Journal of Advanced Transportation

Empirical Research on Pedestrians' Behavior and Crowd Dynamics

Lead Guest Editor: Milad Haghani

Guest Editors: Nikolai Bode, Maik Boltes, Alessandro Corbetta, and Emiliano Cristiani

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Editorial

Empirical Research on Pedestrians' Behavior and Crowd Dynamics

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The increasing urban population around the world means that transportation hubs and large-scale buildings host a rising number of users and occupants; and mass gatherings are more frequent than ever before. Therefore, the monitoring, design and management of crowded spaces in which people move on foot is paramount for urban planners, event organisers and safety authorities. A scientific approach to these problems requires data and this special issue is thus aimed at encouraging and collecting empirical research into pedestrian behaviour and crowd dynamics.

Different research questions and application areas mean that pedestrian behavior and crowd dynamics are investigated across a broad range of spatial and temporal scales. The papers collected in this special issue demonstrate that methodological and technological developments now make it possible to cover spatial scales ranging from confined bottleneck scenarios to city quarters and temporal scales from minutes to days. Similarly, this special issue also highlights the diversity of questions that can be and are being investigated empirically, including assessments of pedestrian behaviour on stairs, when boarding trains and in the presence of people with mobility impairments, for example.

Empirical data on pedestrian behavior and crowd dynamics is not only useful to directly inform our understanding or to facilitate the development of monitoring methodologies, but it also helps to test the theory developed in this field. A substantial research effort has been directed at investigating pedestrian behavior and crowd dynamics theoretically using mathematical or computational models [1–3]. Empirical data is essential to link numerical simulation models to real-life crowd phenomena to ensure that they represent the real world and hence can be used for prediction, planning and policy making. Although numerical models are often formulated for descriptive capabilities, it is not clear how they can be reliably utilised for prescriptive purposes [4]. In addition, it is also essential to ascertain via experimental or observational data the validity of the hypotheses that are obtained from models.

This special issue is in line with the increasing recognition that experimental and data driven studies of crowd dynamics have received in the last few years [5]. We hope that the publication of this special issue can further contribute to the harmonisation of research efforts in this field [6] and to address some of the research gaps outlined earlier. Ten papers were accepted for final publication and are briefly introduced below.

Sparnaaij et al. contribute a paper on the topic of calibration, as a topic that they describe "has received relatively little attention within the field of pedestrian modelling". Their paper highlights the fact that most methodologies proposed for calibration concern only a single movement type or a single metric and that this makes the applicability of such calibration procedures questionable. In addressing this topic, they pursue two goals: "(1) determine the effect of the choice of movement base cases, metrics, and density levels on the calibration results and (2) to develop a multiple-objective calibration approach". Their proposed calibration methodology is based on multiple normalized metrics that are combined as a weighted sum.

Two articles in this special issue are concerned with the flow of dense crowds through narrow bottlenecks. Seriani et al. conduct their study on the effect of the ratio between passengers boarding and alighting at metro stations. They utilise an innovative experimental method where, using a mock-up physical model of a train vehicle, they conduct a series of experiments under different load conditions. The paper by Geoerg et al. addresses how the presence of people with impaired mobility within the crowd affects the movement of pedestrians through narrow bottlenecks. In doing that, the authors use a heterogenous population of pedestrians in their corridor and bottleneck experiments. Their sample of participants includes a mixture of individuals with and without mobility impairment. In this case, the mobility impaired individuals are all wheelchair users. The authors show that the flow-density relation is strongly affected by the presence of participants with disabilities.

The contribution by Ye et al. focuses on the dynamics of pedestrian interactions in a relevant and ubiquitous scenario: staircases. The authors, employing real-life data collected in a metro station in Shanghai, China, investigate the occurrence of overtaking and avoidance behaviors at different levels of services. The analysis, which considers ascending and descending flows, employs macroscopic (frequencies, densities) and microscopic (distances) indicators to characterize critical densities at which these phenomena appear, are maximum, and disappear.

The paper submitted by Hasani et al. looks at a different angle, the safety of pedestrians when crossing roads at signalised intersections. Using multiple data sources and data mining techniques, the authors adopted automated video processing methods to identify signalized intersections with highest risk for walking and bicycling for the case study of the city of San Diego, California, USA.

Railway stations can be used for public transportation, work, commerce, and leisure. Jeong et al. present a method for identifying the indoor space characteristics by clustering trajectories of visitors according to the derived distribution of density, velocity and direction angle. Six categories emerge from the clustering indicating the quality of utilization efficiency, the level of mobility, and the level of comfort. Jeong et al. present a case study for the Samseong station in Seoul, South Korea.

The contribution by Wang et al. highlights the large spatial scales at which pedestrians' movements are being considered empirically by presenting a novel method for integrating localised automated pedestrian counts into pedestrian density maps that span entire city quarters. The substantial improvement in accuracy of these maps compared to existing approaches suggests that real-time monitoring of pedestrian traffic at the city level may soon become technically feasible.

The paper by Gao et al. provides a pedestrian simulation tool which combines the visibility graph at the strategic level, multi-stage route choice scheme at the tactical level, and a variant of the social force algorithm at the operational level. The resulting model can generate a collision-free global route including a local route planning model based on estimated passing time, thus incorporating the tendency of individuals to avoid congestion. The case of passengers passing through a series of gates in Beijing Subway is investigated in detail, comparing simulated and real data.

We, the guest editors, contribute a systematic review of three terms that have been discussed controversially in the pedestrian and crowd dynamics literature: panic, irrationality and herding. We show that there is no consensus in the definition and use of the former two terms, but that there is the nucleus of an empirical investigation of the broad concept often described as herding. We suggest that instead of using the vague concepts of panic, irrationality and herding, tangible and quantifiable terms be used to facilitate empirical and theoretical progress in the field.

In line with the recommendation of the review article by the guest editors, Haghani and Sarvi contribute a paper that aims to operationalise the concept of rationality in collective escape by attributing rationality to 'behavioural optimality'. Haghani and Sarvi suggest that such a shift in perspective can make it possible to measure and quantify the ill-defined notion of rationality in crowd dynamics. The authors make a distinction between behaviour optimality at the level of individuals and the collective level. They also emphasise on the necessity of establishing proper reference points at each level and demonstrate possible reference points for analysis of behaviour optimality using experimental data.

From this brief discussion of the contributions selected for this special issue, it is clear that pedestrian behavior and crowd dynamics are studied empirically across a wide range of spatial and temporal scales. Future work will continue to drive the development of more detailed, longer lasting and further ranging empirical investigation. We hope this special issue provides a useful snapshot not only of what is currently feasible but also of future direction of empirical research on pedestrian behavior and crowd dynamics.

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Conflicts of Interest

The authors declare that there is no conflict of interest.

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Research Article

'Rationality' in Collective Escape Behaviour: Identifying Reference Points of Measurement at Micro and Macro Levels

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Background. Evacuation behaviour of human crowds is often characterised by the notion of 'irrational behaviour'. While the term has been frequently used in the literature, clear definitions and methods for measuring rationality do not exist. *Objective.* Here, we suggest that rationality, in this context, can alternatively and more effectively be formulated as a question of 'optimal behaviour'. Decision optimality can potentially be measured and quantified. The main challenges, however, include (i) distinctly identifying the level at which we measure optimality, and (ii) identifying proper reference points at each level. *Methods.* We differentiate between optimality at the individual (i.e., micro) and the system (i.e., macro/aggregate) levels and illustrate how certain reference points can be established at each level. We suggest that, at the micro level, optimality of individual decisions can be quantified by comparing the outcome of each individual's decision to those of their 'nearly equal peers'. At the macro level, optimality can be measured by simulating the system using parametric numerical models and measuring the system performance while altering the behavioural parameters compared to their empirical estimates. *Results.* Having applied these methods, we observed that variation in micro level decision optimality rises rapidly as the space becomes more heavily crowded. As crowdedness increases in the environment, the difference between 'good' and 'bad' decisions becomes more distinct; and suboptimal decisions become more frequent. In other words, optimality at individual level seems to be moderated by the level of crowdedness. At the macro level, numerical simulations showed that, for certain exit attributes (like exit congestion), extreme marginal valuations (or preferences) were optimal, whereas for certain other attributes (like exit visibility), intermediate levels of valuation were closer to the optimal. In most cases, the natural observed (or estimated) tendency of evacuees (at the aggregate level) was not quite at the optimum level, meaning that the system could improve by modifying individuals' marginal valuations of exit attributes. *Applications and Recommendations.* These results highlight the importance of guiding evacuation decisions particularly in heavily crowded spaces. They also theoretically illustrate the potential benefit of influencing/modifying people's evacuation strategies, so they make decisions that are collectively more efficient. A crucial step to this end, however, is to identify what optimum strategy is and under what circumstances people are likelier to make suboptimal decisions.

1. Introduction

1.1. General Background. We consider the case of emergency escape of a crowd from an enclosed space with limiting capacities (relative to the level of occupancy). In such cases, particularly when facing imminent life-threatening dangers like a case of active shooter, occupants need to utilise exit capacities of their surrounding facility within a limited time-frame. As a result, capacities that may have been otherwise adequate to accommodate the discharge of the crowd become restrictive. Therefore, in such scenario, each individual would face a rather complex choice situation where the outcome (or payoff) of their decision would depend on those of other players involved. In addition to the environment-related attributes (like spatial distances and visibility or familiarity of escape paths), occupants may also take into account the social cues (i.e., the decisions of others) as further sources of information in order to optimise their decision. Some may

see a path chosen by many as the likely quickest option and thus decide to follow the majority's decision; and some may evaluate the same situation in the opposite way assuming that such escape alternative would be likely to further delay their escape. So, what would be the 'rational' strategy to choose?

1.2. Rationality in a Broader Context. When talking about the notion of rationality, it is important to differentiate between the colloquial and economical definitions. Such distinction has not so far been made in clear ways in the context of escape decision-making despite the prevalence of using this term. Colloquially, rationality refers to 'sensible' and 'predictable', 'goal-oriented', or 'consistent' patterns of behaviour. Therefore, from this perspective, rationality is violated as a result of purely random, impulsive, or purely imitative or conditioned decision-making behaviour.

The concept of "rationality" in the economic theories, however, has a rather clearer and more specific definition. It generally refers to a preference ordering that is 'complete' and 'transitive' leading to the action that maximises personal advantage [1]. When the observed decision-making behaviour of people, assumed as infallible payoff maximisers, deviates from the classic assumptions of axiomatic economic decision models (or that of the Homo-economicus [2, 3]), the deviation is often labelled as 'irrationality' [4, 5]. These idealistic assumptions are often relaxed by placing certain bounds on rationality [6–8]. There is a great wealth of research in behavioural and experimental economics literature on how and when people's choices violate these assumptions in financial contexts [9–12].

1.3. Rationality in the Context of Collective Escape. The term 'irrationality' has been loosely in use in the context and the literature of emergency evacuations and crowd modelling, often, without any particular reference to a clear and unified definition [13–15]. According to Drury, Novelli and Stott [16] "The notion of 'mass panic' has a number of problems, which are conceptual, empirical, and practical. Conceptually, while there are various definitions of 'panic', a distinguishing feature of all of them is the crowd's supposed irrationality" (p. 19). It is often stated, both anecdotally and even in the scientific literature, that humans tend to behave irrationally or make irrational decisions in emergency escape scenarios (or statements to that effect). Such statements are prevalent both in the scientific literature on this topic as well as among the general public and the social media. As one example among many, Kirchner and Schadschneider [17] have stated in their study that "we want to apply this model to a simple evacuation process with people trying to escape from a large room. Such a situation can lead to a panic where individuals apparently act irrationally" (page 261). However, as Chertkoff, Kushigian and McCool Jr [18] have put, "the concept of panic is vague and deciding what is rational and people think is rational is tricky business" (p. 118). While examples of citing this terminology in this context abound, a clear or at least operationalizable definition of this notion is still missing in this context. According to Wijermans [19] "The notion of irrationality is often used when people are not behaving in what is seen as the most effective way to achieve a goal, like fleeing out of a building while not following the emergency exits. However, the effectiveness of behaviour is compared to an ideal way of acting. It thus depends on whoever defines the effective or ideal way how and when the label "irrational" is used" (p. 15).

The concept of irrationality in escape decision-making has been so entrenched in the scientific literature that it is often treated as a given (but ambiguous) fact. As a result, computational models have been developed trying to represent irrationality in mathematical formulations, usually based on arbitrarily defined assumptions. While the term irrationality has been cited in ambiguous ways in this context, one thing has been very clear, and this is the fact that the term has been used in an inextricably linked way to the term "panic". Although the theory of mass panic, as a concept originated from sociology literature, has been very extensively criticised as an inaccurate theory [19–26] and has even been referred to by many authors as a "myth" [24, 26–31], the accompanying term affiliated with it, irrationality, still seems to be prevalently in use in evacuation modelling.

In many cases, the transition from rational normal behaviour and irrational panic behaviour is represented by a single parameter [20, 32, 33]. Often, the irrationality of behaviour is attributed to the imitative (or emulative) aspect of the behaviour [13, 14]. Recent empirical studies, however, have shifted, to some degrees, from this point of view [34] and empirical findings have provided evidence to the contrary of this assumption suggesting that people do not show strong imitative tendencies in many aspects of their decision-making behaviour during emergencies [35–39].

Previous studies have shown that emergency escape behaviour of humans is neither purely random nor purely based on imitation. People display consistent patterns of behaviour in their decision-making that can be modelled and thus predicted. Such empirical models have allowed the dominant behavioural patterns to be identified. The current state of the literature suggests that the behaviour resembles more like a multiattribute pattern of decision-making [37, 40–46] rather than decision-making based on single rules or criterion, a pattern that is fairly predictable based on a range of variables as opposed to being purely random. As a result, this body of empirical studies has increasingly ruled out the appropriateness of defining irrationality as a purely random form of decision-making in this context.

Given the above discussion, we believe that the debate around rationality of escape behaviour most likely concern the notion of decision 'optimality' (rather than imitative or purely random behaviour). From this perspective, this is still a relevant and also underexplored question. For example, as one of the recent studies that makes explicit reference to the term 'panic', Shen, Wang and Jiang [47] stated that "the stampede caused by panic usually endangers the human's life. Much effect has been focused on methods to efficiently escape from the threatened situations, such as optimal strategy involved mixture of individualistic behaviour to escape" (page 614). Measuring the optimality level would be helpful for identifying the circumstantial factors that moderate the rationality of choice in such context (i.e., circumstances

that makes choices less rational). This helps us identify the conditions under which humans' choice of escape strategy is more likely to suffer from the boundedness of rationality.

As mentioned earlier, in a scenario with constraining capacities and multiple exit alternatives, the effectiveness of the strategy chosen by each individual would depend on the decisions of others and thus cannot be estimated deterministically. In other words, the complexity arises mainly from the intensified significance of interindividual interactions when demand for utilisation of exit capacities suddenly heightens. Of course, in an observational setting, one should theoretically be able to evaluate the optimality of each decision observation by comparing the payoff associated with the chosen strategy with those of the nonchosen alternative strategies. But, as stated by Drury, Novelli and Stott [16] "To judge a response as irrational requires a frame of reference, but the frame of reference is often unclear in a mass emergency" (p. 19). That lays out a major challenge is defining and measuring rationality in an operationalizable way. Since the act of choosing the nonchosen alternatives (and thus, their associated payoffs) is not actually materialised, it cannot readily be determined whether the observed decision has been the optimal decision (and if not, how suboptimal the chosen strategy has been). In this decision context, payoffs are not exogenously given to the choice maker; rather, they are collective outcomes of interactive decisions [13, 14].

As suggested by previous studies "not all occupants pick an adequate destination or the optimal route" [45]. An evacuation of a crowded system is a dynamic system in which agents compete for limited resources while impacting each other's decisions. It that sense, such system can be viewed as a complex adaptive system [48]. Therefore, it still appears to be a fair question to ask whether individuals in such interactive and competitive decision scenarios can be assumed to be perfect payoff optimisers (with payoff being defined as the negative of their evacuation times) or will their behaviour fall more accurately in the category of 'bounded rationality' [8] or 'stochastic rationality'.

In order to answer that question (particularly, based on empirical observations), one major obstacle towards evaluating optimality of the decision strategy would be the estimation of payoffs for the alternatives that were not chosen by the decision maker. Here, we propose how the optimality of individual direction decisions can be analysed in a more tangible fashion by contrasting decisions of "nearly equal peers". In addition, we suggest that the problem can alternatively be analysed from the more aggregate (or collective) perspective of 'system optimality' as opposed to 'individual-decision optimality'. In fact, one may argue that optimality at the system level would possibly bear more relevance to practical applications of evacuation management, than optimality at the individual level. The distinction that we make between the notion of rationality at the individual and system level is in line with the suggestions of authors that have previously reflected on the concept of rationality. As Wijermans [19] pointed out "The notion of irrationality is often used when people are not behaving in what is seen as the most effective way to achieve a goal, like fleeing out of a building while not following the emergency exits. However, the effectiveness of behaviour is compared to an ideal way of acting. It thus depends on whoever defines the effective or ideal way how and when the label "irrational" is used". Therefore, the question from the system perspective (as opposed to the individual perspective) will focus on what strategies are collectively closer to optimum for the system of evacuees, regardless of the optimality for every single individual.

2. Methods

In this work, we would like to make an attempt of formalising and refining the use of the term irrationality in the context of escape behaviour. Having reviewed the recent studies in this field [36], our best assumption is that, in most instances where this term is cited in the evacuation dynamics literature, it is not a reference to purely random or purely imitative behaviour. At least the recent studies in this field indicate that. It seems that the term is being treated as more of a fancy terminology to refer to the fact that people may make "bad" or "suboptimal" decisions in escape scenarios. Therefore, we try to look at the problem from this perspective in this work. Our main focus will be on making distinctions between decision optimality at the individual and system levels and identifying possible ways to measure optimality by establishing proper reference points at each level.

The most important question that arises immediately is what defines how "good" or "bad" a decision is in this context, and how can we measure (or ideally, quantify) the optimality. And even more importantly, optimal from whose perspective, system, or the individual decision maker? The answer to these questions is of great importance given the increasing use of experimental studies of decision-making in this context that would provide observations to be explored by researchers for such quantitative analyses. With such empirical datasets becoming increasingly available, it would serve a purpose to have unified ideas of how the concept of rationality can be measured or analysed using such observations. Potential findings of such analyses can be eventually geared towards improving crowd and evacuation management strategies [49] and optimising evacuation processes in meaningful ways.

Let us assume that an individual's escape decision has been observed, either in an experimental or potentially in a real emergency. How can we know whether this decision has been good from that individual's perspective? Similarly, we can assume that a process of crowd evacuation has been observed experimentally (or potentially, in a real scenario). How can we know if that crowd has behaved in an optimal or suboptimal way? We refer to this as a system perspective to the question.

In this context, the objective of each individual in the system and the objective of (an imaginary) person who may wish to optimise the system are similar, and that relates to minimising the "evacuation time". However, each individual tries to make a decision that he/she believes would result in the shortest evacuation time for himself/herself, whereas, a system optimiser wishes the crowd to behave in a way that overall minimises the total evacuation time (or the average

of individual evacuation times). It is reasonable to assume that efficient decisions at the level of individuals would push the system towards more optimal states. Although, as proven mathematically in other interactive complex system of many-agents like transport networks [50–54], the states of social and individual optimum may not perfectly coincide and this necessitates the distinctions at these two levels.

Here, we limit the discussion to the exit-route decision-making, a choice between multiple discrete alternative exits. However, the general approaches we propose here could be potentially adopted to analyse rationality in relation to other aspects of evacuees' decisions. From an individual perspective, let us assume that an individual has made a decision in an escape scenario. The evacuation time can be measured for that individual. But how can the efficiency of that decision be measured in light of the evacuation time outcome for that individual observation? Clearly, for an individual who had multiple directional alternatives to choose from, the evacuation-time outcome can only be measured for the chosen alternative. For the nonchosen alternatives, the choice did not take place and one may assume that the potential evacuation time associated with those can therefore not be measured. In order for us to know the efficiency of that decision, it would be essential to know the evacuation-time outcome for all other directional alternatives that the person could have potentially experienced, had he/she chosen those alternatives. Here, we suggest that these payoffs/outcomes associated with the nonchosen alternatives can in fact be approximated and estimated in crowded scenarios. The only requirement is that there are enough people in the proximity of every individual. Since those neighbours may choose other alternatives, their decision can be used as a proxy.

Therefore, we suggest that, in crowded scenarios, the problem can be approximated. An escaping crowd is a system of many individuals who make a variety of decisions. While this is not a general rule, but in many physical setups, it is possible that a decision scenario experienced by an individual has been similarly experienced by his/her "equal" peers/neighbours, those who faced a very similar choice situation. The equal peers could be referred to all other individuals that were physically located in about the same place at about the same time as our individual of interest, and thus, faced a decision scenario with the same set of alternatives and approximately similar attributes to those of our individual of interest. We suggest that since various individuals make various decisions, comparing the outcomes of each individual's decision with those of his/her equal peers (who might have chosen other alternatives or strategies) may be an approximate way towards estimating decision optimality.

From a system perspective, however, the question is relatively more straightforward, but requires (1) prior empirically aggregated estimates of the behavioural tendencies (i.e., behavioural parameters) and (2) flexible computer simulation tools that embody those empirically estimated decision-making models (allowing the analyst to be able to alter behavioural tendencies in any direction and to any extent, even to extremes). In our earlier studies, we have reported on the aggregate calibration of multiattribute econometric choice models for directional escape decision-making of humans based on experimental disaggregate observations [42]. Such models, as we had indicated earlier, have the potential to be directly implemented for simulation and prediction should they are integrated with other required layers of modelling including the mechanical-movement layers.

These fully parameter models of choice offer certain advantages. Firstly, they can be directly calibrated through the experimental data should disaggregate observations are extracted from the experimental footage. Secondly, the parameters of these models carry tangible behavioural interpretations, as each show the valuation of the individuals for certain attributes. Therefore, the value of these parameters basically set the behavioural tendencies and changing those values would therefore be equivalent of changing the tendencies and strategies of decision makers. When applied for computer simulations, this offers a great opportunity for the analyst to manipulate different aspects of behaviour (on a continuum) and measure the system efficiency accordingly. This could be viewed as a way of creating a computational laboratory through which the optimum (or most rational, as some may prefer to say) types of evacuation behaviour could be investigated. We utilise this approach in this work in order to explore the question of behavioural optimality from an aggregate (or system level) perspective and in relation to direction choice-making.

3. Rationality Analysis at the Micro (Individual) Level

3.1. Experiment Setups. Following the method described earlier, we use observations of individual evacuation times from two sets of experiments. The experiments used in this work have been preliminary designed for data extraction and analysis of exit choice, as reported in an earlier work [42]. But here, we only extract and analyse individual evacuation time observations from these experiments and utilise them for the measurement of individual-level decision rationality. We use observations of 12 simulated escape scenarios from a set of experiments that performed in 2015, as well as 6 simulated escape scenarios from a set of experiments conducted in 2017. These subsets of scenarios have been selected from more general sets of experiments on the basis of three criteria. Firstly, we only picked the scenarios from each experiment that were most crowded. This includes scenarios for which we used all of our available participants (147 persons for the 2015 experiments and 114 persons for the 2017 experiments). Secondly, we only used the scenarios in which exit widths were limiting (those in which the exits were mostly 50cm wide). And thirdly, we only used the scenarios that we treated as "rapid evacuations" (as opposed to "orderly/slow evacuations"), those during which we instructed subjects to hypothesise an imminent life-threatening danger and run as fast as they desire.

A still image from each of these experimental scenarios has been provided in Figure 1. Across these scenarios, we had varying number of exits available in the escape environment

Figure 1: Still images from each experimental scenario. Subplots 1-12 represent the scenarios from the experiment performed in 2015 (with 145 participants) and subplots 13-18 represent the experimental scenarios performed in 2017 (with 114 participants). Within each set of experiments, each scenario is unique and differs from others based on the number of available exits, the locations of exits, or the presence of barricades.

(between 2 to 5 exits, depending on the scenario). We had all the participants wait in the holding areas (one holding area for the 2015 experiments, and two holding areas for the 2017 experiments) and asked them to run into the experimental room and escape it. We video-recorded the movement and movement trajectories of each individual were extracted one by one, in order to generate disaggregate exit choice observations. As side information, however, we also measured and extracted each individual's evacuation time. The processes of the video-tracking and choice data extraction have been detailed in [42].

3.2. Measurements and Outcomes. In both of the experiments mentioned earlier, individuals flow into the evacuation room

Figure 2: Scatterplots of the individual evacuation times for a sample of four experimental scenarios. Each plot orders the individuals based on the time of their appearance (entrance) in the system. On each plot, a pair of points have been singled out. Each of these pairs of points represents two individuals who entered the environment consecutively (at nearly the same time), but their decisions had majorly different outcomes in terms of the evacuation time.

from the holding areas. Therefore, the participants appear in the system in a certain order. Once we extracted the individual evacuation times, we ordered them on the basis of the time (i.e., the frame number) at which they appeared in the system (i.e., the evacuation room). Using scatterplots (Figures 2 and 3), we then visualised the evacuation times of individuals in each scenario based on their order of appearing in the system. This way, the points that are within a close range according to the horizontal axis (which represents the order of entrance) are related to the individuals who faced approximately similar choice situations (i.e., those who stepped into the room at about the same time). Therefore, the evacuation times of these individuals are approximately comparable as they are "(nearly) equal peers". In Figure 2, we have singled out and exampled the scatterplots associated with four of those scenarios while the full analyses have been reported in Figure 3.

We observed that the scatterplots of individual evacuation times ordered based on the moment of their appearance in the system shows an upward trend. This was intuitively expected given that, as time went by, more and more individuals entered the room in each scenario and the room became more congested. The first individuals who entered the room faced a choice of exit in a lightly crowded room, and as the congestion built up, subsequent individuals faced exit choice in more crowded situations; therefore evacuation times increased by the order of entrance.

What was not intuitive and only became apparent after this analysis, however, was the heteroscedasticity effect that we observed in the scatterplots. Individuals who entered first (and thus faced lightly congested scenarios) had similar values of evacuation times to one another. This is similar to and indicative of a condition described by equilibrium in which no agent can unilaterally increase their payoff by shifting their decision to a different direction strategy. Therefore, this indicates that when the room was lightly congested, individuals predominantly made optimum exit decisions. However, according to the graphs, such equilibrium-like condition that appears to exist in the beginning of evacuation process (where evacuation time of equal peers is nearly equal) is disturbed as the congestion grows in the space. Subsequent individuals who entered the room made decisions that were increasingly and notably different from one another in terms of the efficiency of their outcomes. As a result, the plots become more scattered around the trend line as one moves forward along the horizontal axis. This means that when the space was not heavily crowded, the difference between the good and bad decisions was not substantial, but once the

Figure 3: Scatterplots of the individual evacuation times for all 18 experimental scenarios, along with the "irrationality index" visualised at each point in time, shown by the orange fluctuating lines and represented by the right vertical axes of each plot.

crowd built up in the space, the difference between good and bad decisions became more noticeable.

In Figure 2, we have singled out and exampled a number of cases in which (nearly) equal peers made directional decisions with substantially different outcomes. For example, in part (a) of this graph set, we have singled out individuals number 116 and 117 who were (nearly) equal peers and appeared in the system consecutively (i.e., at about the same time), but one escaped the room in less than 5 seconds and the other escaped in nearly 14 seconds. There is a nearly 180% relative difference between the optimality of the decision of these two individuals. In other words, given the condition of the system at the moment that individuals 116 and 117 entered the system, individual 117 could have unilaterally switched his/her exit direction strategy to that of individual 116 and received a nearly 180% greater payoff. This was the pattern that we exclusively observed when the scenarios were heavily crowded and when the exit capacities were limiting. As the space became even more crowded, more individuals made suboptimal (or irrational) decisions, and the difference between good and bad decisions became more substantial.

The scatterplots associated with all 18 scenarios have been reported in Figure 3. In addition, in order to make an attempt to give more quantitative elements to the conceptualisation of the individual-level decision irrationality, we also defined, quantified and visualised an "irrationality index" at each point in time (shown by the fluctuating orange lines and represented by the right vertical axes in each scatterplot). To measure this index, we calculated the moving maximum and the moving minimum of the individual evacuation times (with a step size of five individuals) after we sorted the individuals based on their moment of appearance in the system. The relative percentage of difference between the moving maximum and the moving minimum at each point in time determines the irrationality index at that point in time in the system. A large value of irrationality index at a particular point in time in the system indicates a large difference between the optimality levels of the "best" and the "worst" decisions made in the environment around that time. This measure (as an empirical measure of irrationality and not a theoretical formulation of the concept) is subject to large variations over time. Nevertheless, in majority of cases, the irrationality index generally increased by time or peaked in the middle of the evacuation process, substantiating our previous observations as to the increasing occurrence of (relatively) bad decisions at about the peak of the congestion in the system.

