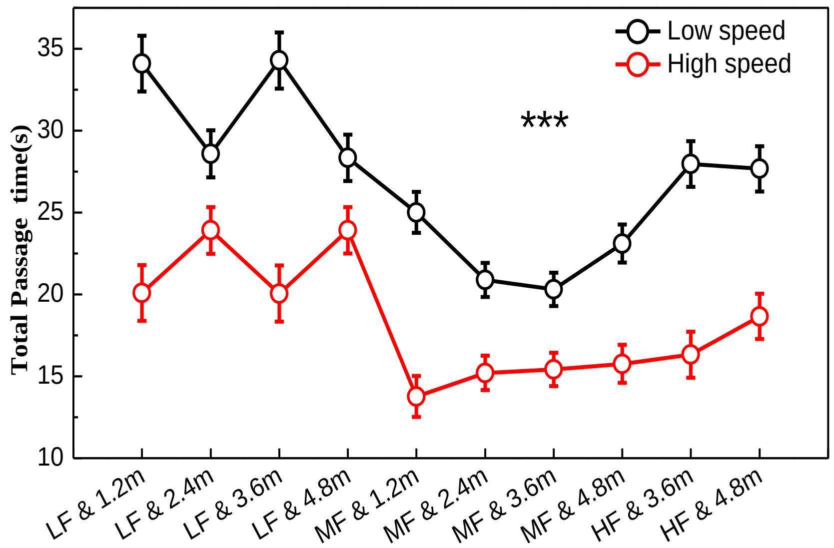


Figure 5.10: Comparison of the travel time at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m). The (***) indicates statistical significance at a 99% confidence level.

5.2.3.2.2 Comparison of individual travel time

This section presents a comparison between the collective escape behaviour, referred to here as individual travel time (ITT), at low speed and high speed. Our results showed that the effect of the obstacle size on pedestrian average travel time seems unclear in that the average travel time does not display a constant upward or downward trend with different obstacle sizes. We made a statistical analysis of the difference in ITT at low and high speeds, and our results (**Figure 5.11**) were statistically significant in both experiments ($p < 0.0001$).

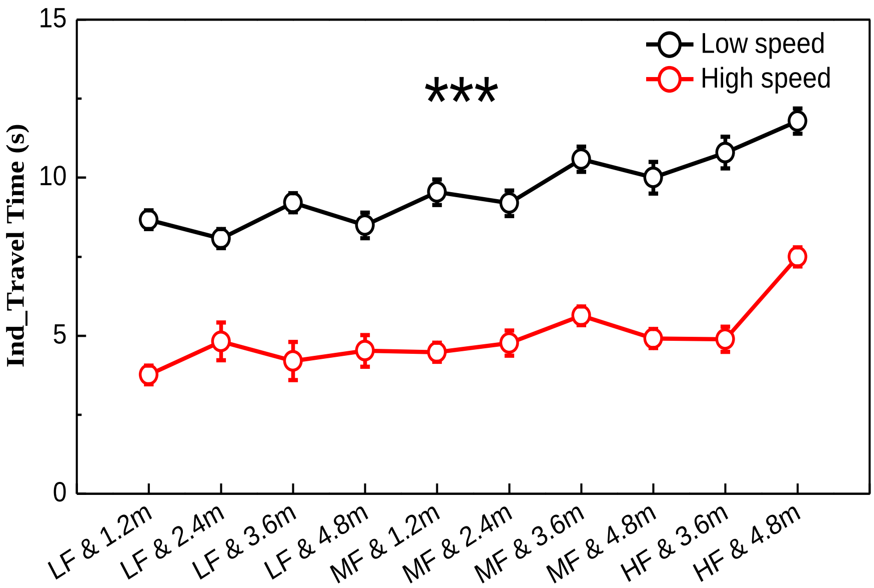


Figure 5.11: Comparison of the average individual travel times (ITT) at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m) MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m). The (***) indicates statistical significance at a 99% confidence level.

5.2.3.2.3 Comparison of individual travel distance

In this section, we compare the average travel distance for each individual (ITD) in all experiments at low and high speed. According to our data, ITD was shorter in high-speed experiments than in low-speed experiments. A second observation is that there was a small increase in ITD when the size of the obstacle increased in each experiment except in the HF & 4.8 m experiment, in which the ITD increased much more at high speed. A third observation is that the ITD was affected by the different inflow rates; specifically, the ITD decreased whenever the inflow rate increased. Next, we made a quantitative comparison between the ITDs in each experiment at low and high speed. Our results found no significant differences between ITDs at low and high speed, as presented in **Figure 5.12**.

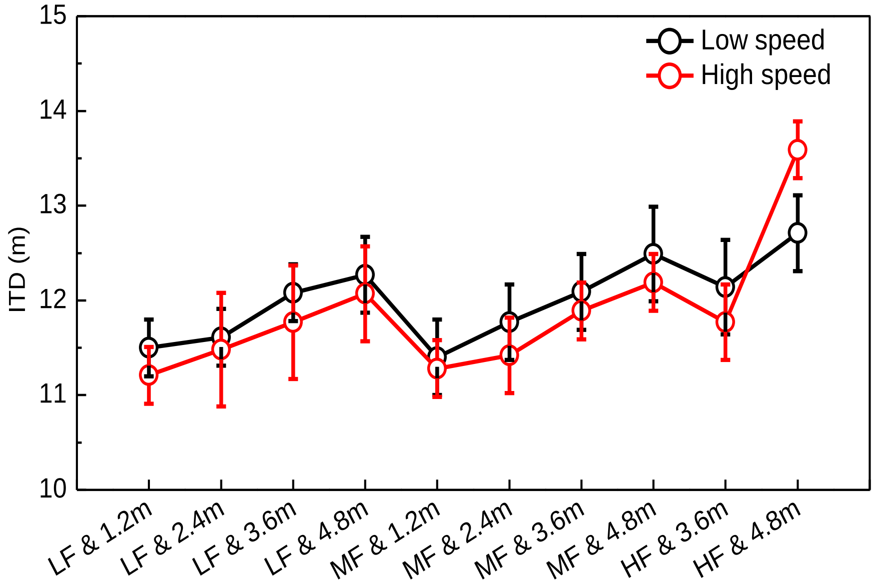


Figure 5.12: Comparison of the average individual travel distance (ITD) at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m).

5.2.3.2.4 Comparison of overall speed

In this section, we look at the effect of obstacle avoidance on pedestrian speed. To determine that effect, we calculated the average velocity before and after the obstacle's location. Our data are presented in **Figure 5.13**. An immediate observation that can be drawn from this figure is that a higher inflow rate could lead to lower pedestrian movement speed in both speed regimes. For example, at low speed, the average velocity in low-flow conditions was a little higher than in medium-flow conditions, which in turn had a slightly higher average velocity than high-flow (HF) conditions. A second observation is that obstacles had more influence on velocity when the participants were moving at high speed. There was less difference between average velocity before and after the obstacle in low-speed experiments than in high-speed experiments, which showed a greater decrease in average velocity after the location of the obstacle. Nevertheless, the average velocity decreased with an increase in the obstacle size at all three flow levels.

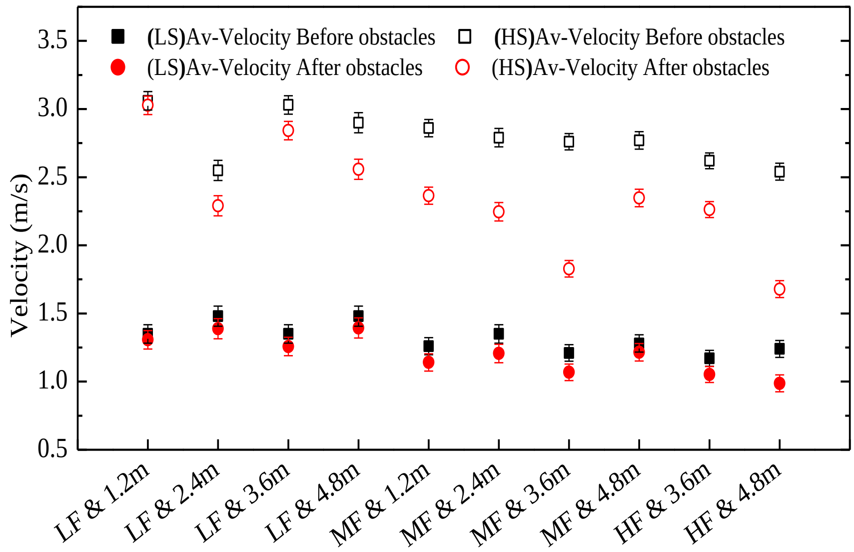


Figure 5.13: Comparison of the average velocity of the participants before and after obstacles at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m).

5.2.3.2.5 Comparison of the relationship between speed and the number of evacuees

In this section, we explore other pedestrian behaviours by comparing the relationship between pedestrian velocity and the cumulative number of evacuees in the chamber in each scenario. Our results are presented in **Figure 5.14**. Three main observations can be made about these results. First, at low flow rates, the obstacles had more impact on the total number of evacuees in both speed regimes compared to medium and high flow rates. Second, at low and medium flow rates and high speed, the velocity increased whenever the number of evacuees increased. The best pattern for evacuation efficacy was found in this layout for all obstacle sizes. Third, the velocity decreased when the flow rate increased, as seen in the high-flow experiments. At higher flow rates, speed increased less or even decreased as evacuee numbers increased. That means that people's speed is affected by other people as well as obstacles; therefore, the speed increased or decreased based on the different flow rates in each experiment.

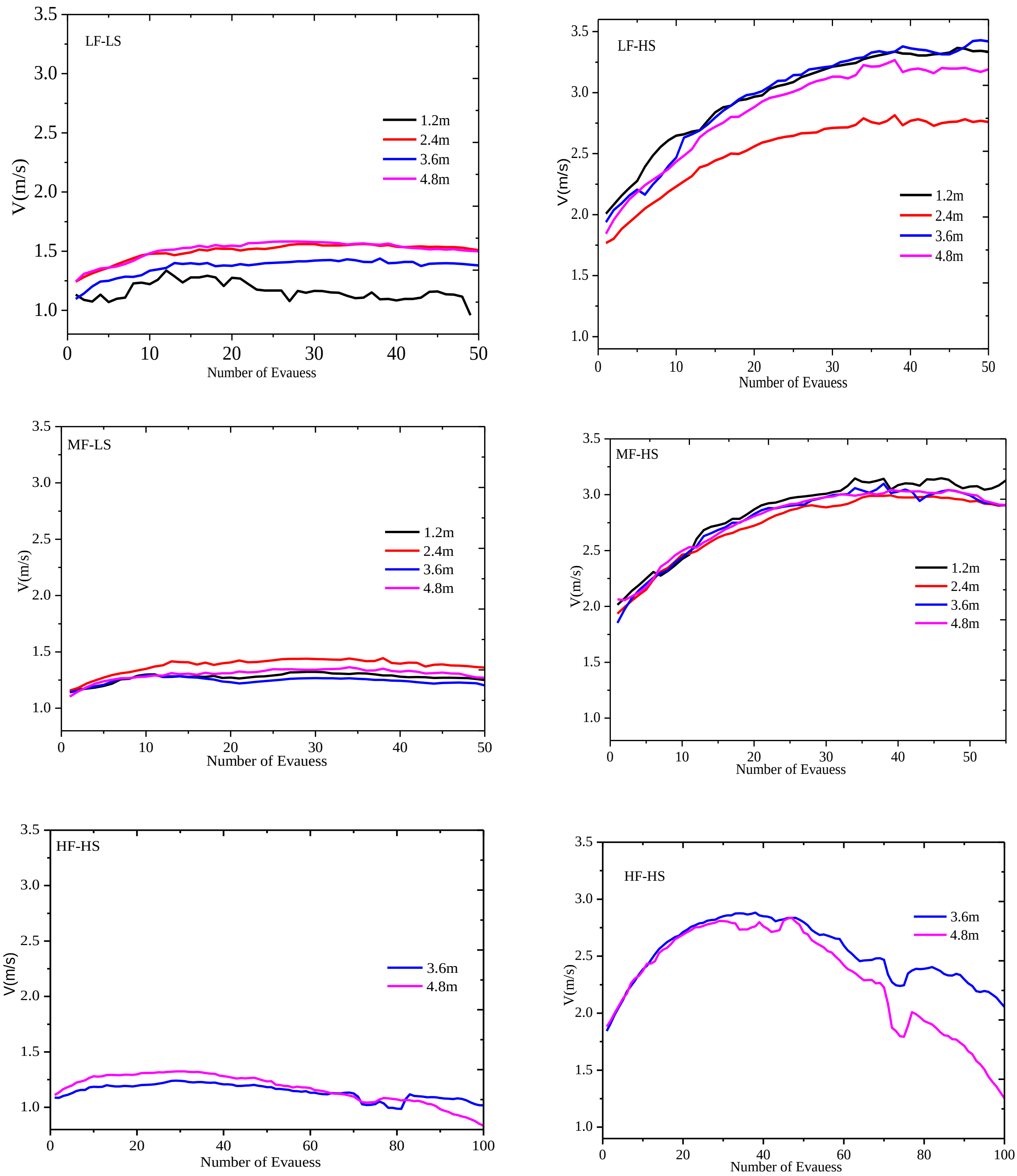


Figure 5.14: Comparison of the relationship between velocity and the number of evacuees at LS and HS in LF–LS (obstacle size 1.2 m, 2.4 m, 3.6 m and 4.8 m), LF–HS (obstacle size 1.2 m, 2.4 m, 3.6 m and 4.8 m), MF–LS (obstacle size 1.2 m, 2.4 m, 3.6 m and 4.8 m), MF–LS (obstacle size 1.2 m, 2.4 m, 3.6 m and 4.8 m), HF–LS (obstacle size 3.6 m and 4.8 m) and HF–HS (obstacle size 3.6 m and 4.8 m).

5.2.3.3 Lateral behaviour

Lateral behaviours are the pedestrian's lateral movements while passing an obstacle. We investigated several factors that relate to the individual's lateral movement around the edges of an obstacle, such as lateral distance, swaying, deviation angle and safety distance from the obstacle's location. More details will be provided in each of the following sections.

5.2.3.3.1 Comparison of lateral distance

In this section, we calculate the lateral distance, which can be defined as the average space between the edges of each obstacle and the average of the trajectories in each experiment. We considered lateral distance by locating different obstacles (1.2 m, 2.4 m, 3.6 m and 4.8 m) on the y-axis after finding the |y| coordinate of MP, where MP is 7 m, on the x-axis for each obstacle (see **Figure 4.2**). In addition, in **Figure 4.3** we calculated the average lateral distance at the edges of the obstacles, where MP is |x| = 7 m and |y| = a coordinate value of each participant at the edge of the obstacle. We then compared the average trajectory values and the obstacle locations in y coordinate of MP, to calculate the difference between the obstacle edges and the average trajectory values. Finally, we compared the average lateral distance at MP for each experiment with the actual locations of the edges of the obstacles in both speeds. The results are presented in **Figure 5.15**.

Our results indicated that the different speed regimes seem to have little impact on average pedestrian lateral distance. In most experiments, the average lateral distance in the low-speed regime was equal to that of the high-speed regime. The only differences were found in MF & 3.6 m and HF & 4.8 m, where the average lateral distances in the LS regime were about 0.3 m and 0.1 m less than those in the HS regime, respectively. Moreover, the average distance also varies with different obstacle sizes. For LF experiments, the average lateral distance was about 0.3 m with a 1.2 m obstacle; it then increased to 0.5 m with a 3.6 m obstacle and dropped to 0.4 m with a 4.8 m obstacle. For MF experiments, the average lateral distance fluctuated by about 0.4 m with the four obstacle sizes. And for HF scenarios, the lateral distance was just 0.3 m with a 3.6 m obstacle, while the distance increased to 0.6–0.7 m with a 4.8 m obstacle. The average lateral distance for all of the experiments was calculated to be 0.45 m, which will be used in the calibration parameter which was used in the calibration parameters of this study.

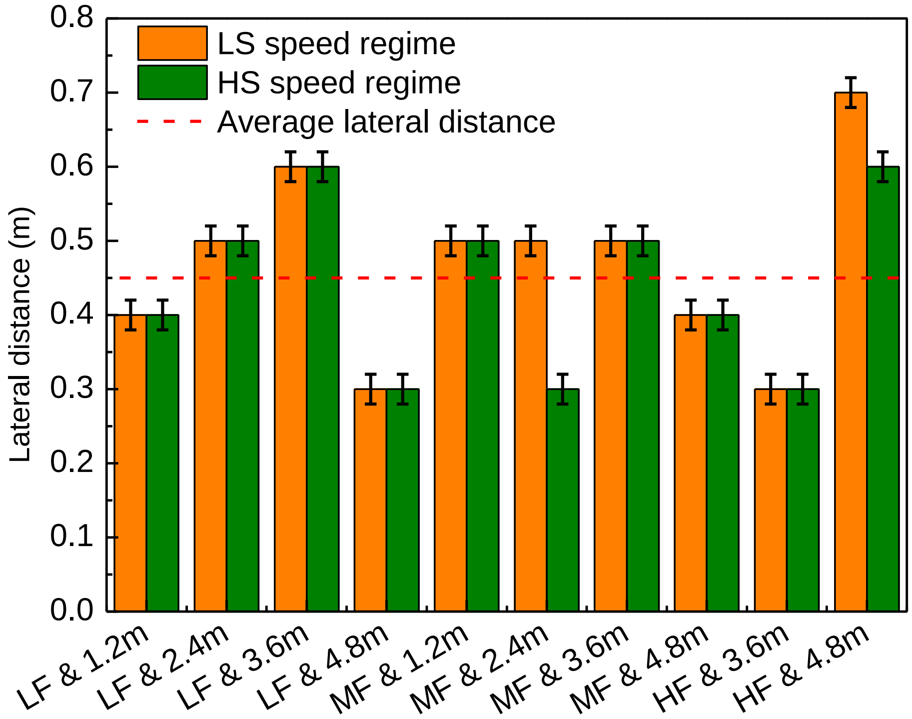


Figure 5.15: Comparison of lateral distance while passing by the edges of obstacles at three flow levels (LF, MF and HF), where orange is low speed and green is high speed, with errors bars.

5.2.3.3.2 Comparison of body sway

In this section, we apply the previous assumption that there is a variation trend that appears in the pedestrian trajectories during obstacle avoidance such as. The variation could be described as body sway *k*. For each participant *i*, the body sway *k* at time step *t* is defined as: $k_i\ (t)$, which is calculated based on the participant's coordinates with a step of five frames, as presented in **Equation (5-1)**[87]:

$$k_i(t) = \left| \frac{y_i(t+2)\text{-}y_i(t\text{-}2)}{x_i(t+2)\text{-}x_i(t\text{-}2)} \right| \tag{5-1}$$

Therefore, we calculated the slope *k* for all of the pedestrians for each experiment. The pedestrians' walking behaviour is presented on the x-axis, and the *k* values are presented on the y-axis, as the corresponding slope curve behaves somewhat like periodic waves due to the natural oscillation of human movement stepping from the left foot to the right and back. These movements could describe the body sway presented in the experiment's trajectories in **Figure 4.3**. This behaviour could be interpreted as the swaying steps of walking and running.

To find the negative correlation between body sway and velocity that was mentioned in our literature review [113], we compared the average *k* for all experiments in both speed regimes, as presented in

Figure 5.16. Two points can be noted from our data. First, the average *k* was less in all of the high-speed experiments compared to the low-speed experiments. Second, the average *k* increased as obstacle size increased at both speeds. However, this behaviour disappeared in the scenarios with a high flow rate. In HF & 4.8 m, the *k* values at both speeds were equal.

The average slope *k* in this study was from 0.057 m to 0.23 m at LF and LS and from 0.040 m to 0.21 m at LF and HS. At MF and LS it was from 0.053 m to 0.25 m and at MF and HS it was from 0.044 m to 0.20 m. Finally, at HF and LS it was from 0.01 m to 0.1 m and at HF and HS it was from 0.12 m to 0.02 m. The average slope *k* for all of the experiments was 0.124.

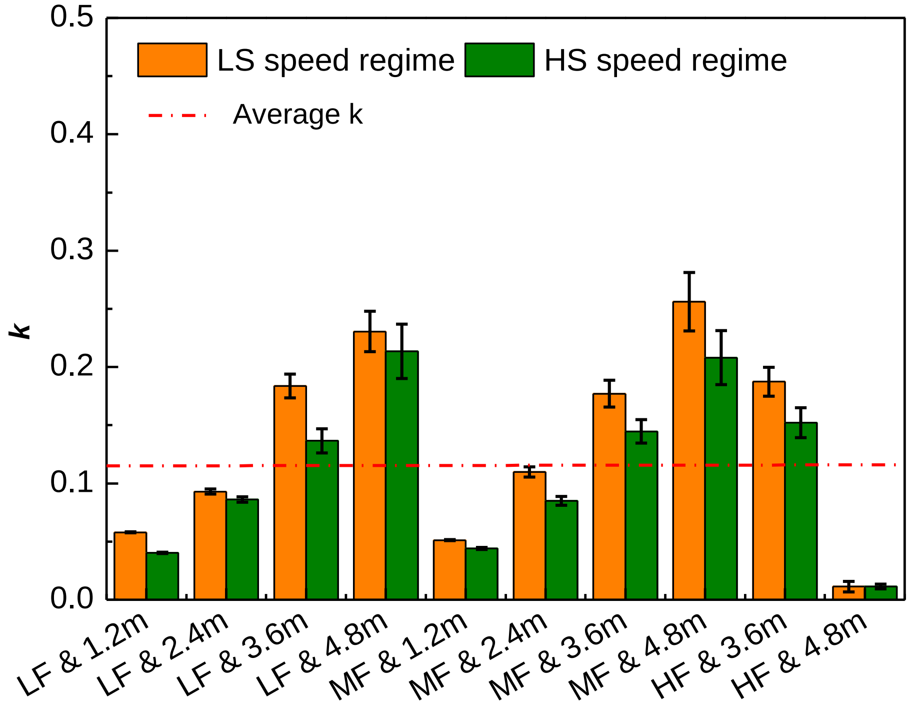


Figure 5.16: Comparison of average *k* slopes with error bars at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m).