In relation to this conceptualisation of the rationality, one word of caution seems to be necessary. The irrationality index, as we defined it in this case, does not give us enough information to conclude whether or not the increasing occurrence of the bad decisions (or the increasing difference between the good and bad decisions) is purely a result of individuals becoming less capable of choosing the best directional way when facing a decision in more crowded situations. This could as well be partly the result of bad decisions being inherently more consequential when the place is more crowded. These two explanations, however, are not mutually exclusive; and it is possible that this observation is the result of a mixture of both these effects to certain extents.

Our analysis of the optimality at the individual level identified the effect of crowdedness level as a moderator of the decision optimality. From a practical perspective, this highlights the importance of providing guidance [55–59] or assisting the decisions of evacuees, when the evacuations take place in heavily crowded facilities.

4. Rationality Analysis at the Macro (System) Level

4.1. Simulated Experiments Setup. For the analyses of optimum behaviour from a system perspective, we computer-simulated a variety of systems (or evacuation setups) while varying the behavioural tendencies of simulated agents in terms of their exit decision-making behaviour. We devised two general physical geometry (geometry 1 and geometry 2), shown in Figures 4 and 5, respectively. Each setup has three exits of equal size. However, in light of the previously mentioned observation as to the effect of the crowding level on decision optimality, for each general geometry, we examined three levels of general crowding by creating setups with various exit widths. We examined three different widths of exit: 150cm, 100cm and 50cm, to create three general levels of crowding in each geometry. Therefore, in total we simulated six different simulated setups. Setup 1 (geometry 1, exit widths=150cm), setup 2 (geometry 1, exit widths=100cm), and setup 3 (geometry 1, exit widths=50cm) have been shown respectively in subfigures (a), (b), and (c) of Figure 4. Setup 4 (geometry 2, exit widths=150cm), setup 5 (geometry 2, exit widths=100cm), and setup 6 (geometry 2, exit widths=50cm) have been shown respectively in subfigures (a), (b), and (c) of Figure 5.

In each setup, we simulated the evacuation of 400 agents. For the setups of geometry 1, agents are generated at the rate of 15 per second in an auxiliary rectangular room from which they enter the main room through a wide intermediate gate. For setups of geometry 2, there were two auxiliary rectangular rooms (one at each side) and agents were generated at the rate of 10 per second in each one.

4.2. Simulation Method. The simulation tool that we have developed has three main layers of modelling active for the setups that we analysed in this work. These are exit choice, local pathfinding, and step-taking modules. At the highest level of the modelling, we generate (i.e., probabilistically simulate) a choice of exit for each simulated agent [60–63] once they enter the main multiexit room. The choice is simulated from a multinomial logit model (see (1)) with five attributes (see (2)). At the moment of decision-making for each simulated agent n (i.e., the time step at which n enters the multiexit room), we measure the following attributes for each exit i.

$(DIST)_{in}$ The spatial distance (in meters) from the position of agent n to the centre of exit i.

$(CONG)_{in}$ The size of congestion (queue) at exit i.

(a) (b) (c)

Figure 4: Still images from the simulation setups 1, 2, and 3 (Images (a), (b), and (c), respectively). The three setups share the same type of geometry except for their widths of exits. In setups 1, 2, and 3, exit widths are, respectively, 150cm, 100cm, and 50cm. Therefore, they create evacuation scenarios in the same geometric layout and under three different levels of crowding.

(a) (b)

(c)

Figure 5: Still images from the simulation setups 4, 5, and 6 (Images (a), (b), and (c), respectively). The three setups share the same type of geometry except for their widths of exits. In setups 1, 2, and 3 exit widths are, respectively, 150cm, 100cm, and 50cm. Therefore, they create evacuation scenarios in the same geometric layout and under three different levels of crowding.

$(FLOW)_{in}$ The size of flow (the number of agents) moving to i.

$(VIS)_{in}$ The visibility status of exit i from the position of agent n, equating 1 if visible and 0 otherwise.

The variables $(FLTOVIS)_{in}$ and $(FLTOINVIS)_{in}$ are composite variables that interact the FLOW and VIS variables: $(FLTOVIS)_{in} = (FLOW)_{in} \times (VIS)_{in}$ and $(FLTOINVIS)_{in} = (FLOW)_{in} \times (1 - (VIS)_{in})$. See Figure 6 for a visual illustration of these attribute measurements. In these formulations, P_{in} and V_{in} are respectively the probability and utility of exit i for agent n, S_n is the choice set (set of alternative exits) for agent n, and β's are utility coefficients. During the simulation analyses, we vary the value of these parameters one at a time while keeping the value of others constant. Therefore, we need some base values for these parameters. These base values have been calibrated based on a set of 3015 disaggregate exit choice observations extracted through image processing of the 2015 experiments described earlier. For each individual in the experimental setting, the choice and the attributes of the different alternatives in that choice situation were extracted in a consistent way with the definitions of the exit attributes detailed above (see images (b) and (c) in Figure 6 for illustrations of the choice data extraction process). A maximum-likelihood estimation method was applied to this dataset of disaggregate choice observations to calibrate the parameters of the utility function in (2). These calibrated

(a) (b) (c)

Figure 6: Visual illustration of the exit attributes during the simulation process (image (a)) and during the data extraction process (image (c)). The choice of exit is modelled based on five variables obtained from four different attributes. These attributes include spatial distance (DIST), congestion level (CONG), flow sizes (FLOW), and visibility (VIS) associated with each alternative exit.

(a) (b) (c)

Figure 7: Visual illustration of the spatial grid and penalty weights (image (a)), shortest weighted paths (image (b)) and actual mass trajectories of movements (image (c)). The presence of other pedestrians penalises the nodes and their adjacent links on the spatial mesh (grid) (image (a)). For every simulated pedestrian, once the choice of exit is simulated, the shortest weighted path on the grid is calculated between the location of the pedestrian and the mid-point coordinate of the chosen exit. That shortest path is subsequently truncated to generate a smooth path (image (b)).

base values are as follows: β_1=-0.256, β_2=-0.138, β_3=-0.024, β_4=+0.093, and β_5=+0.710.

$$P_{in} = \frac{\exp\left(V_{in}\right)}{\sum_{j\epsilon S_n} \exp\left(V_{jn}\right)} \tag{1}$$

$$V_{in} = \beta_1 \left(DIST\right)_{in} + \beta_2 \left(CONG\right)_{in} + \beta_3 \left(FLTOVIS\right)_{in} + \beta_4 \left(FLTOINVIS\right)_{in} + \beta_5 \left(VIS\right)_{in} \tag{2}$$

The simulated choice of exit for agent n is subsequently communicated to the lower level of simulation modelling, the local pathfinding algorithm. The algorithm is basically a weighted shortest path algorithm that is run on a spatial grid system overlaid on the movement space. This grid system discretises the space. See Figure 7(a) for a visualisation of this grid. The links and nodes of this grid or mesh system are penalised by the presence of pedestrians and barricades. The algorithm returns the shortest weighted path that connects the location of the agent to the chosen exit as well as a

Figure 8: Visual illustration of the final modelling step of the simulation process, the step-taking model. This layer of simulation is a calibrated social-force module. The virtual forces from other agents and the walls as well as the driving force of the agent (determined by the local pathfinding algorithm illustrated in Figure 7) are calculated and the net force determines the point is space to which the pedestrian moves at each time step of the simulation process.

truncated version of this path to produce smooth movement patterns. The algorithm is basically equivalent of an A∗-pathfinding algorithm as a widely used method in computer gaming [64]. The paths are updated at a certain frequency to take the changes of congestion distribution in the environment into account. See Figure 7(b) for a visualisation of these paths at a particular moment of simulation for all agents in the scene. Figure 7(c) visualises the actual trajectories of all agents in the scene as well as for those already evacuated.

The information generated form the truncated weighted shortest path algorithm for agent n is then communicated to a lower layer of modelling, the step-taking module. This layer is basically a calibrated but standard social-force model [65]. This information determines the desired direction and therefore the desired force of agent n which in combination with the social and wall forces determines the next step of the pedestrians at each time step of the simulation. The simulation is run at a time resolution of 0.0001 second. See Figure 8 for a visual illustration of this layer of the model; and see [66] for details of the parameter calibration of the most critical social-force parameter based on empirical data. See the online supplementary material of this article for a sample video of the simulation calculation process (available here).

In our simulation analyses, for each given setup, we attended to one parameter of the exit choice model at a time. For any given value of that parameter, we simulated the setup 50 times (we call it a simulation cycle) and measured the total evacuation time and average individual evacuation time at each run and subsequently averaged those quantities over the entire cycle. We varied the values of the parameters at small increments until we reached the regions of insensitivity. Nearly 100 values were examined for each parameter. Given that we had 6 different simulation setups and 5 parameters, a total of nearly 6×5×100×50=150'000 simulation runs were performed. The duration of the calculations depended on various factors, most importantly, on the type of the setup, with heavily congested setups taking the most amount of time to calculate. With a rough average of nearly 30 seconds per run, more than 1200 hours of computation was necessary for these analyses.

4.3. Simulation Outcomes. The outcomes of the simulation analyses have been summarised and reported in Figures 9–13. These figures are respectively related to the analyses on the values of the coefficients for DIST, CONG, FLTOVIS, FLTOINVIS and VIS (labelled as "marginal utility" for those attributes). In each figure, the measurements of the total evacuation time and average individual evacuation times have been plotted respectively by solid blue lines (represented by the left vertical axis) and dashed red lines (represented by the right vertical axis). The error bands represent the standard deviations of the measurements. On each plot, we have also superimposed by vertical lines the value of the base (i.e., estimated) parameter (on the horizontal axes of the graphs) as well as its empirically estimated 95% confidence interval. This may as well be interpreted as the "natural" or "observed" level of valuation for that attribute in contrast to the values that we synthetically superimposed and simulated during these analyses.

One interesting and preliminary observation was that both measurements that we examined showed, in most cases, a consistent pattern of variation. There were strong correlation and parallels between the variations of the total evacuation time and individual evacuation times as a result of changing the marginal utility values. This may be regarded as a secondary observation of our analyses with implications for formulating optimisation programs of crowd evacuation

Figure 9: Variations of the simulated total evacuation times (blue solid lines; left vertical axis) and simulated average individual evacuation times (red dashed lines; right vertical axis) as a result of changes in the marginal utility of DIST attribute in exit decision-making of the simulated evacuees. Error bands show the standard deviations of the measurements. The vertical solid lines represent the empirically estimated value for the marginal utility of DIST, and the vertical dashed lines visualise the 95% confidence interval of that estimate.

[67]. The finding suggests that these two measurements can be used in an exchangeable way as the objective function of the evacuation optimisation programs.

According to Figure 9 (on the effect of the marginal utility of DIST parameter on aggregate evacuation times), the effect of transformation from a dominant distance-minimisation strategy (associated with extremely large and negative values for the DIST parameter) to a dominant distance-maximisation strategy is detrimental to the efficiency of the system. According to the majority of the setups that we simulated, as soon as the parameter of DIST enters the positive zone, simulated evacuation times increase sharply. However, there is limit on how much the system can benefit from amplifying the distance-minimisation tendency in exit decision-making. In most cases, moderately negative or extremely negative values for this parameter, both had the same outcome for the system. The observed (or natural) magnitude of valuation for this parameter was observed to be in the efficient zone according to the majority of the setups. In other words, the collective efficiency of the system could not be much improved by unilaterally changing the marginal valuation of the DIST. The estimated valuation for this attribute based on the observed behaviour (i.e., empirical estimates of this parameter) seemed to be close to the optimal, indicating that individuals are relatively good at minimising distances.

According to Figure 10 (on the effect of the marginal utility of CONG parameter on aggregate evacuation times), almost monotonically and almost irrespective of the simulated setup, the crowd benefits from amplified avoid-the-congestion tendencies (associated with larger negative values for the CONG parameter), and vice versa. Positive valuations of the CONG factor harm the system, but the amount of the harm does not increase much by further amplifying the parameter in the positive zone. The lines of variation flatten out as soon as we enter the zone of positive values for this parameter. The natural estimated behaviour of humans was not in a highly suboptimal zone, but the system could potentially benefit from further amplification of the avoid-the-congestion tendency, according to our analyses. In other words, according to these simulated outputs, in majority of the scenarios, the system could benefit by unilaterally

Figure 10: Variations of the simulated total evacuation times (blue solid lines; left vertical axis) and simulated average individual evacuation times (red dashed lines; right vertical axis) as a result of changes in the marginal utility of CONG attribute in exit decision-making of the simulated evacuees. Error bands show the standard deviations of the measurements. The vertical solid lines represent the empirically estimated value for the marginal utility of CONG, and the vertical dashed lines visualise the 95% confidence interval of that estimate.

amplifying the marginal valuation of CONG, meaning that people are not collectively perfect in minimising evacuation time through avoiding the congestion in their decisions. An amplified tendency to avoid congestion (compared to the estimated tendency) can make the system more efficient. This observation does not mean that individuals do not have an inherent tendency to avoid congestion. It might rather be attributable to the fact that they cannot evaluate congestion attributes with great accuracy in crowded spaces. This is consistent with our observation at the individual level that showed that at higher levels of crowdedness, suboptimal decisions become more frequent.

Figures 11 and 12 present the outcomes of the simulation for the FLOW variables, for the visible and invisible exits respectively. The outcomes of the simulation for these two parameters were largely case sensitive and the patterns of variation differed substantially across the simulated setups. According to Figure 11, for example, the simulated setup 2 is nearly insensitive to the valuation of the FLTOVIS parameter in exit decision-making, whereas, setups 1 and 3 are highly sensitive to the value of this parameter. For these two setups (which are respectively lightly and heavily crowded scenarios relative to setup 2 which is moderately crowded), the system could benefit from positive valuation of this attribute to certain degrees. According to these two setups, as the value of FLTOVIS parameter increases (whose interpretation is magnifying the tendency to follow the crowd flows moving towards visible exits), aggregate evacuation times decrease but there is a limit to this. The evacuation times increase sharply again when the value of this parameter tends to the two extremes. Setup 4, however, indicates that the benefit of increasing the marginal utility of FLTOVIS attribute is almost monotonic. A Similar pattern of substantial case-sensitivity was also observed in relation to the marginal utility of the FLTOINVIS attribute.

According to Figure 13 (on the effect of the marginal utility of VIS parameter on aggregate evacuation times), according to the majority of the setups, there is an intermediate optimum for the valuation of choosing visible exits in exit decision-making. According to the majority of the setups (except for the setup 4), extreme valuation for the marginal utility of VIS is suboptimal. In other words, both choosing-only-visible-exits and choosing-only-invisible-exits strategies are suboptimal strategies. The system can benefit the

Figure 11: Variations of the simulated total evacuation times (blue solid lines; left vertical axis) and simulated average individual evacuation times (red dashed lines; right vertical axis) as a result of changes in the marginal utility of FLTOVIS attribute in exit decision-making of the simulated evacuees. Error bands show the standard deviations of the measurements. The vertical solid lines represent the empirically estimated value for the marginal utility of FLTOVIS, and the vertical dashed lines visualise the 95% confidence interval of that estimate.

most from a positive but moderate degree of valuation for this attribute in exit decision-making. The natural estimated valuation of humans for this attribute appeared to be relatively close to this optimal region. However, in the majority of the scenarios, it was possible for the system to unilaterally become slightly more efficient by decreasing the marginal valuation of VIS.

5. Summary, Discussions, and Future Research

5.1. Summary of Findings. This study was aimed to be one of the first attempts to formalise the ambiguous notion of "rationality/irrationality" used in relation with the escape behaviour of human crowds. In doing so, we drew a clear distinction between the colloquial and economic definition of the rationality, also between the rationality at the individual and system levels. We suggested that the existing body of empirical research in this field has overwhelmingly shown that humans' escape decision-making behaviour is not purely imitative or purely random. Rather, empirical testing is predominantly suggesting that humans make such decisions in a fairly predictable manner while considering a combination of factors (as opposed to pure imitation). Therefore, we concluded that such evidence rules out the relevance of defining irrationality as purely random and unpredictable behaviour. The general suggestion of our study was that it would be of benefits for the research in this area to look at this problem from a more tangible and operationalizable perspective of "optimality" which has more practical implications. The difference that this transition in terminology and perspective can make is that decision optimality can be measured and even be quantified, as opposed to the ambiguous term irrationality which offers mixed connotation and no clear way to be measured. For the first time, we empirically tested the optimality of escape decisions using experimental observations as well as numerical simulation testing.

As a proof of this concept, we suggested that decision optimality can be viewed and even measured from both microscopic and macroscopic perspectives. At the level of individuals, we suggested that the optimality of decisions can be measured in terms of their evacuation time outcomes and

Figure 12: Variations of the simulated total evacuation times (blue solid lines; left vertical axis) and simulated average individual evacuation times (red dashed lines; right vertical axis) as a result of changes in the marginal utility of FLTOINVIS attribute in exit decision-making of the simulated evacuees. Error bands show the standard deviations of the measurements. The vertical solid lines represent the empirically estimated value for the marginal utility of FLTOINVIS, and the vertical dashed lines visualise the 95% confidence interval of that estimate.

in contrast with those of the equal peers (who might have chosen different strategies). Applying this simple concept to a series of experimental observations, we identified a connection between the optimality of individual decisions and the level of crowding in the environment. Our observation indicated that when individuals face a choice scenario in a heavily congested situation, the difference between the optimal and suboptimal decisions magnifies.

From a macroscopic system perspective, we suggested that fully parametric choice models offer the possibility of measuring behavioural optimality using computer-simulated experiments [68, 69]. The fully parametric approach can be viewed as establishing a computational behavioural laboratory [70] that would allow the analyst to numerically explore various behavioural strategies. Applying this approach, we identified certain types and degrees of (close-to-optimal) exit attribute valuations that can benefit crowd evacuation systems.

For certain attributes, like exit visibility, extreme levels of valuation were suboptimal and intermediate valuation was instead closer to optimal. The interpretation of this is that, an always-choose-the-(in)visible-exit strategy (associated with an extreme valuation of this attribute) is not likely to be an optimal exit strategy. For certain attributes, like distance to exit, extreme valuation was only suboptimal in one direction (i.e., the positive direction). The negative direction was closer to the optimal. For certain attributes, like exit congestion, extreme valuation in one direction was in fact the optimal valuation. Results indicated that a crowd of evacuees will not incur detriment from an amplified avoid-the-congestion strategy (although the marginal benefit of the negative valuation of this attribute diminishes at some point). For certain other attributes, there appeared to exist significant amount of case-sensitivity in regard to the level of valuation that is beneficial to the system. Therefore, there appears to be no universal type of optimum valuation for those attributes.

5.2. Discussions. Our numerical analyses at the macro level is an addition to an emerging stream of studies that attempts to identify optimal behaviour during evacuations [47] using parametric models and flexible simulation methods that allow modification of behaviour through their parameter

Figure 13: Variations of the simulated total evacuation times (blue solid lines; left vertical axis) and simulated average individual evacuation times (red dashed lines; right vertical axis) as a result of changes in the marginal utility of VIS attribute in exit decision-making of the simulated evacuees. Error bands show the standard deviations of the measurements. The vertical solid lines represent the empirically estimated value for the marginal utility of VIS, and the vertical dashed lines visualise the 95% confidence interval of that estimate.

settings. This approach appears to be a simple but practical solution to answering a range of questions that this field has raised so far with potential practical applications in crowd management. Questions that could be addressed based on this approach can embody both the mechanical locomotion aspect of evacuation behaviour [71] such as 'whether rushing to exits and displaying competitive behaviour could be an optimal conduct in evacuations' [66, 72, 73] to decision-making and strategic aspects of the behaviour. The questions of decision optimality are much more diverse and can include aspects such as 'should all agents decide to initiate their movement at the same time or certain degrees of waiting strategy could mitigate the congestion and thus benefit the system?' [74, 75]. 'Does herding strategies in decision-making benefit/hurt the system and if so, to what extent?' [76] Or similarly, 'does herding in decision adaptation (as opposed to decision-making) benefit/hurt the system, and if so to what extent and under what conditions?' [77].

Questions of this nature are quite diverse and can advance capabilities of evacuation managers for training and providing general advice [78]. Here, we only focused on crowds of homogenous composition where the behavioural tendencies of evacuees are generated, in a probabilistic fashion, from the same decision-rule and utility coefficient set. An extra dimension that could to be recognised is the individual variation (or heterogeneity) in strategy choosing that also could be subjected to tests of optimality using numerical analyses [79–81]. This stream of behavioural optimisation studies can be regarded as a complementary domain to that of the architectural optimisations that seek to facilitate evacuations through physical modifications of the environment (as opposed to the behaviour of evacuees) [82–85] or the approach of route-planning optimisations [67, 86–94].

In performing our macro scale analyses, we modelled the agents as utility maximisers (with varying forms and degrees of preferences). This leads to a question as to whether such practice would be in contradiction with our previous observations that showed not every agent's decision is necessarily an optimal decision? Can we still think of evacuee agents as utility maximisers? [95–97] Or taking it even further, given the time limit that the individuals face for making escape decisions, would evacuees be even capable of

evaluating utilities [98]. Answer to these questions should be given in consideration of multiple factors as discussed below.

Firstly, evacuation time (i.e., the choice outcome) and utility (i.e., representation of preferences) in this modelling framework were treated as two different entities. The utility model stipulates that the agent chooses the direction with maximum perceived utility (i.e., the preference) while agent being under the implicit assumption that such choice would lead to the minimum possible evacuation time (i.e., the indirect choice outcome/payoff). In other words, the assumption is that the individual chooses the strategy with the greatest perceived desirability (utility), but this may or may not translate to the most optimum outcome and that is permissible within the framework of the random-utility maximisation theory. From that perspective, evacuees' lack of perfect ability to minimise evacuation time is not a contradiction of the utility maximisation assumption. Discrete choice models do allow and account for errors in judgment and perception. Therefore, observation of imperfect individual decisions is in fact consistent with the outputs of discrete choice models.

5.3. Directions for Future Research. As a final note, the authors wish to clarify that this paper was not meant to set an absolute benchmark for measuring decision optimality in evacuations. The main purpose of our study was to make an actual transition from the relatively ambiguous term, rationality, to a more operationalizable and measurable term, optimality, and to demonstrate that optimality can indeed be quantified and measured at both micro and macro scales. The crucial element is how to set an appropriate reference point to make the measurements of optimality possible. Our proposed reference points and measurement methods are perhaps not the only possible way to achieve this aim. We acknowledge that there may be alternative ways that could be identified for measuring decision optimality. The proposed methods however, can potentially be applied to measure optimality in various aspects of decision-making such as the decision of when to evacuate [74, 75], or how to change direction choices [77, 99]. And we would like to emphasise that this transition from the notion of rationality to optimality as a quantifiable term is of great practical significance. This is because it gives us insight into questions such as 'under what conditions' people make 'bad' evacuation choices and 'how' those decisions can be improved either through training, education, increasing awareness, better design of the facilities, better guidance or effective management. For example, we realised that 'bad' direction choices become more frequent when the space becomes more crowded. This gives us an indication that better guidance to exits could be of higher priority for the evacuation of highly crowded venues. We believe that quantification of decision rationality in the aspects of evacuation behaviour could produce further insight into how the behaviour can be improved.

Data Availability

The experimental time series evacuation-time data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Supplementary Materials

The supplementary video visualises the process of numerical simulation as part of the measurements for optimal (or 'rational' behaviour). The natural tendencies of people for making escape decisions observed in empirical settings are aggregated into numerical estimates and those estimates are introduced to a numerical simulation model. The system is subsequently simulated using this model while modifying the empirically inferred tendencies and measuring the response of the system. The process shows whether unilateral modification of decision-making tendencies can improve the system efficiency. The sample video in the supplementary materiel is associated with a scenario where parameters are all set at their empirically estimated values. *(Supplementary Materials)*

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Review Article

Panic, Irrationality, and Herding: Three Ambiguous Terms in Crowd Dynamics Research

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Background. The three terms "panic", "irrationality", and "herding" are ubiquitous in the crowd dynamics literature and have a strong influence on both modelling and management practices. The terms are also commonly shared between the scientific and nonscientific domains. The pervasiveness of the use of these terms is to the point where their underlying assumptions have often been treated as common knowledge by both experts and lay persons. Yet, at the same time, the literature on crowd dynamics presents ample debate, contradiction, and inconsistency on these topics. *Method*. This review is the first to systematically revisit these three terms in a unified study to highlight the scope of this debate. We extracted from peer-reviewed journal articles direct quotes that offer a definition, conceptualisation, or supporting/contradicting evidence on these terms and/or their underlying theories. To further examine the suitability of the term herding, a secondary and more detailed analysis is also conducted on studies that have specifically investigated this phenomenon in empirical settings. *Results*. The review shows that (i) there is no consensus on the definition for the terms panic and irrationality and that (ii) the literature is highly divided along discipline lines on how accurate these theories/terminologies are for describing human escape behaviour. The review reveals a complete division and disconnection between studies published by social scientists and those from the physical science domain and also between studies whose main focus is on numerical simulation versus those with empirical focus. (iii) Despite the ambiguity of the definitions and the missing consensus in the literature, these terms are still increasingly and persistently mentioned in crowd evacuation studies. (iv) Different to panic and irrationality, there is relative consistency in definitions of the term herding, with the term usually being associated with '(blind) imitation'. However, based on the findings of empirical studies, we argue why, despite the relative consistency in meaning, (v) the term herding itself lacks adequate nuance and accuracy for describing the role of 'social influence' in escape behaviour. Our conclusions also emphasise the importance of distinguishing between the social influence on various aspects of evacuation behaviour and avoiding generalisation across various behavioural layers. *Conclusions*. We argue that the use of these three terms in the scientific literature does not contribute constructively to extending the knowledge or to improving the modelling capabilities in the field of crowd dynamics. This is largely due to the ambiguity of these terms, the overly simplistic nature of their assumptions, or the fact that the theories they represent are not readily verifiable. *Recommendations*. We suggest that it would be beneficial for advancing this research field that the phenomena related to these three terms are clearly defined by more tangible and quantifiable terms and be formulated as verifiable hypotheses, so they can be operationalized for empirical testing.

1. Introduction

As researchers working in the field of pedestrian dynamics, we have experienced that a presentation of a piece of research on the topic of crowd evacuation, whether to an academic audience or lay audience, barely goes by without researchers being confronted with these questions: How about the effect of panic? How do you model/experiment panic? To a lesser

extent, we also similarly receive questions of this nature during peer review processes. The question is also often accompanied by follow-up questions on irrational behaviour during evacuations and herding phenomena and how we take those into account in our computational models or experimentations.

We have also observed that these debates are often not resolved with a rigorous argument based on facts and empirical evidence and are, rather, addressed with some level of speculation and resorting to intuition. Nevertheless, researchers often concede that these might be limitations of their study and phenomena that they still have not been able to tackle. Sometimes, researchers take a more defensive position facing this question and present counterarguments that are meant to dismiss these phenomena as matters that should not concern us when designing our research experiments or formulating our models.

The question that arises is why, after so many years of research in this field, have these terms remained intractable? Does this stem from a lack of clear definitions and/or a lack of well-conditioned theoretical conceptualisation? Is this a sign that these terms are still not well defined and that they may, to some degree, be misdirecting the research in this field?

The issue of panic constitutes a rather frequent disclaimer at the discussion section of publications on crowd evacuation dynamics and a common ground for criticising the modelling and experimentation efforts in this field [1]. Such disclaimers often appear in wordings such as: These experiments were conducted under nonpanic conditions [2], or the influence of panic has been excluded from the experiment/model [3, 4]. This gives the indication that simulating/modelling panic is going to be a future development in this field something that the research is headed towards, but one that we have not been able to tackle just yet.

What is, however, very clear is that the terms, panic, irrationality, and herding are among the most ubiquitous terms in the crowd dynamics literature. A peculiar characteristic is that they are used as commonly shared language between the scientific literature, the public, and the media to describe collective evacuation behaviour [5]. As stated by Quarantelli [5], "what constitutes panic is illustrated by presentations of anecdotal examples from stories of disaster behavior in journalistic and popular sources". Here, we investigate what level of consensus exists on their definition and meaning. We survey the scientific literature of crowd dynamics and analyse the use of these three terms with the aim of identifying (i) whether the literature offers unified definitions, (ii) how different segments of the literature view these terms and their theories in general, (iii) how well supported they are in various segments of the literature, and (iv) how they can potentially influence experimentation, modelling, and management practices in this field.

2. Methods

The main purpose of the review is to perform a structured literature search on the use of the terms panic, irrationality, and herding in the context of emergency evacuation of crowds. This will help to establish whether unified definitions can be identified, and it will identify possible inconsistencies or contradictions. In performing this analysis, we also aim to provide an overall reflection of how different research fields perceive each of these terms. The literature review puts together studies from a range of disciplines including physical sciences, social sciences, and biological sciences.

The structured literature analysis is mainly performed on direct quotes from peer-reviewed research articles where these terms have appeared. The main criterion for the selection of the underlying studies was that they had to be exclusively in the context of emergency behaviour, and particularly the behaviour of humans within crowds. For example, the use of the term herding in financial or other contexts where the term is frequently used is not considered here.