5.2.3.3.3 **Comparison of safety distance**

We also investigated the safety distance (m), an important characteristic that describes the distance between the participants' shoulder and the edge of the obstacle or the minimum space between the participant and the edge of the obstacle (see **Figure 4.2**). We calculated the safety distance by applying **Equation (5-2)**:

$$Safty\ distance\ (m) \quad = \sqrt{x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{5-2}$$

where (x_2, x_1) and (y_2, y_1) are coordinates of participants at the x- and y-direction at location MP.

As shown in **Figure 5.17**, different behaviour was displayed in the collective movements when the participants tried to avoid different obstacles. We compared the minimum safety distance for the participants in each scenario and found differences between low and medium flow rates and between low-speed and high-speed experiments. Low-speed experiments had a smaller safety distance than high-speed experiments except at high flow rates. We interpret this to mean that at low speeds, the participants had little concern about being hurt while passing the obstacle. At high flow rates, pedestrians may have felt safer closer to the obstacle, but they may also have been pushed by their neighbours. The average safety distance for all of the experiments (0.18 m ≈ 0.2 m) is presented as a red line in **Figure 5.17**.

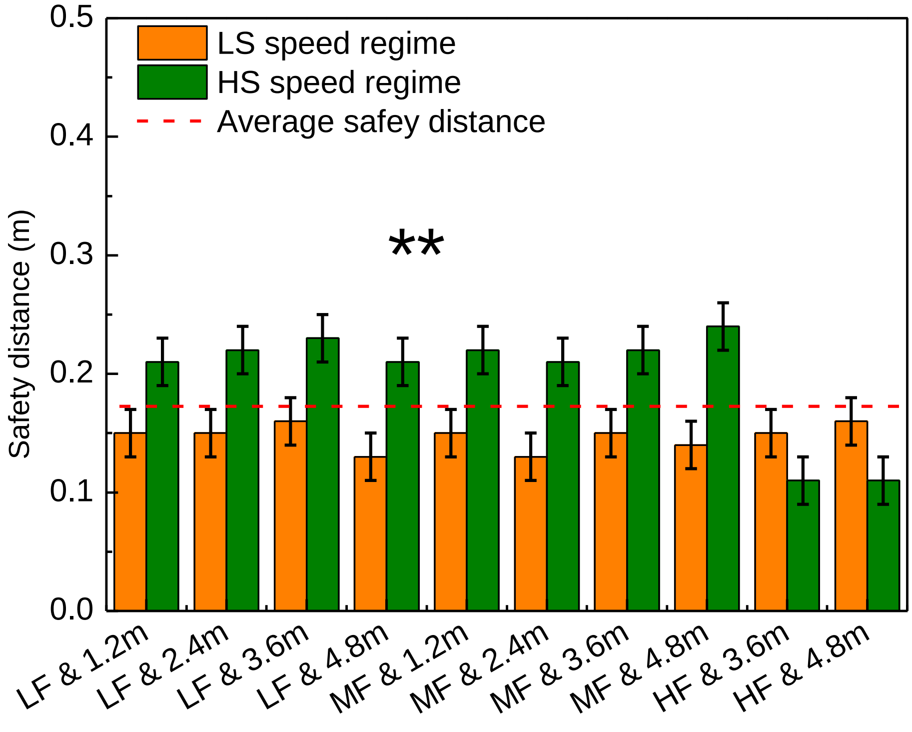


Figure 5.17: Comparison of safety distance for all experiments at low and high speed. The (**) indicates the significant difference between low- and high-speed experiments at a 95% confidence level.

5.2.3.3.4 Comparison of the deviation angle

We also investigated the deviation angle (θ), which describes an important aspect of pedestrian behaviour, and the deviation degree (max degree) during avoidance of different obstacles (see **Figure**

4.2). The average deviation degree (*ADA*), which looked like an average of each individual's movements from SP to EP, was calculated by applying **Equation (5-3)**:

$$\text{Deviation}\ (\theta) = \tan^{-1}\left(\frac{x_2 - x_1}{y_2 - y_1}\right) \tag{5-3}$$

where (x_2, x_1) and (y_2, y_1) are coordinates of participants at the x- and y-direction.

As shown in **Figure 5.18,** different behaviour was discovered in the collective movements while the participants tried to avoid different obstacles. We compared the ADA for the participants in each scenario and found differences between low, medium and high flow rates. High-speed experiments had a smaller ADA than low-speed experiments. The ADA increased whenever the size of the obstacle increased in all experiments. We interpret this to mean that in low-speed experiments, the participants could deviate from the location of the obstacle later as compared to high-speed experiments, in which participants deviated earlier. Therefore, a high flow rate will reduce the effect of the ADA, as shown in this example.

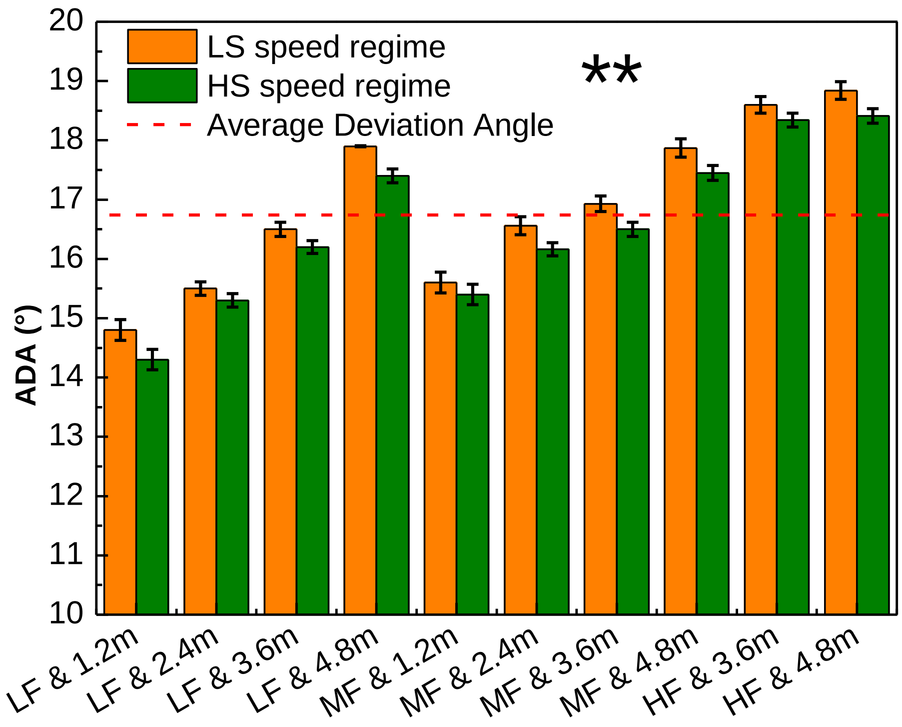


Figure 5.18: Comparison of the average deviation angle for all experiments at low and high speed. The (**) indicates the significant difference between low- and high-speed experiments at a 95% confidence level.

5.2.3.4 Deviation behaviour analysis based on pedestrians going left or right

5.2.3.4.1 The decision-making point for going left or right

We assumed that pedestrians would walk a short distance before changing direction, deciding to go either left or right to avoid a collision. Then we investigated reaction distances from the different obstacles to determine how far the pedestrians walked before responding to the different obstacles. We visualised the way that changes in trajectory increased with increasing obstacle size by plotting the pedestrian trajectories and the average trajectory for each experiment on each side (left and right). The pedestrians' responses to the different obstacles can be seen in **Figure 5.19**.

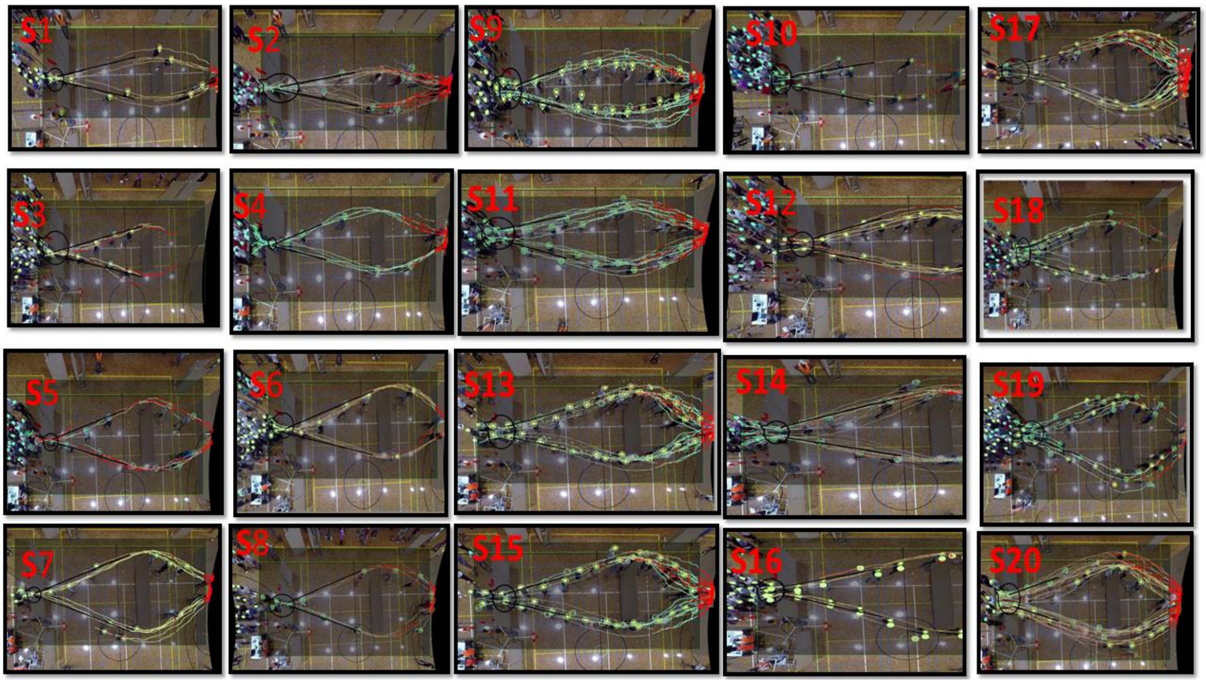


Figure 5.19: Trajectories for all of participants while passing (1.2 m, 2.4 m, 3.6 m and 4.8 m) obstacles, showing the decision-making locations for going around the obstacles in each experiment.

5.2.3.4.2 Collision-avoidance behaviours in each path

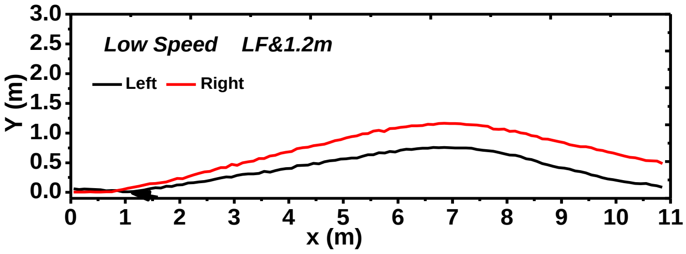
Pedestrians' collision-avoidance behaviour in each path (left or right) can be classified as either a direct or an indirect reaction. The former is when a pedestrian changes direction in response to an obstacle immediately, while in the latter, the pedestrian walks some distance before changing direction. To determine indirect reaction distances, we applied the average trajectory in each experiment using a binning method [118], which divided the first value on the y-axis for each side (left and right) to get the

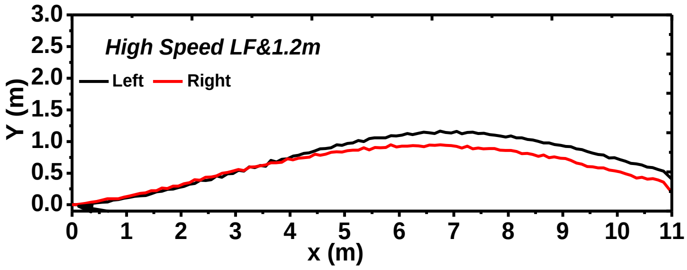
|y| value, as presented in **Figure 4.2**. The binning method allowed us to find the drop-down path and the indirect reaction distance in each experiment.

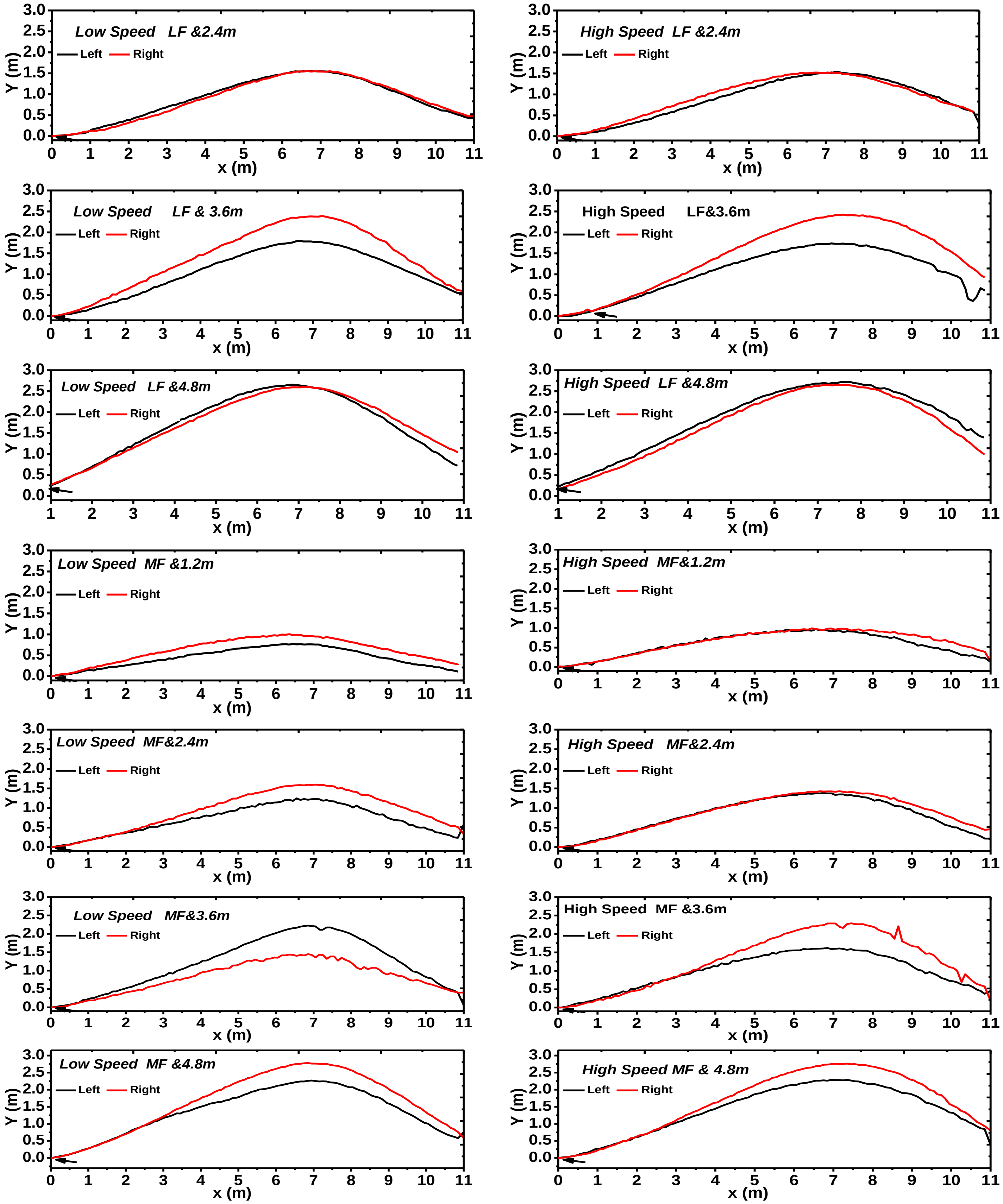
Our results showed indirect reaction occurring only once: when pedestrians passed the 1.2 m obstacle at low speed, they walked 1.10 m before changing direction (**Figure 5.20**, Low speed_LF&1.2m. Note the arrow in the lower left of the graph). This suggests the pedestrians responded to the obstacle at an early stage: 5.90 m from the obstacle. Differences between the left and right average trajectories were also clear. **Figure 5.20** shows that in experiment LF&1.2m, the left-hand path, in black, was shorter than the right, in red, at low speed, whereas the opposite result was seen at high speed. In experiment LF&2.4m, however, the left and right paths were the same at low speed, while the shorter path was to the left at high speed. In experiment LF&3.6m, the left was shorter than the right at both low and high speed. In experiment LF&4.8m, however, both left and right were equal at low speed, and the shorter path was to the right at high speed.

In the medium-flow scenario MF&1.2m (**Figure 5.20**), the left path was shorter than the right at low speed, and the two were initially equal at high speed, but this changed after the obstacle was passed. This pattern was repeated in MF&2.4m. The right was shorter at low speed and longer at high speed in experiment MF&3.6m. Finally, in experiment MF&4.8m, the shorter path was to the left at both low and high speed.

In the high-flow scenario HF&3.6m (**Figure 5.20**), at both low and high speed, the paths were equal until participants reached the obstacle. The left-hand path was shorter at both low and high speed in experiment HF&4.8m.






Low Speed LF &2.4m
High Speed LF &2.4m
Low Speed LF & 3.6m
High Speed LF&3.6m
Low Speed LF &4.8m
High Speed LF &4.8m
Low Speed MF &1.2m
High Speed MF&1.2m
Low Speed MF&2.4m
High Speed MF&2.4m
Low Speed MF&3.6m
High Speed MF &3.6m
Low Speed MF &4.8m
High Speed MF & 4.8m
Left
Right
Y (m)
x (m)

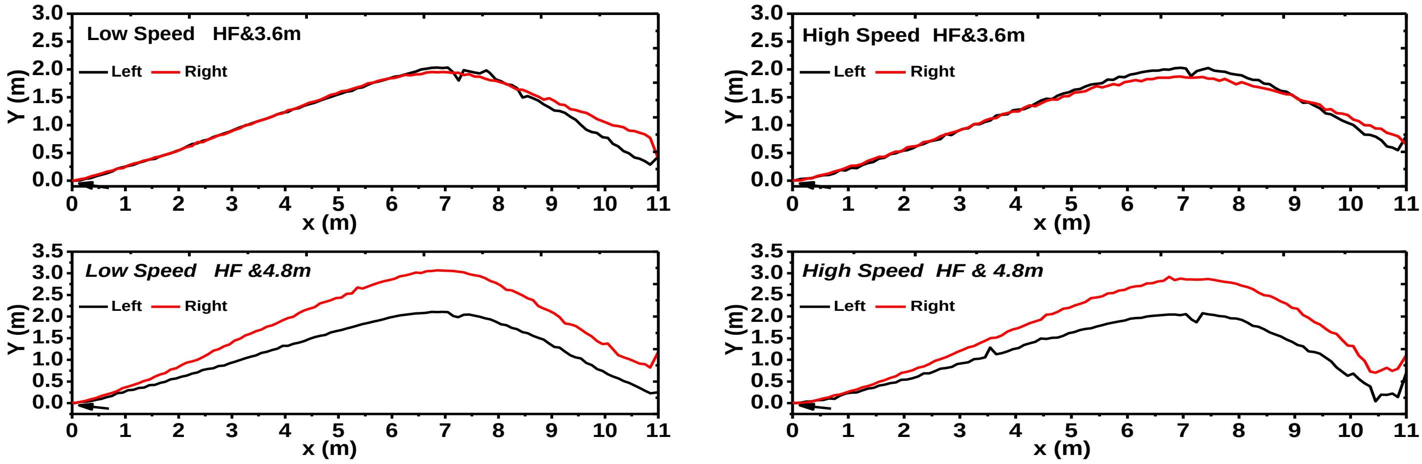


Figure 5.20: Average trajectories (black is left, red is right) and decision-making points for going left or right at low, medium and high flow rates.

5.2.3.4.3 (3) Pedestrian velocity on the left and right paths

After analysing the extracted participant trajectories, we measured pedestrian speed toward minimal scatter using the method of Steffen and Seyfried [117]. To find the average velocity from SP to EP for all individual subjects, we applied **Equation (5-4)**:

$$Instan\_Velocity = \frac{\sqrt{(y_{t+\Delta t} - y_t)^2 + (x_{t+\Delta t} - x_t)^2}}{\Delta t} \qquad (5\text{-}4)$$

where x and y are the positions of the subjects and Δt is the change over time. Table 5.5 shows the average individual velocities in each experiment and the standard deviation (SD) of the left or right trajectories. The table also shows the t-test results as p-values, indicating that if $p < 0.01$, left/right bypassing has a significant impact on the velocity. Otherwise, left/right bypassing does not have a significant impact on the velocity values. The results of the 20 experiments are arranged in the order of their experiment number (see **Table 4.1**) for low- and high-speed scenarios.

Table 5.5: Comparison of average velocity along the left and right paths for each experiment

LF

Experiment Number	**Low-Speed Scenarios (LS)** Velocity(m/s) & SD		**T-Test Result as a *p*-value**	**Experiment Number**	**High-Speed Scenarios (HS)** Velocity(m/s) & SD		**T-Test Result as a *p*-value**
	Left	Right			Left	Right	
LS&1.2m	1.15 (0.23)	1.73 (0.28)	$p < 0.01$	HS&1.2m	3.25 (0.060)	3.28(0.064)	$p > 0.05$
LS&2.4m	1.43 (0.27)	1.55 (0.36)	$p > 0.05$	HS&2.4m	3.28(0.012)	2.44 (0.83)	$p < 0.01$
LS&3.6m	1.45 (0.25)	1.14 (0.27)	$p < 0.01$	HS&3.6m	3.33(0.011)	3.17 (0.50)	$p > 0.05$
LS&4.8m	1.37 (0.29)	1.42 (0.31)	$p > 0.01$	HS&4.8m	3.27(0.052)	2.95(0.059)	$p > 0.05$

MF	LS&1.2m	1.24 (0.31)	1.32 (0.29)	$p > 0.05$	HS&1.2m	3.28 (0.080)	2.78 (0.59)	$p < 0.01$
	LS&2.4m	1.48 (0.33)	1.32 (0.35)	$p > 0.05$	HS&2.4m	3.15(0.061)	2.58(0.059)	$p < 0.01$
	LS&3.6m	1.35 (0.30)	1.14 (0.19)	$p > 0.05$	HS&3.6m	3.23(0.077)	1.84(0.038)	$p < 0.01$
	LS&4.8m	1.56 (0.01)	1.26 (0.34)	$p < 0.01$	HS&4.8m	2.94(0.049)	2.8(0.054)	$p > 0.05$
HF	LS&3.6m	1.29(0.022)	1.29(0.025)	$p > 0.05$	HS&3.6m	2.67 (0.69)	2.37 (0.65)	$p > 0.05$
	LS&4.8m	1.17(0.023)	1.42(0.022)	$p < 0.01$	HS&4.8m	2.75 (0.65)	1.95 (0.15)	$p < 0.01$

5.3 Macro-level analysis

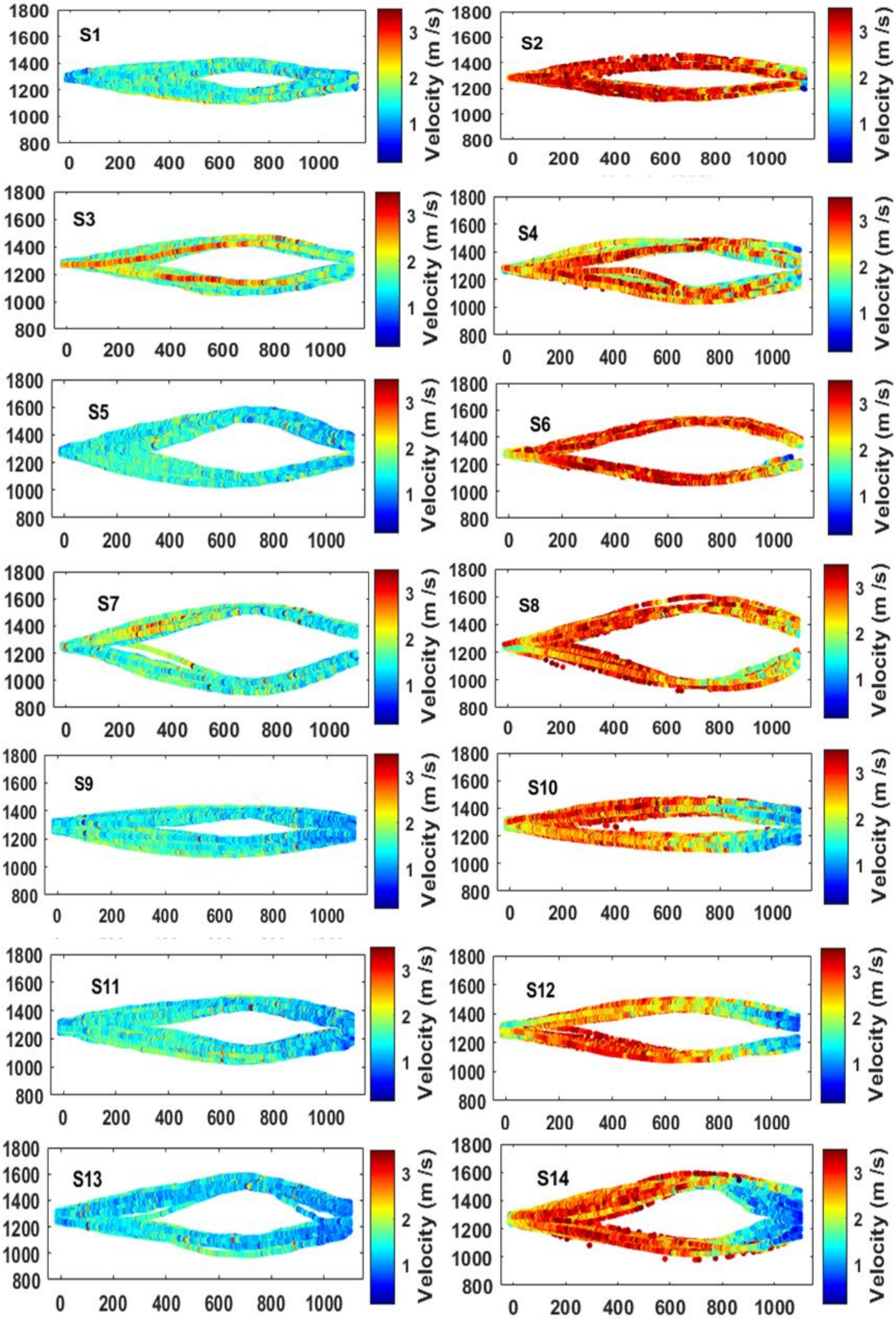
In this section, we apply a qualitative and quantitative investigation based on the information we obtained from the extracted trajectories. Speed, density and the cumulative flow rate were extracted in order to explore pedestrian behaviour based on the participants' movements while performing each experiment.

5.3.1 Egress congestion analysis

To assess egress congestion, we compared the velocity before and after the obstacles (before the exit). We have noted that obstacle size had a stronger influence on pedestrian behaviour at medium and high flow rates, as seen in **Figure 5.21** (S9 to S20). In these experiments, the congestion increased after the obstacle's location in both speed regimes, while the low-flow experiments showed no congestion in either speed regime. This can be seen in **Figure 5.21** (S1 to S8).

5.3.2 Individual speed analysis

We also calculated the velocity of each individual in each experiment. The average individual velocity in low-flow, low-speed scenarios ranged from 1.1 m/s to 1.3 m/s, and in low-flow, high-speed scenarios it ranged from 2.1 m/s to 2.5 m/s. For MF conditions, the average individual speed was around 1.2 m/s in LS and 2.2–2.4 m/s in HS. For HF conditions, the average individual speed in LS and HS was around 1.0 m/s and 1.9–2.2 m/s, respectively. The estimated average individual speeds in all flow conditions all indicated significant difference between LS and HS, with a 99% confidence level.


S1
S2
S3
S4
S5
S6
S7
S8
S9
S10
S11
S12
S13
S14
Velocity (m /s)
1800
1600
1400
1200
1000
800
0
200
400
600
800
1000
1
2
3

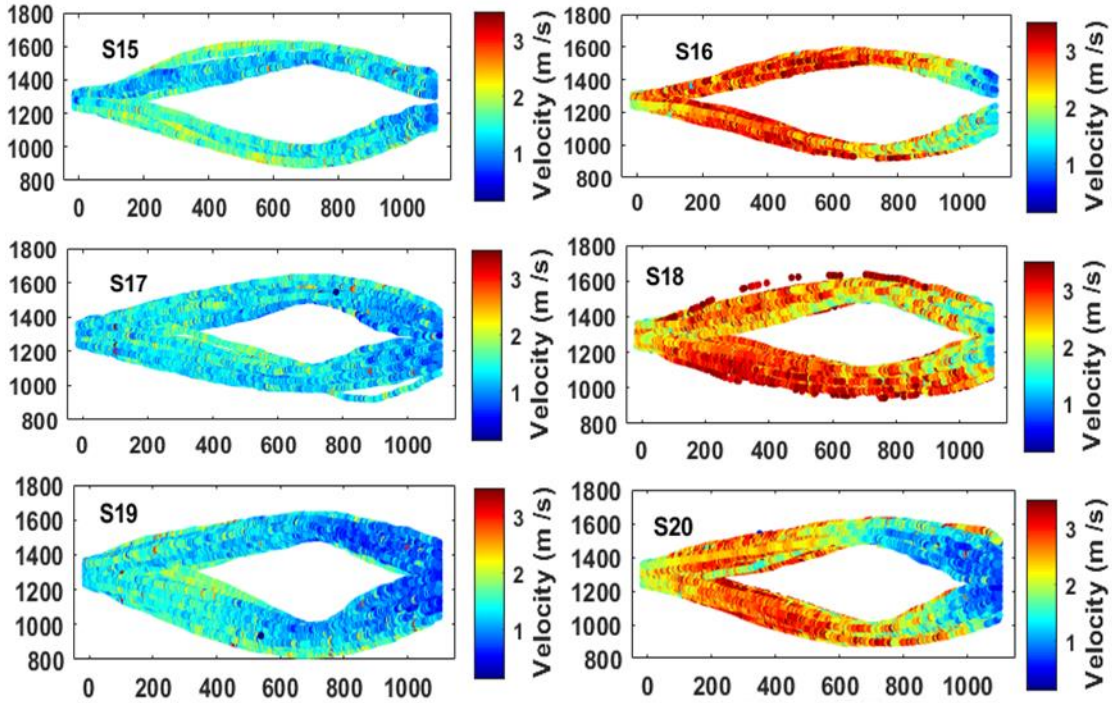


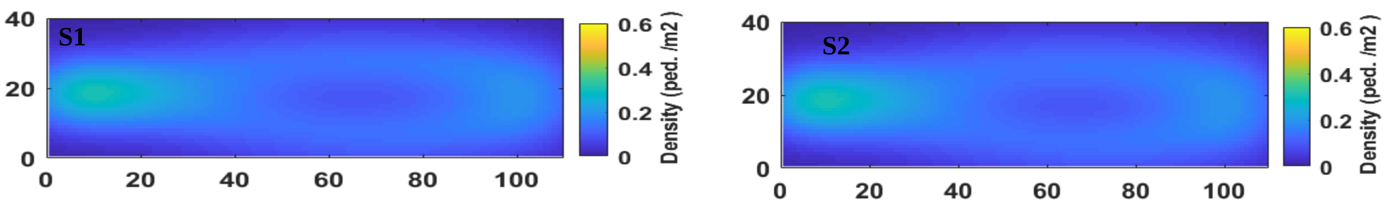
Figure 5.21: Comparison of the extracted trajectories of experiments 1 to 20 at low and high speed. The trajectories are colour–coded based on the subject's movement velocity in LF, MF and HF conditions (unit, cm).

5.3.3 Collective movement behaviour at different density levels

Figure 5.22 shows a comparison of the density levels at low and high speed for each experiment. The figure is colour-coded based on the subject's movements in LF, MF and HF, demonstrating a significant difference in density levels between low- and high-speed regimes.

5.3.4 Egress congestion analysis based on density

In the second part of the egress congestion analysis, we compared the density levels before and after the location of the obstacle (before the exit). We have noted that obstacle size had more influence on pedestrian behaviour at medium and high flow rates, as seen in **Figure 5.22** (S9 to S20). In these experiments, congestion increased after the obstacle's location in both speed regimes, while the low-flow experiments showed no congestion at either speed regime, as seen in **Figure 5.22** (S1 to S8).



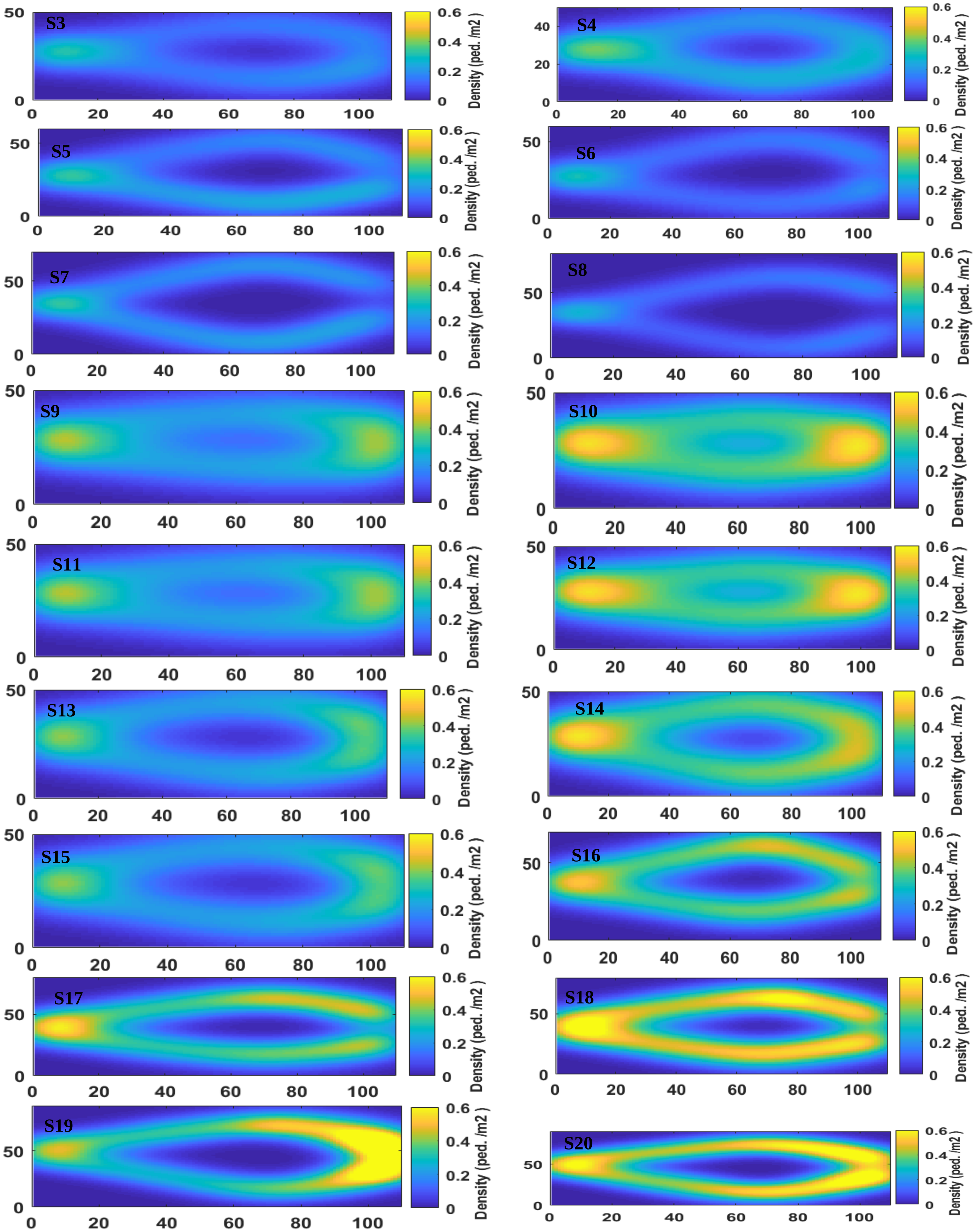
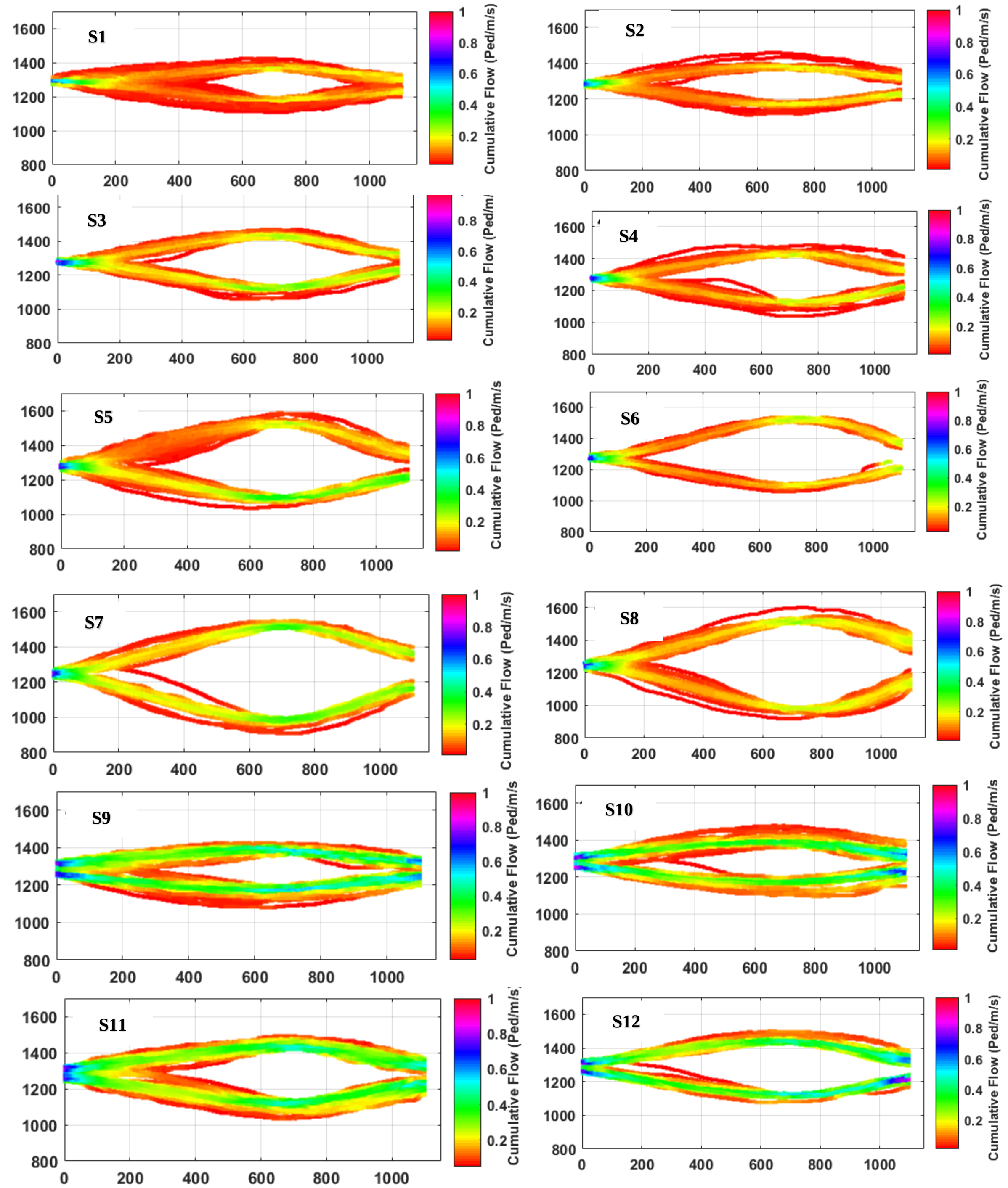


Figure 5.22: Comparison of density levels at low and high speed for each experiment, colour–coded based on the subject's movements in LF, MF and HF conditions.

5.3.5 Collective movement behaviour in the cumulative flow

Figure 5.23 shows a comparison of the cumulative flow at low and high speed for each experiment. The figure has been colour-coded based on the subjects' inflow rate in LF, MF and HF, revealing a significant difference in the cumulative flow rate between low- vs high-speed regimes.



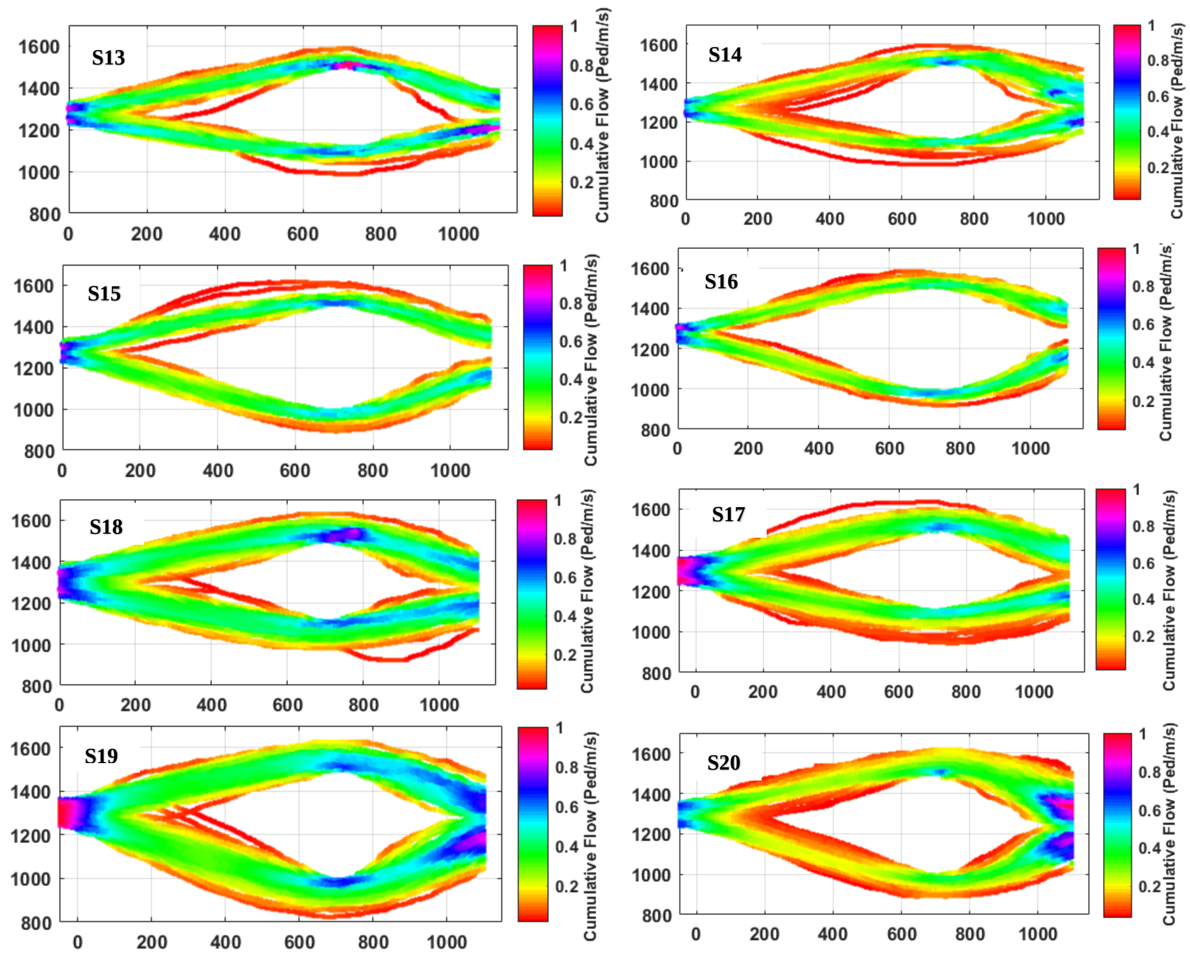


Figure 5.23: Comparison of the cumulative flow at low and high speed for each experiment, colour-coded based on the subjects' inflow rate in LF, MF and HF (unit, cm).