Using Scopus as our primary database, we performed title-keywords-abstract searches by applying all possible combinations between the terms "pedestrian, evacuation, crowd, escape, disaster, emergency", and the set of three focus terms of this study "panic, irrational, herd" while separating them by the operator "AND". Each search outcome was limited to Articles and Reviews as Document Types, and exclusively Journals as Source Types. No particular date was specified. This search was initially performed in August 2018. It was subsequently updated in January 2019, limiting the outputs to 2018 and 2019 as Year of publication. For each search, the outputs underwent an initial screening to identify the relevant articles. This screening was performed first on the title of the articles that appeared in search outputs and then on their abstract and keywords only if necessary (i.e., only if the title did not give clear indication of whether the study would be potentially relevant to the content of the review). The search was also supplemented by a prior and less systematic search on a personal reference database that includes nearly 2000 selected articles in the context of crowd dynamics, as well as a variety of Google Scholar searches using similar combination of terms used in Scopus.

This process generated a shortlist of nearly 200 articles whose full texts were screened for the purpose of extracting quotes relevant to the context of this review. The full text of each article was searched for the use of the terms 'panic', 'irrational(ity)', and 'herd(ing)' separately. The criteria for choosing quotes where these terms appeared were that the quote has to convey some form of definition on the term, characterise the term (or its underlying phenomenon), or make some comment on the validity of their underlying theory or the commonness of the phenomenon real-life emergencies. We use these broad inclusion criteria to achieve a comprehensive and objective perspective on how these terms are perceived and used in various subdivisions of the literature.

Out of the nearly 200 shortlisted articles whose full texts were analysed for the use of these terms, half of them (101 items) produced at least one quote that met our criteria outlined above. These quotes were extracted from each article and were stored in separate Word files for further subsequent analyses. In the subsequent analyses, mainly for the purpose of keeping this review to a reasonable length, quotes within

studies that had produced more abundant material had to be prioritised. In such cases, where a study had produced several and often lengthy quotes relevant to our review topic, the quotes with similar content were compared together and briefest ones were chosen. Also, for quotes in which more than one of the three terms had appeared, the quote was only categorised in one of the three sections related to these terms by identifying the term that was dominant in the quote (i.e., the term that constituted the primary theme of the quote). This way, we avoided repeating individual quote for the analyses on our three terms.

The selected quotes were subsequently further analysed and categorised. We differentiated between the quotes in terms of whether they offer a definition/characterisation on the term or just comment on the commonness/likeliness of the underlying phenomenon. Where possible we also recorded whether the quote sentiment is in support of the underlying theory or the use of the term, or instead, contradicts or rejects that idea. Also, in order to demonstrate how intertwined these terms are within the scientific literature, we recorded when the quote links (at least) two of the three terms together. We categorised the source study of each quote into one of the three main disciplines, social sciences, physical sciences, and biological sciences. This categorisation is predominantly based on the discipline of journal that has published the study as well as the main theme of the study. In most cases, these criteria aligned with one another, but in cases where one single categorisation was not possible, more than one category was assigned to the source article. This categorisation was primarily meant to indicate whether and how the perception of these three terms varies across researchers from different disciplines. The studies that we surveyed had one (or sometimes more) of these three themes as their main focus: modelling, empirical testing, and conceptualisation. We categorised each quote based on the primary category of its underlying study among these three categories. Often more than one category were applicable to the source study of a quote. In those cases, we allowed belonging to more than one category. The purpose of this categorisation was to identify whether there is a noticeable difference in definition and/or perception of our three terms of interest across studies whose main focus is on modelling compared to empirical studies or those that only conceptualise these phenomena. Although this is a somewhat crude categorisation of studies and should be interpreted as such, we suggest that it facilitates some coarse insights. The quotes that we extracted from individual studies were quite diverse. However, we were able to identify common themes across clusters of these quotes. Therefore, to further summarise and categorise these individual quotes, we identified these common themes and added them as short comments to each quote. In cases where the quote did not fit any of those common themes no comments were added to the quote.

The outcome of the analysis outlined above is summarised and reported in Tables 5, 6, and 7, respectively, for terms panic, irrationality, and herding. For each quote listed in these tables, the source reference from which the quote has been extracted is cited. The table also determines whether the quote links each term to either (or both) of the two other terms. It also determines whether the quote offers any definition or conceptualisation on this term (when applicable) and whether it conveys support for the panic/irrationality/herding theory or challenges/contradicts it (when applicable). Then, in order to identify how these characteristics of the quotes are influenced by the discipline from which the study originated, the source reference of the quote is categorised in one (or, occasionally, two) of the three disciplines: social sciences, physical sciences, and biological sciences. The source reference is also categorised based on the nature of the study. If the study is heavily focused on numerical simulation and modelling without much connection to empirical analysis, then it is categorised as a "modelling" type study. If the study presents noticeable empirical components it is categorised as "empirical testing". If the study only offers conceptualisation on this term or its underlying theory, then it is categorised as a "conceptualisation" study. Occasionally some studies had to be categorised in more than one of the two study types.

In order to establish whether 'herding', as a terminology, is suitable and accurate enough for describing the phenomena that it is meant to embody, it seemed necessary to examine this term based on the findings of empirical studies. Therefore, we decided to perform a supplementary survey on the herding phenomenon in evacuation exclusive to the studies that have experimented this question in one form or another. This supplementary survey is not based on the analysis of the quotes per se, rather than concerns the individual studies, those that have provided experimental findings on herding behaviour in evacuations. In collecting a comprehensive set of references related to this supplementary survey, we first extracted relevant studies from a previous review of the empirical studies in crowd dynamics whose reference database was last updated in April 2017 [6]. In order to identify studies that were published after April 2017 we conducted supplementary search in Google Scholar and Scopus, with the main selection criterion being that the experiment report on some form of empirical testing or experimentation on the topic. In total, 24 articles qualified for this supplementary literature analysis. The supplementary analysis allowed us to focus deeper on the herding phenomenon beyond the use of terminology by assembling all existing empirical findings to date. Our conclusions and recommendations regarding the suitability of the term herding are mostly grounded in this secondary analysis.

3. Quotes on the Term 'Panic'

The original quotes on the term panic have been listed and analysed in Table 5 in Appendix. The extracted quotes on the term panic were subsequently analysed and after identifying the common themes across the quotes; they were categorised into 22 reduced comments. Table 1 lists these reduced comments along with the frequency of their occurrence in the original comments extracted on the term panic. The table also shows how many times each theme has been repeated in studies across the three different disciplines we considered (i.e., social sciences, physical sciences, and

Table 1: Reduced comments on the term panic and their frequency among the original quotes.

No.	Comment	Frq.	Discipline			Study type		
			Soc.	Phys.	Bio.	Mod.	Emp. Test.	Conc.
1	Panic is common occurrence in the face of imminent danger	4	1	3	0	3	1	0
2	Panic is a very pervasive assumption in modelling literature	6	6	0	0	0	1	6
3	Panic is rare occurrence in the face of imminent danger	1	0	1	0	1	0	0
4	Panic is a cause of injuries in crises	13	3	10	0	7	2	6
5	Panic can affect evacuation efficiency, in both beneficial or detrimental ways	1	0	1	0	1	0	0
6	Panic can affect evacuation efficiency	7	1	6	0	4	0	3
7	Panic is manifested as random (erratic) behaviour (chaos)	4	1	3	0	2	0	2
8	Panic is manifested as increased stress (nervousness/fear)	6	2	4	0	4	1	4
9	Panic is manifested as imitative (herd) behaviour	7	1	6	0	7	1	2
10	Panic is manifested as elevated physical competition	9	1	8	0	8	0	3
11	Panic is manifested as non-humanistic behaviour	5	4	1	0	0	1	4
12	Panic can occur without any distinguishable cause	1	0	1	0	1	0	0
13	Panic lacks a clear definition	12	11	1	0	1	4	11
14	Panic is common media language	6	5	1	0	1	2	5
15	Panic can be represented by simple parameters in simulation models	4	0	4	0	4	0	1
16	Panic theory lacks empirical support	27	22	5	0	4	10	23
17	Panic leads to imbalanced utilisation of exits	3	1	2	0	0	0	3
18	Panic leads to exit blockages	6	0	6	0	6	0	2
19	There are various kinds of panic	4	2	2	0	2	2	4
20	Social affiliation theory presents an alternative to the panic theory	7	7	0	0	0	2	6
21	Panic theory has significant implications for crowd management	3	3	0	0	0	0	3
22	What seems to be panic behaviour, may be individual's best perceived course of action	2	2	0	0	0	0	2

"Frq." indicates *frequency*.
"Soc.", "Phys.", and "Bio.", respectively, indicate *social sciences*, *physical sciences*. and *biological sciences*.
"Mod.", "Emp. Test.", and "Conc.", respectively, indicate *modelling*, *empirical testing*, and *conceptualisation*.

Figure 1: Visualising the frequency of quotes on the term panic that convey support for the theory versus those that challenge it. The pie charts on the left show the frequency of the supporting comments across the disciplines (on the top) and across the study types (in the bottom). Similarly, the pie charts on the right show the frequency of the contradicting comments again across the disciplines (on the top) and across the study types (in the bottom). The column chart in the middle compares the frequency of these comments in total regardless of the discipline or type of the study from which the comments were extracted.

biological sciences) as well as across the three different study types that we considered (i.e., modelling, empirical testing, and conceptualisation). Figure 1 visualises the frequency of the quotes that indicate support for the panic theory versus those that challenge (or contradict) the theory, again across disciplines, and across study types. Figure 2 illustrates the outcome of a temporal analysis on the frequency of the quotes.

One of the most recurring themes in the extracted comments on the term panic concerns the fact that the theory of panic is not well supported by empirical testing [7, 8] (comment #16 in Table 1). Out of nearly 112 comments extracted on the term panic, this theme repeated 27 times. According to Table 1, the majority of such comments originated from studies in the social sciences. Another theme that was very common among the quotes was statements indicating that panic in and of itself is a major cause of injury in emergency incidents and crises and can aggravate the harm caused by the actual crisis [9, 10]. Quotes of this nature were repeated in 13 cases according to Table 1 (comment #4) and the majority of the quotes originated from modelling-type studies published within the domains of physical sciences. Third in this ranking was a noticeable set of quotes that pointed out to a major problem regarding the use of panic in evacuation modelling; the fact that the literature has so far not been able to produce a unified definition for the term panic and that has left the theory of panic largely unverifiable and subject to mere speculation and debate [11, 12]. This comment (#13 in Table 1) was repeated in 12 cases in the quotes extracted on the term panic and again is one of the areas along which the social and physical science studies divide. The vast majority of the quotes that pointed this issue out were obtained from the social science and conceptualisation studies whereas modelling studies have largely downplayed this problem. This highlights a major problem for modelling practice that aim to represent the so-called panic behaviour in their modelling formulations. In the absence of a clear definition on what panic means, efforts to mathematically represent it in the models will largely be subject to the interpretation of the modeller. In addition, even in the domain of social sciences, panic has a very broad definition ranging from aspects such as extreme emotions, groundless fear, uncontrolled flight behaviour, impatience, the quick transmission of excessive fear (i.e., emotional contagion), or the disappearance of normal social bonds [13]. According to Quarantelli [5], early definitions in sociology textbooks and articles view panic as "the crowd in dissolution" or "collective flight based on a hysterical belief" or "dysfunctional escape behavior generated by fortuitous, ever varying circumstances, but involving impending danger". The author also continues to point out that "early approaches to panic were vague in defining the phenomena. However, most formulations view panic as either extreme and groundless fear, or flight behavior". The inconsistency and the variety of the definitions make the practice of integrating them with predictive models (as aimed by physical scientists working in this domain) more arbitrary and rather subjective.

Of those studies that attempted to offer some definitions on the term panic, we found quotes indicating that panic refers to random, unhinged and erratic behaviour [14]

Figure 2: Visualising temporal analyses on quotes that include the term panic. The column chart on the top represents the total number of quotes and the one in the bottom splits the frequency based on whether the quotes support or contradict the theory (chart on the left) and based on the study discipline (chart on the right). To account for the fact that the last time interval includes 6 years as opposed to the rest of the time intervals that include 5 years, the numbers associated with the last interval have been scaled down by a factor of 5/6. The very few studies covered by this review and published prior to 1993 or in 2019 we accommodated in the first and last intervals, respectively.

(comment #7 in Table 1), comments that referred to panic simply as an extreme state of fear or stress during emergencies [11] (comment #8 in Table 1), and also those that described panic manifested as nonhumanistic behaviour [15], imitative behaviour [16], or physically competitive behaviour [17]. It is unlikely that all these conditions can exist at the same time which suggests the theory of panic is not clearly defined and has remained so for many years. The mere fact that modellers try to represent panic using model parameters [18] per se contradicts the idea that panic means people showing random behaviour, because something that is completely random cannot be modelled or predicted. Also, the idea that panic is accompanied by an increased tendency to follow the crowd [19] further contradicts the idea of random behaviour, because following the majority is itself a strategy and is not a random act.

The social identity and the affiliative behaviour theory [13, 15] proposed by social scientists present arguments against the point of view of the mass panic theory as selfish and uncontrolled behaviour. In contrast to the panic theory, social psychologists have in recent years developed and tested a conceptual model of affiliative collective behaviour in emergencies and disasters that explains how "a sense of common fate is the source of an emergent shared social identity among survivors, which in turn provides the motivation to give social support to others affected". [13]

Similarly, the studies that attribute the inefficiency of crowd evacuation behaviour and the occurrence of exit blockages to the increased physical competitiveness caused by panic have also been challenged by recent empirical work that suggests increased physical competition does not necessarily translate to inefficient egress processes [20–22]. Related to this interpretation (or manifestation) of panic behaviour, Heliövaara, Ehtamo, Helbing, and Korhonen [23] have pointed out that "In the literature of social psychology, the pushing behavior is often related to panic. Panic occurs in situations of scarce and dwindling resources and panicking people tend to behave irrationally and adopt a selfish attitude. However, there has been a consensus for decades that actual panic occurs rarely in real crowds and evacuating people tend to behave rationally".

Another common theme that does not come at the top of the list in terms of the frequency of repeating in the quotes but points to an important problem is comment #21 which recognises that "panic theory has significant implications for crowd management" [24]. It pertinently reminds us of the implication that the term panic and the assumptions that it implies may have on how managers and emergency

Figure 3: Visualising the frequency of quotes on the term irrationality that convey support for the theory versus those that challenge it. The pie charts on the left show the frequency of the supporting comments across the disciplines (on the top) and across the study types (in the bottom). Similarly, the pie charts on the right show the frequency of the contradicting comments again across the disciplines (on the top) and across the study types (in the bottom). The column chart in the middle compares the frequency of these comments in total regardless of the discipline or type of the study from which the comments were extracted.

responders decide to communicate information to the crowd in incidents of emergency. It recognises that this assumption may be used as a justification to withhold information from the crowd in order to avoid panic and minimise the harm that it may cause. As Heide [25] has pointed out, "The problem with the panic misconception is that the public, the media, and even emergency planners and public officials believe it. Because of this, officials may hesitate to issue warnings because they are convinced that the resulting panic will cause more damage than the disaster itself". He also continues that "this belief has led to recommendations to avoid panic by (1) providing minimal information to occupants in the event of a building fire and (2) carrying on normal activities until the last possible moment". Similar concern has been voiced by Proulx [26] who has stated that "During emergencies, the anticipation of mass 'panic' has been a favoured argument to delay warning the public". This group of studies that pointed to this problem argue extensively that withholding information from potential evacuees cannot reasonably be the best course of action in emergencies [24, 25].

The plots presented in Figure 1 provide an illustration of the divide that exists between social science and physical science studies on how they view the term panic. While the quotes extracted in this review show a relatively balanced split in terms of the number of quotes that support the theory of mass panic versus those that contradict it, a clear difference is noticeable when a comparison is made across the disciplines or across the study types. According to these plots, while the majority of the quotes obtained from studies in the domain of physical sciences (mostly, modelling studies) treat the existence of panic as a proven fact, the situation is completely reverse when one considers the quotes extracted from the studies published by social scientists on this topic. Modelling studies have predominantly tried to represent a partial representation of what is known as panic behaviour in their mathematical formulations using simple parameters (that make agents show more noisy behaviour, or more imitative behaviour or more physically competitive behaviour) while assuming panic and its characterisation as proven by their predecessor studies, whereas social scientists have placed a heavier focus on identifying empirical evidence that supports the idea of collective panic behaviour in mass emergencies and have in most cases failed to observe such evidence [27, 28].

The temporal analysis presented in Figure 2 further highlights this disconnect between disciplines in how they view the term panic. It further illustrates that, despite the increasing debate on the appropriateness of this term in evacuation literature, the term is increasingly appearing in the scientific literature. According to the set of quotes extracted in this review, while the use of the term among these quotes shows a relatively stable pattern that the social science studies in terms of the frequency of mention, its frequency of being mentioned has surged among the modelling studies. It is also interesting to note, at least among the quotes that were extracted here, that there is no mention of the term panic in physical science studies published prior to year 2000.

Figure 4: Visualising temporal analyses on quotes that include the term irrationality. The column chart on the top represents the total number of quotes and the ones in the bottom splits the frequency based on whether the quotes support or contradict the theory (chart on the left) and based on the study discipline (chart on the right). To account for the fact that the last time interval includes 6 years as opposed to the rest of the time intervals that include 5 years, the numbers associated with the last interval have been scaled down by a factor of 5/6. The very few studies covered by this review and published prior to 1993 or in 2019 we accommodated in the first and last intervals respectively.

4. Quotes on the Term 'Irrationality'

The original quotes extracted on the term irrationality are listed in Table 6 in Appendix where similar type of categorisation has been conducted to that of the panic term as explained in the previous section. These quotes were categorised subsequently into 11 common themes presented as reduced comments on the term irrationality in Table 2. Figure 3 provides a visual illustration of the frequency of the comments on the term irrationality based on the total set of comments, the discipline of their origin and the type of their study of origin. And Figure 4 provides the outcome of a temporal analysis on these comments based on the year of publication for their study of origin.

The most common theme that was observable among the quotes that were extracted in this work were those that attribute irrationality very closely to panic, by stating that making irrational decisions is one of the aspects of collective panic (comment #1 in Table 2) [29]. In other words, these were the comments which suggest that panic implies irrational behaviour too. According to Quarantelli [5], for example, "present day discussions about panic also revolve around whether or not the behavior is irrational, and whether it is highly contagious or not". We also found a relatively substantial number of quotes challenging the theory of irrationality and stating that the theory cannot be regarded as an accurate and verifiable description of a behavioural phenomenon in the face of threats [15, 30, 31]. This comment was the second most common in the list of reduced comments on irrationality (comment #7).

Another group of statements pointed to a set of very important dimensions which are often neglected in discussions of the topic of irrational behaviour and that includes (1) irrational from whose perspective and (2) irrational relative to which reference point. These statements are collectively reflected in comments #9, 10, and 11. As pointed out by Drury, Novelli, and Stott [24], "To judge a response as irrational requires a frame of reference, but the frame of reference is often unclear in a mass emergency". Therefore, it is not sufficient to merely talk about the rationality of human responses without measuring the effectiveness of the response relative to a proper reference point and that is an element that is often missing from the discussions on this topic. How such a reference point can be set and how the efficiency or rationality or optimality of behaviour can be measured against it is certainly a matter of research in this area [32], but its necessity seems to be indisputable. Further on that issue, a considerable number of studies that were reviewed pointed out that what seems an irrational act may be an individual's best perceived course of action. Drury,

Table 2: Reduced comments on the term irrationality and their frequency among the original quotes.

No.	Comment	Frq.	Discipline			Study type		
			Soc.	Phys.	Bio.	Mod.	Emp. Test.	Conc.
1	Irrational behaviour is a symptom of panic	10	9	1	0	1	1	9
2	Herding is a sign of irrational behaviour	4	1	3	0	3	0	1
3	Choosing familiar exits is a sign of irrational behaviour	1	0	1	0	1	0	0
4	People can maintain rationality during crises	3	0	3	0	2	1	1
5	Irrationality means deciding randomly	1	0	1	0	1	0	0
6	Rationality is associated with evacuation efficiency	7	3	3	1	3	0	5
7	Irrationality is not an accurate theory for evacuation behaviour	9	9	0	0	0	2	9
8	Irrationality theory has significant implications for crowd management	6	6	0	0	0	0	6
9	Measuring rationality requires a reference point	3	3	0	0	0	0	3
10	What seems irrational act, may be individual's best perceived course of action	7	6	1	0	0	2	6
11	Irrationality lacks a clear definition	1	1	0	0	0	1	1

"Frq." indicates *frequency*
"Soc.", "Phys.", and "Bio.", respectively, indicate *social sciences*, *physical sciences,* and *biological sciences.*
"Mod.", "Emp. Test.", and "Conc.", respectively, indicate *modelling*, *empirical testing,* and *conceptualisation*.

Novelli, and Stott [24] stated that "Fleeing, fear, screaming or other responses to perceived danger may therefore be entirely reasonable [rational] given the limited information – and limited choices – available to people in the midst of an emergency". In a more recent study, Drury [13] further elaborates on the importance of taking into consideration who judges the behaviour as irrational. He points out that "what appears post hoc and from an external perspective to be an overreaction (such as running frantically following a bomb blast) might be reasonable and proportionate from the perspective of those involved". Similarly, Kelley, Condry Jr, Dahlke, and Hill [33] mentioned that "The individual is no less rational or moral in the panic than in any other situation. He is always in pursuit of his own interests and acts on the basis of his current estimates of where these lie". The comment by Sheppard, Rubin, Wardman, and Wessely [34] stating that "Incorrect decision-making due to incomplete information or insufficient resources is not the same as irrational decision-making and as such is not sufficient to categorise someone as panicking" as well as the conclusion of the study of Heliövaara, Ehtamo, Helbing, and Korhonen [23] stating that "The jams created at bottlenecks along the exit route are often considered to be caused by irrational behavior, a state of psychological panic. However, this study shows that, under threatening conditions, clogging may be caused by crowd members who act rationally according to simple and intuitive assumptions" are also along those lines. Further to that, we also suggest that the research in this area needs to differentiate between what is traditionally known as "social optimum" versus "individualistic optimum" in scenarios where humans interact with one another in their decision-making and particularly those in which they compete for limited resources (which is the case in situations of emergency with the resources being the limited capacity for escape) [35]. In such systems, these two types of optimums often do not coincide with each other. What is optimum course of action from an individual decision-making perspective may not necessarily be the optimum behaviour from a system perspective. We suggest that this is another dimension that needs to be considered in conversations on this topic and in moving towards more operational definitions for rationality.

The plots shown in Figures 3 and 4 demonstrate that, similar to the term panic, the use of the term irrationality in studies of evacuation is increasing according to the quotes collected in this work. These figures, compared to Figures 1 and 2, demonstrate that there were lesser numbers of mentions of the term irrationality compared to that of panic, according to the references that we reviewed. However, there is a relatively higher percentage of the quotes that do not support the theory of collective irrationality in escape scenarios compared to the nearly even split that was identified on the term panic (the column charts in the middle). In other words, irrationality appears to be a less popular and less common term in the studies that we surveyed in this review and is cited much less frequently in modelling studies especially compared to the term panic which appears to be more pervasive. We only had a handful of quotes that supported the theory of irrationality, whereas we extracted a relatively considerable number of quotes, 26 quotes, challenging this idea, and those quotes split evenly between the social and physical science studies according to Figure 3.

5. Quotes on the Term 'Herding'

The original quotes on the term herding have been listed in Table 7 in Appendix. In addition to the analysis on the quotes that have mentioned this term, a detailed analysis was conducted on empirical studies about the herding assumption in evacuations. Figure 5 provides a visual illustration of the frequency of the comments on the term herding based on the total set of comments, the discipline of their origin and the type of their study of origin. And Figure 6 provides the outcome of a temporal analysis on these comments based on the year of publication for their study of origin.

The most common theme across the set of quotes that we analysed was related to the definition of the term herding in evacuation. According to these quotes, herding in evacuation refers to an increased tendency to follow the crowd, or more specifically to imitate the action of the majority [36, 37]. This theme was repeated in 15 quotes out of 72 quotes that were identified on this term (comment #18 in Table 3). Unlike the set of quotes on the term panic and irrationality that did not provide any consensus in terms of the definition and rather added to the mixture on the definition of these terms, the quotes on herding indicated that the majority of studies perceive this term in a roughly similar way. This is of course beside the point of how accurate or suitable this term is for application in evacuation research which is a matter we will discuss below. It merely reflects and describes the current state of the literature and the dominant view on how this term is used and what it refers to.

Another common theme among the quotes we obtained was the use of imbalanced utilisation of exits observed in crowd escape scenarios (regardless of how likely that is to occur) as evidence for herding [17, 38, 39]. This constitutes the reduced comment #20 in Table 3 that was repeated 11 times across all the quotes. The statements reflected by this reduced comment basically assumed that if the crowd shows an imbalance in the utilisation of exits in spaces where there are multiple exit options, then that can be regarded as evidence that individuals within the crowd tend to copy the action of majority. However, whether this imbalanced use of exit capacities stems from an inherent tendency for copying the action of the majority (that individuals made a conscious decision to follow the crowd) or is attributable to other reasons is a matter of debate which will be discussed in more detail in the following sections [40–42].

A considerable body of studies that we reviewed provided comments that indicate herd behaviour, as a feature of escape panic, is a common form of behaviour in evacuations and thus it should be a common assumption for numerical modelling (i.e., numerical models need to produce herding effect in order to be deemed realistic) [18, 43–46]. These are collectively reflected in reduced comments #1, 2, 4, and 6 in Table 3. While we leave examination of the validity of this assumption to our discussion on empirical studies, we only mention here that as opposed to these abundant set of

Table 3: Reduced comments on the term herding and their frequency among the original quotes.

No.	Comment	Frq.	Discipline			Study type		
			Soc.	Phys.	Bio.	Mod.	Emp. Test.	Conc.
1	Herding is a feature of panic behaviour	10	1	7	2	7	3	1
2	Herding is common evacuation behaviour	10	1	7	2	7	3	0
3	Herding is not common evacuation behaviour	3	1	1	1	0	3	0
4	Herding is common modeling assumption	6	0	6	0	5	1	0
5	Pure herding is not an accurate modeling assumption	1	0	1	0	0	1	0
6	Producing herding effects is a common criterion for verifying simulation models	1	0	1	0	1	0	0
7	Herding can be beneficial to evacuation efficiency	1	0	1	0	1	0	0
8	The effect of herding on evacuation efficiency is unclear	3	0	3	0	1	2	0
9	Herding is detrimental to evacuation efficiency	5	0	4	1	4	1	0
10	Mixture of herding and individualistic behavior is beneficial to evacuations	1	0	0	1	0	1	0
11	Stress increases herding tendency	3	0	3	0	1	2	0
12	Stress does not increase imitation tendency	1	0	1	1	0	1	0
13	Herding tendency is moderated by stress level	1	0	1	0	0	1	0
14	Herding tendency is moderated by the crowdedness level	3	0	3	0	0	3	0
15	Herding tendency is moderated by the level of uncertainty	8	0	7	1	4	4	0
16	Herding results from following neighbours	1	0	1	0	0	1	0
17	Herding is not the same as imitation	2	1	1	0	0	2	0
18	Herding means imitating/following others/majority	15	0	12	3	9	6	0
19	Herding is observable in movement initiation	1	0	1	0	0	1	0
20	Imbalanced use of exits is evidence for herding	11	0	7	4	5	6	0
21	Herding theory in evacuation has been influenced by animal models of behaviour	7	0	1	6	1	6	0
22	Herding tendency should be considered in conjunction with individual differences	2	0	2	0	0	2	0
23	Herding theory is in need of empirical testing	1	0	0	1	0	1	0

"Frq." indicates *frequency*.
"Soc.", "Phys.", and "Bio.", respectively, indicate *social sciences*, *physical sciences*, and *biological sciences*.
"Mod.", "Emp. Test.", and "Conc.", respectively, indicate *modelling*, *empirical testing*, and *conceptualisation*.

Figure 5: Visualising the frequency of quotes on the term herding that convey support for the theory versus those that challenge it. The pie charts on the left show the frequency of the supporting comments across the disciplines (on the top) and across the study types (in the bottom). Similarly, the pie charts on the right show the frequency of the contradicting comments again across the disciplines (on the top) and across the study types (in the bottom). The column chart in the middle compares the frequency of these comments in total regardless of the discipline or type of the study from which the comments were extracted.

comments, we had quotes that provided a different view and disregarded the assumption that people show herd mentality in escape situations [47] in addition to quotes from studies that recognise that unless people face substantial amount of uncertainty in their surroundings, they will not be likely to take imitative actions [48].