5.4 Summary

In this section, we focus on determining the influence of obstacles on pedestrian behaviours and their characteristics using two levels of analysis: microscopic and macroscopic. In the micro-level analysis, we experimentally investigated the walking and running characteristics of individuals using different obstacles and flow rates to test the effect of obstacles on human movement speed. We focused primarily on the effects of instantaneous speed, speed in the movement direction and lateral speed. Then we compared the minimum, maximum and mean speeds for all 20 experiments carried out in this research as shown in Tables 2, 3 and 4. Our results suggested that in the low-speed experiments, different obstacle sizes did not affect the participant's speed, as shown by instantaneous speed and speed in the movement direction. However, the obstacles caused an effect at high speed. To explore the effect of the obstacles at both speeds, we had to analyse lateral speed and movement. In terms of avoidance behaviour, which refers to collision-avoidance phenomena, our results showed that, according to the average trajectories in each experiment at low and high speed, pedestrians responded to the obstacles and prepared to avoid collision early. Their early response was evident in the fact that pedestrians changed their walking or running direction to avoid objects starting from the entrance in all experiments. The reasons for this behaviour may be related to the width of the experimental area. In terms of velocity, our results indicated that velocity was a little higher in low-flow experiments as compared to medium- and high-flow experiments. Velocity decreased with an increase in obstacle size in each experiment at all flow levels, so the obstacle size did affect ingress and speed. In terms of travel time, the results suggested that in medium- and high-flow experiments, participants were less affected by the different obstacles (1.2 m, 2.4 m, 3.6 m and 4.8 m); therefore, this layout could provide greater efficiency for building design and for walking facilities. Our results indicated that travel time was shorter in medium-flow, low-speed experiments with 3.6 m obstacles and in medium-flow, high-speed experiments with 1.2 m obstacles. Notably, the results for these experiments were very close to the results for medium-flow experiments with obstacles of 2.4 m, 3.6 m and 4.8 m. Furthermore, the average travel time decreased as obstacle size increased and increased as flow rates increased.

Additionally, the study found a difference in lateral space (participants' distance from the edge of the obstacle). Lateral space ranged from 0.3 m to 0.7 m in both low- and high-speed regimes. The average lateral distance was affected by different flow levels. The average lateral distance increased with an increase in obstacle size and a low flow rate in both low-speed and high-speed regimes. The lateral distance increased from 0.4 m for a 1.2 m obstacle to 0.5 m for a 2.4 m obstacle and then again to 0.6 m for a 3.6 m obstacle. It then decreased with a 4.8 m obstacle. In medium-flow conditions, the average lateral distance remained the same with obstacles of 1.2 m, 2.4 m and 3.6 m at low speed. However, the average lateral distance decreased at high speed with a 2.4 m obstacle and at both speeds with the 4.8 m obstacle. Finally, in high-flow conditions, the average lateral distance decreased in both low- and high-speed regimes with the 3.6 m obstacle and increased with the 4.8 m obstacle. The average lateral distance for all experiments was 0.45 m.

In terms of body sway, obstacles had more impact on body sway in low- and medium-flow experiments. That impact was seen in the fact that *k* values increased as obstacle size increased, although that pattern disappeared in high-flow experiments at both speeds. This indicates that sway and speed correlate with an entrance width from 0.5 m to 1.5 m and an obstacle size of 3.6 m or less. Outside of that range, *k* will be less affected by speed. In terms of safety distance, which refers to the minimum distance between the edge of the obstacles and the pedestrian's shoulders, our results found a significant difference in safety distances in low- vs high-speed regimes. Finally, in terms of deviation angle, our results showed an increase in deviation angle whenever the size of the obstacle was increased in all of the experiments, and the deviation angle was shorter in high-speed experiments than low-speed experiments.

A deviation behaviour analysis based on pedestrians going left or right was used to explore pedestrians' direct and indirect reaction behaviours. Our results indicated that the pedestrians mostly took action immediately to avoid an obstacle; indirect reaction behaviour appeared in only one experiment at a walking distance of 1.10 m. Here, the pedestrians began to avoid the collision 5.90 m ahead of the obstacle. In addition, we found differences in the average trajectory along left- and right-hand paths. Finally, speed in each path was calculated based on the instantaneous speed of each individual on the same path, and our results showed a significant impact on the pedestrian speed in 50% of all the experiments on both the left and right paths.

At the macro-level of investigation, we explored three pedestrian behaviours in this study: egress congestion behaviour, individual speed and density and cumulative flow rate. With regard to individual speed behaviour, our results showed a significant impact on pedestrian speed at both speed levels. A difference was also found in the egress congestion analysis for pedestrians in medium- and high-flow experiments only; this behaviour disappeared in low-flow experiments. In the comparison of density level and cumulative flow rate, our results showed a significant impact on both results at both speeds. Therefore, this section has achieved the first objective of this study.

Chapter 6: Modelling: How the Presence of Others Influences the Pedestrian's Choice of Direction While Circumventing an Obstacle

6.1 Introduction

6.1.1 Pedestrian behaviour in an emergency

Understanding pedestrian behaviour is important for improving the safety of crowds [26, 119] and has attracted the attention of many researchers in recent decades [26, 28, 90, 120]. This is especially the case in crowd evacuation management and panic situations [90]. Several pedestrian simulation models have indicated that some phenomena cannot be represented because of certain movements within crowd dynamics [58, 60, 61, 121]. Many computer models of emergency and evacuation conditions have been developed to investigate the dynamics of pedestrians in normal and evacuation conditions by studying common characteristic phenomena in both conditions [4, 5, 84]. Moreover, Haghani, Sarvi [47] investigated human safety in crowded environments where pedestrians must react to threats and emergencies. They found that human safety is a critical consideration when planning for disaster management and public safety. Hence, the study and investigation of mechanisms that might threaten crowds have attracted the attention of many researchers, among whom [119] stated that 'The principal factors that affect pedestrian movement are the other pedestrians, the geometry of the facility in which the pedestrian is moving and the choices the pedestrian may have to make when faced with multiple competing goals'.

However, there are still many disasters, and perhaps they are increasing all over the world [1, 122]. Therefore, improving the safety of enormous crowds in all situations – not just emergencies – is still a major challenge and an important topic for research [123]. The focus should be on the safety of sizeable crowds when they are moving [123]. In recent years, many models of crowd dynamics have been proposed, namely agent-based models including social force models [5], cellular automata models [16], Schadschneider [54], generalised centrifugal-force models [124] and SGEM models [35], which can describe pedestrian behaviour and motion, collective behaviour and the ways people respond to different objects. Although these models can provide some suggestions and predictions that aid evacuation planning for pedestrian crowds, they also occasionally produce unrealistic simulation results

[2]. Therefore, they do not necessarily represent pedestrian movements realistically or provide useful results for evacuation and design purposes. In a recent study, Haghani, Sarvi [47] stated that there is still a lack of understanding with regard to pedestrian behaviour, the influence of different built environments and geometrical features. This lack of knowledge mainly stems from the difficulties involved in the provision of experimental data for all aspects of pedestrian crowd behaviour.

6.1.2 Background for escape behaviour and herd behaviour assumptions

One of the most important concepts presented by Helbing, Farkas [2] is the role of herd behaviour during panic or emergency evacuation. This concept has spawned many theoretical studies [2, 7] and many non-human experiments with either escaping ants [108, 125] or escaping mice [81, 126-128]. It has also been tested in models of human behaviour [9, 53, 57, 59, 69, 121]. In the current evacuation literature, the term 'herding' represents imitation, copying or following other pedestrian behaviours [129]. Haghani and Sarvi [130] characterised herding in this way: 'In the event of an evacuation, people will often be affected by the actions of others and may mimic their behaviour'. Van den Berg, van Nes [131] defined herding behaviour as 'watching certain people act and thinking that what they do is a viable solution, culminating in doing same'. There have been many studies of herding behaviour in crowd dynamics [119, 130, 131], but some focused specifically on the choice of direction during escape. Haghani and Sarvi [130] investigated and analysed herding behaviours in emergency escape scenarios and noted that 'Humans don't imitate the direction choice of the majority'. Thus, the objective of many studies is to identify herding behaviour and test it in a human experiment to see if people flow in the direction of the majority or the minority by using different layouts.

6.1.3 Applying the concept of herd behaviour in current modelling

According to the literature on evacuation modelling, herding behaviour is commonly assumed to be an important component in the development and formulation of pedestrian simulation models [44, 119, 130]. Therefore, many computational models have developed from rules of behaviour intended to produce herd flows. For example, Pan, Han [56] presented a simulation framework for evacuation modelling using herding behaviours, queuing and competition. In their research, they questioned fluid or particle approaches to modelling because they failed to account for herding activity, multi-directional flow and irregular crowd densities. They reported that ‘herding activity frequently encountered during the expulsion of the crowd in a room with two exits, in which one is, plugged while another is, not entirely adopted’. Song, Gong [34] demonstrated a method for simulating crowd evacuation with bioterrorism in a micro-spatial environment. Their research was focused on simulated geographical settings, and one of the behavioural principles implemented in that paradigm was that some inhabitants could lose their decision-making ability and, following herding behaviours, obey a single person. Referring to the recent work of [130] and [46], they explained their use of the hypothesis of herd behaviour to model the passenger decision-making process that leads to self-evacuation when they integrate their model with pedestrian simulation software. As per some scholars in the Model System section, they state when a commuter is conscious of an emergency, (they) presume the (entity) he or she knows the closest three individuals to be, followed. The provisional relocation goal D is defined, through that path by which these three persons are going.

We draw attention to the presumption of the validity of herding behaviour because it is employed as a measure of accuracy for crowd escape models or virtual reality tests, and models are not deemed reliable until they generate herd patterns [132]. Therefore, based on our earlier group of studies [119, 130], we have performed several simulations of crowd escape experiments under emergency conditions with sketched outlines of people to provide information at the individual level. In these studies, our organisation received and detailed modelling data using this unusual perspective of the operation [133]. A disaggregated data set was used to develop course options for the simulated rescue exercises, and it was found that selection based on majority decision had limited advantage. However, only a few density levels were applied. The findings showed that this kind of net gain is negative (indicating that even more people taking a path will decrease the acceptability of that path) if there is no preference uncertainty in the settings. In cases with selection ambiguity, we noticed that the cumulative impact of peer control was modellded by the selection uncertainty correlated for each alternate route. Based on this definition, we will continue to focus on this topic and attempt to establish some herd-type trend in human choice that may be the basis for further work. **Figure 6.1 (a)** shows a sample from the PeTrack software for experiment E9 indicating the pedestrians’ selection of an exit, and **(b)** shows trajectories for all participants, indicating the decision-making points for all individuals while choosing their exit from the entrance location.

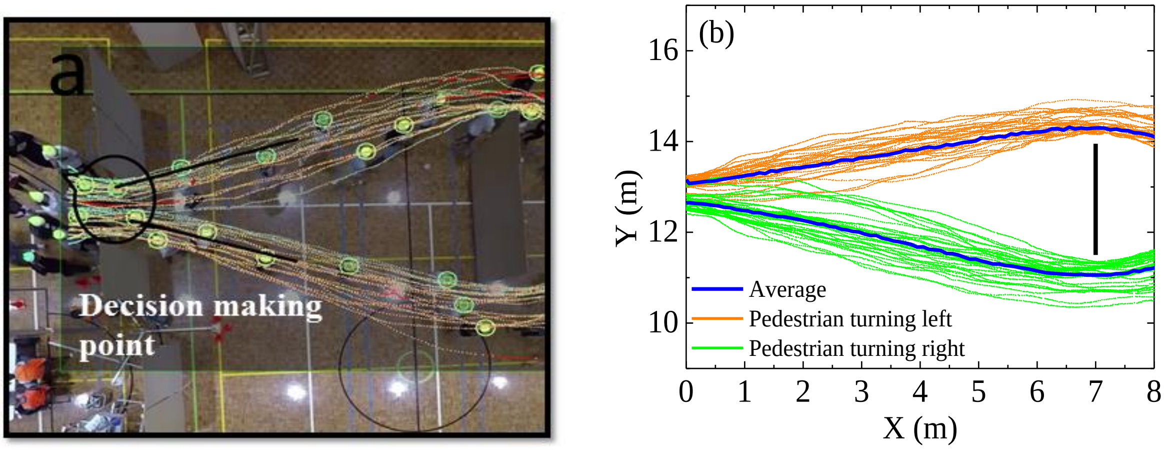


Figure 6.1: (a) Snapshot from the raw footage of experiment E9 showing the pedestrians deciding on an exit point; (b) Trajectories for all participants, showing decision-making points for all individuals while choosing their exit from the beginning.

6.2 Results

6.2.1 Escape time

This section presents our analysis in an informative way before presenting the results of our models. We made a quantitative comparison between the collective escape behaviour in low-speed and high-speed experiments by using a sub-sample of the experiments presented in **Figure 6.2**. We calculated total escape time (TET) and individual escape time (IET) in all of the experiments. Our results indicated that there was less difference between the average total escape time and the average individual escape time in the high-speed experiments compared to the low-speed experiments. Because of that difference, our results were statistically significant in both experiments ($p < 0.0001$).

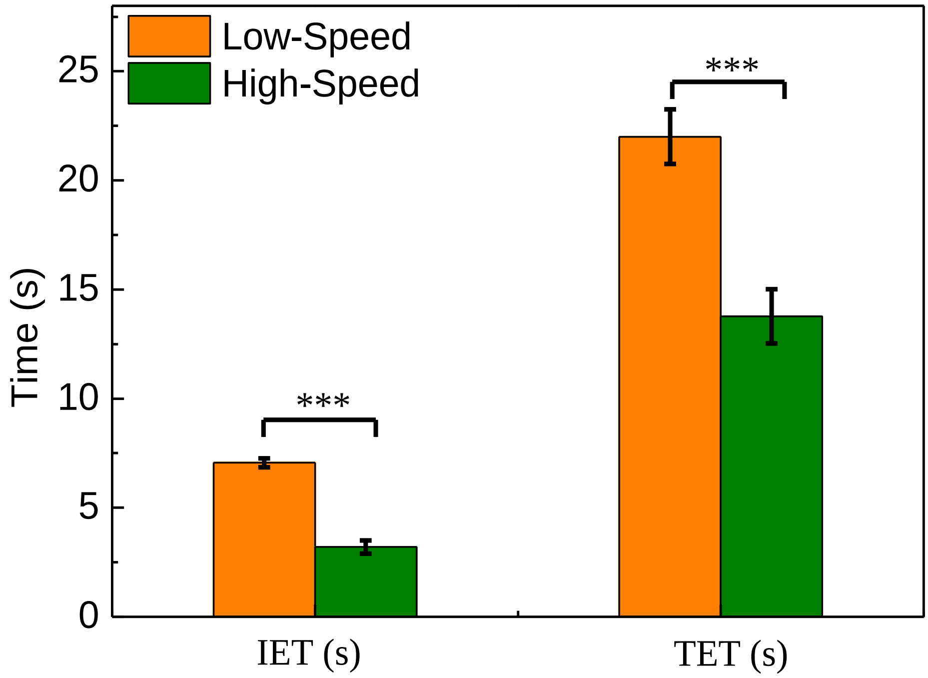


Figure 6.2: Comparison of the average individual escape time (IET) and total escape time (TET) in low-speed and high-speed experiments for E9 and E10. The error bars represent the standard deviation, and (***) indicates statistical significance at a 99% confidence level.

6.2.2 Predicting the exit choice factors based on statistical analysis

To predict the exit choice factors, we applied logistic regression concepts for a binary choice. This was done to investigate the effects of the four main explanatory variables on the binary variable, based on the factors introduced in the software. The results matched the outcomes of the predicted human behaviours on all factors related to pedestrian decision-making while choosing their exits, indicating that the total number of agents in front of the pedestrian, the number of agents in each direction and the distance between the agents are the only sub-factors that affect the individual's choice of majority or minority direction for exiting. Moreover, these sub-factors were statistically significant, and the corresponding *p*-values were larger than 0. In contrast, the variable of speed level was not associated with the pedestrian's decision, since $p > 0.542$, as seen in **Table 6.2**. The above sub-factors will be explained in the next section.

Table 6.1: Predicted factors associated with human decision-making in exit preference

Styles of Exit Preference	Odds Ratio	Standard-Error	z	P>|z|	95% confidence interval	
Logit Parameters						
Speed_levels	1.047727	0.0800979	0.61	0.542	.901933	1.217087
W_Flow_Size_Diff	.8136469	0.0481803	-5.48	0.000	0.724489	0.9137768

Diff_(Min-Maj)	.6227326	.0504032	-3.85	0.000	0.5313814	0.9137768
Total_ahead_agent	1.25621	0.0507039	5.65	0.000	1.160661	1.359624

6.2.3 Model specifications for exit choice

After predicting the related factors that affect exit choice, we defined these sub-factors in our model (e.g. the number of people in front of each target pedestrian, the number of people in the area or the interpersonal distance between the agent and the people in front of them). **Figure 6.3** demonstrates the choice point and the distance between participants. We also tracked the number of people at each exit in order to study collective escape behaviour in the route adopted by the majority or the minority. We assumed that there was a binary choice of exits: participants could either follow the majority or the minority choice. The benefit of adopting the majority direction, U_{MAJ}, is given by the equation below **(Eq6-1)**, where V_{MAJ} *and* ε_{MAJ} are probabilistic error segments of the utility in the system and the utility coefficients of the utility variables are indicated by β_s. To define the majority and minority directions, we set the utility coefficients as the minority direction is 0 and the majority direction is 1. Then we ran our model without a 'constant' variable (Note that the constant in this case would reflect how much the agent would inherently like the majority vs minority-direction). To avoid any equal chosen number between (majority vs minority) in the chosen direction, we deleted from the data 4 experiments that contained equal data between the (majority and minority) direction. The variable *Total_ahead_agent* refers to the crowding level, we calculated this variable based on the sum of the number of individuals in the majority and the minority direction. The variable *Speed_ Level* refers to the urgency levels. The variable *W_Flow_Size_Diff* is the distance in (meter), and it refers to the average distance between the participants in each direction, which can be found as the weighted value. To find the difference in weighted flow size between the majority and the minority direction exits, we used the weight factor $D_i^{-\propto}$: the variable (*W_Flow_Size_Diff*) is calculated as *W_Flow_Size_Diff* = $(\sum_i D_i^{-\propto})_{Maj}$ - $(\sum_i D_i^{-\propto})_{Min}$, where D_i is the distance in (meter) between the individual i in the majority or minority direction flow. Finally, for *Diff (Min-Maj)*, which refers to the difference between the number of individuals in each direction, we applied the same concept as for the previous variable. The probabilities of choosing each option were determined by the logit function, and the parameters of the models were estimated using the maximum likelihood method in **(Eq 6-1)**:

$$U_{MAJ} = V_{MAJ} + \varepsilon_{MAJ} = \beta_1(W\_Flow\_Size\_Diff) + \beta_2\ (Speed\_levels) + \beta_3\ (Total\_ahead\ \ the\ \ agent) + \beta_4\ (Diff(Min - Maj)) + \varepsilon_{MAJ} \quad (6\text{-}1)$$

(a) (b)

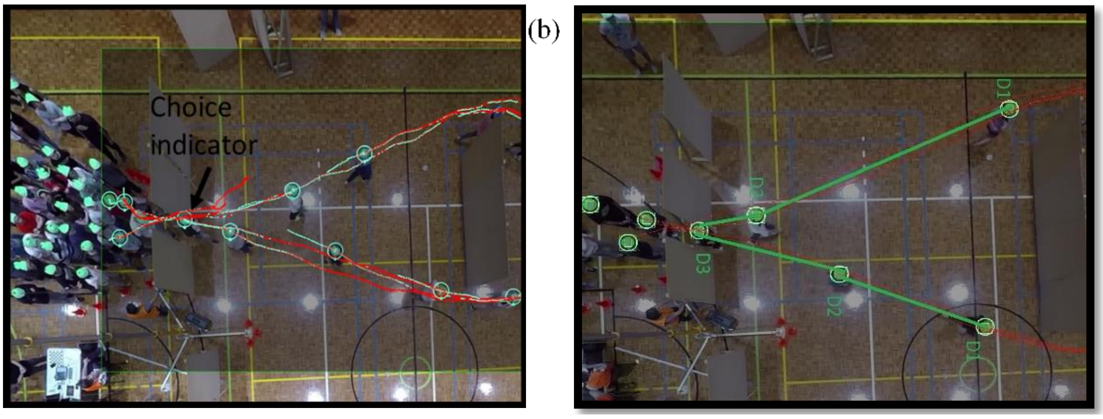


Figure 6.3: (a) Extraction of the individual's choice of direction along with the majority or minority route, showing the individuals at their moment of direction choice and their exit choice; (b) Coordinate of each individual in the majority or minority direction, used to calculate the interpersonal distance between participants.

6.2.4 Direction choice model and majority or minority route outcomes

To investigate the herding assumption and human behaviour based on the majority and minority direction, we divided our group into the three density levels shown in **Table 6.1**, along with the two different speed levels. According to our direction choice model, 57.17% of the individuals chose the minority direction and 42.83% chose the majority direction. The sub-factors that have weighted values, *W_Flow_Size_Diff*, *Diff_(Min-Maj)* and *Total_ahead_agent*, were statistically significant, and the corresponding *p*-values are larger than 0 as presented in **Table 6.3**. This table shows the estimated outcomes model, which improved the model outcomes by focusing on the predicted human behaviours for all factors, and the results suggested that *Speed_levels*, *W_Flow_Size_Diff*, *Diff_(Min-Maj)* and *Total_ahead_agent* are the variables that improve the model outcomes. The results of the model are presented in the following table (the *p*-values are significant from 0.000 to 0.001).

Table 6.2: Estimation outcomes for the exit choice model

Exit Choice models (direction)	Coef	Std. Error	t	P>|t|	95% confidence interval	
Logit model I Parameters						
Speed_levels	.1395427	.0177547	7.86	0.000	0.1047058	.1743797
W_Flow_Size_Diff	-.0417784	.0127072	-5.29	0.001	-.0168452	-.0667116

Diff_(Min-Maj)	-.097684	.0169445	-3.76	0.000	-.1309312	-.0644368
Total_ahead_agent	.062189	.0084918	7.32	0.000	.0455271	.078851
Logit Model I goodness-of-fit-measure						
Log-likelihood value	−735.30354	-	-	-	-	-
Log-likelihood ratio	0.0104	-	-	-	-	-
No. of observations	1102	-	-	-	-	-

6.3 Conclusion

In this chapter, the characteristics of pedestrians either walking or running around different obstacles were investigated in three different crowd-density scenarios. Our experiments were designed to test the assumption of herding behaviour or copying of direction choice during situations requiring emergency escapes. We used logistic regression to investigate the effect of specific sub-factors on the individual's choice of majority or minority direction. Our results indicated that 57.17% of the participants chose the minority direction and 42.83% chose the majority direction. The only sub-factors that affected the pedestrians' decisions were *W_Flow_Size_Diff*, *Diff_(Min-Maj)* and *Total_ahead_agent*. The speed of the individuals (low or high) did not significantly affect their choice of majority or minority direction, which confirms the findings of our literature review regarding exit choice [88]. To improve our results in the model, the Stata software suggested that *Speed_levels*, *W_Flow_Size_Diff*, *Total_ahead_agent* and *Diff_(Min-Maj* will enhance the model outcomes based on our data in the previous table.

Chapter 7: Calibration and Validation

7.1 Calibration

To calibrate the pedestrian's behaviours in normal and evacuation conditions, we organised decision-making in the simulation into two levels. The first is the operational level, which focuses on the pedestrian’s movements as in a social force model. The second is the tactical level, which describes the route choice, direction choice and pathfinding. To simulate the tactical level, we applied a probabilistic econometric model of discrete choice. The outcome of the tactical level model is generated as an input of the operational level, which generates the simulated movements.

7.2 Parameters calibration

In this part, we first referred to the Pedestride (https://www.pedestride.com), a Crowd Simulation Tool developed at The University of Melbourne. This model has a sophisticated methodology using a hybrid approach of mathematical modelling (e.g., social force modelling, route choice behaviour, and obstacle avoidance behaviour, etc.) and several rules to capture the realistic movement of pedestrian crowds. The route choice and pathfinding also referred to as "tactical manoeuvre" is explained in Ref [47, 95, 134]. However, considering that in this study we only focus on pedestrian flow movement from a chambe with obscals located close to the pedestrian. Therefore, in this paper, the simulated scenarios will only use the basic functionality of the social force model embedded in the simulation. The terminologies and occasional notations consistent with Helbing *et al.* [135] model as listed in the below equations.

$$\vec{f}_i = m_i \frac{d\vec{v}_i}{dt} = \vec{f}_{des,i} + \sum_{j(\neq i)} \vec{f}_{ij} + \sum_{w} \vec{f}_{iw} + \xi \qquad (7\text{-}1)$$

$$\vec{f}_{des,i} = m_i \frac{\vec{v}_i^d \vec{e}_i^d - \vec{v}_i}{\tau_i} \qquad (7\text{-}2)$$

$$\vec{f}_{ij} = \left\{ A_i \exp\left[\frac{r_{ij} - d_{ij}}{B_i}\right] + k_p G(r_{ij} - d_{ij}) \right\} \vec{n}_{ij} + K_p G(r_{ij} - d_{ij}) \Delta v_{ji}^t \vec{t}_{ij} \qquad (7\text{-}3)$$

$$\vec{f}_{iw} = \left\{ A_i \exp\left[\frac{r_i - d_{iw}}{B_i}\right] + k_w G(r_i - d_{iw}) \right\} \vec{n}_{iw} - \mathrm{K}_w G(r_i - d_{iw})(v_i^t \vec{t}_{iw}) \vec{t}_{iw} \quad (7\text{-}4)$$

$$\vec{n}_{ij} = \frac{1}{d_{ij}}(\vec{r}_i - \vec{r}_j) = (n_{ij}^1, n_{ij}^2) \quad (7\text{-}5)$$

$$\vec{t}_{ij} = (-n_{ij}^2, n_{ij}^1) \quad (7\text{-}6)$$

$$\Delta v_{ji}^t = (\vec{v}_j - \vec{v}_i) \bullet \vec{t}_{ij} \quad (7\text{-}7)$$

As stated in Eq.1, the total force f_i of agent *i* has received in the social force model was calculated by four components, the driven force $f_{des,i}$, the interaction force between pedestrians f_{ij}, the repulsive force between pedestrians and obstacles f_{iw} and random force ξ, respectively. The driven force $f_{des,i}$ (which as shows in Eq.2) was sourced from the desired velocity v_i^d, which shows the level of the desire of agent *i* hope to movement to avoied obstacle or egress in the current environment or scenario. (Eq.7-3 and Eq.7-4) illustrate the calculation of the interaction force between pedestrians f_{ij} and the repulsive force between pedestrians and obstacles f_{iw}. These two types of forces including the total radial force between pedestrians or walls and the total sliding friction force between pedestrians or walls. The radial unit vector, tangential unit vector and the tangential velocity between agent *i* and another agent were estimated by Eq.5, Eq.6 and Eq.7, respectively. Besides, variable τ and m_i means the relaxation time and the agent mass. κ_p and κ_w are the sliding friction parameters, K_p and K_w are the radial repulsion parameters. A_i and B_i represent the intensity and spatial magnitude of social forces between pedestrians. With the above equations, we can get the instantaneous speed v_i of agent *i* at step *t*. The variables mentioned above are all key parameters determining pedestrian movement.

7.2.1 Operational model specifications

7.2.1.1 Social force model specifications

The specifications of the social force model were developed by Helbing and Molnar [5], who presented this model in a mathematical formula that describes human behaviours based on different forces. This model was improved by different researchers [136-138]. The main assumption force for this model is that each agent has his/her own goal of reaching a certain point at the target time. Therefore, this assumption is described in the following:

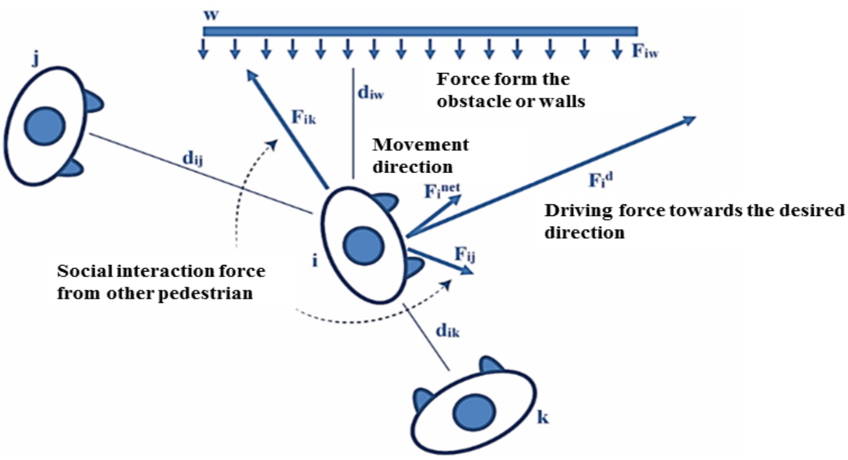


Figure 7.1: Social force-based model for pedestrian walking behaviour that was applied in this study at the operational level of the simulation [130].

$$\vec{F}_i^{net} = b_i \frac{d\vec{v_i}}{dt} = \vec{F}_i^d + \vec{F}_{ij} + \vec{F}_{iw} \tag{7-8}$$

$$\vec{F}_i^d = b_i \frac{v_i^d \vec{e}_i^d - \vec{v}_i}{T_i} \tag{7-9}$$

$$\vec{F}_{ij} = \left(A_i\, e^{(r_i+r_j-d_{ij})}/B_i + K_1 G(r_i+r_j-d_{ij})\right)\vec{n}_{ij} + K_2 G(r_i+r_j-d_{ij})\, \Delta v_{ij}^t\, \vec{t}_{ij} \tag{7-11}$$

$$\vec{F}_{iw} = \left(A_i\, e^{(r_i-d_{iw})}/B_i + K_1 G(r_i-d_{iw})\right)\vec{n}_{ij} + \vec{n}_{iw}^{-}\, K_2 G(r_i-d_{iw})\, (\vec{v}_i.\vec{t}_{iw})\, \vec{t}_{iw} \tag{7-12}$$

where the function $G(r_i + r_j - d_{ij})$ is equal to $r_i + r_j - d_{ij}$.

Table 7.1: Social force model components

Model components	Description
$\boldsymbol{i}$	Each pedestrian
$(\vec{F}_i^{net})$	Each step motion for the pedestrian at net
$\vec{F}_i^d$	The driving force motivating pedestrian i towards their preferred direction
$\vec{F}_{ij}$	The social interaction force from another pedestrian where i≠j

$(\boldsymbol{w})$	Walls, obstacles or barriers that the pedestrian avoids collision with
$\vec{\boldsymbol{F}}_{\boldsymbol{iw}}$	The force from the walls or obstacles
$\boldsymbol{b_i}$	The body mass of pedestrian i
$\vec{\boldsymbol{v}}_{\boldsymbol{i}}$	The vector of the velocity of the pedestrian where $\vec{v}_i = {d\vec{r}_i}/{dt}$
$\vec{\boldsymbol{r}}_{\boldsymbol{i}}$	A signification vector for the position of pedestrian i
$\boldsymbol{t}$	The time. dt signifies the time increment
$\vec{\boldsymbol{e}}_{\boldsymbol{i}}^{\boldsymbol{d}}$	The desired direction of the pedestrian
$\boldsymbol{v_i^d}$	The desired magnitude of the velocity for pedestrian i to accomplish his her goal
$\boldsymbol{d_{ij}}$	The inter-individual Euclidian distance between the pedestrian and j
$\boldsymbol{r_i}$	Body radius
$\vec{\boldsymbol{n}}_{\boldsymbol{ij}}$	The unit vector that connects the pedestrian j to i.
$\boldsymbol{j\ and\ e}$	The natural exponential function
$\boldsymbol{d_{iw}}$	The distance of pedestrian i from obstacle or wall w
$\vec{\boldsymbol{n}}_{\boldsymbol{iw}}$ & $\vec{\boldsymbol{t}}_{\boldsymbol{iw}}$	The unit vector following the direction vertical to wall w from the position of each pedestrian i (following the same concepts as $\vec{n}_{ij}\ and\ \vec{t}_{ij}$)
$\boldsymbol{T_i}$, $\boldsymbol{A_i}$, $\boldsymbol{B_i}$, $\boldsymbol{K_1 and\ K_2}$	The calibrated parameters

The model's components are defined by the following equation:

$$\vec{F}_i^{net} = b_i \quad (7\text{-}5)$$

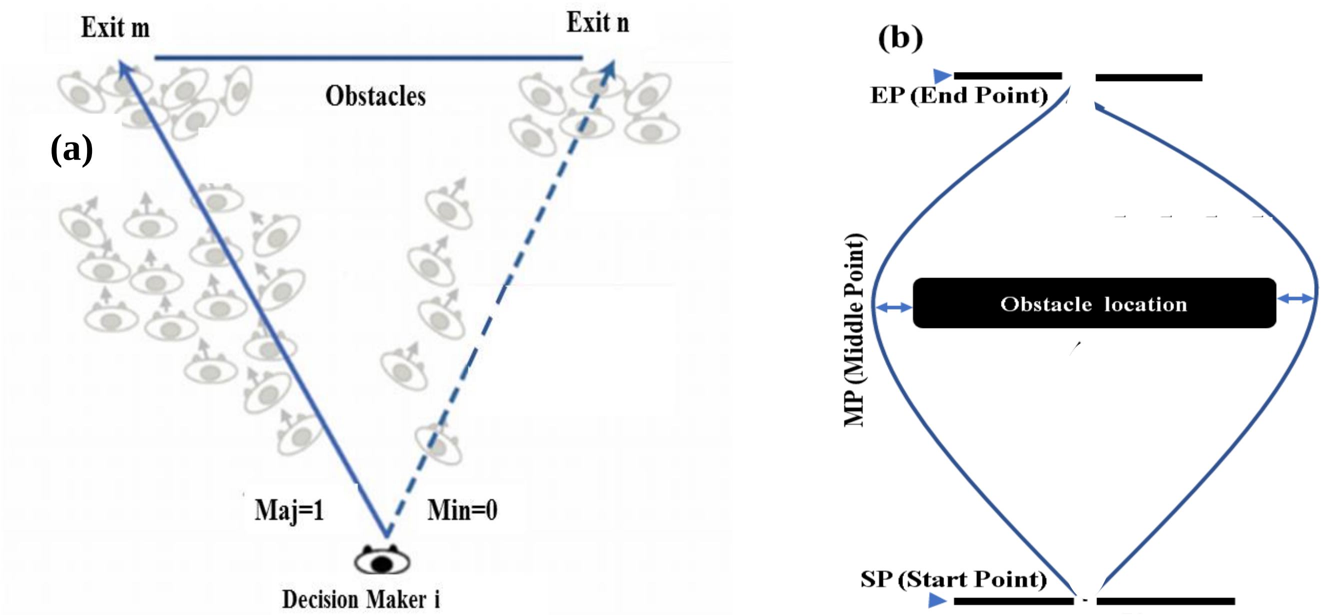


Figure 7.2: Tactical-level model that was applied in the simulation in this study [130]. (a) shows exit choice behaviour and (b) shows avoidance behaviour.

7.2.1.2 Tactical model specifications and the application of methodology

To achieve the second objective of this study, we determined several sub-factors that we predicted would influence pedestrian decision-making. We calibrated the individual's choice of direction along with the majority or minority route based on the interpersonal distance between the agents, the total number of agents in front of the pedestrian and the number of agents in each direction. These were selected as sub-factors because we believed they would affect the decision of individuals facing a choice of majority or minority direction to an exit.

Our objective was to apply the methodology or model to predict and enhance crowd safety around obstacles and turning areas. We specified three strategic steps in the model:

(1) The starting point is the decision-making point, where each agent makes a decision regarding majority or minority direction. This point can control the agent's decision for going left or right and also controls the turning area based on $\vec{\boldsymbol{e}}_{\boldsymbol{i}}^{\boldsymbol{d}}$, which controls the desired direction of the pedestrian.

   a. Speed is controlled by the parameter $\vec{\boldsymbol{v}}_{\boldsymbol{i}}$, where $\vec{v}_i = {d\vec{r}_i}/{dt}$ and $\boldsymbol{v}_{\boldsymbol{i}}^{\boldsymbol{d}}$ is the desired magnitude of the velocity for pedestrian i to accomplish his /her goal.

   b. Reaction time is controlled by $\vec{\boldsymbol{r}}_{\boldsymbol{i}}$, where $\vec{\boldsymbol{r}}_{\boldsymbol{i}}$ is a signification vector for the position of individual i.

   c. Collision avoidance behaviour is controlled by $\vec{\boldsymbol{n}}_{\boldsymbol{iw}}$ & $\vec{\boldsymbol{t}}_{\boldsymbol{iw}}$, where $\vec{\boldsymbol{n}}_{\boldsymbol{iw}}$ & $\vec{\boldsymbol{t}}_{\boldsymbol{iw}}$ are the unit vectors on the direction vertical to wall w from the position of each pedestrian i (this follows the same concept as $\vec{n}_{ij}$ and $\vec{t}_{ij}$).

(2) The middle point is controlled by two distances:

   a. Lateral distance is $\vec{n}_{ij}$ and $\vec{t}_{ij}$, represented as a horizontal line that controls the distance between the agent and the edges in the system.

   b. Safe distance is controlled by $\vec{\boldsymbol{n}}_{\boldsymbol{iw}}$ & $\vec{\boldsymbol{t}}_{\boldsymbol{iw}}$, representing the space between the shoulder of each agent and the edge of the obstacle.

(3) The end point, assigned as each exit.

7.3 Validation

To achieve the third objective of this study, we needed to validate the software with empirical data. To do so, we set up our software to run and repeat each experiment 50 times and execute the outcome in a separate file. This file showed coordinates for each agent in each run for 50 trials. Next, we had to use these data to analyse the simulation outcomes and compare them with the empirical data extracted from the human trials. The results of 1,000 runs are discussed in the following section after setting the simulation parameters as shown in **Table 7.2**.

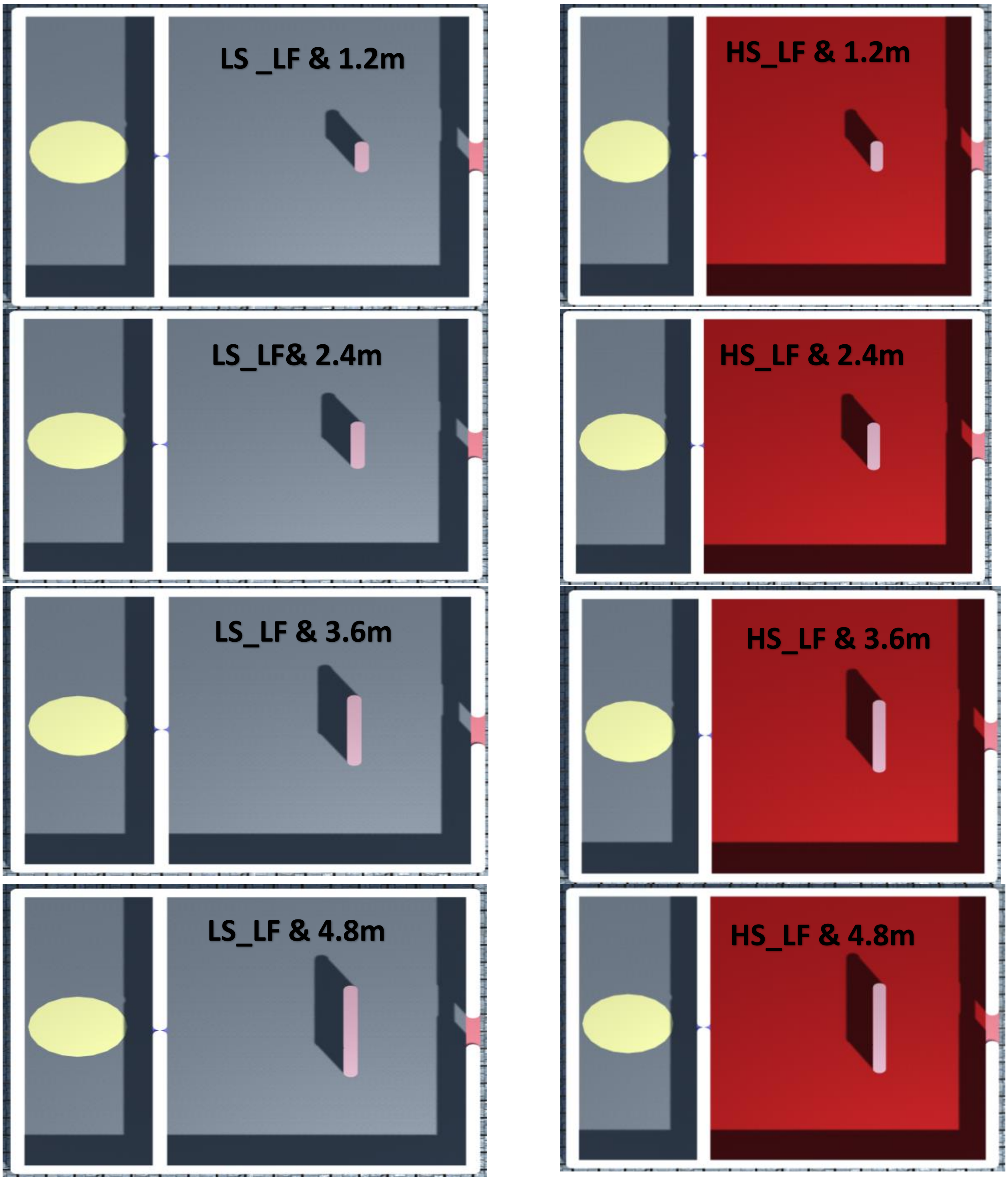
Table 7.2: Simulation parameters settings.

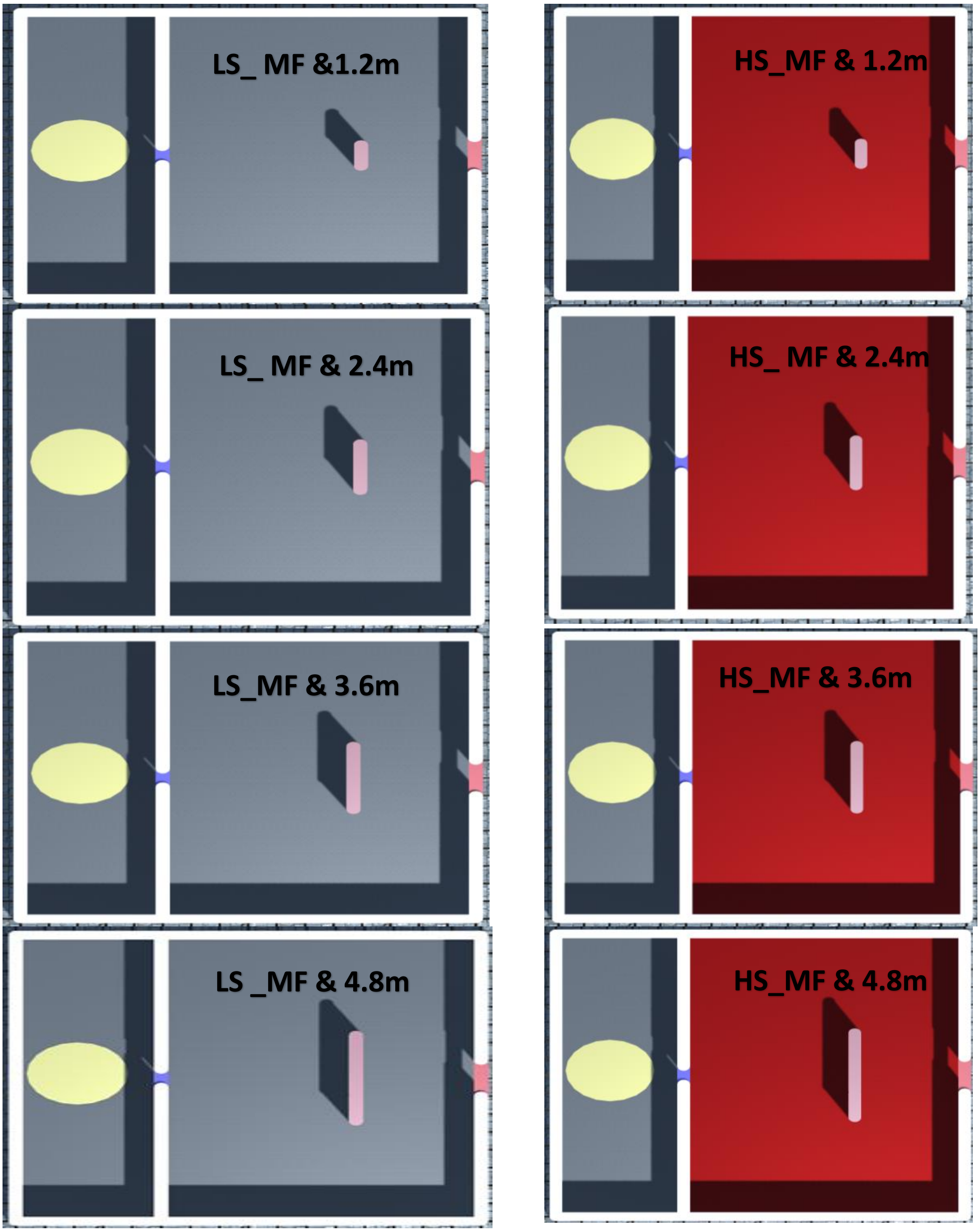
Parameters	Normal	Emergency
For pedestrian motion module		
Agent Radius	0.22	0.22
Agent Weight	75	75
Agent velocity	1.24	3.0 m/s
Reaction time	0.11	0.12
Frictional Force	5500	5500
Wall or obstacle Force	2000	2000
Safe Wall Dist	0.12	0.12
Replusion Dist	0.3	0.3
Attractive Force	5	5
Repulsive Force	2500	2500
Neighbr Radius	1.5	1.5
For pedestrian path decision module		
DIST	-0.256	-0.156
CONG	-0.138	-0.138
TOVIS	-0.024	-0.024
TOINVIS	0.093	0.093
VIS	0.71	0.71

7.3.1 Microscopic analysis

7.3.1.1 Comparing obstacle avoidance characteristics based on empirical and simulation outcomes

In this section, we apply quantitative analysis to compare the simulation data with the human data at two different speed levels. This is done to explore the difference between the agent's movements in the simulation and the human's movements in a real situation. We compared several factors, such as the average trajectories in each experiment, that described collision avoidance behaviours, speed, travel time, travel distance and lateral distance. **Figure 7.3** shows the experimental layout in the simulation for experiments 1 to 20 at low and high speeds and in low-flow, medium-flow and high-flow experiments, with comparison results for each factor.