A number of quotes that we extracted considered how herding tendencies influences efficiency of collective crowd egress. These quotes ranged from suggesting that herding behaviour is a detriment to efficient evacuations [37, 49] to those that believe this effect is still unestablished [39, 40, 50] and that there may be scenarios where herding tendencies are beneficial to an escaping crowd [18]. The subset of these quotes that have not been derived from any simulating testing and are more of a speculative nature did not made it clear which aspect of evacuation decision-making they refer to when connecting herding to the escape efficiency. This is basically a distinction that has not thus far been common in the literature. In line with this question, the phenomenon of mixed strategy (i.e., mixture of herding and individualistic behaviour) has been investigated by several numerical studies. A number of those findings reflect on the findings of such studies. These studies have also contributed a mixture of evidence to the literature with some suggesting that a crowd can benefit from mixed strategies [19] and some suggesting that any percentage of herding strategy within the crowd has a negative impact on the evacuation efficiency [51].

The plots in Figure 5 suggest that unlike panic and irrationality, the herding terminology is a much better accepted term in the crowd dynamics literature. We found many quotes that support this theory and this is far more common among the modelling studies published in the physical science domain. However, the temporal analysis in Figure 6 reveals that firstly, the number of quotes on the term herding shows a surge in the more recent publications and secondly, those that contradict or challenge the herding theory (or the terminology) have only emerged within the last five years and that could be attributable to the rapid increase in the empirical studies within that period many of which observed evidence that did not support this theory [41, 48, 52]

6. Experimental Findings on 'Herding'

Unlike the terms of panic and irrationality for which a lack of clear definition was one of the most noticeable aspects of our review, the term herding has a clearer, although largely implicit, definition in the literature. The majority of the quotes indicated that this term is used to describe imitation behaviour or the act of following others. Whether the 'following' specifically means copying the action of the 'majority' was less clear. Nevertheless, given this higher clarity of meaning, the hypothesis of herding behaviour (or as we prefer to say, the role of social influence) has been more operationalizable and this has allowed the hypothesis to be empirically tested in various forms by considerable number of studies mostly published within the last five years. Here, we comprehensively review these studies and their findings to see what we currently know about this behavioural theory. We

Figure 6: Visualising temporal analyses on quotes that include the term herding. The column chart on the top represents the total number of quotes and the ones in the bottom splits the frequency based on whether the quotes support or contradict the theory (chart on the left) and based on the study discipline (chart on the right). To account for the fact that the last time interval includes 6 years as opposed to the rest of the time intervals that include 5 years, the numbers associated with the last interval have been scaled down by a factor of 5/6. The very few studies covered by this review and published prior to 1993 or in 2019 we accommodated in the first and last intervals, respectively.

also discuss the variety of terminologies that have been used to describe this phenomenon along with their implications.

The set of studies that we reviewed often identify as experiments on peer effect, social influence or neighbour effect in evacuations [53–56] and some directly frame the study as an investigation of herding behaviour [50, 57]. This section provides a comprehensive review of these studies. In total, 24 studies were identified on this topic which have used empirical data of some form. The characteristics of these studies were analysed and subsequently summarised in Table 8 in Appendix. This table shows four main aspects or dimensions of each of these studies: (i) what aspect of the evacuation behaviour was investigated in relation to the peer effect, (ii) what method they used for their data collection (this could be virtual-reality, real crowds, or nonhuman crowd experiments), (iii) did the study find evidence of herding effect (which according to the majority of the body of studies, refers to imitative behaviour), and (iv) what is the main interesting aspect of their findings (this part is provided as a short comment alongside each reference). This analysis is the first to officially recognise that studies and discussions on herding in evacuation should be performed in relation to specific aspects of evacuee's decisions as opposed to discussing the topic in broad terms such as whether people generally show an amplified tendency towards mass behaviour (in all aspects of their decision-making). We have identified and reported the specific aspect of the decision-making that has been investigated in connection with peer influence for each of the studies listed in Table 8 .

6.1. Definitions and Alternative Terminologies for Herding. As mentioned previously, the problem has been framed using a range of terminologies such as imitation [49], allelomimetic behaviour, or allomimetic behaviour [46] (defined as a range of activities in which the performance of a behaviour increases the probability of that behaviour being performed by other nearby animals), social influence [54, 55], peer behaviour effect [53], neighbour behaviour effect [56], follow-the-crowd behaviour [48], and of course, herding or herd-type behaviour [41, 50, 52, 57, 58]. The phenomenon is also referred to by a substantial body of studies as "symmetry breaking" [42, 59–62]. From a linguistic perspective, however, the term does not exactly equate imitation. According to the Longman Dictionary [63], the verb "herd" means "to bring people together in a large group" or "to make animals move together in a group". However, as shown in the previous section, the term is used almost as a substitute for "imitation" in the crowd dynamics literature.

As a pioneer study in the field of crowd dynamics Helbing, Farkas, and Vicsek [19] discussed the phenomenon and

introduced it to numerical simulations. In their conceptualisations "pure herding behaviour implies that the entire crowd will eventually move into the same and probably blocked direction, so that available exits are not efficiently used". These numerical testings were conducted in relation to a simulated room with two exits. Therefore, we assume that the term herding in its original form was specifically used in relation to exit choice behaviour. And this is in fact a common characteristic of the main body of studies that have so far investigated the herding assumption using empirical methods. They predominantly interpret herding in the context of exit choice making. However, the literature has been increasingly recognising the role of social influence in other aspects of evacuation decision-making and a few studies have looked into this problem in connection with reaction responses of evacuees [55, 58, 64] and exit choice adaptation (or exit choice changing) behaviour [65, 66] of evacuees. Hence, in our analysis of the 24 empirical studies on this topic, we have categorised each item into one (or occasionally two) of these three categories: exit (direction) choice, exit (direction) choice changing, and reaction times. We also identified four general experimental methods that have been adopted to study this topic: human crowd (laboratory or evacuation drill) experiments, virtual-reality experiments, experiments with groups of ants, and experiments with groups of mice (as analogical experiments of human crowds).

In the following subsections, we first investigate the origins of the term herding in crowd dynamics and review the first experiments (predominantly based on social insects) which referred to this notion as the 'symmetry breaking' phenomenon. We subsequently review the findings of empirical studies that investigated the role of the social influence in relation to each of the three behavioural sublayers that identified earlier. We then discuss two questions in subsections that follow: (1) can observations of herding with social insects or animals be reliably extrapolated to humans and (2) is the term herding itself a suitable terminology to be used in crowd dynamics.

6.2. Herding and Symmetry Breaking. The first attempt to empirically test the herding assumption in the context of crowd escape dates back to 2005 (five years after the publication of the pioneer paper in *Nature* [19]) where a study published by *American Naturalist* reported on observing "symmetry breaking" effects in experiments with groups of ants [62]. According to the authors, "The phenomenon of herding is a very general feature of the collective behavior of many species in panic conditions, including humans" and this statement constitutes the main premise of their study. The authors observed in this work that groups of ants confined in a chamber show an elevated level of imbalanced exit utilisation when repelled by an aversive stimulus (a certain dose of repellent chemical) and inferred that as a sign that herding phenomenon exists in collective escape scenarios and that the behaviour is shared across a range of species including humans: "Our experimental results, combined with theoretical models, suggest that some features of the collective behavior of humans and ants can be quite similar when escaping under panic." Another statement that the authors have made in their study is that "It has been predicted theoretically that panic induced herding in individuals confined to a room can produce a nonsymmetrical use of two identical exit doors". In evaluating this statement, we argue on a major factor that seems to have been neglected and that is the differentiation between exogenous and endogenous modelling assumptions in numerical simulation methods. The assumption of herding in Helbing, Farkas, and Vicsek [19] was clearly an exogenous assumption meaning that the authors formulated and imposed this assumption in the formulation of their numerical model. Clearly, when one formulates a certain type of phenomenon in the form of mathematical models and implements that model, observing that phenomenon (formulated exogenously) cannot reasonably be regarded as a proof of that phenomenon. We believe that this is a distinction that in a number of cases like this the literature has failed to make when concluding from numerical studies in this field in general. The conclusion from this study has also been cited as an evidence that greater levels of stress and urgency make humans to be more inclined towards imitating the majority's action in an emergency escape context.

The assumption and terminology of symmetry breaking were subsequently followed up by further studies that adopted the ant experiment technique and often made variations to the type of the aversive stimulus [61]. This includes the study of Chung and Lin [59] where using controlled heat-induced aversive stimulus, they observed that the degree of asymmetry increased linearly with the temperature, and also the study of Li, Huan, Roehner, Xu, Zeng, Di, and Han [60] who investigated the effect of density on the extent of symmetry breaking and observed that the degree of asymmetry increased then decreased by ants' density. The most recent study of this kind has shown that symmetry breaking is associated with the difference in the width of exits in proportional ways, thereby concluding that there are, in fact, some patterns of symmetry in symmetry breaking phenomenon in ant groups [42].

6.3. Herding in Movement Initiation. Laboratory crowd experiments in virtual and real(istic) environments have increasingly furthered the knowledge on the role of social influence within the recent years [67]. The problem of premovement time in particular has received attention in this context. According to Bode and Codling [68], "Social influence occurs when individuals respond to the behaviour of others and it is an important factor that needs to be considered in research on premovement times in evacuations". The virtual-reality experiments of Kinateder, Müller, Jost, Mühlberger, and Pauli [55] and Van den Berg, van Nes, and Hoogendoorn [58] have both provided evidence on the significant role of peer behaviour effect on reaction to threat (or movement initiation) responses of evacuees. They have shown that the presence of passive virtual agent made subjects delay their movement reaction, the more people someone sees leaving, the more inclined this person is to leave, and that seeing people leave has more impact

than seeing people stay. The two experiments have been conducted at different levels of virtual crowd density and they collectively suggested that evacuees' reaction to an emergency signal is impacted by their neighbours' behaviour and the direction of influence is towards taking imitative actions, regardless of whether or not the crowd in dense. In relation to the premovement time response, we only know of one study in nonvirtual experimental setting and that is the study of Nilsson and Johansson [64] who utilised the data from an evacuation drill in a cinema. According to Galea, Deere, Hopkin, and Xie [69], "a subset of data from these trials was later analysed to explore the impact of social influence of close neighbours on response time" and "the authors did report that response time for an individual was related to that of a neighbour, so that participants acted more like their neighbours than to others". They concluded from their analysis that social influence is an important factor in reaction time, especially when cues about dangers are unclear, and that social influence (on reaction time) increases with decreasing distance between visitors.

In terms of the influence of imitation in movement initiation on evacuation efficiency, we do not know of any study that has empirically tested this question, but a recent numerical study has shown that lesser variability in reaction times (which could be achieved when individuals tend to initiate their movement as soon as their peers/neighbours do so) shortens the duration of the evacuation [70]. And this has been shown to be the case across a variety of density levels (up to extreme densities). This suggests that herding in movement initiation could be a beneficial form of behaviour (although we should mention that numerical evidence to the contrary of this finding also exists [71] suggesting that a "staged" evacuation strategy (or waiting strategy) could be more efficient than instant collective response).

6.4. Herding in Exit Choice. As mentioned earlier, a significant portion of the empirical knowledge on the role of social influence has been obtained from experiments that investigated exit choice behaviour. The experiments reported by Bode and Codling [52] adopted a simplified form of virtual-reality setting in which the subjects have a top-down view of a two-dimensional computer-simulated crowd evacuation scene and control and navigate their simulated agent using mouse clicks while interacting with simulated agents. The setting of this study simulates relatively dense crowd escape scenarios. No distinct pattern of herding behaviour was observed in this study. Experiments of direction/exit choice in three-dimensional forms of virtual-reality have been reported in [54, 55, 72, 73] where the experimental setting often simulated a not-heavily crowded scene. As indicated by the analysis in Table 8 , these studies have generally found evidence for social influence in the direction of imitation. The virtual-reality exit choice experiments reported by Lovreglio, Fonzone, dell'Olio, and Borri [50] have been framed and analysed in the form of discrete choice experiments and represent relatively dense crowds. Using mixed logit models, the authors estimated the relative importance of different factors on exit choice. Their findings suggest that on average social influence, measured as the number of people at exits, reduces the likelihood of exits being selected. Therefore, this study suggests that social influence has an effect, but that the effect is the opposite to what is commonly proposed under the herding assumption. The findings in this work also qualitatively match those reported in [74], derived from an independent discrete choice survey, which again does not support the herding assumption. Another aspect that is shared between these two studies and also the virtual-reality studies of Kinateder, Comunale, and Warren [56] and Bode, Wagoum, and Codling [75] is that they have all produced evidence that suggest exit choice making is a multiattribute trade-off (between time-dependant and time-independent factors [75]). While peer behaviour appears to have significant effect on evacuees' exit decision, it is also traded off with a range of other factors.

These findings have demonstrated that one cannot assume that peer behaviour is the sole determinant of exit choices and that is one of the main reasons we suggest that the term herding may not be the most suitable terminology to be used in this context. First of all, it indicates, by implication, that the influence of observing peer behaviour is always to the direction of imitation (whereas, sometimes the opposite is the case) and secondly, it dismisses the role of other contributing factors that compete with peer behaviour effect. It implies a decision-making mechanism that is predominantly governed by social influence. The overall message of the virtual-reality experiments has been that in not-heavily crowded scenes social influence acts to the direction of imitation and in heavily crowded scenarios the direction of influence largely reverses. But in all those cases, one also needs to take into account the effect of other contributing attributes to the decision-making (other than social influence) as well as the role of individual differences in perceiving the social influence [76].

Recent experiments conducted using crowds of volunteers, particularly those from which individual-level exit choice observations were extracted [48], generally confirm the findings of the virtual-reality experiments discussed above. Particularly, the presence of multiattribute trade-off between a set of factors that include peer influence appears to be a recurring theme in all those studies [77]. In highly dense laboratory crowd experiments, the dominant pattern of exit choice behaviour has been avoiding the majority [65]. However, Haghani and Sarvi [48] have shown that when attribute ambiguity is introduced, the peer behaviour can act at a positive direction (meaning people tend to perceive direction chosen by majority more positively or at least, less negatively in relation to the alternatives for which attribute ambiguity exists). Therefore, it has been suggested that the influence of peer behaviour in evacuation contexts is moderated by the extent of decision uncertainty that evacuees face.

In a recent study, Haghani and Sarvi [41] tested the effect of urgency level as well as the density level on the perception of peer behaviour and the results overall suggested that none of these factors lead to an increased tendency to imitate others. Under higher levels of simulated urgency or when faced with a larger total number of people, decision-makers became

actually less likely to follow the direction chosen by the majority. In terms of how imitation in exit choices influences egress efficiency, we currently only can resort to the evidence from numerical simulations that suggest any elevated degree of imitation in exit choice making negatively influences total evacuation times. The suggestion from numerical studies is that, when familiar with the location of exits, a crowd of evacuee is best off avoiding a follow-the-majority strategy [49].

6.5. Herding in Exit Choice Adaptation. The empirical evidence on the role of peer effect in how evacuees change/adapt their decisions is very sparse. The topic of decision adaptation [78–80] within the general framework of evacuee's decision-making [81] is in general highly underrepresented in the crowd dynamics literature. In particular, when contrasted with the growing body of studies that have experimented exit choice behaviour within the recent years [56, 75–77, 80, 82–85] very little attention has relatively been paid to the mechanisms of exit choice changing. Proportionately, much less is known about the influence of peer behaviour on this aspect of evacuee's behaviour compared to the influence on exit choice. Recent studies that have experimented this problem, however, have shown that, in crowded evacuation scenarios (where queues form at exits), observing other people changing their exit decisions is a trigger for the observer to change the initial decision and imitate that action [65, 66]. It has been shown in these experiments that once one evacuee decides to leave a queue formed at an exit and join another queue at another exit, it increases the likelihood of decision changing by others followed by a burst of decision changes. This phenomenon, however, even though it indicates imitation, is not precisely consistent with a definition of herding as "following the majority". It is consistent with a definition of herding as "imitating others" but "others" in this case are often the minority. In such scenarios, at any point in time, there are more people not changing their decisions compared to the number of individuals who decide to change their initial choice. Numerical testing in a recent study [86] has also been shown that certain degrees of imitation in exit choice making enhances the efficiency of crowd evacuations from a system perspective.

6.6. Herding and Extrapolation of Behaviour from Social Insects and Animals to Humans. The findings of the experiment reported by Haghani and Sarvi [41], as outlined earlier, may be regarded as evidence opposite the symmetry breaking. The experiment showed that as urgency increases, people show even less tendency to follow the direction chosen by more people. The stark contrast between this experiment and those of the symmetry breaking experiments with ants could be worthy of note. The symmetry breaking phenomenon has been proven with ants through several independent experiments. However, recent evidence is overwhelmingly suggesting that the phenomenon does not seem to be replicable when tested with humans. This might be only one of the areas where the escape behaviour of insects and humans differ fundamentally and thereby, generalisation across the two should be avoided [87].

An implication of identifying such inconsistent observations between collective escape behaviour of insects and humans may be that, wherever possible, behavioural experimentation in this domain should take place with humans as opposed to alternative animals/insects as proxies for humans. In some research the notion can arise that findings from research using social insects can be extrapolated directly to emergency evacuations involving humans. However, there are fundamental differences between species that go beyond obvious physical distinguishing factors. For example, the genetic make-up of ant colonies is largely homogeneous which is likely to affect the trade-off between individual survival and survival of other colony members. This could explain why entire ant colonies reenter previously evacuated nests in an attempt to save their brood (D. Parisi, personal communication), behaviour that is unlikely to occur at this scale in humans.

An argument in response to our proposition is that such experiments are often conducted to help us replicate the sense of real danger which cannot be possibly considered in experiments with human subjects. It should, however, be noted that in many cases, proxies for life-threating dangers, such as creating the sense of urgency using monetary incentives, could be used within the frameworks of ethical experimentation and without imposing any real danger on participants. This possibility could be taken into consideration as offering a trade-off between using a proxy urgency-inducing treatment with real humans (an accepting a certain level of contextual approximation) as opposed to using real urgency-inducing stimuli with animals/insects (and accepting their fundamental behavioural differences as a very different kind of approximation).

6.7. Is 'Herding' an Accurate Terminology? Previous discussions in Section 5 revealed that the term herding is being used in the literature with lesser degrees of inconsistency in terms of the definition, compared to the terms panic and irrationality. According to the quotes that we extracted, most authors use this term as a reference to the act of (blindly/passively) following others. There are alternative interpretations as well, such as 'synchronisation of actions' or 'congregations of people' or 'large groups moving to the same direction'. But these definitions are not as common as 'copying' or 'imitation' or 'conforming to the behaviour of the neighbours or the majority'. However, in light of the empirical findings that we reviewed in this section, here we argue that, despite this relative consistency in definition, the term herding per se lacks accuracy in conveying the meaning that it is meant to embody.

Firstly, herding is a term that has been originally used in relation to animal groups. In that sense, it implicitly coveys an irrational collective unconsciousness where individuals surrender their own wisdom to the group and copy the group blindly (thus, by a stretch of meaning, it may implicitly convey the meaning of 'acting like a group of animals'). In that sense, the term is indeed linked to the panic/irrationality theory which our review suggested to be not so well supported. A change of terminology may help dissociate this concept from panic/irrationality. Further, the mere use of the

term herding in the scientific literature gives the indication that there are similarities between the escape-from-danger responses of humans and those of animals, thereby, justifying experimentation of animals'/insects' behaviour as a proxy for that of humans. As we discussed earlier in Section 6.5, the emerging empirical evidence has not produced much promising evidence for such analogies. Secondly, our review of empirical findings showed that people exhibit various kinds of tendency towards copying or not copying the actions of others in evacuation contexts. Their behaviour appears to be rather complex. For certain aspects of their behaviour (or under certain contextual circumstances), they show tendency to avoid the action of the majority rather than follow. Also, in some cases, they might show imitative tendency but towards the action of the minority rather the majority. The literature is clearly showing that social influence on evacuation behaviour differs depending on the type of action (e.g., movement initiation, direction choice, and decision changing) and also, depending on certain contextual factors (e.g., how crowded the space is and how familiar the occupant is with the surrounding environment), not to mention the role of individual differences in all that. Therefore, there is a great amount of nuance involved in this phenomenon that the term herding fails to capture. The term gives the indications that when we talk about the social influence, we essentially mean 'following others', whereas, the term social/peer/neighbour influence itself maintains neutrality and flexibility in that regard. It embodies both tendencies to follow or to avoid others, as well as tendencies to follow the majority or the minority. For these reasons, we suggest that while the idea behind exploring the role of social influence in evacuation is legitimately valid and even essential, the problem does not need to be formulated as a question about herding. We argue that this term comes with an unnecessary amount of predisposed connotation (partly inherited from the panic theory) as opposed to the nuance, neutrality and flexibility that is required for describing a rather complex phenomenon like this.

7. Discussion

We have adopted a literature survey approach to investigate, in an open-minded way, if preferred or dominant definitions for the three terms we investigate have emerged over time in the literature. While we cannot claim that our literature search is completely exhaustive, we argue that the number of publications included is sufficiently large to adequately support our findings. We acknowledge that the way we have prioritised comments on the terms we investigate within papers and the way we have grouped or reduced comments and categorised supportive or unsupportive comments, as well as the disciplines that publications belong to, is to some extent subjective. We hope that this qualitative analysis is nevertheless a useful synthesis of the complete body of comments we found which we report in full in the Appendix, Tables 5–7. Given the ambiguity/inaccuracy that we found regarding the use of these terms and the lack of empirical evidence for them (except for "herding" which is comparatively a better-defined concept), it was not possible to perform a quantitative meta-analysis or metasynthesis on the evidence pertaining to "panic" and "irrationality". As the empirical base for research into human crowd dynamics continues to grow [6], such meta-analyses will become an attractive option to test the support for specific hypotheses by incorporating evidence across several studies in a similar way to what has been done in other fields of research [88]. However, we anticipate that such an analysis will not be possible for the three terms we discuss here. The unification of behavioural terminologies and hypotheses could be a major useful step towards shaping the literature in that direction.

Our survey of the crowd dynamics literature illustrated that the three terms that we reviewed do not have an unequivocally accepted definition in the literature. This is particularly the case for the terms panic and irrationality. While these terms are still used in increasing numbers of publications, they are also discussed controversially. And in the case of "irrationality", most publications are explicitly critical of the use of this term. An additional and complicating aspect suggested by our literature search is that the terms are used and treated differently in studies from different broad disciplines of research. This is particularly evident for the term "panic" which seems accepted and used (albeit in different ways) in studies which we classified as belonging to the physical sciences but is mostly opposed in studies we classified as belonging to the social sciences. Based on this, we suggest that at present, the use of the three terms "panic", "irrationality" and "herding" in the scientific literature does not contribute constructively to describing, understanding or even predicting evacuation behaviour.

A recent multidisciplinary effort to define terms frequently used in research on pedestrian dynamics does not include definitions for the terms "panic", "irrationality", and "herding" [89]. Instead, this glossary even includes the suggestion that some terms, including "panic", and "herding" that lack a clear definition or could lead to misunderstandings should not be used. This is in line with what we have found by searching the literature extensively for uses of these three terms, as well as the suggestions of several authors in the field of social psychology. As Quarantelli [5] already concluded in a seminal study titled "The sociology of panic" in 2001, "There are two questions that will loom even larger in the future. One is why despite the research evidence, the idea of "panic" captures the popular imagination and continues to be evoked by scholars of human behavior. A second basic question is whether there is still any scientific justification for the continuing use of the concept in any technical sense in the collective behavior area". Our review suggested that the use of these terminologies has not constructively contributed value to the evacuation dynamics literature and if anything, in some cases, the clear lack of definitions for (at least two of) these terms has ambiguated the research field and hampered the efforts of the researchers. Having reviewed the use of these terms, for example, we were not able to identify a definition for the term panic that can be framed as a testable hypothesis. As a result of this issue in this research domain, assumptions have been made that can neither be verified not rejected and computational prediction models have been formulated that cannot be objectively validated.

These issues do not imply that anything loosely related to the three terms cannot be investigated systematically. Our detailed investigation of empirical evidence related to the term "herding" suggests a constructive way forward. While herding is arguably a vague concept, researchers have specified concrete behavioural phenomena instead, such as imitative behaviour, that lend themselves to scientific investigation via observations, experiments or models. In a similar vein, instead of focussing on the high-level ambiguous term "panic", we suggest it is a legitimate question to ask "how intense levels of urgency, stress or fear influence evacuation behaviour", "how optimality of evacuees' decisions can be measured, quantified or improved", "under what circumstances evacuees make more suboptimal decisions", "how observing peer behaviour influences various aspects of evacuee's decisions" or "under what circumstances evacuees are more/less inclined to imitate actions of others". Importantly, framing these questions in the form of ambiguous terms, such as "panic", "irrationality", or "herding", may act as an impedance in scientifically investigating the topics broadly related to the terms by obfuscating an otherwise operationalizable set of questions. In particular, the imprecise assumptions that can accompany these terms may dissuade or divert research from studying these phenomena at the level of nuance that they require. Therefore, we argue that it would be beneficial for the progress of research in this field that the questions related to the three terms discussed here are clearly stated in terms of verifiable hypotheses and be operationalized for empirical testing.

As an illustration for why the language that is used to describe behavioural phenomena in this context matters and can potentially have a significant influence on shaping and directing the research in this field and even management practices, consider the following examples. The assumption that phenomena related to the term panic are not testable in experimental settings with humans has made many authors favour pure numerical methods over experimentation or favour experimentation with animals or insects over experiments with human crowds [59–62, 90–97]. In terms of management practices, the theory could be cited in crises situations as a reason for withholding information from the crowd by managing authorities in order to save more lives. According to the studies that we reviewed, this is based on the rationale that if people know about a critical situation, it might agitate them, ultimately causing them to panic which will lead to irrational behaviour. In contrast to this line of thinking, several authors like Heide [25] have argued that "Evacuation warnings should not be withheld or delayed for fear of precipitating widespread panic". Similar important implications are also conveyed by the term herding. The term, as we showed in our detailed analysis of quotes, has largely been used in the literature to convey imitative type of behaviour [49]. However, the use of this (largely animalistic) term does not make it clear whether there will be contexts or aspects of behaviour in which people do not tend to imitate. It also depicts a mechanism of decision-making in which peer influence is the only factor or the dominant factor while trivialising the role of other potential contributing factors to human responses.

The research on evacuation dynamics has been actively in progress for several decades. Many scholars from a range of disciplines have been researching this topic and significant progress has been made. However, we argued that, if thus far, this ample effort has not converged to any well-defined and empirically supported characterisation or a well-accepted numerical model for panic, then it may be unlikely that such goal be achieved in the future. This may be an indication that some parts of the literature in this field may be in need a fundamental reformulation. It warrants that some of the concepts or terminologies, including those studied in this review, be revisited and replaced with more proper substitutes. In conclusion, we suggest that instead of framing their investigation under the umbrella of the frequently used, but ambiguous terms, "panic", "irrationality", and "herding", researchers could simply state the precise assumptions or hypotheses underlying their work. In doing so, a more integrative approach between the numerical, empirical, and social science studies could prove useful. Table 4 lists a summary of the conclusions that we drew based on this review regarding the use of each of the three terms, along with our recommendations.

Appendix

A.

See Table 5.

B.

See Table 6.

C.

See Table 7.

D.

See Table 8.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Table 4: A summary of the conclusions and the recommendations associated with each of the three terms.

Panic	*Conclusions*	(i) Panic lacks a formal clear definition (ii) Panic lacks a unified well-defined characterisation (iii) Panic cannot be tested as a verifiable hypothesis (iv) Panic is not theoretically well-conceived (v) Panic is not empirically well supported (vi) Despite lack of clear definition, the term panic persists to be increasingly mentioned in the evacuation dynamics literature, particularly in numerical studies (vii) Alternative theories have been proposed by social scientists challenging the theory of panic (viii) There is a sharp divide between how social and physical scientists see the panic theory and its relevance to disaster research
	Recommendations	(i) The evacuation dynamics literature does not benefit from the use of the term panic as it pushes numerical studies towards unverifiable assumptions and non-testable model formulations (ii) The evacuation dynamics literature does not seem to benefit from the use of the term panic as it pushes empirical studies away from human experiments towards alternatives such as experiments with insects/animals (iii) The question of panic can be substituted by operationalizable questions, such as, how fear and stress influences collective behaviour in disasters
Irrationality	*Conclusions*	(i) Irrationality is an implied notion in the panic theory, thus, same comments largely apply as above (i) Irrationality does not need to be associated with panic (as a feature of panic behaviour). The two can be dissociated. Behavioural rationality could be investigated in its own term without the link to panic (ii) Rationality can be re-framed as (replaced by) optimality of behaviour so it can be measured/tested
	Recommendations	(iii) Measuring rationality requires clear points of reference (iv) Rationality could be measured at both collective and individual levels, each requiring their own reference points (v) Experimental studies could give insight into how rational (optimal) human evacuation is, and under what circumstances their behaviour becomes more/less rational (vi) Numerical simulation models can further our understanding about how we can enhance collective optimality (rationality) in emergency response
Herding	*Conclusions*	(i) Empirical studies do confirm the role of social influence in evacuation behaviour (ii) There is relative consensus on the definition of the term herding, although not perfectly (iii) Herding is an animalistic and rather sensational term (iv) The term herding implies that the direction of social influence is always "imitation" (not always the case, sometimes the opposite "avoiding others" is the case) (v) Herding implies that the direction of social influence is always following the majority (not always the case, sometimes, following the minority is the case) (vi) Herding implies that social influence is the single dominant factor in decision making (not always the case, often people make a trade-off between various factors) (vii) The empirical literature so far has suggested that people do show tendency to imitate when it comes to evacuation movement initiation or decision change initiation. (viii) Some empirical studies have shown opposite tendency to herding when it comes to direction choice making especially in heavily crowded situations (ix) Contextual factors such as the crowding level, the stress level or the level of environmental familiarity have shown to change the magnitude and direction of the social influence
	Recommendations	(i) The term social influence is more suitable than the term herding. (ii) Herding does not need to be associated with panic (as a feature of panic behaviour). The question of social influence can be legitimately investigated in its own terms (iii) The question about the role of social influence should be studied in association with different specific aspects of the behaviour. The effect varies across various behavioural aspects.