LS_ MF &1.2m
HS_MF & 1.2m
LS_ MF & 2.4m
HS_ MF & 2.4m
LS_MF & 3.6m
HS_MF & 3.6m
LS _MF & 4.8m
HS_MF & 4.8m

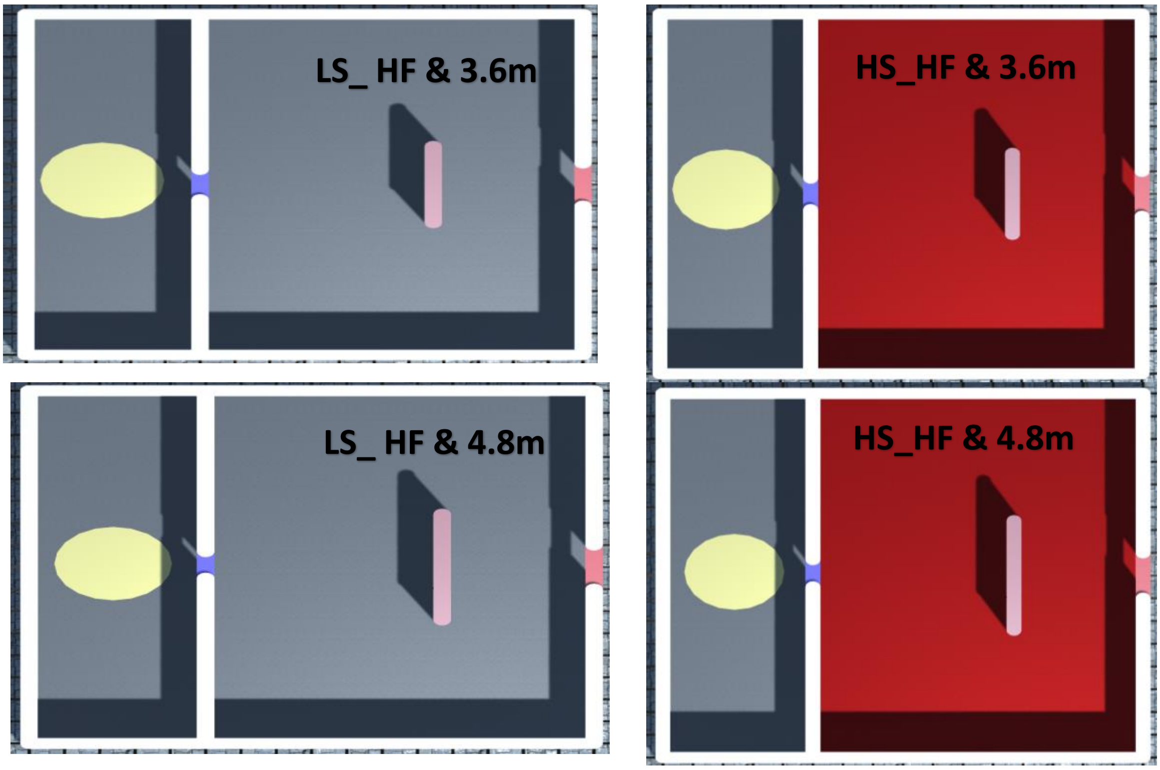


Figure 7.3: Experimental layout in the simulation, showing experiments 1 to 20 at low and high speed in LF, MF and HF. A red environment indicates a high-speed experiment, and a grey environment indicates a low-speed experiment.

7.3.1.2 Comparison of average trajectories

In this section, we examine the average trajectories in each trial in order to compare collision avoidance behaviours in the simulated and the human trials. **Figure 7.4** shows the collision avoidance behaviours in low-flow, medium-flow and high-flow conditions. Our results indicated that there was a difference between collision avoidance behaviours in the two types of experiments (simulation and human) for all flow and speed conditions.

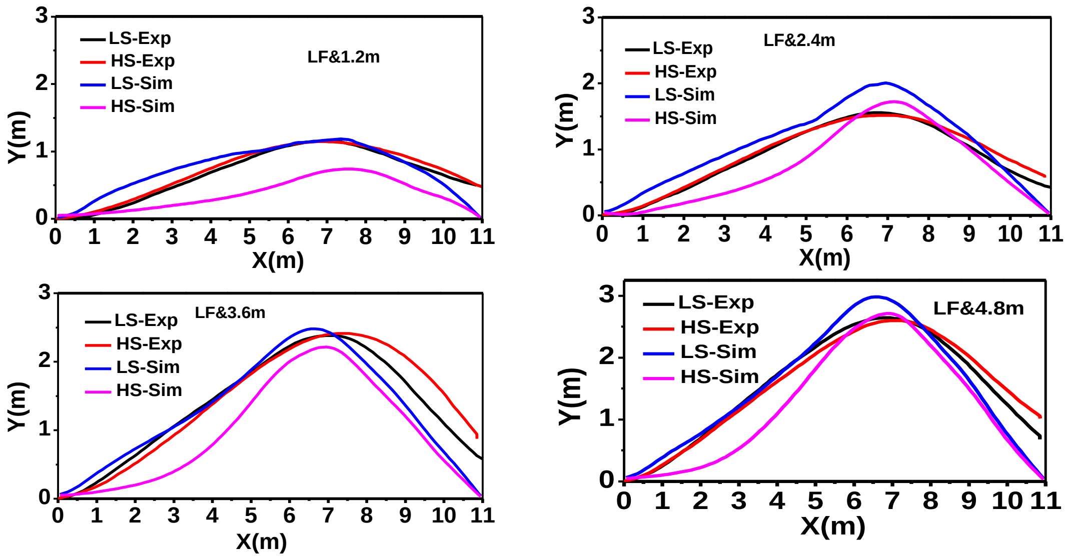
The first indication of this was that the average trajectories lengthened when the size of the obstacle increased in all experiments, but there were different gaps between the average trajectories in the two types of experiments at different speeds. The second indication was that the average trajectories in the human trials were equal in both speed regimes, indicating that pedestrians responded to the obstacle from the entrance location and avoided it. In contrast, the average trajectories in the simulation trials were shorter in the high-speed regime for all three flow rates. This indicates that agents in the simulation took a longer path to avoid the obstacles.

For example, in low-flow (LF) experiments, including scenarios LF&1.2m, LF&2.4m, LF& 3.6m and LF&4.8m, the average trajectories were shorter at high speed compared to low speed. Our interpretation for that is that the agent in the simulation walked some distance without changing direction and the effect of the obstacles was less than can be seen in LF&1.2m, which had a big gap between LS_Exp, HS_Exp and LS_Sim. That gap reduced when the obstacle size increased, as seen in LF&2.4m, LF&3.6m and LF&4.8m.

In medium-flow scenarios, such as MF&1.2m, MF&2.4m, MF&3.6m and LF&4.8m, the average trajectories in the LS_Sim were longer than those in other trials. Our interpretation for that is that the agent in the simulation walked long distances to avoid the obstacles, as seen in MF&1.2m, MF&2.4m and MF&3.6m, which had a sizeable gap between the LS_Exp, HS_Exp and HS_Sim. That gap reduced when the obstacle size increased to 4.8 m.

In the high-flow scenarios (HF&3.6m and HF&4.8m), our data showed no major difference between the results we discussed earlier for MF&3.6m and HF&4.8m.

In summary, we showed the results of the comparison between the human empirical outcomes and the simulation outcomes. We compared the average trajectories under two speed levels, LS and HS. We compared each obstacle under two speed levels in both human and simulated trials, and our data found differences between the human empirical and the simulation outcomes at both speed levels.



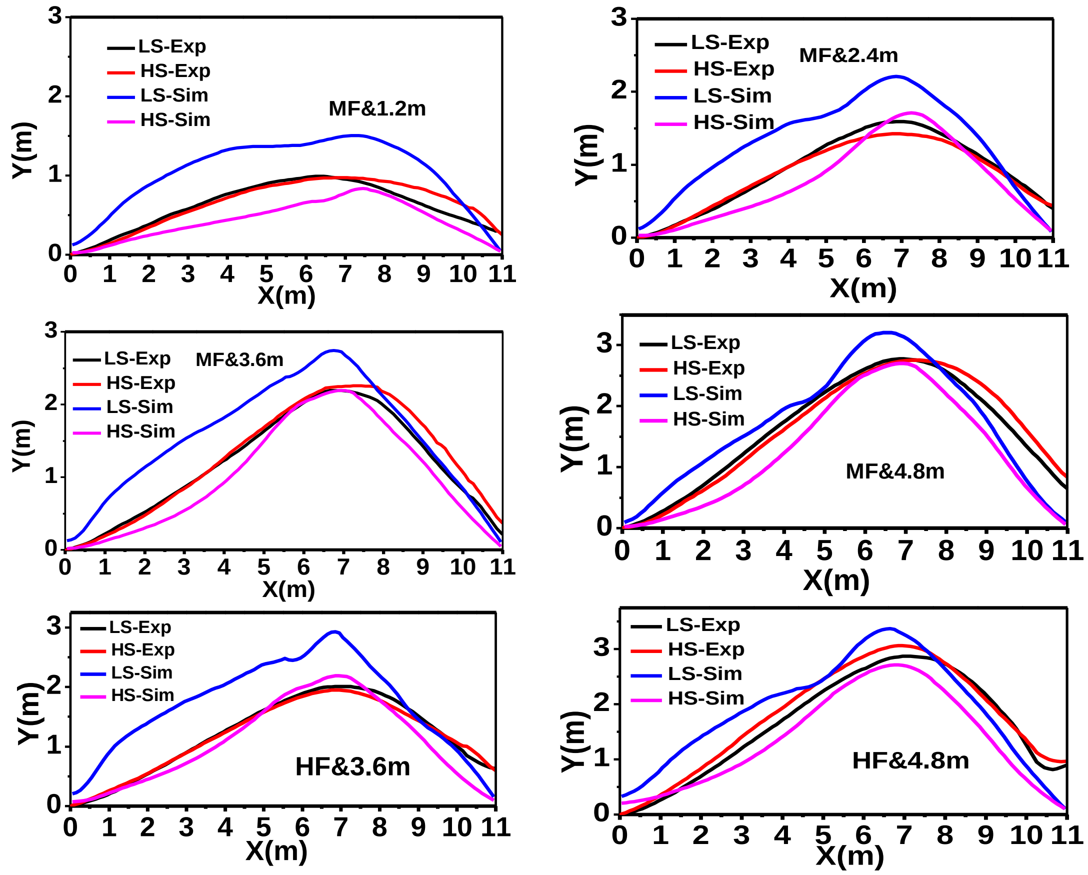


Figure 7.4: Comparison of the average trajectories at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m).

7.3.1.3 Comparison of instantaneous speeds

In this section, we compare the average speed in both trials (human and simulation), as seen in **Figure 7.5**, at two speed levels and in low-flow, medium-flow and high-flow conditions. We calculated the instantaneous speed for all experiments in the simulation after assigning the average speed only with no standard deviation. This was done to establish one speed for all agents in our simulation. Our results, showing no significant impact, are presented in **Figure 7.5** and **Table 7.3**.

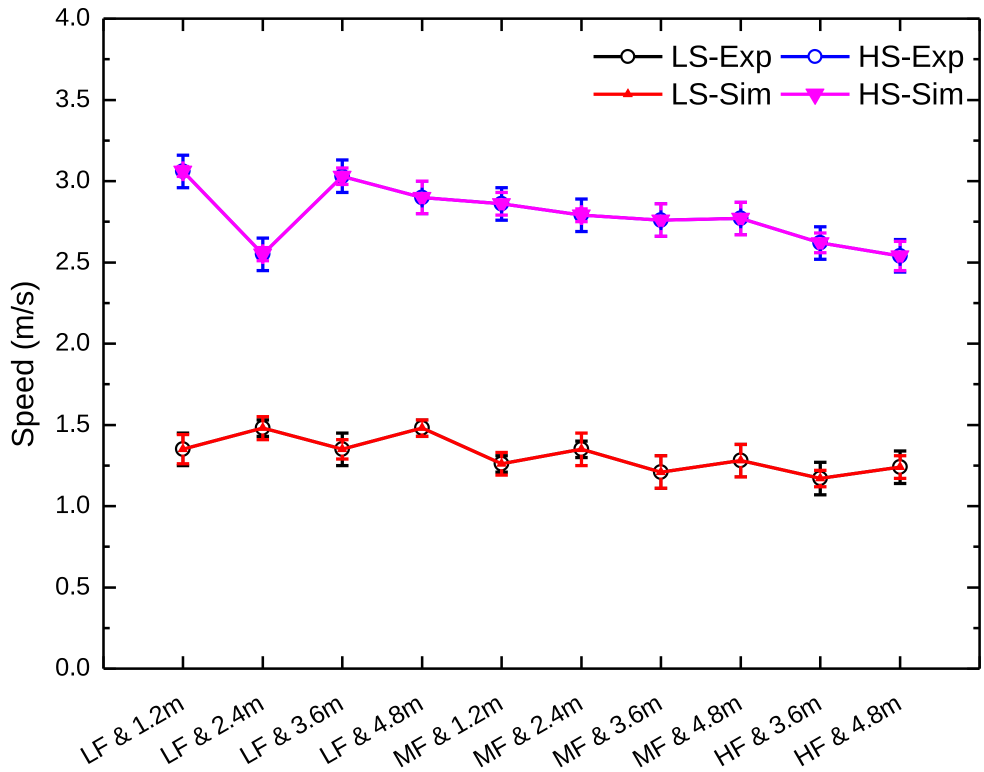


Figure 7.5: Comparison of the average speed at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m).

Table 7.3: *p*-values for the comparison of the individual's speed

Exp. No	P-value for LS-Exp vs LS-Sim	P-value for HS-Exp vs HS-Sim
LF &1.2m	0.44	0.43
LF &2.4m	0.41	0.59
LF &3.6m	0.315	0.55
LF &4.8m	0.16	0.67
MF &1.2m	0.36	0.08
MF &2.4m	0.57	0.12
MF &3.6m	0.46	0.14
MF &4.8m	0.56	0.12
HF &3.6m	0.46	0.12
HF &4.8m	0.56	0.13

7.3.1.4 Comparison of travel times

In this section, we explore other pedestrian behaviours in both trials (human and simulation). We compared the average travel time for each individual in both speeds regimes after applying the following equation based on SP and EP (see **Figure 4.2**). For target people *i*, the travel time ($t_{i,travel-time}$) from SP to EP calculated as below:

$$t_{i,travel-time} = t_{i,out} - t_{i,in} \tag{7-1}$$

Where $t_{i,in}$ means the time when people *i* entered the chamber (SP) and $t_{i,out}$ means the time when people *i* left the chamber (EP).

The first observation that can be drawn from **Figure 7.6** is that the travel times in the low-speed regime LS_Exp and LS_Sim are different for all of the ten experiments. In contrast, travel times in HS_Exp and HS_Sim are equal in most of the experiments. For example, in low-speed experiments in low-flow, medium-flow and high-flow scenarios, the results showed a significant difference between both trials LS_Exp and LS_ Sim (human and simulation), indicating a significant difference in average travel time ($p < 0.001$ and $p < 0.0001$).

On the other hand, in high-speed experiments in low-flow, medium-flow and high-flow scenarios, the results showed no significant difference between both types of experiment, indicating no significant difference between average travel time in low-flow and medium-flow scenarios ($p < 0.05$), while significant difference was found in the high-flow scenario ($p < 0.001$). The *p*-values for all of the experiments are presented in **Table 7.4**.

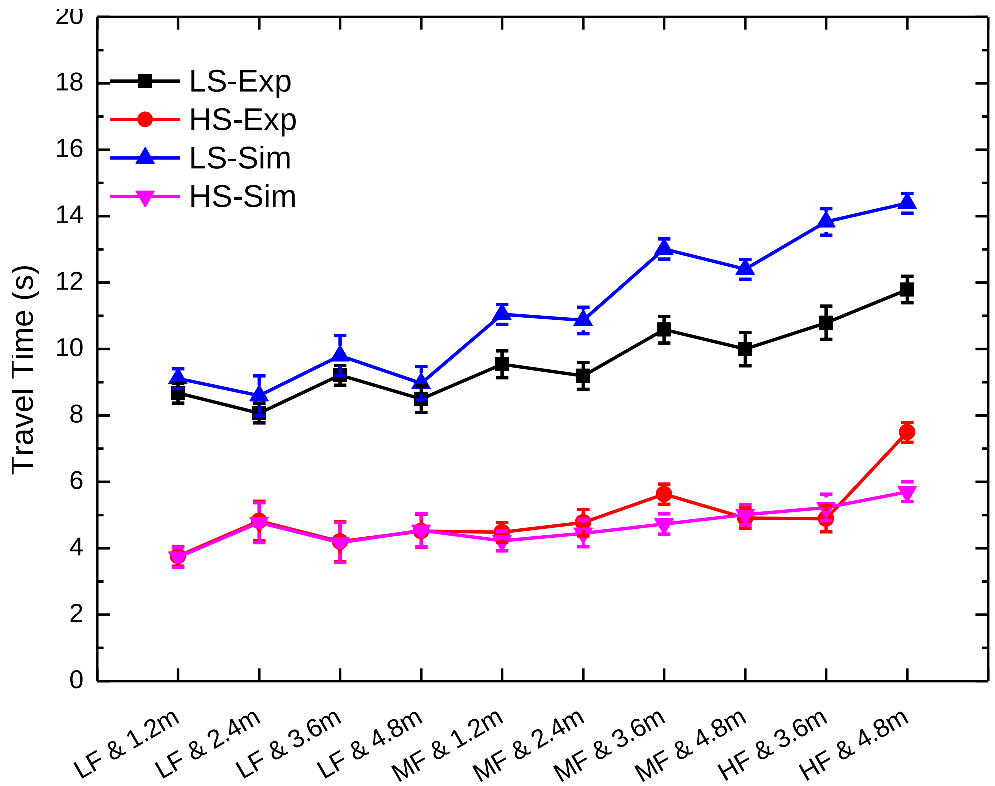


Figure 7.6: Comparison of the average travel time for individuals at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m).

Table 7.4: *p*-values for the comparison of travel time

Exp. No	***p*-value for LS-Exp vs LS-Sim**		***p*-value for HS-Exp vs HS-Sim**	
LF &1.2m	0.000	***	0.56	
LF &2.4m	0.000	***	0.79	
LF &3.6m	0.00	**	0.75	
LF &4.8m	0.00	**	0.87	
MF &1.2m	0.000	***	0.06	
MF &2.4m	0.000	***	0.0142	
MF &3.6m	0.000	***	0.0014	**
MF &4.8m	0.00	**	0.0162	
HF &3.6m	0.00	**	0.3	
HF &4.8m	0.000	***	0.001	

*** indicates statistical significance at the 99% level, and ** indicates statistical significance at the 95% level.

7.3.1.5 Comparison of travel distances

Additionally, we compared the average travel distance for each individual at both speed regimes after applying **Equation (7-2)**, which is based on SP and EP in **Figure 4.2**. For target people *i*, the travel distance ($D_{i,travel-diatance}$) from SP to EP calculated as below:

$$D_{i,travel-diatance} = \sqrt{(x_{i,t+\Delta t} - x_{i,t+\Delta t})^2 + (y_{i,t+\Delta t} - y_{i,t+\Delta t})^2} \qquad (7\text{-}2)$$

Where $x_{i,t}$ and $y_{i,t}$ represent the location of people *i* at time *t*, Δt represents the interval time.

The first observation that we can draw from **Figure 7.7** is that the travel distance in LS_Sim was different for all of the ten experiments compared to the other experiments (LS_Exp, HS_Exp and HS_Sim). This indicates that in low-speed experiments in low-flow, medium-flow and high-flow scenarios, the results showed a significant difference between human and simulation trials, indicating a significant difference between average travel distances ($p < 0.000$ and $p < 0.00$).