Table 5: Original quotes on the term panic.

Quotes	Qu. Ref. No	Implications of the quote			The source study								Comments/ Interpretations
					Discipline					Study type			
		Links to H.	Links to Ir.	Def./ Cha. P.	Supp. P.	Cont. P.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
(i) Whenever we (such as pedestrians) perceive a high density or imminent danger in a confined space, we tend to be panic, which can lead to severe injuries even in the absence of real dangers. (ii) Mass behaviors induced by *panic* usually cause great loss, even for human's life	(1) [9]		•		•			•		•			(i) Panic is common occurrence in the face of imminent danger (ii) Panic is a cause of injuries in crises
(i) Results show that moderate *panic* reduces the escape time (ii) Simulation results show that moderate *panic*, meaning that two escape strategies are mixed, reduces the escape time. (iii) In addition, the results indicate that moderate *panic* can improve the efficiency of escape (iv) Finding indicates that panic in specific condition can improve the efficiency of escape, which also can be useful for designing evacuation strategies.	(2) [9]		•		•			•		•			Panic can affect evacuation efficiency, in both beneficial or detrimental ways
(i) Because pedestrians tend to random motion under *panic*, the probability of random moving that can characterize the panic is thus the panic parameter. (ii) When p = 1, it indicates that pedestrian moves in a completely random strategy, that is pedestrian remains at an intense panic	(3) [9]			•				•		•			Panic is manifested as random (erratic) behaviour (chaos)
In situations of escape *panics*, individuals are getting nervous, i.e., they tend to develop blind actionism. Furthermore, people try to move considerably faster than normal, etc. (o.c.)	(4) [11]	•		•				•		•			(i) Panic is manifested as increased stress (nervousness/fear) (ii) Panic is manifested as imitative (herd) behaviour (iii) Panic is manifested as elevated physical competition
"*Panic*: People flight based on a sudden subjective or 'infected' fear; People are moving imprudently; The cause of this movement cannot be recognized by an outsider" (o.c.)	(5) [11]		•	•				•		•			Panic can occur without any distinguishable cause
(i) Up to now, the terminology "*panic*" is highly controversial and usually avoided. In this manuscript, we use "fear"… (ii) There is no precise accepted definition of *panic* although in the media usually aspects like selfish, asocial or even completely irrational behavior and contagion that affects large groups are associated with this concept	(6) [11]	•	•			•		•		•			(i) Panic lacks a clear definition (ii) Panic is common media language
In spite of such measures, empirical knowledge has shown that the real danger comes not from the actual cause but from what is called "unpredictable" or "non-adaptive" behavior of a crowd under *panic*.	(7) [10]				•			•		•			Panic is a cause of injuries in crises
It is shown that the variation of the model parameters allows describing different types of behaviour, from regular to *panic*.	(8) [18]				•			•		•			Panic can be represented by simple parameters in simulation models
The phenomena observed during *panics* can be quite different from those found in "normal" situations. Nevertheless, it is desirable to have a model which is able to describe the whole spectrum of possible pedestrian behaviour in a unified way.	(9) [18]				•			•		•			Panic can be represented by simple parameters in simulation models

Table 5: Continued.

Quotes	Qu. Ref. No	Implications of the quote			The source study								Comments/ Interpretations
							Discipline			Study type			
		Links to H.	Links to Ir.	Def./ Cha. P.	Supp. P.	Cont. P.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
In *panic* situations many counter-intuitive phenomena (e.g. "faster-is-slower" and "freezing-by-heating" etc. [o.c.]) can occur.	(10) [18]			•	•			•		•			(i) Panic leads to exit blockages (ii) Panic can affect evacuation efficiency
Crisis circumstances often involve considerable uncertainty, confusion, and *panic*.	(11) [98]			•	•		•				•		Panic is common occurrence in the face of imminent danger
..stress can end up with *panic* [o.c.] and even with aggressive behaviours	(12) [99]			•	•			•		•			(i) Panic is manifested as increased stress (nervousness/fear) (ii) Panic is manifested as elevated physical competition
. . .little study has been carried out to examine these interactions under *panic* situation due to scarcity of data on human *panic*.	(13) [100]				•			•		•			Panic theory lacks empirical support
Crowd safety has emerged as an important issue all around the world as there have been numerous incidents in which crowd *panic* has resulted in injuries and/or death.	(14) [100]				•			•		•			Panic is a cause of injuries in crises
The bulk of the literature is restricted to the study of normal (non-*panic*) pedestrian dynamics or normal evacuation processes.	(15) [100]			•	•			•		•			
The use of term *panic* and emergencies in this study refer to situations in which individuals have limited information and vision (due to high crowd density and short time for egress), and which result in physical competition and pushing behavior.	(16) [100]			•	•			•		•			(i) Panic is manifested as elevated physical competition
In 1954, Quarantelli was the first social scientist to find that there is no proof of the presence of panic in cases of major disasters.	(17) [7]					•		•				•	Panic theory lacks empirical support
An increased stress level is not the same as *panic*, which can be defined as irrational, illogical and uncontrolled behaviour	(18) [7]		•	•	•			•				•	Panic is manifested as random (erratic) behaviour (chaos)
Under the *panic* state the agents cohere closely and almost do not change the target exit. So other alternative exits are ignored.	(19) [101]			•	•			•				•	(i) Panic leads to imbalanced utilisation of exits (ii) Panic can affect evacuation efficiency

Table 5: Continued.

Quotes	Qu. Ref. No	Implications of the quote			The source study								Comments/ Interpretations
					Discipline					Study type			
		Links to H.	Links to Ir.	Def./ Cha. P.	Supp. P.	Cont. P.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
People under *panic* are usually willing to move along known routes, even if this means they run towards the fire, which may lead to more fatalities.	(20) [101]		•	•	•			•				•	(i) Panic leads to imbalanced utilisation of exits (ii) Panic can affect evacuation efficiency
Empirical data have shown that usually the escape *panic* can cause more casualties than the actual disaster	(21) [101]		•		•			•				•	Panic is a cause of injuries in crises
Some may lose their own decision-making capacity and the herding behavior may appear for following specific individual. Some may accelerate the speed of movement due to the panic. Some may panic that cannot choose the right exit or even lose destination.	(22) [16]	•	•	•	•			•		•			(i) Panic is manifested as imitative (herd) behaviour (ii) Panic is manifested as elevated physical competition
Panic: Breakdown of ordered, cooperative behavior of individuals due to anxious reactions to a certain event. . . characterized by attempted escape of many individuals from a real or perceived threat. . ., which may end up in trampling or crushing of people in a crowd.	(23) [102]			•	•			•		•		•	(i) Panic is manifested as increased stress (nervousness/fear) (ii) Panic is manifested as elevated physical competition
Critical situations may occur if the arrival flow is much higher than the departure flow, especially if people are trying to get towards a strongly desired goal ("acquisitive *panic*") or away from a perceived source of danger ("escape *panic*") with an increased driving force.	(24) [102]			•	•			•		•		•	There are various kinds of panic
In the worst case, such behavior can trigger a "phantom *panic*", i. e. a crowd disaster without any serious reasons. Under extreme conditions (high densities or panic), however, coordination may break down, giving rise to "freezing-by-heating" or "faster-is-slower effects", stop-and-go waves or "crowd turbulence".	(25) [102]			•	•			•		•		•	(i) There are various kinds of panic (ii) Panic leads to exit blockages
We have proposed a consistent theoretical approach allowing a continuous switching between seemingly incompatible kinds of human behavior (individualistic rational behavior vs. irrational *panic* behavior)	(26) [103]	•	•	•	•			•		•		•	Panic can be represented by simple parameters in simulation models
One of the most disastrous forms of collective human behaviour is the kind of crowd stampede induced by *panic*, often leading to fatalities as people are crushed or trampled.	(27) [19]			•	•			•		•		•	Panic is a cause of injuries in crises
The characteristic features of escape *panics* can be summarized as follows: (1) People move or try to move considerably faster. . .. (2) Individuals start pushing. . .. (3) . . .passing of a bottleneck becomes uncoordinated. (4) At exits, arching and clogging are observed. (5) Jams build up. (6) The physical interactions in the jammed crowd add up and cause dangerous pressures... (7) Escape is further slowed by fallen or injured people acting as 'obstacles'. (8) People show a tendency towards mass behaviour, that is, to do what other people do (9) Alternative exits are often overlooked. . .[o.c.]	(28) [19]	•		•	•			•		•		•	(i) Panic is manifested as increased stress (nervousness/fear) (ii) Panic is manifested as imitative (herd) behaviour (iii) Panic is manifested as elevated physical competition

Table 5: Continued.

Quotes	Qu. Ref. No	Implications of the quote			The source study								Comments/ Interpretations
							Discipline			Study type			
		Links to H.	Links to Ir.	Def./ Cha. P.	Supp. P.	Cont. P.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
In the event of an emergency, unnecessary *panic* can spread rapidly amongst metro passengers, leading to self-evacuation.	(29) [43]				•			•		•			Panic is common occurrence in the face of imminent danger
In a panic, information spreads so rapidly that passengers often self-evacuate.	(30) [43]			•	•			•		•			Panic is common occurrence in the face of imminent danger
Human behavior in an emergency is quite different from that in daily life or even evacuation rehearsal. People in a fire scene are very likely to be affected by people around as a result of uneasiness and *panic*. They would like to be close to the crowd and follow the route of the mass rather than the route made by their own judgment.	(31) [104]	•		•	•			•		•			Panic is manifested as imitative (herd) behaviour
Casualties during crowd evacuation in many unexpected events are closely related to *panic* behaviors.	(32) [105]			•	•			•		•			Panic is a cause of injuries in crises
The evolution of herding people to *panic* people is interpreted by a specific concept of "herding–*panic* threshold," as well as its utility threshold model	(33) [105]	•			•			•		•			Panic can be represented by simple parameters in simulation models
Although the term "*panic*" is a controversial topic, in which some interview data and case studies demonstrate that *panic* is a very rare occurrence in fires. . . the idea of *panic* and the term continue to be used by the public as well as fire experts.	(34) [105]				•	•		•		•			Panic is rare occurrence in the face of imminent danger
In many emergencies. . .*panic* does exist and induces tragic catastrophes, which cannot be attributable to building design or its management	(35) [105]			•	•			•		•			Panic is a cause of injuries in crises
Panicking individuals will block up an exit that they could pass through safely at normal walking speed.	(36) [38]			•	•			•		•		•	Panic leads to exit blockages
Assuming escaping behavior of individuals in emergency is rational rather than out of *panic* according to recent findings in social psychology, we investigate the behavioral evolution of large crowds from the perspective of evolutionary game theory	(37) [8]		•			•		•		•			Panic theory lacks empirical support
In *panic* conditions, individuals' speeds increase above normal, interactions between persons become highly physical and movements are uncoordinated [o.c.]. At exits, clogging and collisions occur, as well as rainbow-like arching structures.	(38) [17]			•	•			•		•			(i) Panic leads to exit blockages (ii) Panic is manifested as elevated physical competition
This model does not account for crushing behaviors and thus limits the interpretation of *panic* in this context.	(39) [106]			•				•		•			Panic is manifested as elevated physical competition
When the *panic* emotion emerges in someone in a crowd, his/her neighboring individuals tend to be infected via what is termed emotional contagion.	(40) [107]			•	•			•		•			Panic is manifested as imitative (herd) behaviour

Table 5: Continued.

Quotes	Qu. Ref. No	Implications of the quote			The source study								Comments/ Interpretations
							Discipline			Study type			
		Links to H.	Links to Ir.	Def./ Cha. P.	Supp. P.	Cont. P.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
In order to intervene in and manage a large-scale crowd in which individuals can move freely in the case of large-scale *panic*, some managers or guides should be organized to calm the crowd members	(41) [107]				•			•		•			Panic can affect evacuation efficiency
With such a model, additional characteristics of human behavior in a disaster evacuation scenario could be captured such as erratic action and *panic*.	(42) [14]			•	•			•		•			Panic is manifested as random (erratic) behaviour (chaos)
(i) The "faster is slower" effect induced by *panic* was analyzed. (ii) A state of panic is associated with high values of vd [desired velocity] i.e., individuals try to move faster and faster towards the exit door.	(43) [108]			•	•			•		•			Panic leads to exit blockages
The continuity of both curve (. . .) shows the tendency of people to follow the majority during *panic*.	(44) [1]	•		•	•			•		•			Panic is manifested as imitative (herd) behaviour
. . . the flow rate of pedestrian going out through an exit door of width L is considered a linear function of L [Under normal evacuation conditions (no *panic*)]. . .under *panic* situation, this is no longer valid.	(45) [109]			•	•			•		•			Panic leads to exit blockages
Song et al. distinguished the crowd in panic situations. . .according to people who will (a) select the closest exit, (b) be in total *panic*, and (c) follow the flow of the crowd around them (41). The percentage in each group was 90%, 5%, and 5%, respectively.	(46) [110]	•			•			•		•			
Panicked individuals may have a negative impact on other people and, on the contrary, the calm leadership of certain evacuees may inspire orderly movement of others.	(47) [105]				•			•		•	•		Panic can affect evacuation efficiency
The emotion of the crowd often is in an unreason state. Negative emotions, such as *panic*, may induce disastrous forms of collective human behaviors, e.g., crush and trample	(48) [107]				•			•		•			Panic is a cause of injuries in crises
Panic has been associated with individualistic responses and characterised by "self-preservation at all costs, by 'irrational' animalistic behaviour involving the breakdown of group ties. . . Evidence will be presented to show that this is an inaccurate generalisation	(49) [12]		•	•		•	•					•	Panic theory lacks empirical support
There has been a resistance to psychological studies of human action in fire because of the belief [o.c.] that the term '*panic*' provides a sufficiently accurate description of people's response to hazardous events. Sime [o.c.] has pointed to the essential difficulty associated with the use of the term '*panic*', in that it has "ruled out attempts to examine directly people's experiences of coping in a fire situation".	(50) [12]					•	•					•	(i) Panic lacks a clear definition (ii) Panic theory lacks empirical support
Wood has found that behaviour during fires is influenced by social roles and that different groups within the sample displayed distinctive patterns of response. This would suggest that evacuation is not a random, irrational '*panic*' response even though people are acting under stress.	(51) [12]		•	•		•	•					•	Panic theory lacks empirical support
In the past these factors have been considered the classic situational determinants of competitive flight or '*panic*' behaviour. . .An alternative model of 'affiliative' escape behaviour is examined in the present paper.	(52) [15]					•	•					•	Social affiliation theory presents an alternative to the panic theory
It has been argued that many of the assumptions about escape behaviour in the fire regulations and design literature derive from the notion that when faced by a fire threat, people have a tendency to '*panic*'.	(53) [15]						•					•	Panic is a very pervasive assumption in modelling literature

Table 5: Continued.

Quotes	Qu. Ref. No	Implications of the quote			The source study								Comments/ Interpretations
							Discipline			Study type			
		Links to H.	Links to Ir.	Def./ Cha. P.	Supp. P.	Cont. P.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
(i) The *panic* model of escape behaviour assumes that people threatened by entrapment will revert automatically to primitive, highly emotional, irrational behaviour (ii) The panic and physical-science models are inextricably linked through the analogy made between people and non-thinking objects	(54) [15]		•	•			•					•	Panic is manifested as non-humanistic behaviour
(i) The word '*panic*' is frequently used in media accounts and statements of survivors of emergency evacuations and fires, but what does it really mean, is it a phenomenon that actually occurs? (ii) Despite the data demonstrating that panic is a very rare occurrence in fires, the idea of panic and the term continue to be used by the public as well as fire experts	(55) [30]					•	•					•	(i) Panic is common media language (ii) Panic theory lacks empirical support (iii) Panic is a very pervasive assumption in modelling literature
There are various accounts in the literature of 'mass *panic*', all of which assume psychological vulnerability, since they claim that, in the context of threat, the crowd becomes a conduit for inherent tendencies towards dysfunctional behaviour, delusory beliefs and social pathology.	(56) [24]		•	•			•					•	Panic can affect evacuation efficiency
Theories of '*panic*' typically suggest that loss of behavioural control, and hence selfishness and disorder, is generic in emergencies. However, reviews and case studies of emergencies show that cooperation is relatively common within and across crowds.	(57) [24]			•		•	•					•	(i) Panic is a very pervasive assumption in modelling literature (ii) Panic theory lacks empirical support (iii) Social affiliation theory presents an alternative to the panic theory
The concept of '*panic*' has served to justify the restriction of such essential public information – based on a concern that the crowd might '*panic*'.	(58) [24]						•					•	Panic theory has significant implications for crowd management

Table 5: Continued.

Quotes	Qu. Ref. No	Implications of the quote			The source study								Comments/ Interpretations
							Discipline			Study type			
		Links to H.	Links to Ir.	Def./ Cha. P.	Supp. P.	Cont. P.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
This general model provides a strong basis on which to refute the '*panic*' description of behaviour. It supports and refines Wood's [16] earlier finding that fire victims do not behave in an irrational manner	(59) [12]		•			•	•					•	Panic theory lacks empirical support
Crowd quakes are a typical reason for crowd disasters, to be distinguished from crowd disasters resulting from 'mass *panic*' or 'crowd crushes. …Accordingly, things can go terribly wrong in spite of no bad intentions from anyone.	(60) [111]				•			•			•		Panic is a cause of injuries in crises
It is widely believed that one of the most disruptive consequences of a terrorist attack… would be public *panic*. Indeed, this is one of the probable goals of the terrorists.	(61) [112]				•		•					•	Panic is a cause of injuries in crises
The results contradict most of the predictions of the mass *panic* model and add to the dominant affiliation and normative approaches. …These results support a hypothesis according to which (emergent) collective identity motivates solidarity with strangers.	(62) [113]					•	•					•	(i) Panic theory lacks empirical support (ii) Social affiliation theory presents an alternative to the panic theory
Images of group *panic* and collective chaos are ubiquitous in Hollywood movies, mainstream media and the rhetoric of politicians. But, contrary to these popular portrayals, group *panic* is relatively rare. In disasters people are often models of civility and cooperation.	(63) [114]					•	•					•	(i) Panic theory lacks empirical support (ii) Social affiliation theory presents an alternative to the panic theory (iii) Panic is common media language
(i) I report evidence showing that *panic* did not cause the death and injury of numerous young people prior to a concert. (ii) I conclude that theoretical models of *panics* or "crazes" within the literature on collective behavior are not very useful in explaining this type of incident.	(64) [115]					•	•				•	•	Panic theory lacks empirical support
Many social scientists would categorize the crowd behavior described above form of panic-usually termed an "acquisitive panic" (o.c.) or "craze" (o.c.). Smelser distinguishes it from the classic panics of escape, e.g., flight from a burning building, in that the latter is a "headlong rush away from something" while the craze is a rush "toward something [the participants] believe to be gratifying.	(65) [115]			•			•				•	•	There are various kinds of panic
Although many collective behavior theorists discuss the phenomenon, systematic studies of *panic* are uncommon. Researchers conducting such studies generally conclude that *panic* is a rare form of crowd behaviour. Quarantelli and Dynes (1972) report that they have found few instances of *panic* after years of disaster research.	(66) [115]					•	•				•	•	There are various kinds of panic
Although not in complete agreement, writers on *panic* before Mintz had tended to emphasize perceived danger and mutual influence (suggestion, contagion, mimicry) as the key factors in the development and spread of incoordinated and nonadaptive "*panic*" behavior	(67) [33]	•		•			•				•	•	(i) Panic is manifested as increased stress (nervousness/fear) (ii) Panic is manifested as imitative (herd) behaviour
Intense fear is shown not to be important because even in its absence there occurs "behavior analogous to that occurring in *panics*	(68) [33]					•	•				•	•	
The notion of 'mass *panic*' shares with classical 'crowd science' the assumption that the crowd is less intelligent and more emotional than the lone individual (o.c.) and hence reactions to an emergency will be disproportionate to the actual danger.	(69) [116]		•	•			•				•	•	Panic is a cause of injuries in crises
In the field of mass emergency and disaster research, the notion of mass *panic* has been largely discredited by the finding of orderly, meaningful mass behavior in disasters. However, some influential practitioners, including crowd modellers in the fields of engineering and design, still draw upon the notion.	(70) [116]			•		•	•				•	•	(i) Panic is a very pervasive assumption in modelling literature (ii) Panic theory lacks empirical support

Table 5: Continued.

Quotes	Qu. Ref. No	Implications of the quote					The source study						Comments/ Interpretations
							Discipline			Study type			
		Links to H.	Links to Ir.	Def./ Cha. P.	Supp. P.	Cont. P.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
The term '*panic*' is a commonsense cliché. The term is often used when what in fact is being described is simply flight from the source of danger.	(71) [116]			•		•	•				•	•	Panic lacks a clear definition
Analyses of 9-11 refer to the relative absence of *panic* (o.c.), the calm and orderliness of the evacuation (o.c.), and the frequency of helping and acts of 'mundane heroism' amongst strangers (o.c.).	(72) [116]					•	•				•	•	Panic theory lacks empirical support
Shared identity in an emergency crowd enhances expressions of solidarity and reduces '*panic*' behaviour and. . .such a shared identity can arise from the shared experience of the emergency itself	(73) [27]					•	•				•	•	Social affiliation theory presents an alternative to the panic theory
It is suggested that the 'mass *panic*' approach is correct to suggest a discontinuity between everyday and mass emergency behaviour, but wrong in its account of what that behaviour is.	(74) [27]					•	•				•	•	Panic theory lacks empirical support
[Keating] pointed out that people did not *panic*, did not become animals, and did not abandon their ties to others. Instead they continued to be social actors . . .	(75) [117]			•		•	•					•	Social affiliation theory presents an alternative to the panic theory
Collective solidarity can mitigate fear and negative emotions, thus reducing the risk of *panic*.	(76) [118]						•				•		Social affiliation theory presents an alternative to the panic theory
The mass *panic* approach describes individuals as acting in a purely selfish manner.	(77) [118]			•			•				•		(i) Panic is manifested as non-humanistic behaviour
Indeed, participants referred to 'orderly' behaviour, and cooperation, even when they said the threat of death was present. '*Panic*' was therefore being used as a description of events that was not consistent.	(78) [28]					•	•				•	•	(i) Panic theory lacks empirical support (ii) Panic lacks a clear definition
(i) More empirically oriented studies have consistently reported little collective *panic*, as well as a great deal of solidarity and pro-social behavior during mass emergency situations. (ii) Many studies in the fields of sociology and social psychology have systematically questioned the existence of mass panic in disasters and mass emergency contexts.	(79) [119]			•		•	•					•	(i) Panic theory lacks empirical support (ii) Social affiliation theory presents an alternative to the panic theory

Table 5: Continued.

Quotes	Qu. Ref. No	Implications of the quote					The source study						Comments/ Interpretations
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Defining 'mass *panic*' in a scientifically sound manner has long been recognized as a difficult task.	(80) [119]						•					•	Panic lacks a clear definition
Panic in crowds is still an important theoretical postulate of scholars interested in the modeling of collective behavior	(81) [119]						•					•	(i) Panic is a very pervasive assumption in modelling literature
[People] report having been in a state of *panic* to describe their lack of information about an event. This is even the case when they in fact stayed calm and behaved in a rational and prudent fashion.	(82) [119]		•			•	•					•	Panic theory lacks empirical support
As usually defined, individual *panic* would include a "reaction involving terror, confusion, and irrational behavior, precipitated by a threatening situation often including physical symptoms as well, and *panic* as a social phenomenon is defined as simply an aggregate of such responses"	(83) [120]		•	•			•					•	(i) Panic is manifested as increased stress (nervousness/fear) (ii) Panic is manifested as elevated physical competition
[As opposed to *panic*] I prefer the term unregulated competition as the descriptive label.	(84) [120]						•					•	Panic lacks a clear definition
In this emergency situation, the survivors of the bombings came together to tend to the injured and find a way of evacuating safely. In contrast to portrayals of crowds as *panicking* and acting selfishly to evacuate, research has shown that the opposite occurred.	(85) [121]			•		•		•		•	•		Panic theory lacks empirical support
There is good reason to think that the behaviour of human crowds is quite similar to these animal groups and that studying humans might help elucidate the origins of crowd *panic* and other dangerous instabilities that can lead to injury or loss of life.	(86) [122]				•			•				•	(i) Panic is manifested as non-humanistic behaviour (ii) Panic is a cause of injuries in crises
While mass *panic* (and/or violence) and self-preservation are often assumed to be the natural response to physical danger and perceived entrapment, the literature indicates that expressions of mutual aid are common and often predominate, and collective flight may be so delayed that survival is threatened.	(87) [123]					•	•					•	Panic theory is not empirically well supported
(i) The term "*panic*" refers to inappropriate (or excessive) fear and/or flight. (ii) Whether defined as inappropriate or as highly intense fear or flight, instances of *panic* are difficult to identify in practice	(88) [123]			•		•	•					•	Panic theory is not empirically well supported
Rushing for exits in a structural fire may be the only rational course of action to take. Hence, the decision to label instances of collective flight as *panic* is arbitrary.	(89) [123]		•	•		•	•					•	What seems to be panic behaviour, may be individual's best perceived course of action

Table 5: Continued.

Quotes	Qu. Ref. No	Implications of the quote			The source study								Comments/ Interpretations
							Discipline			Study type			
		Links to H.	Links to Ir.	Def./ Cha. P.	Supp. P.	Cont. P.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
Studies are revealing several misconceptions about the types of responses that emergencies evoke in people. For example, a number of widely-held beliefs among the public and the media have been shown to be incorrect, such as that looting, mass *panic*, and selfish behaviour are common in disasters, and should be abandoned in favour of realistic, proactive emergency knowledge.	(90) [124]					•	•				•	•	(i) Panic theory lacks empirical support (ii) Panic is common media language
The review of the existing research literature, together with our own studies, support the view that mass *panic* is a myth, and that crowd behaviour in disasters and emergencies is meaningful rather than irrational; and that such behaviour is characteristically orderly and co-operative rather than disorderly and individualistic.	(91) [125]		•	•		•	•				•	•	Panic theory lacks empirical support
Mass *panic* is said to occur when a crowd has only limited opportunity for escape from impending danger. It supposedly explains the high numbers of avoidable fatalities in emergency evacuations.	(92) [31]						•					•	Panic is a cause of injuries in crises
Mass *panic* occurs when a group of persons fleeing from imminent danger find their escape route impeded or blocked. Under these circumstances they lose all sense of judgment and discretion. They become impervious to communication or direction, trample over one another, and fail to seek other exits of escape even if available. For these reasons mass *panic* rarely occurs in outside disaster circumstances.	(93) [29]		•	•	•		•					•	(i) Panic is manifested as non-humanistic behaviour (ii) Panic leads to imbalanced utilisation of exits
From around 200 accounts of the World Trade Center survivors published in the media, *panic* was seldom mentioned instead many emphasized the calm and altruistic behaviour of the evacuees.	(94) [126]					•	•					•	Panic theory lacks empirical support
The popular image of disaster has often centered on the theme of personal chaos. Such an image is frequently documented by isolated anecdotes used to prove the universality of such behavior. This image suggests that individuals *panic* and that individuals lose their concern for others.	(95) [25]			•		•	•					•	(i) Panic is manifested as random (erratic) behaviour (chaos) (ii) Panic is manifested as non-humanistic behaviour
The issue of *panic* in disasters is frequently clouded by a lack of understanding of what the term means. The word is often very loosely and incorrectly used to describe virtually any type of fear, flight, or uncoordinated activity.	(96) [25]			•			•					•	Panic lacks a clear definition
The problem with the *panic* misconception is that the public, the media, and even emergency planners and public officials believe it. Because of this, officials may hesitate to issue warnings because they are convinced that the resulting *panic* will cause more damage than the disaster itself. (i) This belief has led to recommendations to avoid *panic* by (1) providing minimal information to occupants in the event of a building fire and (2) carrying on normal activities until the last possible moment. (ii) Evacuation warnings should not be withheld or delayed for fear of precipitating widespread *panic*.	(97) [25]						•					•	(i) Panic theory has significant implications for crowd management (ii) Panic is common media language
Governments and commentators perceive the public to be prone to *panic* in response to terrorist attacks. . .Evidence from five such incidents suggest that the public is not prone to *panic*, although people can change their behaviours and attitudes to reduce the risk of themselves being exposed to a terrorist incident.	(98) [34]					•	•					•	Panic theory lacks empirical support

Table 5: Continued.

Quotes	Qu. Ref. No	Implications of the quote			The source study								Comments/ Interpretations
							Discipline			Study type			
		Links to H.	Links to Ir.	Def./ Cha. P.	Supp. P.	Cont. P.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
We suggest that although the public may change their behaviours or attitudes, in ways that might be viewed as irrational by public authorities,. . .these actions tend to have an internal logic and as such are amenable to change. Assumptions of *panic* may therefore be counterproductive.	(99) [34]		•			•	•					•	What seems to be panic behaviour, may be individual's best perceived course of action
During an emergency evacuation, for instance, the presence of heightened anxiety and distress among the evacuees combined with a fear of dying is not sufficient to label them as *panicking*	(100) [34]					•	•					•	Panic lacks a clear definition
Despite considerable effort by many individuals found in this article's reference list, the myth of mass panic stubbornly refuses to die.	(101) [127]					•	•					•	Panic is a very pervasive assumption in modelling literature
During emergencies, the anticipation of mass '*panic*' has been a favoured argument to delay warning the public. Such delays have contributed to subsequent flight behaviour and the crush of people who had only a few seconds left to react once the situation unexpectedly got out of hand.	(102) [26]						•					•	Panic theory has significant implications for crowd management
Perhaps the most frequently used term in connection with disasters and crises is the word "*panic*". . .an observation by Jordan unfortunately still is true today. As he noted: "The literature on panic research is strewn with wrecked hulks of attempts to define '*panic*'. When these definitions are placed side by side. one is confronted by chaos.	(103) [128]						•					•	Panic lacks a clear definition
Panic flight was so rarely found that eventually the very concept of "panic behavior" was deemed useless for fire research purposes	(104) [128]					•	•					•	Panic is a rare occurrence
To conclude, collective *panic* flight in disasters is such a rarity that it is not a major problem and has very little overall negative consequences compared with other bad effects.	(105) [128]					•	•					•	Panic theory lacks empirical support
While some current researchers continue to use the word "*panic*" in imaginative ways (o.c.), we personally think the term should be dropped as a social science concept. . .A major move in such a direction would free social scientists from the ambiguities and imprecisions of continuing to use a word drawn from popular discourse.	(106) [128]					•	•					•	Panic lacks a clear definition
In stress situations, one aspect of social behavior that has been subjected to little experimental investigation is *panic* behavior. . .By far the great majority of the literature consists of post hoc impressionistic reflections that contain little substantive material amenable to systematic, analytic interpretation.	(107) [129]						•					•	Panic theory lacks empirical support

Table 5: Continued.

Quotes	Qu. Ref. No	Implications of the quote			The source study								Comments/ Interpretations
							Discipline			Study type			
		Links to H.	Links to Ir.	Def./ Cha. P.	Supp. P.	Cont. P.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
For ethical reasons, however, there is a serious lack of experimental data regarding crowd *panic*. While *panic* has recently been studied in animal experiments with mice and ants [o.c.], there is still an evident lack of data on critical conditions in human crowds.	(108) [130]							•		•	•		Panic theory lacks empirical support
Mass-emergencies are very popular in the news, whether we watch news on TV or read a newspaper. In most of these news we are able to read that people were fallen in *panic* or a mass-*panic* occurred. This is a simple, but often used explanation why people died in such situations. But is that the truth?	(109) [131]					•	•				•	•	Panic is common media language
Several researchers in the field of engineering or sociology have written special papers (e.g. [3]) or books (e.g. [4, 5]) about the phenomenon of *panic*, but a complete definition of *panic* cannot be found in the literature.	(110) [131]						•				•	•	Panic lacks a clear definition
Based on this short overview the authors want to point out that the terms "*panic*", "stampede" and "crush" are very language specific, thus one has to read articles in one's native language and at least in one foreign language to ensure, that both language specific views are considered.	(111) [131]						•				•	•	Panic lacks a clear definition
This and other definitions are used to investigate 127 cases of mass-emergencies. The results show, that *panic* behavior in case of mass-emergencies does not as often occur as suggested.	(112) [131]					•	•				•	•	Panic theory lacks empirical support

"Qu./Ref. No." means *Quote/Reference number.*
"Links to Ir." means *(The quote) links Panic (P.) to Irrationality (Ir.).*
"Links to H." means *(The quote) links Panic (P.) to Herding (H.).*
"Def. Cha. P." means *(The quote) defines/characterises Panic.*
"Supp. P." means *(The quote) supports (the theory of) Panic.*
"Cont. P." means *(The quote) contradicts (the theory of) Panic.*
"Soc. Sci." means *(The source of the quote) is a study in Social Sciences.*
"Phys. Sci." means *(The source of the quote) is a study in Physical Sciences.*
"Bio. Sci." means *(The source of the quote) is a study in Biological Sciences.*
"Mod." means *(The source of the quote) is a study with a main focus on Modelling.*
"Emp. Test." means *(The source of the quote) is a study with a main focus on Empirical Testing.*
"Conc." means *(The source of the quote) is a study with a main focus on Conceptualisation.*
Note that individual studies can belong to multiple categories (e.g. multiple disciplines).

Table 6: Original quotes on the term irrationality.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to H.	Links to P.	Def./ Cha. Ir.	Supp. Ir.	Cont. Ir.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
Here we want to apply this model to a simple evacuation process with people trying to escape from a large room. Such a situation can lead to a panic where individuals apparently act *irrationally*.	(1) [18]		•		•			•		•			Irrational behaviour is a symptom of panic
They think that the transition between the "*rational*" normal behavior and the apparently "*irrational*" panicbehavior is controlled by a single parameter, the "nervousness", which influences fluctuation strengths, desired speeds, and the tendency of herding.	(2) [11]	•	•					•		•			Herding is a sign of irrational behaviour
We aspire to give answers to the following specific questions what is the impact between choosing the escape route based on familiarity as opposed to *rationally* following the fire exits.	(3) [10]			•				•		•			Choosing familiar exits is a sign of irrational behaviour
We do not want to imply that individuals would always behave *irrational* in emergency situations. It has been observed that, even in such situations individuals can behave highly self-controlled, coordinated, *rational*, and social	(4) [103]			•		•		•		•		•	People can maintain rationality during crises
Recent researches in social psychology about herding effect in emergency [o.c.] indicate that, escaping behaviors among individuals are *rational* actions instead of crowd panic and a series of phenomena including herding effect are the result of *rational* choices in behaviors for escaping agents.	(5) [8]	•	•			•		•		•			People can maintain rationality during crises
Most microscopic simulation models [o.c.] in the field of emergency evacuation up to now are generally based on the assumption that panic instead of *rational* actions induces herding effect.	(6) [8]	•	•					•		•			Herding is a sign of irrational behaviour
Irrationality: Accounting for the idea that individuals in a crowd lose *rational* thought	(7) [99]			•	•			•		•			
(i) High herding causes a crowd of high *rationality* (especially in normal circumstances) to become more "vying" in behaviour. (ii) The high-*rationality* crowd is shown to spend more evacuation time than a low-*rationality* crowd in emergency situations.	(8) [36]		•	•				•		•			Rationality is associated with evacuation efficiency
Persons with high *rationality* deal with various situations according to their precise judgment, while persons of low *rationality* choose strategy at random.	(9) [36]			•				•		•			Irrationality means deciding randomly

Table 6: Continued.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to H.	Links to P.	Def./ Cha. Ir.	Supp. Ir.	Cont. Ir.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
Computer simulation results show that. . .(2) in an emergency situation, individual hyper-*rationality* among evacuees diminishes evacuation efficiency; (3) the imitation effect enhances cooperation among evacuees, yet reduces evacuation efficiency.	(10) [37]	•		•				•		•			(i) Rationality is associated with evacuation efficiency (ii) Herding is detrimental to evacuation efficiency
The underlying behavior could be called "*irrational*", as all of these effects decrease the chances of survival compared to normal pedestrian behavior.	(11) [103]			•				•		•		•	Rationality is associated with evacuation efficiency
For a low level of panic, a great number of individuals are still able to choose autonomously the best exit but, as soon as their stress level increases, more and more persons imitate other persons around them, discarding any *rational* behaviour.	(12) [17]	•	•	•	•			•		•			Herding is a sign of irrational behaviour
Gabriel Tarde (1901) (cited in van Ginneken, 1992). . .suggested that by mere proximity people become a crowd, and hence subject to uncritical imitation and hence *irrational* behaviour.	(13) [132]	•		•	•		•					•	Herding is a sign of irrational behaviour
Despite the evidence, a number of myths about disasters persist in public discourse, some of which suggest that collective behavior in emergencies is maladaptive, *irrational*, and even pathological.	(14) [31]		•		•	•	•					•	Irrationality is not an accurate theory for evacuation behaviour
The idea that the majority of people in such circumstances are acting '*rationally*' at least in their own terms contrasts with the conventional escape model which assumes everyone is panicking	(15) [15]		•			•	•					•	Irrationality is not an accurate theory for evacuation behaviour
Over several decades, studies specifically looking at panic behaviour in fires have consistently shown that non-adaptive and *irrational* behaviours are actually a rare occurrence	(16) [30]		•	•		•	•					•	Irrationality is not an accurate theory for evacuation behaviour
Although evacuees might be anxious, and frequently use the word 'panic' to describe their own or others' reaction to events, they do not behave in an *irrational* or antisocial manner.	(17) [30]		•			•	•					•	Irrationality is not an accurate theory for evacuation behaviour
One important impact of the rejection of the concept of panic is that management authorities should envision the building occupants as allies during a fire rather than a mass of *irrational* people who need to be controlled	(18) [30]		•			•	•					•	Irrationality theory has significant implications for crowd management
However, many studies on human behaviour in fire and crowd disasters have showed that even under extremely critical conditions people do not panic but they behaved quite *rationally* helping each other	(19) [50]		•			•		•			•		People can maintain rationality during crises
There are various definitions of 'panic', a distinguishing feature of all of them is the crowd's supposed *irrationality*, which is linked to the 'contagion' of emotion.	(20) [24]		•	•			•					•	Irrational behaviour is a symptom of panic

Table 6: Continued.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to H.	Links to P.	Def./ Cha. Ir.	Supp. Ir.	Cont. Ir.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
To judge a response as *irrational* requires a frame of reference, but the frame of reference is often unclear in a mass emergency.	(21) [24]						•					•	Measuring rationality requires a reference point
Fleeing, fear, screaming or other responses to perceived danger may therefore be entirely reasonable [rational] given the limited information – and limited choices – available to people in the midst of an emergency	(22) [24]			•		•	•					•	What seems irrational act, may be individual's best perceived course of action
A leading example of supposed *irrational* crowd behaviour 'panic', which is generally conceptualised as *irrational* flight in which fearful people may end up hurting or killing themselves and others.	(23) [133]		•	•			•					•	
Myth of *irrationality*: crowds may cause people to behave *irrationally* or to engage in panic *irrational* flight.	(24) [133]		•	•		•	•					•	Irrational behaviour is a symptom of panic
Renzetti and Curran. . .claim that while people may copy one another or look to others for indications of how to behave, this does not mean that they lose their *rationality* when in a crowd or similar type of collectivity.	(25) [133]	•				•	•					•	Irrationality theory has significant implications for crowd management
(i) Couch (o.c.) argued that some crowds may appear irrational in that they do not support the ideas "supported by the established institutions of the day." (ii) Couch's analytic approach suggests that the concept of irrationality and its counterpart, rationality, may have "limited applicability for sociological analysis".	(26) [133]			•		•	•					•	Irrationality theory has significant implications for crowd management
In buildings people choose the route they know or when not familiar with the building their exit route is the way they entered the building. Although it might not be the most optimal route, this does not imply *irrationality* or randomness. . . .[This] can be considered a risk assessment.	(27) [134]			•		•	•					•	What seems irrational act, may be individual's best perceived course of action
The notion of *irrationality* is often used when people are not behaving in what is seen as the most effective way to achieve a goal, like fleeing out of a building while not following the emergency exits. However, the effectiveness of behaviour is compared to an ideal way of acting. It thus depends on whoever defines the effective or ideal way how and when the label "*irrational*" is used	(28) [134]			•		•	•					•	(i) Rationality is associated with evacuation efficiency (ii) Measuring rationality requires a reference point
The fact is that people in crowds do not behave *irrationally*, i.e. do not encounter a cognitive shut-down. Actually, the available evidence supports the opposite: individuals behave *rationally* given the information they have and they pursue goals effectively	(29) [134]					•	•					•	(i) Irrationality theory has significant implications for crowd management (ii) Measuring rationality requires a reference point

Table 6: Continued.

Quotes	Qu. Ref. No.	Implications of the quote				The source study							Comments/Interpretations
						Discipline				Study type			
		Links to H.	Links to P.	Def./ Cha. Ir.	Supp. Ir.	Cont. Ir.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
Panic has been associated with individualistic responses and characterised by "self-preservation at all costs, by '*irrational*' animalistic behaviour involving the breakdown of group ties (i.e. 'non-social' behaviour: ignoring of group members, or 'antisocial' behaviour: kicking, trampling)'" [o.c.]. . .this is an inaccurate generalisation; however, this type of description has implications for the ways in which motivation to escape is explained.	(30) [12]			•		•	•					•	Irrationality theory has significant implications for crowd management
Mintz suggested that ineffectual escape in an evacuating crowd is due to individual calculation of costs and benefits, rather than to a contagious outburst of mass *irrationality*, as assumed by the early mass panic models.	(31) [113]					•	•					•	(i) What seems irrational act, may be individual's best perceived course of action (ii) Irrational behaviour is a symptom of panic
The several sociological and social psychological theories of collective behavior which consider panic. . . they make very different assumptions about the process producing the competition, variously attributing it to *irrational* behavior produced by fear and social contagion	(32) [115]		•				•				•	•	Irrational behaviour is a symptom of panic
The individual is no less *rational* or moral in the panic than in any other situation. He is always in pursuit of his own interests and acts on the basis of his current estimates of where these lie.	(33) [33]		•			•	•				•	•	What seems irrational act, may be individual's best perceived course of action
The concept of panic is vague and deciding what is *rational* and people think is *rational* is tricky business	(34) [135]		•			•	•				•	•	Irrationality lacks a clear definition
The concept of mass panic is also still influential in crowd modelling (o.c.), where its *irrationalist* assumptions have implications for the design of public spaces and evacuation procedures.	(35) [27]		•				•				•	•	Irrationality theory has significant implications for crowd management
(i) Popular representations of crowd behaviour in disasters are often characterised by *irrationalist* discourses, in particular 'mass panic' despite their rejection by current scientific research (ii) It is concluded that the term 'panic' is so deeply embedded in popular discourse that people may use it even when they have reason to reject its *irrationalist* implications.	(36) [28]		•			•	•				•	•	Irrationality is not an accurate theory for evacuation behaviour
One classical way of defining panic is to refer to an excessive and groundless feeling of fear which make people take an *irrational* and inappropriate course of action in an attempt to secure themselves.	(37) [119]		•	•			•					•	(i) Irrational behaviour is a symptom of panic (ii) Rationality is associated with evacuation efficiency

Table 6: Continued.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to H.	Links to P.	Def./ Cha. Ir.	Supp. Ir.	Cont. Ir.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
There are two possible ways that *irrationality* may be involved. First, definitions of panic often include exaggerated beliefs about threat and overreactions and so on. Second is the idea that the act of escape may be self-defeating.	(38) [119]		•	•			•					•	(i) Irrational behaviour is a symptom of panic (ii) Rationality is associated with evacuation efficiency
A common assumption regarding individual behavior in emergency is that. . .they panic and react in an antisocial and/or *irrational* manner: they show self-preserving behavior and little or no concern for their neighbors. . . a great deal of solidarity and pro-social behavior has been reported in such situations.	(39) [119]		•	•		•	•					•	Irrationality is not an accurate theory for evacuation behaviour
In the accounts, rather than the *irrational* panic or small group behaviour that has been suggested in previous simulations of crowd behaviour, survivors often described people forming orderly queues, acting calmly despite the emergency situation	(40) [136]		•	•		•	•				•	•	Irrationality is not an accurate theory for evacuation behaviour
The judgment of panic is usually made retrospectively, especially if serious loss of life occurred. But what may be considered inappropriate, excessive, *irrational* or highly intense by others may not be so judged by participants themselves.	(41) [123]		•			•	•					•	What seems irrational act, may be individual's best perceived course of action
Early accounts of 'mass panic' similarly suggested that collective behaviour was *irrational* because it was governed by primitive bio-psychological processes.	(42) [132]		•	•			•					•	Irrational behaviour is a symptom of panic
The most well-documented of these is "mass panic." This refers to an exaggerated or *irrational* fear that is said to spread through "contagion," leading to escape behaviors that are over-hasty, unthinking, and unrestrained by social rules.	(43) [31]	•	•	•			•					•	Irrational behaviour is a symptom of panic
In its more limited and correct usage, panic denotes *irrational* behavior in which judgment and consideration of reality factors are so poor that self-destructive activity may occur.	(44) [29]		•	•	•		•					•	(i) Irrational behaviour is a symptom of panic (ii) Rationality is associated with evacuation efficiency
In fact, 'panic' in the form of *irrational* behaviour is rare during fires and researchers have long ago rejected this concept to explain human behaviour in fire.	(45) [126]		•			•	•					•	Irrationality is not an accurate theory for evacuation behaviour

Table 6: Continued.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to H.	Links to P.	Def./ Cha. Ir.	Supp. Ir.	Cont. Ir.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
Incorrect decision-making due to incomplete information or insufficient resources is not the same as *irrational* decision-making and as such is not sufficient to categorise someone as panicking	(46) [34]		•			•	•					•	What seems irrational act, may be individual's best perceived course of action
Sime (1980) has fully explained the arguments to consider the concept of 'panic' as a poor and ineffective explanation of human behaviour in fire. In fact, 'panic', in the form of *irrational* behaviour, is rare in a majority of fires.	(47) [26]		•			•	•					•	Irrationality is not an accurate theory for evacuation behaviour
(i) It is possible to argue that the choice to herd can be result of a *rational* decision (i.e. a choice "procedurally reasonable in light of the available knowledge and means of computation") (ii) Herding behaviour can be the result of a *rational* decision-making process instead of an "*irrational*- panic" decision	(48) [50]	•	•					•			•		What seems irrational act, may be individual's best perceived course of action

"Qu./Ref. No." means Quote/Reference number.
"Links to P." means (The quote) links Irrationality (Ir.) to Panic (P.).
"Links to H." means (The quote) links Irrationality (Ir.) to Herding (H.).
"Def. Cha. Ir." means (The quote) defines/characterises Irrationality.
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"Soc. Sci." means (The source of the quote) is a study in Social Sciences.
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"Mod." means (The source of the quote) is a study with a main focus on Modelling.
"Emp. Test." means (The source of the quote) is a study with a main focus on Empirical Testing.
"Conc." means (The source of the quote) is a study with a main focus on Conceptualisation.
Note that individual studies can belong to multiple categories (e.g., multiple disciplines).

Table 7: Original quotes on the term herding.

Quotes	Qu. Ref. No.	Implications of the quote			The source study								Comments/Interpretations
							Discipline			Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
(i) The behaviour here is typical for panic situations, e.g. the *herding* tendency dominates. (ii) Such a behaviour is relevant for panic situations where this *herding* tendency becomes important and has been observed empirically (o.c.)	(1) [18]	•			•			•		•			(i) Herding is a feature of panic behaviour (ii) Herding is common evacuation behaviour
We found a non-monotonic dependence of the evacuation times on the coupling constants. These times depend on the strength of the *herding* behaviour, with minimal evacuation times for some intermediate values of the couplings, i.e., a proper combination of *herding* and use of knowledge about the shortest way to the exit.	(2) [18]				•			•		•			Herding can be beneficial to evacuation efficiency
(i) A large value of k_D implies a strong *herding* behaviour which has been observed the case of panics. (ii) The behaviour here is typical for panic situations, e.g. the *herding* tendency dominates.	(3) [18]	•		•				•		•			(i) Herding is a feature of panic behaviour (ii) Herding is common evacuation behaviour
Models of pedestrian crowds have generated a number of surprising or counterintuitive predictions. For example, panic should induce "*symmetry breaking*" in which some available exits or escape routes from enclosed spaces are jammed while others go under-utilized.	(4) [100]	•		•	•			•		•			(i) Herding is a feature of panic behaviour (ii) Herding is a common modelling assumption
We hypothesize that, under time and monetary pressure, subjects would increase their tendency to follow their neighbours as suggested in an early model of crowd panics [o.c.], which would give rise to the observed *herding* pattern under high stress.	(5) [40]	•		•	•			•			•		(i) Stress increases herding tendency (ii) Herding results from following neighbours

Table 7: Continued.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
When the panic happens, the agents want to evacuate as quickly as possible and may try to choose the closest exit. At the same time, they may have the *herd* mentality.	(6) [101]	•			•			•		•			Herding is a feature of panic behaviour
Herding is stronger under high stress than under low stress. . .[but], pedestrians had a higher probability of following their neighbours when stress was high, simply because the neighbouring individuals were more numerous due to the increased density level. *Herding*, therefore, resulted from the crowdedness and not from a change in the individual tendency to imitate neighbours.	(7) [40]			•				•			•		(i) Stress increases herding tendency (ii) Herding tendency is moderated by the crowdedness level (iii) Herding is not the same as imitation
It remains unclear to what extent pushing, overcrowding and peer imitation [herding] can affect the efficiency of egress. The main obstacle to answering these questions is the scarcity of detailed empirical data.	(8) [40]							•			•		The effect of herding on evacuation efficiency is unclear
Although people often display obvious *herding* behavior, their judgment may not be to follow the crowd.	(9) [47]				•	•	•				•		Herding is not the same as imitation
Many studies (o.c.) have reported that *herding* behavior often occurs in relatively large number of people in panic situations.	(10) [47]	•			•		•				•		(i) Herding is a feature of panic behaviour (ii) Herding is common evacuation behaviour

Table 7: Continued.

Quotes	Qu. Ref. No.	Implications of the quote				The source study							Comments/Interpretations
						Discipline				Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
(i) Because *herding* behavior is not the dominant preference of people, peacetime training of how to escape an acute crisis would be critically important. (ii) We present novel evidence showing that people prefer searching for an exit and avoiding smoke rather than following the crowd [*herding*] regardless whether with intuition or deliberation when the crisis situation was activated. (iii) Reliable and consistent evidence shows that when facing a crisis (e.g., fire), searching for an exit and avoiding smoke are preferred by people rather than following the crowd [*herding*]	(11) [47]					•	•				•		Herding is not common evacuation behaviour
Herding coefficient. . . α indicates an evacuee's tendency to emulate others' strategies, and (1-α) reflects the degree to which evacuees prefer to choose their own strategy based on personal experiences.	(12) [36]			•				•		•			Herding means imitating/following others/majority
Most individuals (90% of total individuals in subway station) select the evacuation exit that is closest to them, while others totally panic (5% of total individuals in subway station) and follow the flow of the crowd around them [*herding*] (5% of total individuals in subway station).	(13) [16]	•		•	•			•		•			Herding is a feature of panic behaviour
While we can thus rule out the *herding* effect in our experiment, we should point out that in different scenarios tendencies to follow others could be more prominent. For example, consider the case of an environment in which the exit routes are less clear than in our experiment or even entirely unknown.	(14) [52]			•		•			•		•		(i) Herding means imitating/following others/majority (ii) Herding is not common evacuation behaviour (iii) Herding tendency is moderated by the level of uncertainty

Table 7: Continued.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
The direction that more pedestrians moving to is more attractive. Such behavior is the *herding* behavior.	(15) [137]			•	•			•		•			Herding means imitating/following others/majority
The excessive herding behavior can reduce the evacuation efficiency.	(16) [137]							•		•			Herding is detrimental to evacuation efficiency
Our study just investigates the fundamental collective effects which fluctuations, increased desired velocities, and *herding* behaviour can have, independently of whether all criteria of panics are fulfilled or not.	(17) [103]	•		•	•			•		•		•	
. . .possible mechanisms underlying the effects of escape panic (regarding an increase of the desired velocity, strong friction effects during physical interactions, and *herding*).	(18) [19]	•			•			•		•		•	Herding is a feature of panic behaviour
In case of an evacuation, people may also be influenced by the behavior of other people, and copy this. . .Ariely considers this to be *herding* behavior	(19) [58]			•	•			•			•		Herding means imitating/following others/majority
The models showed that people were inclined to stay at the concert area but when they saw others leaving, they were inclined to leave as well. The results seem to imply that *herding* is impulsive	(20) [58]			•	•			•			•		Herding is observable in movement initiation
The effect of *herding* behaviour might be different when people are in a known environment. . .Collecting data in known environments could provide insights on this.	(21) [58]							•			•		Herding tendency is moderated by the level of uncertainty

Table 7: Continued.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
Knowing how much stress people experience, could show differences in the effect of *herding* on evacuation choices	(22) [58]							•			•		Herding tendency is moderated by stress level
Herding effect (i.e., *herding* behavior), considered as a common phenomenon in various fields such as emergency evacuation of large crowds, has caught much interest of scholars.	(23) [8]				•			•		•			Herding is common evacuation behaviour
For large population to escape from danger in a closed building with two symmetrically located exists or paths, *herding* effect means that the great majority of people adopt the same one in escaping, leaving the other one vacant.	(24) [8]			•	•			•		•			Herding means imitating/following others/majority
(i) *Herding* effect usually means inefficient utilization of resources, thus often leading to inferior outcomes in real life. (ii) Asymmetric utilization of escaping exits in emergency due to *herding* effect will decrease evacuation efficiency and bring disastrous consequences	(25) [8]			•	•			•		•			Herding is detrimental to evacuation efficiency
Herd behaviour is manifested, with underutilisation of other exits.	(26) [17]			•	•			•		•			Imbalanced use of exits is evidence for herding

Table 7: Continued.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
As evacuees choose to follow others during a game, *herding* behavior will occur in the evacuation process.	(27) [37]			•				•		•			Herding means imitating/following others/majority
We use the hypothesis of *herd* behaviour to model the passenger decision-making process that leads to self-evacuation	(28) [43]			•	•			•		•			Herding is common modeling assumption
In an emergency, passengers on the periphery of the event are usually unaware of the details of the situation. Rather, these passengers usually adopt a *herd* mentality and evacuate immediately for their security.	(29) [43]				•			•		•			(i) Herding is common evacuation behaviour (ii) Herding tendency is moderated by the level of uncertainty
We first introduce a new microscopic model characterized by an exploration phase and an evacuation phase. The main ingredients of the model are an alignment term, accounting for the *herding* effect typical of uncertain behavior, and a random walk, accounting for the need to explore the environment under limited visibility.	(30) [44]				•			•		•			(i) Herding is common modeling assumption (ii) Herding tendency is moderated by the level of uncertainty

Table 7: Continued.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
The crowd control technique investigated in the previous sections relies on the fact that pedestrians actually exhibit *herding* behavior in special situations	(31) [44]				•			•		•			Herding is common evacuation behaviour
A prototype system has been developed, which is able to demonstrate some emergent behaviors, such as competitive queuing, and *herding* behaviors.	(32) [39]				•			•		•			Producing herding effects is a common criterion for verifying simulation models
Herding behavior is often observed during the evacuation of a crowd in a room with two exits—one exit is clogged while the other is not fully utilized.	(33) [39]			•	•			•		•			Imbalanced use of exits is evidence for herding
One well-known example of social proof under emergency situations is the *herding* behavior—when under highly uncertain and stressful situations, an individual tends to follow others almost blindly.	(34) [39]			•	•			•		•			(i) Herding means imitating/following others/majority (ii) Stress increases herding tendency (iii) Herding tendency is moderated by the level of uncertainty
Sometimes *herding* behavior helps people to exit safely, and at other times, the *herding* behavior may lead people to a dead end or cause the blockages of some exits even though other exits are not fully utilized.	(35) [39]				•			•		•			The effect of herding on evacuation efficiency is unclear
Building designers often assume that a crowd would exit evenly among multiple exits of a room in case of an emergency; however, *herding* behavior invalidates such an assumption.	(36) [39]			•	•			•		•			Imbalanced use of exits is evidence for herding

Table 7: Continued.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
In this paper the evacuation crowd system is abstracted into a dynamic complex network composed of three types of people, namely calm people, panic people, and *herding* people, as well as their interactions.	(37) [105]	•			•			•		•			Herding is common modeling assumption
If other people's behaviors show a high level of irrationality, such as screaming, rushing, colliding, pushing, etc., which provide salient evidence about panic emotion. . .one who has a certain *herding* level will tend to be "infected" and also present irrational panic behavior	(38) [105]	•	•	•	•			•		•			Herding is common evacuation behaviour
The evacuation of pedestrians from a smoke-filled room with two exits can lead to *herding* behaviour and clogging at one of the exits.	(39) [38]			•	•			•		•			Imbalanced use of exits is evidence for herding
During evacuation. . .Exit behaviors such as following leaders or *herding* to an exit are commonly observed.	(40) [138]				•			•		•			Herding is common evacuation behaviour
The agents choose their actions and evacuation routes by considering individual preferences, as well as the roles and the behaviors of the members in the social group and other neighboring agents [*herding*].	(41) [138]							•		•			Herding is not the sole determinant of the behaviour
In addition to static and dynamic fields, the extended model adopts the smoke and *herding* fields to reflect pedestrian's smoke-avoiding behavior and *herding* behavior.	(42) [137]				•			•		•			Herding is common modeling assumption

Table 7: Continued.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
The direction that more pedestrians moving to is more attractive. Such behavior is the *herding* behavior.	(43) [137]			•				•		•			Herding means imitating/following others/majority
Study of collective behavior of mice has received increasing attention in the field of evacuation. Based on mice, scale-free behavior [o.c.], *herd* mentality [o.c.], learning experience [o.c.], etc. have been investigated.	(44) [90]				•				•		•		Herding theory in evacuation has been influenced by animal models of behaviour
Helbing et al. proposed the ignorance of available exits model, which suggested that neither simple individualistic nor *herding* behavior is optimal for escaping	(45) [59]								•		•		Mixture of herding and individualistic behavior is beneficial to evacuations
Pure *herding* behaviour infers that the whole crowd eventually moves in the same direction while other available exits are not efficiently used.	(46) [59]			•					•		•		Imbalanced use of exits is evidence for herding
Some studies have suggested that the direction of influence is such that we tend to copy the decision of the majority, and this tendency is often referred to as "*herd* behaviour".	(47) [53]			•				•			•		Herding means imitating/following others/majority
Herd behaviour has been assumed by a considerable body of literature (mostly theoretical studies) as a common default behavioural feature of pedestrian evacuees.	(48) [45]							•			•		Herding is common modeling assumption
Results also suggested that a simple *herd*-model may not suffice as a default universal assumption for realistic replication of evacuees' directional choices	(49) [45]					•		•			•		Pure herding is not an accurate modeling assumption

Table 7: Continued.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
The symmetry breaking [*herding*] observed in nature is fascinating. This symmetry breaking is observed in both human crowds and ant colonies. In such cases, when escaping from a closed space with two symmetrically located exits, one exit is used more often than the other.	(50) [60]			•	•				•		•		(i) Imbalanced use of exits is evidence for herding (ii) Herding theory in evacuation has been influenced by animal models of behaviour
(i) We study the efficacy of allelomimesis [*herding*] as an escape strategy of mobile agents (pedestrians) that aim to leave a two-exit room within the shortest possible time. (ii) Allelomimesis is the act of copying one's kindred neighbors. (iii) Allelomimesis provides a simple yet versatile mechanism for studying the egress behavior of confined crowds in a multi-exit room.	(51) [46]			•				•		•			(i) Herding is common modeling assumption (ii) Herding means imitating/following others/majority
It is not hard to see that allelomimesis [*herding*] is a plausible mechanism for driving the emergence of herd behavior in crowds and animal groups.	(52) [46]			•	•			•		•			Herding theory in evacuation has been influenced by animal models of behaviour
When orientation and visibility is poor, such as in smoke-filled rooms or overcrowded areas, only the local information is accessible to each pedestrian. The situation encourages pedestrians to base their decisions on what they know, thus copying the actions of their immediate neighbors, which may result to *herding*.	(53) [46]			•	•			•		•			(i) Herding means imitating/following others/majority (ii) Herding tendency is moderated by the level of uncertainty

Table 7: Continued.