In contrast, in high-speed experiments in low-flow, medium-flow and high-flow scenarios, the results showed no significant difference between both types of experiment, indicating no significant difference for average travel time at any flow level ($p < 0.5$). All *p*-values are presented in **Table 7.5**.

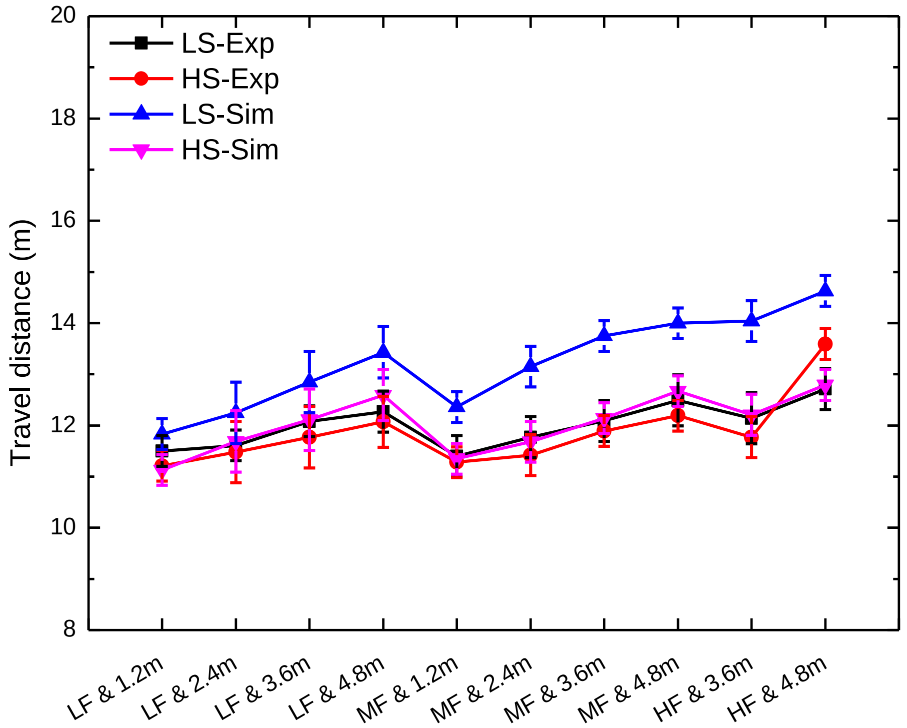


Figure 7.7: Comparison of the average individual travel distance at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m).

Table 7.5: *p*-values for the comparison of individual travel distance

Exp. No	***p*-value for LS-Exp vs LS-Sim**	***p*-value for HS-Exp vs HS-Sim**
LF &1.2m	0.001 **	0.21
LF &2.4m	0.000 ***	0.34
LF &3.6m	0.000 ***	0.45
LF &4.8m	0.000 ***	0.56
MF &1.2m	0.000 ***	0.11
MF &2.4m	0.000 ***	0.41
MF &3.6m	0.000 ***	0.56
MF &4.8m	0.000 ***	0.45
HF &3.6m	0.000 ***	0.11
HF &4.8m	0.000 ***	0.65

*** indicates statistical significance at the 99% level, and ** indicates statistical significance at the 95% level.

7.3.1.6 Comparison of lateral distances

Finally, we calculated the lateral distance, which can be defined as the average space between the edge of each obstacle and the average trajectory in each experiment. We examined the lateral distance for each obstacle by noting the actual location of the obstacle on the y-axis after finding the |y| coordinate of MP, where MP is 7 m, on the x-axis (see **Figure 4.2**). Additionally, in **Figure 7.8**, we calculated the average lateral distance at the edges of the obstacles, where MP is $|x| = 7$ m and $|y|$ = a coordinate value of each participant at the edges of the obstacles. We then compared the average trajectory values and the obstacle locations at y-coordinate MP to calculate the difference between the edges and the average trajectory values. Next, we compared the average lateral distance at MP for each experiment with the actual locations of the edges of the obstacles in both speed regimes for both trials (human and simulation).

Our results indicated that the different speed regimes seemed to have little impact on average pedestrian lateral distance. In most of the human trials, the average lateral distance was the same for low- and high-speed experiments. This was not the case in the simulated trials.

The first observation that we can draw from **Figure 7.8** is that the lateral distance in LS_Sim was different for all of the ten experiments compared to LS_Exp, HS_Exp and HS_Sim. The average lateral distance in LS_Exp in low-flow conditions ranged from 0.3 m to 0.6 m, as compared to a range of 0.4 m to 0.7 m in LS_Sim.

In medium-flow human trials, the average lateral distance ranged from 0.3 m to 0.5 m, as compared to a range of 0.2 m to 0.4 m in HS_Sim. In high-flow conditions, LS_Exp had a range of 0.3 m to 0.6 m, and HS_Sim had a range of 0.3 m to 0.5 m. The average lateral distance for all of the experiments was 0.45 m in both LS_Exp and HS_Exp and 0.48 m in both LS_Sim and HS_Sim. The *p*-values are presented in **Table 7.6**. The table indicates that there was a significant difference between the average lateral distances in human and simulated trials ($p < 0.000$ and $p < 0.00$).

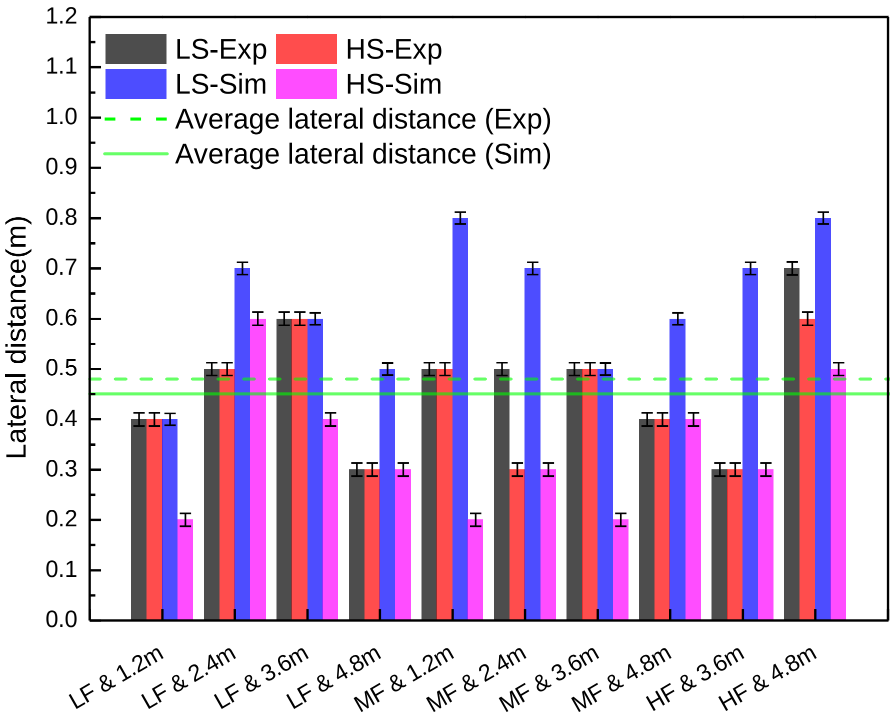


Figure 7.8: Comparison of the average individual lateral distances at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m).

Table 7.6: *p*-values for the comparison of lateral distance

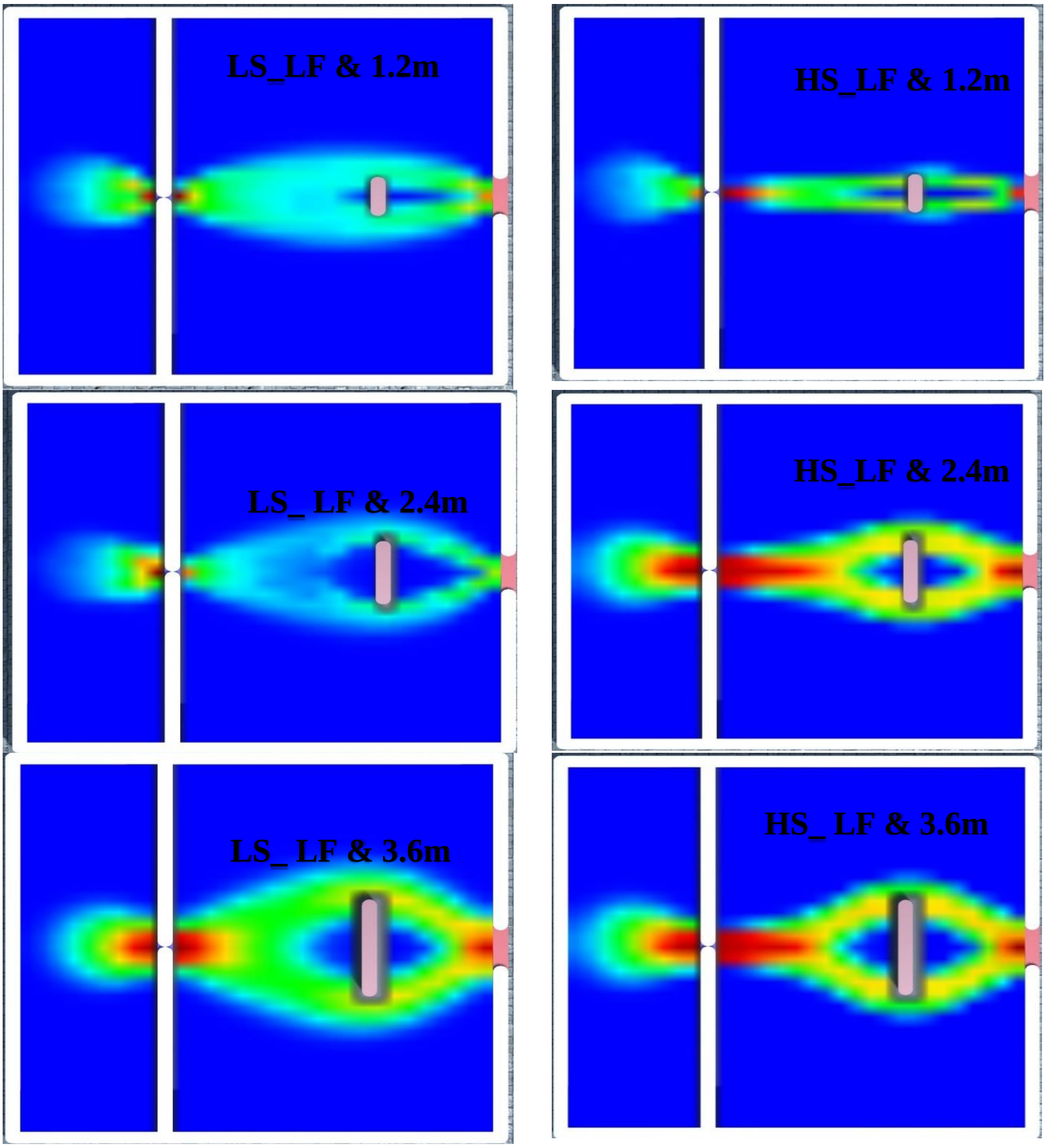
Exp. No	P-value for LS-Exp vs LS-Sim		P-value for HS-Exp vs HS-Sim	
LF &1.2m	0.0087		0.000	***
LF &2.4m	0.14		0.000	***
LF &3.6m	0.44		0.000	***
LF &4.8m	0.042	*	0.579	
MF &1.2m	0.000	***	0.000	***
MF &2.4m	0.000	***	0.045	*
MF &3.6m	0.000	***	0.47	*
MF &4.8m	0.0001	***	0.133	
HF &3.6m	0.0019	**	0.000	***
HF &4.8m	0.000	***	0.000	***

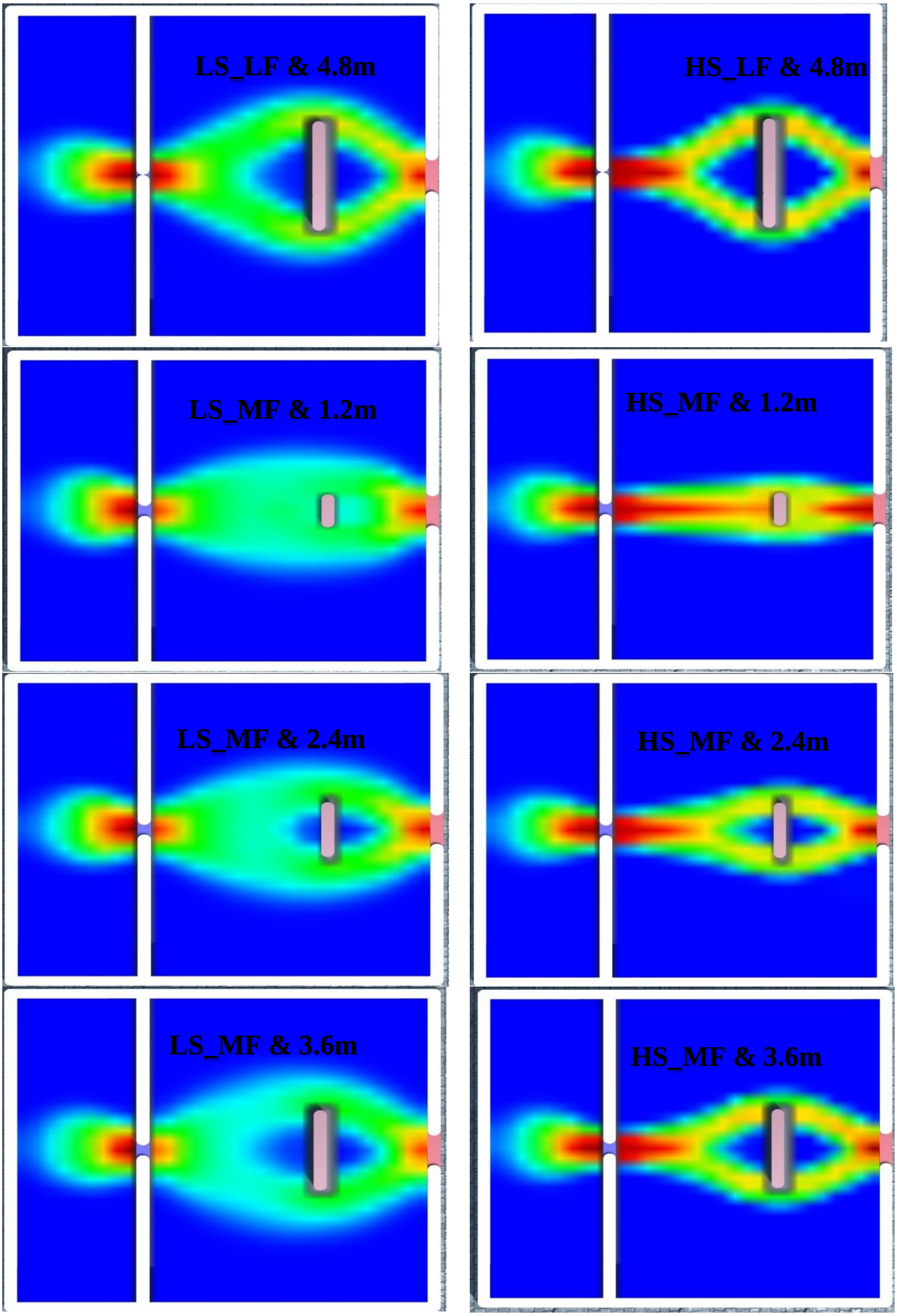
* indicates statistical significance at the 90% level, ** indicates statistical significance at the 95% level and *** indicates statistical significance at the 99% level.

7.3.2 Macroscopic analysis

7.3.2.1 Comparison of density levels based on simulation outcomes

In this section, we explore the simulation results on the aggregate level because this level of investigation will help us understand the software that calibrated agent behaviour. To accomplish this, we explored the density and speed of agents for each experiment. The results for the 20 experiments at all three flow rates are presented in **Figure 7.9**.




LS_LF & 4.8m
HS_LF & 4.8m
LS_MF & 1.2m
HS_MF & 1.2m
LS_MF & 2.4m
HS_MF & 2.4m
LS_MF & 3.6m
HS_MF & 3.6m

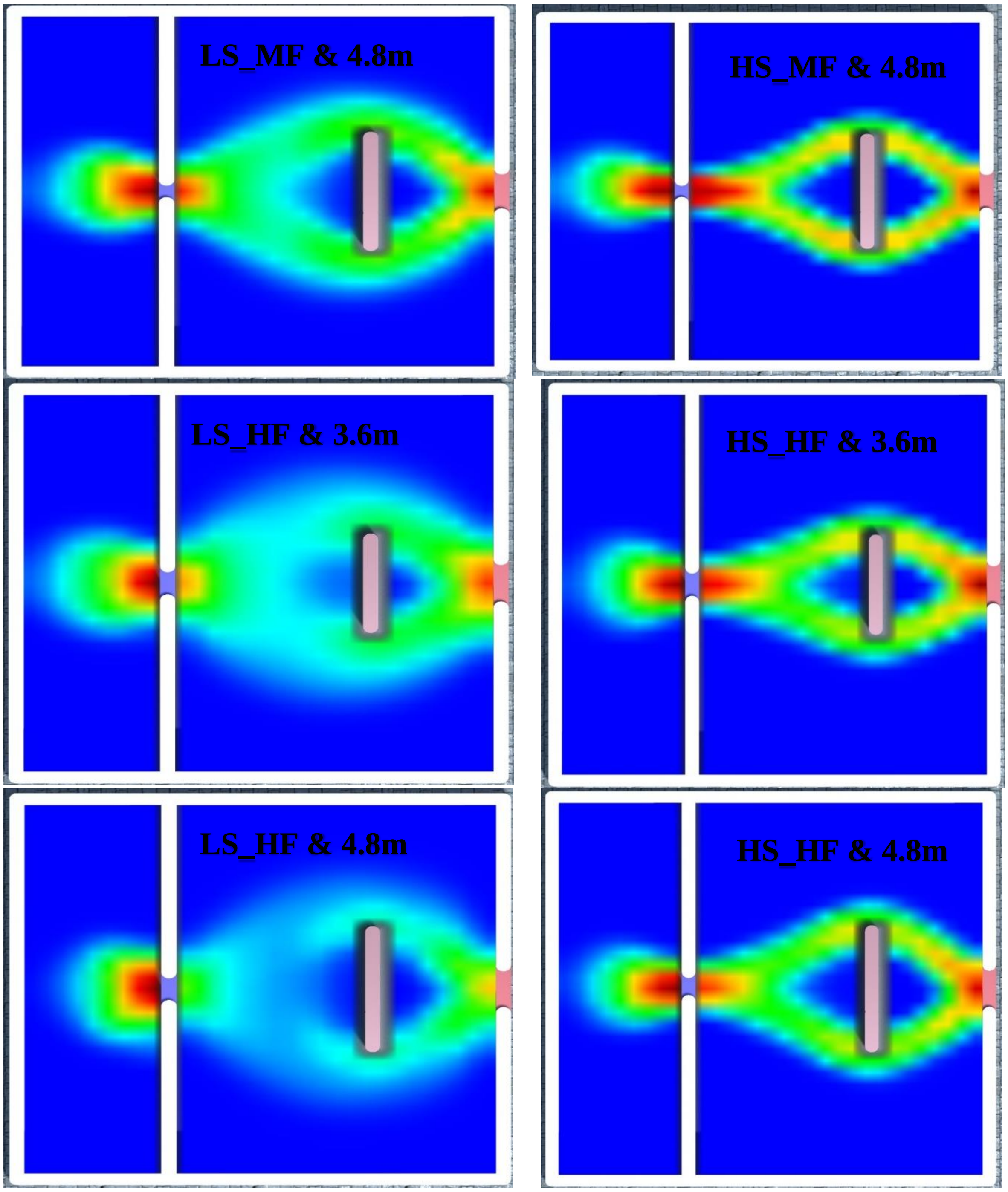


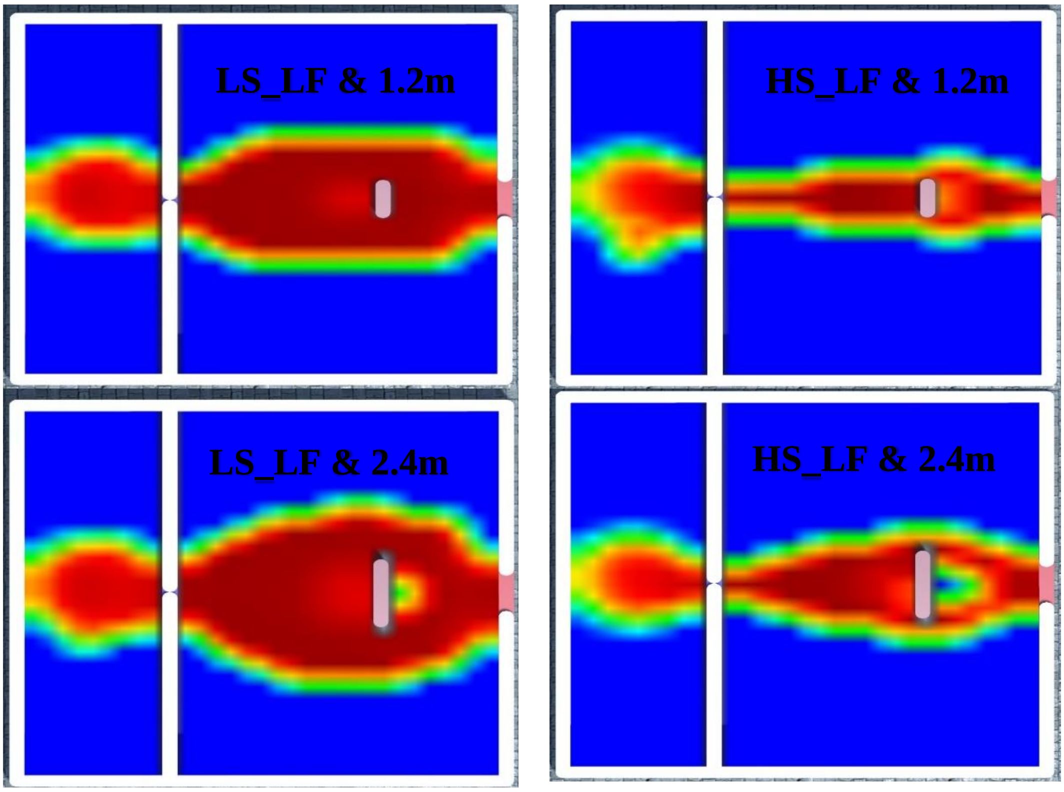
Figure 7.9: Comparison of the density levels in each trial, based on the simulation outcome, at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m).