Quotes	Qu. Ref. No.	Implications of the quote					The source study						Comments/Interpretations
							Discipline			Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
The assumption of *herd*-like behaviour does not necessarily apply to all contexts of evacuations and it should be considered in conjunction with the moderating role of context-specific factors, particularly the level of information available to individual evacuees.	(54) [48]							•			•		(i) Herding is not common evacuation behaviour (ii) Herding tendency is moderated by the level of uncertainty
We found that the ants demonstrated the phenomenon of "symmetry breaking" [*herding*] in this stress situation.	(55) [61]								•		•		Herding theory in evacuation has been influenced by animal models of behaviour
Blind copying promotes *herding* behavior in animal groups often with dire consequences to participants.	(56) [91]			•					•		•		Herding theory in evacuation has been influenced by animal models of behaviour
A binary logit model is proposed showing that the occurrences of HB [*herding* behaviour] are affected by both environmental and personal factors. In particular, the model shows that the personal aptitude to HB can have a key role in selecting an exit.	(57) [50]							•			•		Herding tendency should be considered in conjunction with individual differences
Three types of interactions among evacuees have been identified: *HB* (i.e. following others' behaviour), cooperative behaviour (i.e. working or acting together for the common/mutual benefit) and competitive/selfish behaviour	(58) [50]							•			•		Herding tendency should be considered in conjunction with individual differences
HB occurs whenever a decision-maker prefers, among different options, to follow other people's choices. As regards to the exit choice, this can be explained by the decision of the evacuee to choose an exit just because other evacuees had selected it, instead of striving to identify the exit that would provide them with the best evacuation conditions.	(59) [50]			•				•			•		(i) Herding means imitating/following others/majority (ii) Imbalanced use of exits is evidence for herding
The literature argues that *HB* could have both positive and negative effects depending on the evacuation conditions	(60) [50]							•			•		The effect of herding on evacuation efficiency is unclear

Table 7: Continued.

Quotes	Qu. Ref. No.	Implications of the quote				The source study							Comments/Interpretations
						Discipline				Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
the degree of uncertainty can make the difference in the choice since the higher the uncertainty the more decision-maker could manifest *HB*.	(61) [50]							•			•		Herding tendency is moderated by the level of uncertainty
The model shows that the probability of having an occurrence of *HB* decreases with the increase of the difference between the number of persons close to the most crowded exit and the least crowded exit. . . what this means is that when this difference is very high, a decision maker prefers the least crowed exit	(62) [50]					•		•			•		Herding tendency is moderated by the crowdedness level
This "follow-the-crowd" [*herding*] behavior was proposed as a possible behavior of simulated humans	(63) [139]			•					•		•		Herding is common evacuation behaviour
Herding happens when ordinary people behave as a group, effectively surrendering their ability to function as individuals. In panic situations where decisions have to be made quickly under duress it is likely for individuals to lose their ability to decide on their own. Instead, these impaired individuals tend to imitate the action of their neighbors. The tendency to rely on others is a product of experience.	(64) [140]	•		•	•				•		•		(i) Herding is a feature of panic behaviour (ii) Herding means imitating/following others/majority
The severe congestion and high pressures that are induced or worsened by *herding* continue to exact a high cost to society in terms of infrastructure damage and loss of life and limb	(65) [140]				•				•		•		Herding is detrimental to evacuation efficiency

Table 7: Continued.

Quotes	Qu. Ref. No.	Implications of the quote			The source study								Comments/Interpretations
							Discipline			Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
The role of *herding* in escape panic has been studied using equations of motion in the presence of interaction forces [o.c.]. However, quantitative comparisons between model prediction and experimental result have remained scarce.	(66) [140]	•							•		•		Herding theory is in need of empirical testing
The mice exhibited *herding* behavior while escaping from a pool of water in a two-exit flooded chamber.	(67) [140]				•				•		•		Herding theory in evacuation has been influenced by animal models of behaviour
The phenomenon of *herding* is a very general feature of the collective behavior of many species in panic conditions, including humans. It has been predicted theoretically that panic induced *herding* in individuals confined to a room can produce a non-symmetrical use of two identical exit doors. Here we demonstrate the existence of that phenomenon in experiments, using ants as a model of pedestrians. . . Our experimental results, combined with theoretical models, suggest that some features of the collective behavior of humans and ants can be quite similar when escaping under panic.	(68) [62]	•		•	•				•		•		(i) Herding is a feature of panic behaviour (ii) Herding is common evacuation behaviour (iii) Imbalanced use of exits is evidence for herding (iv) Herding theory in evacuation has been influenced by animal models of behaviour
(i) *Herding* prevented the full utilization of the two exits by the escaping mice. (ii) At the height of panic, allelomimetic tendencies dominate over individual decisions, giving rise to *herding*.	(69) [92]	•		•	•				•		•		(i) Herding means imitating/following others/majority (ii) Imbalanced use of exits is evidence for herding
People in a dark or smoky room are mimicked by "blind" students wearing eye masks… Surprisingly, adding more exits does not improve the situation in the expected way, since most people use the exit that is discovered first, which may be viewed as a kind of *herding* effect based on nonlocal, but direct acoustic interactions.	(70) [141]			•	•			•			•		(i) Imbalanced use of exits is evidence for herding

Table 7: Continued.

Quotes	Qu. Ref. No.	Implications of the quote				The source study							Comments/Interpretations
						Discipline				Study type			
		Links to P.	Links to Ir.	Def./ Cha. H.	Supp. H.	Cont. H.	Soc. Sci.	Phys. Sci.	Bio. Sci.	Mod.	Emp. Test.	Conc.	
Herd behaviour is manifested, with underutilisation of other exits. . .The choice model proposed in this work is based on the '*herding* behaviour': in a panic situation, the individual is inclined not to behave autonomously, but to imitate and follow the surrounding persons	(71) [17]	•		•	•			•		•			(i) Imbalanced use of exits is evidence for herding (ii) Herding is a feature of panic behaviour (iii) Herding means imitating/following others/majority
Humans do not tend to imitate direction choices of the majority [*herding*]. To the contrary, they tend to avoid the direction chosen by the majority, and the bigger the majority is, the less likely they are to follow it. The high-urgency treatment (assumed to be associated with higher degrees of stress) did not reverse, nor did it decrease this avoid-the-majority tendency. If anything, it even amplified it in certain choice situations.	(72) [41]					•		•	•		•		Stress does not increase imitation tendency [in direction choices]
The general level of crowding (i.e. the total number of people in the choice-maker's vicinity) is another factor that can moderate the reaction to peers' decision. Higher levels of crowding also amplified the avoid-the-crowd tendency [opposite the *herding*] in certain direction choice scenarios.	(73) [41]					•		•			•		Herding tendency is moderated by the crowdedness level
Imitative (*herd*) behaviour in direction decision-making hinders efficiency of crowd evacuation processes	(74) [49]							•		•			Herding is detrimental to evacuation efficiency

"Qu./Ref. No." means *Quote/Reference number.*
"Links to P." means *(The quote) links Herding (H.) to Panic (P.).*
"Links to Ir." means *(The quote) links Herding (H.) to Irrationality (Ir.).*
"Def. Cha. H." means *(The quote) defines/characterises Herding.*
"Supp. H." means *(The quote) supports (the theory of) Herding.*
"Cont. H." means *(The quote) contradicts (the theory of) Herding.*
"Soc. Sci." means *(The source of the quote) is a study in Social Sciences.*
"Phys. Sci." means *(The source of the quote) is a study in Physical Sciences.*
"Bio. Sci." means *(The source of the quote) is a study in Biological Sciences.*
"Mod." means *(The source of the quote) is a study with a main focus on Modelling.*
"Emp. Test." means *(The source of the quote) is a study with a main focus on Empirical Testing.*
"Conc." means *(The source of the quote) is a study with a main focus on Conceptualisation.*
Note that individual studies can belong to multiple categories (e.g., multiple disciplines).

Table 8: Review summary of the empirical studies on herding.

Ref.	Aspect of behaviour		Experiment method					Evidence of herding		Further details
	Exit (direction) choice	Exit (direction) choice changing	Reaction time	Human crowds	Virtual reality	Ants	Mice	Observed	Not observed	
[62]	•					•		•		Herding observed in the form of asymmetric use of exits by 'panicked' ants
[59]	•					•		•		The degree of asymmetry increased linearly with the temperature
[60]	•					•		•		The degree of asymmetry increased then decreased by ants' density
[61]	•					•		•		Ants under stress demonstrated the phenomenon of "symmetry breaking".
[42]	•			•		•			•	Symmetry breaking was associated with the difference in the width of exit in proportional ways
[140]	•						•	•		The mice exhibited herding behaviour while escaping from a pool of water in a two-exit flooded chamber
[92]	•						•	•		The mouse experiments yielded lower throughputs caused by herding. Herding prevented the full utilization of the two exits.
[91]	•						•	•		The occurrence of blind copying is suggested by the uneven (biased) utilization of the available pool space and exits by untrained members especially in the larger 30-mouse groups
[52]	•				•				•	Experiments in interactive virtual-reality setting ruled out the herding effect
[54]	•				•			•		[In a non-crowded virtual tunnel evacuation], participants under social influence treatment were more likely to follow the virtual agent
[55]	•		•		•			•		(i) [In a non-crowded virtual tunnel evacuation], Participants were less likely to move to the emergency exit in the conflict conditions compared to the no-conflict condition. (ii) The presence of passive virtual agent made subjects delay their movement reaction

Table 8: Continued.

Ref.	Aspect of behaviour		Experiment method					Evidence of herding		Further details
	Exit (direction) choice	Exit (direction) choice changing	Reaction time	Human crowds	Virtual reality	Ants	Mice	Observed	Not observed	
[56]	•				•			•		(i) [In a non-crowded virtual tunnel evacuation], exit choice is jointly influenced by both exit familiarity and by the egress behaviour of neighbours. (ii) Social influence increases with the number of neighbours
[50]	•				•			•		Occurrences of herding behaviour are affected by both environmental and personal factors.
[47]	•				•				•	People prefer searching for an exit and avoiding smoke rather than following the crowd
[40]	•				•			•		The observed herding patterns do not result from a change in the herding tendency but instead from the crowdedness
[58]			•		•			•		(i) The more people someone sees leaving, the more inclined this person is to leave. (ii) Seeing people leave has more impact than seeing people stay.
[64]			•	•				•		(i) Social influence is an important factor in reaction time especially when fire cue is unclear (ii) Social influence (on reaction time) increases with decreasing distance between visitors.
[48]	•			•					•	Social influence (on exit choice) is moderated by the level of decision ambiguity

Table 8: Continued.

Ref.	Aspect of behaviour			Experiment method				Evidence of herding		Further details
	Exit (direction) choice	Exit (direction) choice changing	Reaction time	Human crowds	Virtual reality	Ants	Mice	Observed	Not observed	
[45]	•			•					•	(i) Social influence (on exit choice) does not necessarily increases with decreasing distance between individuals. (ii) [In a crowded evacuation], exit choice is jointly influenced by both social interactions and physical factors (iii) Social influence increases with the number of neighbours
[53]	•			•					•	(i) Social influence is moderated by the effect of individual differences (ii) Social influence (on exit choice) does not necessarily act to the direction of herding
[41]	•			•					•	(i) Social influence acts to the opposite of herding (ii) Stress does not increase imitation tendency (iii) The number of neighbours moderate the social influence
[49]	•			•					•	Mis-specifying herding tendency can substantially bias modelling outcomes
[65]	•	•		•				•	•	(i) Individuals show clear imitative tendency in changing their exit choice decisions (ii) Individuals do not show herding tendency in their exit choices (iii) Herding tendency of individuals (in exit choice) does not increase by stress
[66]	•	•		•				•	•	(i) Social groups show clear imitative tendency in changing their exit choice decisions (ii) Social groups do not show herding tendency in their exit choices (iii) Herding tendency of groups (in exit choice) does not increase by stress

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Research Article

A Modified Inverse Distance Weighting Method for Interpolation in Open Public Places Based on Wi-Fi Probe Data

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Urban open places with a public service function (e.g., urban parks) are likely to be populated in peak hours and during public events. To mitigate the risk of overcrowding and even events of stampedes, it is of considerable significance to realize a real-time full coverage estimate of the population density. The main challenge has been the limited deployment of crowd surveillance detectors in open public spaces, leading to incomplete data coverage and thus impacting the quality and reliability of the density estimation. To remedy this issue, this paper proposes a modified inverse distance weighting (IDW) method, named the inverse distance weighting based on path selection behavior (IDWPSB) method. The proposed IDWPSB method adjusts the distance decay effect according to visitors' path selection behavior, which better characterizes the human dynamics in open spaces. By implementing the model in a real-world road network in the Shichahai scenic area in Beijing, China, the study shows a decrease in the absolute deviation by 17.62% comparing the results between the new method and the traditional IDW method, justifying the effectiveness of the new method for spatial interpolation in open public places. By considering the behavioral factor, the proposed IDWPSB method can provide insights into public safety management with the increasing availability of data derived from location-based services.

1. Introduction

In Chinese cities, open places serving a public service function (e.g., urban parks) are likely to be populated in peak hours and during public events. The inherent difficulties of surveillance and crowd control in these open spaces highlight the numerous evacuation problems that could arise in an emergency, including the occurrence of stampedes. This is precisely what occurred on February 5, 2004, at the Lantern Festival in Beijing's Miyun Park. In this instance, the primary viewing space was trampled and caused 37 fatalities even though the total number of visitors was far below the park's maximum capacity. Hence, controlling the total number of visitors is insufficient for comprehensive safety management in open public places. It is paramount to realize a real-time and full coverage population density estimate to prevent local overcrowding.

To date, many techniques have been applied to crowd surveillance. Video monitoring recognition is one of the most widely used techniques in public security surveillance. With the development of computer vision, studies on crowd analysis [1, 2] and anomalous detection [3–5] based on video monitoring recognition techniques have made significant strides. Although critical improvements have been made in the video monitoring recognition techniques, it remains infeasible to count the number of people primarily due to the partial occlusions among individuals when the crowd density is extremely high [6]. This difficulty in counting high-density crowds has become a more severe issue for safety management in open public places.

There is an opportunity to overcome this issue by using location-based services (LBSs), such as cellular phone and Wi-Fi probe data. The popularity of smartphones ensures that cell phone data, including cellular signaling data and call detail record data, can fill the gap of individual-based trajectory tracking in urban open spaces [7–10]. Nonetheless, employing cellular phone data has been considered an invasion of people's privacy [11] and, consequently, its widespread

use in exploring individual behavior is restricted. However, the increasing ubiquity of public wireless networks in urban environments creates nascent pathways to understand population dynamics across space and over time [12]. As an emerging location sensor, Wi-Fi probes can conveniently obtain location information from mobile devices [13]. Given the popularity of smartphones today, Wi-Fi probes may prove indispensable in acquiring aggregate movement information in an area of interest [14]. Since Wi-Fi probes merely maintain a unique log of the mobile device, there are little potential privacy infringements [11]. Wi-Fi probe data (called Wi-Fi data hereafter) are consequently becoming an integral component of crowd surveillance [12, 15, 16].

Regardless of how the data collection process ultimately develops, the age-old paradox of expensive detection equipment and limited budgets remains in effect, which leads to the limited deployment of detectors in open public spaces. Moreover, equipment failures and data transmission interruptions diminish the data coverage and severely weaken the quality and reliability of related applications. Thus, the challenge is to realize an acceptable level of the data accuracy within the constraints of a limited budget [17]. The spatial interpolation technique can yield efficient imputations of the missing data while being cost-effective without additional data collection efforts [18]. To this end, various interpolation methods, including the geostatistical and deterministic methods, have been developed in recent decades. The most common geostatistical method applied to traffic interpolation is the Kriging method, which is based on the assumption that the area of interest is an unrestricted region that has spatial autocorrelation with its neighborhoods. Typically, the Kriging method only adopts the Euclidean distance as the distance metric to represent the distance decay effect. Modifications of the Kriging have adopted various distance metrics, such as the road network distance [17, 19] and the great-circle distance [20], which, to a limited degree, can address the limitations associated with the traditional Kriging. The inverse distance weighting (IDW) method is the most widely utilized deterministic method and is commonly applied to big dataset interpolation, including air quality [21] and noise pollution monitoring [22], and has been implemented as a standard spatial interpolation procedure in many geographic information systems (GIS) software packages [23]. The IDW method assumes that each measured point has a local influence on unsampled sites moderated by the distance decay effect. Compared to the Kriging method, the IDW method has a greater ability to adjust the distance metric as it is not restricted by the covariance and variation functions. However, the primary disadvantage of the existing IDW methods is that they only consider objective factors such as the road network structure and spatial distance as decisive factors in the interpolation process while ignoring the influence of individual travel behavior. In an urban open space, an individual's travel often matches their activity demands. The seemingly free-flowing crowd actually has a particular preference for certain paths, referred to as the path selection behavior. The path selection behavior becomes more prominent in emergency situations such as overcrowding [24]. This path selection behavior has not been adequately considered in the existing interpolation methods.

To estimate the spatial distribution of the crowd population in open public places, we have proposed a new interpolation method called the inverse distance weighting method based on path selection behavior (IDWPSB). The path selection behavior is used to adjust the distance decay effect, making the interpolation result more suitable for approximating the actual crowd characteristics. The IDWPSB has been applied to a case study in the Shichahai scenic area in Beijing, China, to verify the computational efficiency and reliability of this new method in estimating the crowd population in road networks.

Table 1: Description of Wi-Fi data.

Field	Description
Probe ID	Wi-Fi probe label
User MAC	MAC address of the mobile device
Start Timestamp	Start time of receiving a probe request
End Timestamp	End time of receiving a probe request
RSS	Received signal strength of the probe request

2. Materials

2.1. Description of Wi-Fi Data. A Wi-Fi-enabled mobile device (e.g., smartphone) can initiate a connection to a Wi-Fi network by continuously broadcasting signals, also known as the probe requests. Each probe request contains a sequence of device information, including the media access control (MAC) address, device type, brand, and manufacturer. For each smart device, the MAC address is unique to the network connection. Since the probe requests are not encrypted, they can be passively captured and decoded with the help of wireless sniffers. In addition, the received signal strength (RSS) of probe requests can also be measured. All these data are uploaded to a server.

The Wi-Fi probe is a type of wireless sniffer. A description of the data collected by the Wi-Fi probe is shown in Table 1. Since there is a clear correspondence between a user and his smart device, the user's MAC address can be regarded as an identifier of a specific individual who is located within the detection range of the Wi-Fi probe. To avoid violations of privacy, the user's MAC address is anonymized by only extracting a fragment from the source record. The timestamp records the temporal information of the Wi-Fi connection. The RSS indicates the connection intensity, which mainly depends on the physical distance between the smart device and the Wi-Fi probe.

2.2. Preprocessing of Wi-Fi Data. Before being analyzed, the raw Wi-Fi data extracted from the server require several steps of preprocessing. First, the RSS needs to be resampled at a regular time step due to the bursty nature of the probe requests, as the probe requests sent by a mobile device are not evenly distributed in time. For example, there can be a sequence of probe requests from one smart device within a few hundred milliseconds, followed by a silent period that

Figure 1: Crowd interpolation in different scenarios. Node o is the unsampled site, and nodes a and b are sampling sites.

lasts several seconds. The number of bursts depends on the working condition of the smart device. To mitigate the uncertainty of the RSS captures, we averaged the RSS values received within a one-second interval [25].

The second step is to uniformize the detection radius among the Wi-Fi probes installed in various environments by data screening. The relationship between the RSS and physical distance is calculated as

$$S = 10^{(P-I)/N} \tag{1}$$

where S is the physical distance from the smart device to the Wi-Fi probe, I is the RSS, P is the calibration parameter of the RSS, and N is the calibration parameter of the distance decay effect. For a given type of Wi-Fi probe, P and N are constants. By setting a maximum detection radius for the Wi-Fi probe, the lower limit of the RSS, I_{min}, can be calculated accordingly, by which the request records with RSS values smaller than I_{min} can be excluded. In addition, to remove individuals who are not outdoor, a threshold for the time duration can be set, defined as the end time minus the start time. All the records with a time duration larger than the threshold value (i.e., one hour) are eliminated because individuals in an indoor environment stay connected longer.

Third, considering that some individuals, such as children and senior citizens, do not carry a smart device, we adjusted the detected population through the detectable rate of the Wi-Fi probe. The detectable rate of the Wi-Fi probe is defined as

$$r_d = \frac{M_d}{M_a} \tag{2}$$

where r_d is the detectable rate, M_d is the population detected by the Wi-Fi probe, and M_a is the actual population in the detection radius. The detectable rate of a Wi-Fi probe is related to multiple factors, including the installation environment, working conditions of the smart devices, and the population under coverage. We obtained the parameter in a field survey, in which M_a was acquired by manually counting the number of people within the scope. By surveying the sampling sites, the detectable rate of each Wi-Fi probe is calibrated. Then, the adjusted detected population can be calculated accordingly as

$$M_{ad} = \frac{M_d}{r_d} \tag{3}$$

where M_{ad} is the adjusted population within the detection radius of a Wi-Fi probe.

3. Methodology

3.1. Inverse Distance Weighting (IDW) Method. First, the local crowd density at the sampling site is calculated as

$$\rho_i = \frac{M_i}{S_i} \tag{4}$$

where ρ_i is the local crowd density and M_i is the adjusted detected population at a sampling site i. S_i is the total area of the road segments in the detection radius of Wi-Fi probe i and is calculated as

$$S_i = \sum_{1}^{n} l_j * d_j \tag{5}$$

where n is the number of road segments within the detection radius of Wi-Fi probe i, l_j is the length of road segment j, and d_j is the average width of road segment j.

According to the principle of the IDW, the estimated crowd density at an unsampled site, (node) o, is calculated as

$$\rho_o = \frac{\sum\left(\rho_i / {D_{o,i}}^2\right)}{\sum\left(1/{D_{o,i}}^2\right)} \tag{6}$$

where ρ_o is the crowd density of the unsampled node, o; ρ_i is the crowd density of the sampling node, i; and $D_{o,i}$ is the shortest path distance from node o to node i.

A series of scenarios were set to simulate the interpolation process for open public places and validate the effectiveness of (6). As shown in Figure 1, we assume that node o is the unsampled site and that nodes a and b are sampling sites. We also assume that the path distance from node o to node a and that to node b are equal. Equation (7) formulates the crowd density at node o as ρ_o, which is estimated based on the observed population on nodes a and b.

$$\rho_o = \frac{\rho_a / {D_{o,a}}^2 + \rho_b / {D_{o,b}}^2}{1/{D_{o,a}}^2 + 1/{D_{o,b}}^2} \tag{7}$$

where ρ_a and ρ_b are the observed population on node a and node b, respectively, $D_{o,a}$ and $D_{o,b}$ are the shortest path distances for segment o-a and segment o-b, respectively.

To further explain Equation (7), we have designed three scenarios, as shown in Figure 1. In Figure 1(a), when there are no road branches, $\rho_o = \rho_a + \rho_b$. Now, we add a junction to the

Figure 2: Activity trajectory in a three-dimensional space.

road, as shown in Figure 1(b). When individuals select roads randomly (i.e., no path selection behavior), the crowd flow will evenly split between *o*-*a* and *o*-*b*. In this case, node *a* and node *b* still contribute equally to the population estimation at node *o*. In Figure 1(c), when node *a* becomes more attractive than node *b*, we adjust the distance weight according to the path selection behavior to reflect the attractiveness of the road segment.

3.2. Inverse Distance Weighting Based on the Path Selection Behavior. Because of the large number of junctions in the road networks of open public places, the distance decay effect with the spatial distance on a straight road is altered by individual preference. Through the observation of individuals' activity trajectories derived from the Wi-Fi data, the path selection behavior pattern, denoted as the transition probability, can be extracted. Adjustment of the distance decay effect according to the transition probability of the path selection behavior can improve the interpolation accuracy.

An activity trajectory Tra_x is defined as a sequence of locations that an individual walks through during a period, denoted as

$$Tra_x \left\{ \left(l_j, t_j \right) \mid j = 1, 2, \ldots, n \right\} \tag{8}$$

where l_j is the jth node on the activity trajectory and t_j is the timestamp of node j, both of which are recorded by a series of Wi-Fi probes located at different sites, and n is the total number of nodes on the activity trajectory. As shown in Figure 2, a cluster of activity trajectories can reveal the diversity of the path selection behavior among the crowd. In a road network, the set of nodes that most activity trajectories contain has a stronger association, regardless of the spatial distance.

The transition probability of the path selection behavior can be calculated from a large number of activity trajectories recorded by Wi-Fi data over a period of time. For a pair of adjacent nodes, *i*-*o*, the transition probability is defined as the proportion of activity trajectories that contain both nodes *i* and *o* to those containing node *i*, calculated as

$$P_{i,o} = \frac{\sum_1^m Tra_x = \{\ldots, (i,t), (o, t+1), \ldots\}}{\sum_1^m Tra_x = \{\ldots, (i,t'), \ldots\}} \tag{9}$$

where m is the total number of individuals recorded by the Wi-Fi probes, and t and t' are arbitrary timestamps on an activity trajectory. For nodes that are not adjacent, the transition probability is the product of the transition probabilities of each pair of adjacent nodes on the shortest path between the unsampled node and the nonadjacent sampling node, calculated as

$$P_{i,o} = \prod_0^k P_{j,j+1} \tag{10}$$

where k is the number of intermediate nodes from node o to node i. It is worth noting that since an activity trajectory has a movement direction, $P_{o,i}$ may not be equal to $P_{i,o}$. Thus, the relationship between node o and node i can be represented as the average of the transition probabilities between nodes o and i, denoted as

$$\overline{P_{i,o}} = \frac{P_{i,o} + P_{o,i}}{2} \tag{11}$$

Then, the transition probability of the path selection behavior is used to adjust the distance decay effect in the traditional IDW metric. The higher the transition probability of the path selection behavior is, the smaller the distance decay is, which is calculated as

$$D_{i,o}^{*\,2} = \frac{D_{i,o}^{\;2}}{\overline{P_{i,o}}} \tag{12}$$

where $D_{i,o}^*$ is the adjusted path distance from node i to node o, $D_{i,o}$ is the shortest path distance, and $\overline{P_{i,o}}$ is the average transition probability between nodes o and i.