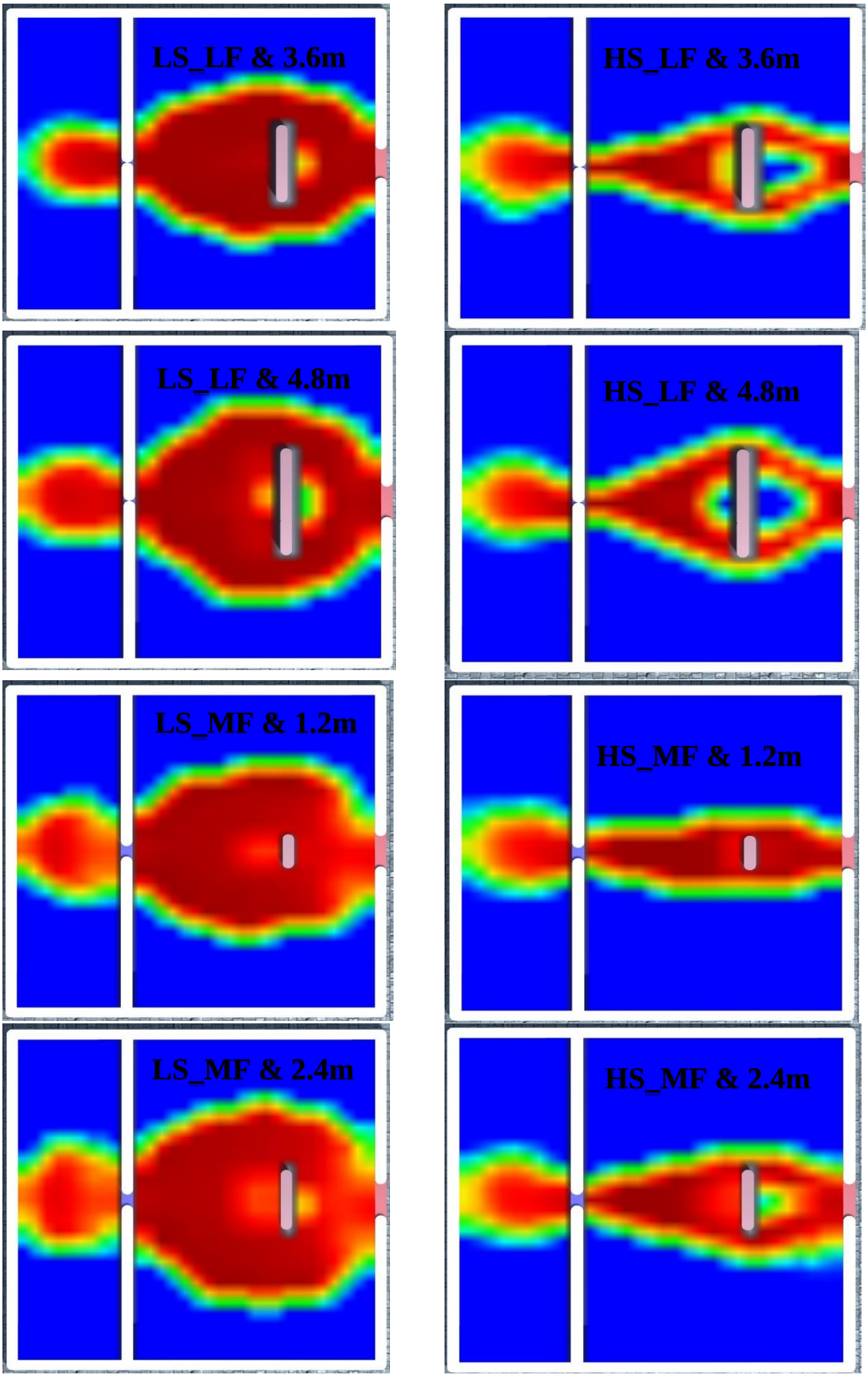
7.3.2.2 Comparison of individual velocity based on simulation outcomes

Figure 7.10 shows the individual velocities based on each agents' movements in the simulation. According to the figure, the average velocity for each agent in LS_LF & 1.2m was 1.1 m/s. The average velocity was 1.3 m/s in LS_LF & 2.4m, 1.1 m/s in LS_LF & 3.6m and 1.3 m/s in LS_LF & 4.8m. In

LF-HS experiments, the average velocity was 2.6 m/s in HS_LF & 1.2m, 2.1 m/s in HS_LF & 2.4m, 2.5 m/s in HS_LF & 3.6m and 2.4 m/s in HS_LF & 4.8m.

For MF conditions, the individual's average speed in the LS speed regime was 1.12 m/s in LS_MF & 1.2m, 1.18 m/s in LS_MF & 2.4m, 1.18 m/s in LS_MF & 3.6m and 1.14 m/s in LS_LF & 4.8m. In MF-HS experiments, the average velocity was 2.36 m/s in HS_MF & 1.2m, 2.24 m/s in HS_MF & 2.4m, 2.24 m/s in HS_MF & 3.6m and 2.18 m/s in HS_MF & 4.8m. For HF conditions, the average individual speed was 1.05 m/s in LS_MF & 3.6m and 1.01 m/s in LS_LF & 4.8m. In MF-HS experiments, the average velocity was 2.23 m/s in HS_MF & 3.6m and 2.89 m/s in HS_MF & 4.8m. A significant difference was found between the estimated individual average speeds at low and high speeds for all flow conditions with a 99% confidence level.




LS_LF & 3.6m
HS_LF & 3.6m
LS_LF & 4.8m
HS_LF & 4.8m
LS_MF & 1.2m
HS_MF & 1.2m
LS_MF & 2.4m
HS_MF & 2.4m

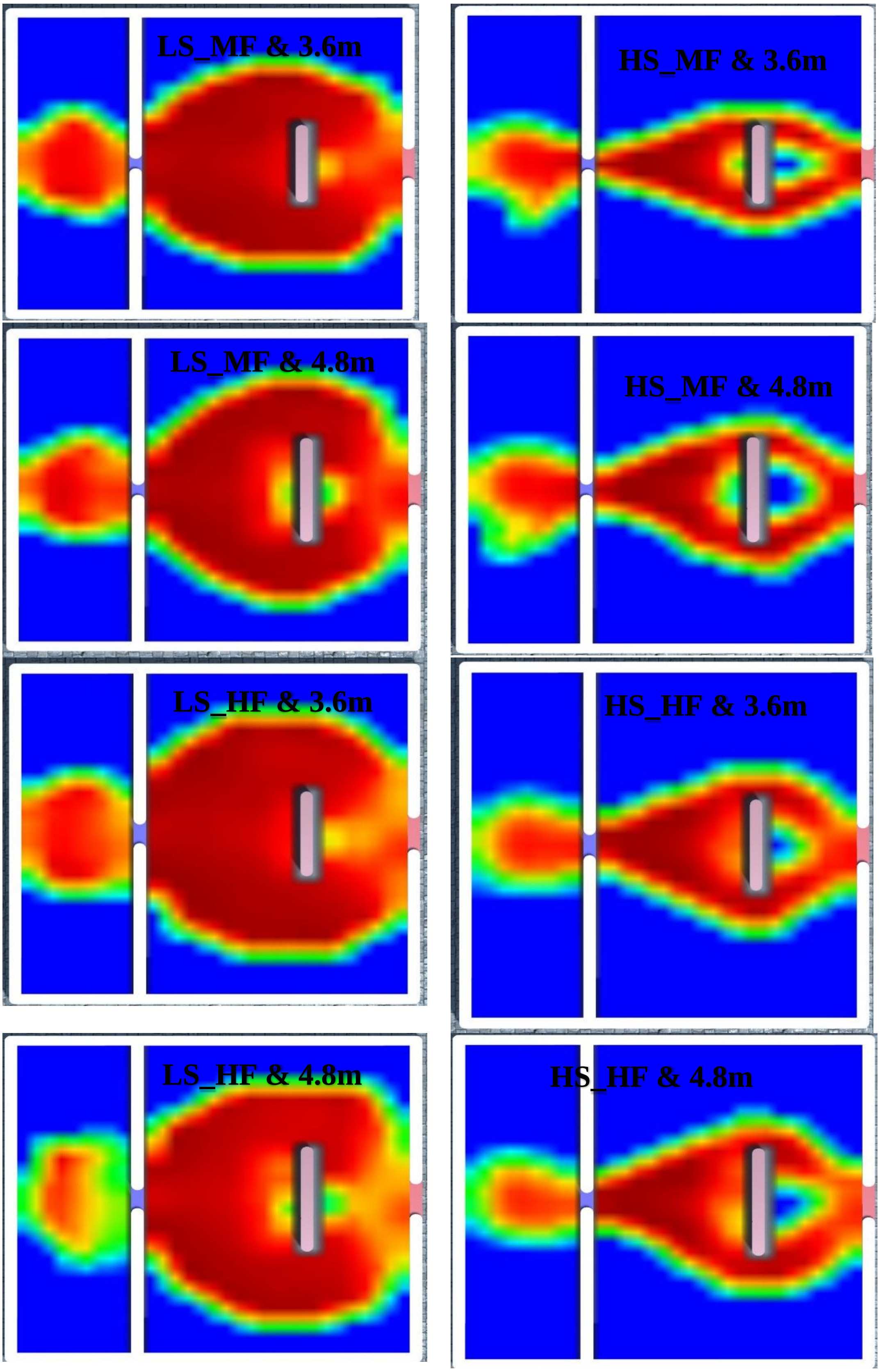


Figure 7.10: Comparison of individual velocity in each trial, based on the simulation outcome, at LS vs HS in LF (LF&1.2m, LF&2.4m, LF&3.6m and LF&4.8m), MF (MF&1.2m, MF&2.4m, MF&3.6m and MF&4.8m) and HF experiments (HF&3.6m and HF&4.8m).

7.4 Summary

In this chapter, we explored the herding behaviour assumption. This assumption was discussed in detail as the question of how the presence of others influences the pedestrian choice of direction while circumventing obstacles. We focused on investigating collective escape behaviour in the choice of direction by applying econometrics modelling concepts. Our results showed that 57.17% of the participants chose the minority direction and 42.83% chose the majority direction. The only sub-factors that affected the pedestrian's decision to follow the majority or minority exit choice were *W_Flow_Size_Diff*, *Diff_(Min-Maj)* and *Total_ ahead_ agent*. Low or high-speed levels did not significantly affect participants' decisions to follow the majority or minority direction. Next, we modelled these outcomes based on Stata software suggestions, which recommended that the factors *Speed_levels*, *W_Flow_Size_Diff*, *Total_ahead_agent*, and *Diff_(Min-Maj)* would enhance the model. To calibrate these outcomes, we assigned the outcome to the tactical level in the simulation based on three strategic steps that controlled behaviour: starting point, middle point and end point.

In the validation section, we compared the empirical data with the simulation data. Several factors were discussed in the above sections. For example, the average trajectories in each experiment describe collision avoidance behaviours in terms of the agent’s speed, travel time and travel distance as well as the lateral distance. With regard to the average trajectory, our results showed significant differences between the human empirical data and the simulation outcome at both speed levels. In terms of the average speed, the simulation was set up to use the same average speed for each individual in each experiment. With regard to travel time, our results found a significant difference between the empirical data and the simulation outcome in the low-speed experiment only. In contrast, in the high-speed experiment, the results were the same for human and simulation trials. The average travel distance in the simulation was higher than in the empirical data in low-speed experiments. Once again, however, there was no significant difference in the high-speed experiments. We also explored the average lateral distance in all experiments including at both speeds and in both types of trials. The average lateral distance was 0.45 in the empirical data and 0.48 in the simulation.

Chapter 8: Discussion and Conclusion

Understanding human interactions with common proximate physical objects, such as obstacles, is important in order to gain a better understanding of the effects of these objects on human movement characteristics. Our results allow the movement characteristics of pedestrians to be modelled using empirical data under different speed and density levels or flow rates. In this work, we have illustrated the general characteristics of avoidance behaviour as a collective movement. These experiments have enabled us to gain a comprehensive understanding of the characteristics of collective motion in walking facilities.

To our knowledge, this is the first time that empirical data related to several characteristics of collective behaviour and collective motion when passing different obstacles have been explored. Bierlaire, Antonini [90] stated that they were unable to obtain real data to apply to this work due to the lack of an appropriate data collection method. Therefore, they used modelling elements and simulation to present their work. They also detailed the two main methodologies used to describe the behaviour of an agent at an entry point, encoding this behaviour in the simulation tools by using the capabilities of agent-based simulation. Various factors were investigated to determine whether the subjects were affected by obstacles of different sizes.

Most of our results are related to socio-psychological factors and behaviours that vary for each person based on factors such as gender, age and culture [139]. For example, the average speed of young people differs from that of old people. The average speed of adolescent males is usually higher than that of adolescent females due to cultural attitudes and associations with regard to walking behaviour [3]. Therefore, our results could contribute to the literature and enhance many simulation models by exploring the collective movement behaviours of pedestrians in the crowd dynamics field with empirical data related to youth or students aged 21 to 25. According to the literature, one of the most important parameters affecting crowd behaviour is speed [90].

Our results suggested that in the low-speed experiments, different obstacle sizes did not affect the participant's speed while walking, as shown by the instantaneous speed and the speed in the movement direction. However, the obstacles caused an effect in high-speed experiments. Additionally, our results indicated that velocity in low flow rate experiments was a little higher than in medium flow rate and high flow rate experiments. The velocity decreased with an increase in the obstacle size in each experiment in the three flow levels, so the obstacle size had an effect in relation to both flow rate and speed level.

To explore the effect of the obstacles in both speeds, we had to apply the lateral speed method. Jia, Feliciani [87] conducted an experiment using a low-speed level, and they noted that the speed was not affected. Additionally, various factors were investigated to determine whether the pedestrians were affected by obstacles of different sizes. Regarding avoidance behaviour, according to a related study by [87], pedestrian behaviour while evading an obstacle was explored using only one density and speed level (walking scenarios). They observed that the pedestrians walked a certain distance and then changed their walking direction to go left or right. In one study, the point of direction change was between 0.8 m to 1.5 m from the obstacle, while another study located this point 2.0 m to 2.64 m from the obstacle [86]. However, our results showed that pedestrians responded to the obstacles earlier, according to the average trajectories in each experiment, preparing themselves to avoid any objects at both low and high speed. Pedestrians changed their walking or running direction to avoid obstacles at the entrance in experiments at all three flow rates.

Our outcomes with regard to travel time suggested that the effect of the obstacle size on average pedestrian travel time was unclear. Travel time did not display a constant upward or downward trend with increasing obstacle size. However, the results could change from one experiment to another depending on the pedestrians' speed and their interactions with other objects, such as obstacles, other pedestrians and the environment [140]. In terms of individual travel distance, our data showed that there was no significant difference in all the different flow rate experiments in both speed regimes, even though the data showed that individual travel distance in the high-speed regime was less than that in the low-speed regime.

The study also investigated the distance at the edges of the obstacles (the lateral space). The lateral space was between 0.3 m and 0.7 m in both low-speed and high-speed regimes. The average lateral distance for all of the experiments was 0.45 m, which could be used for simulation calibration in future studies. The outcome regarding lateral distance in our study fits well with the findings of some relevant studies. For example, the average lateral distance in [87] was 0.4 m in all layouts, and it was 0.45 m in a study conducted by Hoogendoorn and Daamen [113].

In addition, we calculated the safety distance, which refers to the minimum distance between the edges of the obstacles and the pedestrian's shoulders. Our results showed a significant difference between safety distances in low- vs high-speed regimes.

We also explored pedestrians' decisions to go left or right while facing an obstacle. We found differences in the average trajectory along the left- and right-hand side of the obstacle. Then, speed was calculated for each path based on the instantaneous speed of pedestrians on the same path. The results showed a significant impact on the pedestrian speed in 50% of all of the experiments on both left and right paths.

In the modelling section, we answered the following question: How does the presence of others influence the pedestrian's choice of direction while circumventing obstacles? After investigating several factors related to herding behaviour, our results showed that 57.17% of the participants chose the minority direction, while 42.83% chose the majority direction. The only sub-factors that affected the pedestrians' decisions to follow the majority or minority direction were *W_Flow_Size_Diff* (the difference in the distances between pedestrians on each path), *Diff_(Min-Maj)* (the difference between the numbers of people on each path) and *Total_ ahead_ agent* (the total number of agents). The speed level (low or high) did not significantly affect participant's decisions to follow the majority or minority direction.

We also compared the empirical data with the data from the simulation. Many factors were investigated, such as the average trajectories in each experiment, the agent's speed, travel time and travel distance as well as the lateral distance. In regard to the average trajectory, our results showed that there were differences between the outcomes of the human and simulated trials at both speed levels. In terms of the average speed, the simulation was set up to use the same average speed for each individual in each experiment. With regard to travel time, our results found a significant difference between the empirical data and the simulation outcome in the low-speed experiment only. In contrast, in the high-speed experiment, the results were the same for human and simulation trials. The average travel distance in the simulation was higher than in the empirical data in low-speed experiments. Once again, however, there was no significant difference in the high-speed experiments

In summary, the outcome of this study could be used to investigate the obstacles' positions, the exit locations, and the placement of obstacles around the exit to improve the movement of crowds under normal and emergency conditions. The rsults of this study could be used to ebnhance existing aganet based simulation and explore variety of scenarios of crowd movement at high density and prevent disaster and save lives.

8.1 Key finding

8.1.1 Empirical data analysis

In this study, I performed 20 experiments in an empirical investigation of human behaviour while passing different obstacles. I studied several characteristics in two distinct methods: the first method is by using data extracted from controlled laboratory experiments. And it changed this data, in a way that it can provide better results for understanding the avoidance behaviour of pedestrian crowds within different geometrical settings. Several aspects are analysed to explore human behaviour, such as (1) it refers to the impact of speed on pedestrian movement and this section to the speed investigation. (2) Finding the influence of obstacles in pedestrian behaviours and their components. This section contains several features, such as avoidance behaviour, travel behaviours and lateral behaviours. Each factor carries several subs-factors. For example, we find pedestrian behaviours while avoiding blocks, comparing the passage time to find the influence of hindrances on pedestrian movements, observing the impact of speed on pedestrian movement, and finding the lateral distances at the edges of the obstacles. (3) Deviation behaviour analysis based on left or right pedestrians going by using various flow rates in walking and running conditions. Several factors are calibrated and validated, after applying the tactical level in the second layer, and the social force model in the operational layer in the simulation software. And it extracts the second method data and generates the data from the simulation outcome after setting it to replicate the human movement. Data of both the methods are compared, under two different speed levels and varied flow rates, to support the reliability of current simulation models in an agent-based model.

8.1.2 Human experiments:

- Low -speed: A bar-shaped of different obstacles size used, 1.2m, 2.4m, 3.6m and 4.8m in three different flow date. The average speed in low flow experiment is (1.2m/s), in medium flow is (1.5m/s) and in high flow is (1.05 m/s)
- High- speed: A bar-shaped of different obstacles size used, 1.2m, 2.4m, 3.6m and 4.8m in three different flow date. The average speed in low flow experiment is (2.4m/s), in medium flow is (2.3m/s) and in high flow is (2.2 m/s)
- Flow rate level in low- speed: A bar-shaped of different obstacles size used, 1.2m, 2.4m, 3.6m and 4.8m in three different flow date. The average speed in low flow experiment is (1.1m/s), in medium flow is (1.1m/s) and in high flow is (1.1 m/s)
- Flow rate level in High- speed: A bar-shaped of different obstacles size used, 1.2m, 2.4m, 3.6m and 4.8m in three different flow date. The average speed in low flow experiment is (1.1m/s), in medium flow is (1.1m/s) and in high flow is (1.1 m/s)
- The results suggested that in the low-speed experiment, different obstacle sizes did not affect the participant's speed while walking, as shown in the instantaneous speed and the speed in the movement direction. However, the obstacles caused an effect while the participants were in high-speed experiments.
- The velocity decreased with an increase in the obstacle size in each experiment in the three flow levels, so the obstacle size had affected by the fresh flow and speed-levels
- There are no differences in avoidance behaviour in both speeds, the participants changed their walking direction from the beginning of each experiment
- The lateral distance and safety distance (the lateral spaces) were signification in both low and high-speed experiments
- Travel time did not display a constant upward or downward trend with increasing obstacle size.

8.2 Contributions

The contributions may be considered in the following:

- The novelty of this study is, to investigate in trajectories of these trials, which intended to gain other information that associated with the effect of obstacles on the human and explored it.
- Exploring the effect of the obstacles on the collective motion and several phenomena were analysed based on two different speed levels.
- The outcomes of this study could help support and validate pedestrian and crowd simulation models.
- A methodology/model had developed during the study to predict and enhance the safety of the crowd around obstacles and turning areas. This methodology/model will improve the current simulation models with the help of realistic human motion data in a complex environment. The methodology/model will also help to plan strategically for crowd dynamic in the indoor or outdoor environment for pedestrian dynamic, assess planning railway, public gathering space, subways, and stadium. It will help both public and private organizations in managing pedestrian dynamic in the city.

8.3 Future directions

Modelling and simulation of the interaction between the pedestrian and the natural environment are a matter of interest in crowd dynamics. Therefore, an understanding of Crowd Dynamic behaviour is significant to improve the safety of crowds in this field. Movement of people is affected by interactions with other individuals and the bodily environment. The interaction between humans around the visceral atmosphere is a means of concern in crowd dynamics and requires further studies investigating human factors during an emergency is not well understood and more studies are needed.Pedestrian simulation has been recognised as a robust framework and tools for understanding the characteristics and phenomena of a walker in a complex geometries environment and predicting crowd threats during an extreme event. However, for pedestrian simulation to get reliable numerical simulation outputs, the primary point is to calibrate with efficient experiment data and replicate the experimental aspects. One reason is that because of the unclear situation of the empirical data, which leads to serious limitations on the use of such models. Therefore, investigating the effect of factors, i.e. pedestrian competition levels (normal condition and emergency condition) and the number of crowds on the behaviour of pedestrians is urgency.

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