3.3. The Validation Index of the Interpolation. Cross-validation is applied to evaluate the accuracy of the interpolation results by comparing the interpolated crowd density of a sampling node with the adjusted crowd density detected by a Wi-Fi probe. As mentioned before, there is a deviation between the population detected by the Wi-Fi probe and the ground truth data because the detectable rate of the Wi-Fi probe is not 100%. For this reason, some field survey experiments were carried out to calibrate the detection rate of the Wi-Fi probe and to adjust the detected population according to Equation (3), making the adjusted population as close to the ground truth value as possible. Although there is still a deviation between the adjusted population and the ground truth data, assuming that this deviation is a systematic error for each Wi-Fi probe, it is acceptable to use the adjusted population as the ground truth because it does not affect the validation result.

The widely used accuracy indices, the mean absolute error (MAE), and mean bias error (MBE) are used to indicate the absolute deviation and bias of the interpolation results, calculated as

$$MAE = \frac{\sum_{i=1}^n \left| \rho_{adj,i} - \rho_{est,i} \right|}{n} \tag{13}$$

$$MBE = \frac{\sum_{i=1}^n \left(\rho_{adj,i} - \rho_{est,i} \right)}{n} \tag{14}$$

Figure 3: The locations of the installed Wi-Fi probes with the crowd density on a (a) weekday and (b) a holiday.

where $\rho_{adj,i}$ is the adjusted crowd density detected by a Wi-Fi probe on node i, which is regarded as the true value; $\rho_{est,i}$ is the estimated value obtained by IDWPSB method on node i.

The MAE represents the mean value of the absolute deviations between the estimated values and the true values. The smaller the MAE is, the closer the estimated values are to the true values. The MBE denotes the mean bias between the estimated values and the true values; the sign of the MBE suggests underestimation (positive value) or overestimation (negative) of the interpolation results.

4. Study Area and Data Collection

The Shichahai scenic area is a tourist neighborhood in Northwest Beijing, covering an area of 2.31 million square meters. As an open public place in a metropolitan center, the Shichahai scenic area fulfills multiple public service functions, combining a tourist attraction with business and residential sectors. Because of the multifunction role of the area, it is crowded throughout the year. On a typical holiday, the crowd flow can easily reach 20 thousand per hour. Thus, there has been a considerable safety concern and needs of crowd control in this area.

As shown in Figure 3, the road network in this area is rather complex and contains many junctions. To select the optimal locations to install the Wi-Fi probes, first, the road segments considered to be crowded were designated by experts, as illustrated by the purple lines in Figure 3. Then, the three tourist landmarks, including the Yinding Bridge, the former residence of Soong Ching Ling, and the Prince Gong's Mansion, illustrated by pink hollow stars in Figure 3, were also selected as candidates for installation. Taking these factors into account, 23 Wi-Fi probes, denoted as $p1, p2 \cdots p23$, were installed along the main roads to collect the crowd data. By preprocessing the Wi-Fi data, the detection radius of the Wi-Fi probe was uniformized to 50 m.

During the study period from December 23, 2016, to March 16, 2017, the crowd data of more than 6,000,000 individuals were collected by the installed Wi-Fi probes. The mean value of the all-day crowd density during the study period was calculated according to Equation (3) for each sampling site and is shown in Figures 3(a) and 3(b) for a weekday and a holiday. Table 2 shows the exact values of the crowd density at each sampling site and ranks them by sorting the weekday and holiday values in descending order. It can be seen from the table that although the absolute crowd density value differs by the two days, there is no significant difference in the ranks of the crowd density. That is, whether on the weekday or the holiday, the crowding patterns are similar in

Table 2: The summary of the crowd density on a holiday and a weekday.

Probe ID	Crowd density on a weekday (people per square meter)	Rank of crowd density on a weekday	Crowd density on a holiday (people per square meter)	Rank of crowd density on a holiday
1	0.124	16	0.290	16
2	0.303	8	0.629	8
3	0.016	22	0.137	19
4	0.218	10	0.473	10
5	0.199	11	0.418	11
6	0.151	15	0.331	15
7	0.325	7	0.702	7
8	0.901	1	1.895	1
9	0.451	5	0.949	5
10	0.033	21	0.063	22
11	0.804	2	1.636	2
12	0.619	4	1.341	4
13	0.156	13	0.342	14
14	0.662	3	1.357	3
15	0.106	17	0.233	17
16	0.008	23	0.008	23
17	0.079	18	0.172	18
18	0.046	20	0.107	21
19	0.055	19	0.109	20
20	0.181	12	0.387	12
21	0.429	6	0.912	6
22	0.250	9	0.545	9
23	0.153	14	0.343	13

(a) Weekday (b) Holiday

Figure 4: The estimate of the global crowd density by IDWPSB method in the study area on (a) weekday and (b) a holiday.

the study area. The most crowded sites are near the Yinding Bridge, including p8, p11, p14, and p12, which are the core scenic spots.

5. Results and Discussion

5.1. Comparing the Global Crowd Density Estimates by the IDWPSB and IDW Methods. As shown in Figure 4, we selected a typical peak time (3 p.m.) on a weekday (Feb 8, 2017) and a holiday (Dec 25, 2016) as an example to show the interpolation results of the IDWPSB method. The spatial resolution of the interpolation was 5 meter, generating the estimation of 628 unsampled sites in total. Overall, the global crowd density on the holiday was significantly higher than that on the weekday, with more road segments highly populated. The crowd tended to aggregate towards the northeast corner, the Yinding Bridge, on both days; meanwhile, the population was relatively sparse in the southwest quadrant, which is the residential sector.

Additionally, the traditional IDW method was employed to interpolate the population density and was compared with the new IDWPSB method. As shown in Figure 5, the majority of the MAE values at the sampling sites obtained by the IDWPSB method are smaller than those obtained by the IDW method. As shown by the MBE values, the IDWPSB method is less likely to overestimate or underestimate the crowd density in the cross-validation, suggesting a more robust performance than the IDW method. Furthermore, the accuracy improvement ratio, P_{imp}, was calculated as the difference between the IDWPSB MAE and the IDW MAE, as shown in

$$P_{imp} = \frac{\sum \mathrm{MAE}_{IDWPSB} - \sum \mathrm{MAE}_{IDW}}{\sum MAE_{IDW}} \tag{15}$$

For the weekday result, the accuracy improvement ratio is 20.49% and for the holiday, the ratio is 15.69%. In general, the IDWPSB method improves the interpolation accuracy by 17.62%, indicating a better performance than the IDW. In terms of computational efficiency, the interpolation process took 52.4 seconds using the IDW method and 74.3 seconds using the IDWPSB method under the same computing environment. These various aspects of comparison suggest that including the path selection behavior in the IDWPSB method can improve the interpolation accuracy without significantly increasing the computational demand.

5.2. Factors Influencing the Interpolation Accuracy. Several factors may affect the interpolation accuracy and should be taken into consideration. The first factor is the number of sampling sites. We implemented the IDWPSB interpolation by using different numbers of sampling sites ranging from 10 to 22 and then randomly selecting sampling sites from the pool. Figure 6 shows the variation in the MAE value for each sampling site when the site is estimated using cross-validation. It is evident that there is a decreasing trend in the MAE when the number of sampling sites increases in all instances. In reality, the optimal number of sampling sites should be determined by both budget consideration and requirements for accuracy.

Figure 5: Comparison of the interpolation results in MAE and MBE between the IDW and IDWPSB methods.

The second factor is the location of the sampling sites. To evaluate the relationship of the interpolation error with respect to the location of the sampling sites, the all-day crowd density for each sampling site on the weekday and the holiday was estimated for all the other sampling sites using the IDWPSB method. The spatial distributions of the MAE and MBE are shown in Figure 7. It is worth noting that, on either day, the site with the maximum interpolation error is p8, which is the sampling site with the highest crowd density. This result is likely due to the inherent bias of the IDW method in that it fails to extrapolate the maximum value. Thus, we suggest that the deployment of the Wi-Fi probes should cover the sites with the local maximum values.

The third factor is the role of an unsampled node in the road network. We use the node centrality to indicate the importance of an unsampled node in the road network. Here, the centrality of node i is defined as the number of times that node i is on the shortest path between any other two nodes being the origin and the destination. As shown in Figure 8, we investigated the relationship between the node centrality of an unsampled node and its interpolation MAE in the cross-validation. It is evident that there is no relationship between the node centrality and the MAE, suggesting that the accuracy of the interpolation is hardly affected by the role of an unsampled node in the road network. An advantage of the new method is that it requires less consideration of the road network structure.

6. Conclusion

A real-time full coverage estimate of crowd density is essential for safety management of urban spaces. In practice, the trade-off between full coverage monitoring and limited budgets always exists, leading to the partial deployment of crowd surveillance detectors in open public spaces. The incomplete data coverage seriously influences the quality and reliability of

Figure 6: Change of MAE by the number of sampling sites: (1)-(23) corresponding to sampling site p1-p23 when the site is selected in cross-validation and (24) is the overall MAE.

the crowd density estimate. By extracting individual activity trajectories from the Wi-Fi data, this paper proposes a modified IDW method based on the path selection behaviors, named the IDWPSB method. The main improvement of the new method is to adjust the distance decay effect in the IDW method according to the transition probabilities of the path selection behavior. The case study in the Shichahai scenic area of Beijing city demonstrates better performance

Figure 7: The spatial distribution of the interpolation errors (MAE and MBE) in the cross-validation.

Figure 8: The relationship of the MAE for the node centrality of an unsampled site.

of the proposed method than the traditional IDW method. The proposed method can also be applied to urban spaces structured by networks in both indoor and outdoor environments with the availability of LBS data. However, it should be noted that the path preference is not static in time. Thus, the transition probabilities of the path selection behavior should be a function of time, which may vary over time of the day or may differ between weekdays and weekends. The time-dependent calculation will provide a valid context for improving the interpolation method and accommodating dynamic travel environments.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest in the research.

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Research Article

Multiobjective Calibration Framework for Pedestrian Simulation Models: A study on the Effect of Movement Base Cases, Metrics, and Density Levels

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Ideally, a multitude of steps has to be taken before a commercial implementation of a pedestrian model is used in practice. Calibration, the main goal of which is to increase the accuracy of the predictions by determining the set of values for the model parameters that allows for the best replication of reality, has an important role in this process. Yet, up to recently, calibration has received relatively little attention within the field of pedestrian modelling. Most studies focus only on one specific movement base case and/or use a single metric. It is questionable how generally applicable a pedestrian simulation model is that has been calibrated using a limited set of movement base cases and one metric. The objective of this research is twofold, namely, to (1) determine the effect of the choice of movement base cases, metrics, and density levels on the calibration results and (2) to develop a multiple-objective calibration approach to determine the aforementioned effects. In this paper a multiple-objective calibration scheme is presented for pedestrian simulation models, in which multiple normalized metrics (i.e., flow, spatial distribution, effort, and travel time) are combined by means of weighted sum method that accounts for the stochastic nature of the model. Based on the analysis of the calibration results, it can be concluded that (1) it is necessary to use multiple movement base cases when calibrating a model to capture all relevant behaviours, (2) the level of density influences the calibration results, and (3) the choice of metric or combinations of metrics influence the results severely.

1. Introduction

The creation and implementation of a commercial pedestrian simulation will, ideally, consist of multiple steps. One of those steps is calibrating the model whereby the goal is to increase the accuracy of the model predictions by obtaining the parameter set that results in the best replication of reality. As such, calibration is an important step.

Yet, up to recently, calibration has received relatively little attention within the field of pedestrian modelling [1, 2]; this is mainly attributed to the lack of data [1, 3–5] especially at high densities. Despite this issue, there are many studies in which authors calibrate a pedestrian model (e.g., [6–10]) usually by using a fundamental diagram [11] or trajectories. However, as multiple authors mention, the calibration attempts in these studies are limited and mostly focus on only one or a few aspects [1, 4, 5, 11, 12]. Most studies focus on one specific movement base case (e.g., a bidirectional flow in a straight corridor), use only one metric, or do not look at various population compositions.

It is questionable how generally applicable a pedestrian simulation model is that has been calibrated using a limited set of movement base cases. Campanella, Hoogendoorn, and Daamen [13] and Duives [14] show that using different flow situations leads to different optimal parameter values. That is, both studies identify that for general usage (i.e., using a single model for many different applications) one needs to calibrate a pedestrian simulation model using multiple movement bases to capture all relevant behaviours. The effect of using different metrics during the calibration has been investigated by Duives [14] in relation to pedestrian dynamics and among others [15–17] in relation to vehicular traffic. These studies

illustrate that different combinations of metrics clearly lead to different calibration results. Wolinski et al. [18] also calibrate a number of models using different metrics. Though they do not show the effect of using different metrics on the resulting optimal parameter set, the results show clearly that the model fit to the data depends on the metric used. Furthermore, Hänseler, Bierlaire, Farooq, and Mühlematter [19] also note differences between the optimal parameter sets obtained using different metrics or a combination of them when calibrating their macroscopic model.

To overcome the problem of obtaining different results when using different movement base cases and/or metrics, three multiple-objective calibration frameworks have been proposed in recent years which try to take a more inclusive approach. Wolinski et al. [18] propose a framework which can potentially incorporate multiple objectives. However, during their benchmarking tests they only apply combinations of one movement base case and one metric. Campanella et al. [13] show how a microscopic model can be calibrated using multiple movement base cases and how this compares to calibrating the model with only one movement base case. This study still only uses one metric during the calibration. The work by Duives [14] uses multiple movement base cases with multiple metrics and furthermore includes different combinations of weights in the objective function and is thus the most extensive of the three. However, except for the spatial distribution metric, the study does not show the results for the other individual metrics. Hence, it is not possible to exactly determine the effect the different individual metrics have on the resulting optimal parameter set.

So, even though these works illustrate that the choice of the combinations of movement bases and metrics will influence the optimal parameter set obtained during calibration, all three studies have their limitations. For example, they do not explicitly examine the effect of the level of density which might be a relevant factor given that work by Campanella et al. [13] shows that poorness of data can affect calibration results and work by [20] also shows some differences in the obtained parameter sets for a low and high density case of a bidirectional flow. Furthermore, the effects of using different metrics are also still poorly understood. And, as work by Campanella, Hoogendoorn, and Daamen [21] shows that using multiple objectives during the calibration will lead to a better validation score for general usage, it is clear that increased insights into which objectives to use during calibration can improve model validity.

Given these observations the objective of this research is twofold. Firstly, the objective is to determine the effect of the choice of movement base cases, metrics, and density levels on the calibration results. Secondly, the objective is to develop a multiple-objective calibration method for pedestrian simulation models to determine the aforementioned effects, taking into account the stochastic nature common to many microscopic pedestrian models.

This study aims to add value to the current body of literature by means of a more extensive study of the impact of calibration framework setup on the validity of a pedestrian simulation model. This extension provides, among other things, novel insights into the effect of the level of density of the movement base case and more detailed insights into the effect of using a range of metrics in the calibration process. Furthermore, this study features a different type of model (i.e., vision-based model [22]) than the previous most extensive studies (i.e., [13, 14]), which both calibrated NOMAD. Thus, this study also illustrates the replicability of their results and the conclusions of those previous studies.

The rest of the paper is organized as follows. Section 2 briefly describes the microscopic pedestrian simulation model. Section 3 shortly introduces the methodology of the sensitivity analysis and presents the results of the analysis. In Section 4 the calibration methodology is elaborated upon. This is followed by the presentation of the results of calibrating the model using a single objective in Section 5. Section 6 presents the results of the multiobjective calibration. Finally, this paper closes of with a discussion of the results, conclusions, and the implications of this work for practice.

2. Brief Introduction to Pedestrian Dynamics

This section introduces pedestrian dynamics (PD), a microscopic pedestrian simulation model developed by INCONTROL Simulation Solutions. It offers a user the ability to model the movement behaviour of pedestrians at all three behavioural levels (strategic, tactical, and operational). Though, in this research pedestrians only have one activity, namely, to walk from their origin to their destination via a single route, and hence there is no need to model the activity choice, the activity scheduling or the route choice. The model featuring the operational walking dynamics is discussed in more detail underneath.

The operational behaviour of the INCONTROL model consists of two parts, i.e., route following and collision avoidance, which together determine the acceleration of a pedestrian at every time step. PD determines the acceleration of a pedestrian by the combination of 'social forces' and a desired velocity component. The pedestrian itself is represented by a circle with a radius r. At every time step the acceleration of a pedestrian is determined as follows:

$$\frac{d\vec{v}_i}{dt} = \frac{\vec{v}_{\mathrm{des};i} - \vec{v}_i}{\tau} + \sum_j \vec{f}_{i;j} + \sum_W \vec{f}_{i;W} \quad \left[\mathrm{m/s^2}\right] \tag{1}$$

where $\vec{v}_{\mathrm{des};i}$ and $\vec{v}_i$ are, respectively, the desired and current velocity of pedestrian i. $\vec{f}_{i;j}$ and $\vec{f}_{i;W}$ are the physical forces that occur on contact with another pedestrian or a static obstacle. And lastly, τ is the relaxation time. Furthermore, in case the speed of the pedestrian drops below a certain threshold (i.e., the minimal desired speed parameter) the pedestrian does not move until the next time step when the resulting speed is higher than the threshold.

The desired velocity is determined according to the method proposed by Moussaïd et al. [22]. The method uses a vision-based approach to avoid collisions. This approach combines the collision avoidance with the preferred speed and the desired destination to determine the desired velocity. The desired velocity is determined by means of two heuristics, namely,

(1) A pedestrian chooses the direction that results in the most direct path to its desired destination given the presence of both static and dynamic obstacles.

(2) A pedestrian chooses the speed that, in case there is an obstacle in the preferred direction, results in the lowest time-to-collision whereby this time is always larger than τ.

The pedestrian only takes into account obstacles that are within its field of vision ($[-\phi, \phi]$), which is determined by the current orientation of the pedestrian, the viewing angle ϕ, and the viewing distance $d_{\max}$. The desired direction is determined by minimizing (2).

$$d(\alpha) = d_{\max}^2 + f(\alpha)^2 - 2d_{\max} f(\alpha) \cos(\alpha_0 - \alpha), \quad \text{for } \alpha \in [-\phi, \phi] \tag{2}$$

where $f(\alpha)$ is the distance to the closest expected obstacle in the direction of α, which is equal to $d_{\max}$ if there are no obstacles within the viewing range. α_0 is the angle towards the desired destination. The desired speed is given by $v_{\text{des}} = \min(v_i^0, d_h/\tau)$ where v_i^0 is the preferred speed of the pedestrian and d_h is the distance between the pedestrian and the first expected collision in the desired direction. d_h is determined as follows:

$$d_h = \begin{cases} d_{i;\text{exp:col}} - d_{i;\text{pers}} & \text{If the expected collision is with another} \\ & \text{pedestrian travelling in the same direction} \quad [\text{m}] \\ d_{i;\text{exp:col}} & \text{Otherwise} \end{cases} \tag{3}$$

where $d_{i;\text{exp:col}}$ is the distance to the first expected collision in the desired direction α of pedestrian i and $d_{i;\text{pers}}$ the personal distance of pedestrian i. The personal distance is the distance a pedestrian wants to keep between itself and another pedestrian.

There are two important notes regarding the implementation of this method in PD, namely: (1) Regardless of the settings for the viewing angle and viewing distance, the model will only take into account the four closest pedestrians (who are within the field of vision) when determining the desired velocity. (2) Not all parameters can be adapted by the user; the parameters governing the physical forces (i.e., $\vec{f}_{i;j}$ and $\vec{f}_{i;W}$) are, namely, not user-adaptable.

The desired destination of each pedestrian is determined using the Indicative Route Method proposed by Karamouzas, Geraerts, and Overmars [23]. This desired destination is influenced by two (user-adaptable) parameters which are the "Preferred clearance", which influences the minimal distance a pedestrian wants to keep between its desired destination and a static obstacle, and the "Side preference update factor", which influences the strength of the desired destination location changes given the current position of the pedestrian and the current deviation from the originally planned path.

As is the case for many pedestrian models, PD is stochastic by nature (i.e., two simulations with exactly the same parameters and input but with different seeds result in different outcomes). In this study there are three main causes for this stochasticity, namely, the preferred speed, the initial destination point, and the exact point of origin. The first contributes to the stochasticity due to the fact that every pedestrian is randomly assigned a preferred speed from a given distribution. The latter two causes of stochasticity are points whose location influences the desired destination and whose exact position is a randomly determined location within a respective origin or destination area. The fact that the model is stochastic by nature has to be taken into account during the calibration and is discussed in more detail in the next section.

3. Sensitivity Analysis

A sensitivity analysis is performed to determine to which particular parameters the model is sensitive. This section describes the methodology of the sensitivity analysis and presents the results of this analysis. The results of the sensitivity analysis are used to determine which parameters should be incorporated in the calibration process, as recalibrating all model parameters is not feasible within the time frame of this study. How the results are used to determine the calibration search space and why it is not feasible to include all parameters is explained in more detail in Section 4.5, Search Space Definition.

3.1. Methodology of the Sensitivity Analysis. The goal of the sensitivity analysis is to determine which of the 7 model parameters of the INCONTROL model (see Table 1) that influence the operational behaviour most affect the model's results. The authors expect that the sensitivity depends on the scenario. Thus, the analysis is performed for all seven scenarios used in the calibration. These scenarios are as follows: A high density bidirectional flow, a high density corner flow, a high density t-junction flow, a bottleneck flow and low density variants of the bidirectional, corner, and t-junction flows. For a detailed description of the scenarios, see Section 4.1.

The distribution of the instantaneous speeds of all pedestrians is used as the sole metric. This distribution contains all instantaneous speeds of all pedestrians and all replications. This metric is chosen because the distribution of the speeds is able to give insight into both the efficiency of the flow (a higher mean speed indicates a more efficient flow) and into the underlying behaviour (e.g., a high variance can indicate

Figure 1: Overview of the sensitivity analysis methodology. The process depicted in the figure is performed for all combinations of the 7 scenarios and 7 parameters.

Table 1: The seven parameters included in the sensitivity analysis.

Route following:	Preferred clearance
	Side pref. update factor
Collision avoidance:	Relaxation time
	Viewing angle
	Viewing distance
	Min. desired speed
	Personal distance

that interactions are not solved efficiently causing pedestrians to change their speed a lot).

The Anderson-Darling test [24] is used to determine if enough replications have been performed to allow for the comparison of two distributions of the instantaneous speed. This statistical test determines whether a distribution has converged (for more details see Section 4.6).

To limit the amount of simulations only first-order effects are investigated. Note that the number of replications is already extensive due to the incorporation of seven scenarios and a vast number of replications to account for model stochasticity. Figure 1 depicts the process which is applied to every combination of a scenario and a parameter. The remaining text in this subsection describes the process and its steps in more detail. For every scenario, the first step is to obtain the speed distribution using the defaults values. This distribution serves as the base line. Accordingly, for all combinations of the 7 parameters and 7 scenarios, the value of the parameter in question is increased by 25%. After which the distribution of the speeds is again obtained. The same procedure is followed for a decrease of the parameter values by 25%. The limit of 25% is chosen as the INCONTROL model already has undergone some basic calibration and hence it is assumed that the optimal values will not deviate much from the current default values.

For all these new distributions of speeds accordingly the following two checks are identified: (a) is the new distribution significantly different from the default distribution according to the Anderson-Darling test and (b) are the differences between the means and standard deviations of the distributions larger than one would expect based on the influence of the stochasticity (for more details see [25]). The second check provides insight into the magnitude of the difference and, thus, the degree of the sensitivity of the model to changes in this parameter. If both these conditions hold (i.e., significant differences are found between the new and old distributions) all distributions between the 25% boundary and the default value, using a precision of 1% point, are obtained to gain insight into how the model's sensitivity changes as the deviation from the default value increases.

For a more detailed description of the methodology the reader is referred to [25].

3.2. Results of the Sensitivity Analysis. Based on the methodology described above the following results are obtained. Firstly, the model is not sensitive to changes in the "Preferred clearance" parameter and changes in the "Viewing distance" parameter. Even in high density cases the model is not sensitive to changes in the viewing distance parameter. This is most likely the result of the fact that PD only takes into account the four closest pedestrians within the viewing field, which might all reside well within this radius.

In general, the model is not sensitive to changes in the "Personal distance", the "Side pref. update factor", and the "Min. desired speed". In the case of the "Personal distance", the model is slightly sensitive to changes in this parameter in the case of the bottleneck scenario. In the case of the "Side pref. update factor", the model is slightly sensitive to the t-junction high density scenario. The model is also slightly sensitive to changes in the "Personal distance" for both scenarios. However, as the maximum differences between the means and the standard deviations are at most 2%, we conclude that within the ±25% range changes in these parameters will not affect the model results much.

The only parameter to which the model is sensitive in all seven scenarios is the relaxation time. The model is, furthermore, sensitive to the viewing angle in all four high density scenarios. Figure 2 presents that, for both parameters and the seven scenarios, the differences between the mean and the standard deviation of the distributions are obtained using an increased or decreased parameter value. From this figure a number of observations can be made. Firstly, the figure clearly shows that the model is more sensitive to changes in the relaxation time than to the changes in

Figure 2: Results of the sensitivity analysis.

the viewing angle. Secondly, clear differences between the scenarios can be identified. For example, the model is more sensitive to changes in the parameters when simulating high density scenarios. And thirdly, in many cases, an asymmetry can be observed between the slope and shape of the curve left from the default value (i.e., the decreased parameter values) and the one on the right. Overall, we conclude that the effect of changing a parameter's value differs a lot between the two parameters and the seven scenarios.

In conclusion, overall the INCONTROL model is not very sensitive to changes in many of the parameters given the ±25% boundaries. The model is primarily sensitive to changes in the relaxation time, whose value influences the outcome of the simulation in all seven scenarios, and the viewing angle, in the case of the high density scenarios.

4. Methodology

This section presents the reasoning behind the newly developed calibration methodology. Figure 3 depicts the multiple-objective calibration methodology and its parts. In line with previous research, the methodology uses multiple scenarios and multiple metrics. For every combination of a scenario and a metric an objective value is obtained which represents the difference between the simulation and the reference data for the given parameter set. These objective values are then combined into a single objective value which in turn is used by the optimization method to determine if the current parameter set is optimal. In case the current parameter set is deemed optimal, the calibration stops and the next step would be to validate the model (which is not part of this study). Alternatively, in case the parameter set is not deemed optimal a new parameter set is created and the calibration process continues.

All of these parts are discussed in more detail in this section. First the scenarios are identified. Accordingly, the metrics and the objective function are presented. This section furthermore elaborates on the optimization method and the manner that the stochasticities of the pedestrian simulation model are handled.

Figure 3: Overview of the multiple-objective methodology where S_1 to S_n are the used scenarios, M_1 to M_k the used metrics, ϵ_1 to ϵ_k the individual errors, and E_i the combined error for scenario i, ϵ the combined error and θ the parameter set.

4.1. Scenarios. Contemporary, several datasets are available that feature the movement of pedestrians in multiple movement base cases and a similar population of pedestrians, among others [26–28]. Since the experiments within the HERMES project represent the most comprehensive set of movement base cases featuring a similar population and different levels of density, this dataset will be used in this calibration procedure. Based on this dataset seven scenarios are constructed whereby every scenario contains a single movement base case and a single density level. Four movement base cases are studied; these are a bidirectional flow, a unidirectional corner flow, a merging flow at a t-junction, and a bottleneck flow. All base cases have both a low and high density variant except for the bottleneck which only has a high density variant. Figure 4 shows the layout of the four simulated movement base cases. For a more detailed overview of the experimental setup within the HERMES project the reader is referred to [27]. Care is taken to ensure a similar flow pattern over time, speed distribution, and route choice; details on the exact simulation setup of the seven scenarios in PD are mentioned in [25].

4.2. Metrics. In this multiple-objective framework four different metrics are used to identify how different metrics impact the calibration results. In this research the choice is made to use two metrics at the macroscopic level, the flow and the spatial distribution, and two at the mesoscopic level, the travel time distribution and the effort distribution. These metrics are chosen because, on both levels, they describe different aspects of the walking behaviour. Microscopic metrics, i.e., trajectories, are not used for three reasons. Firstly, calibration based on trajectories requires a different approach than calibrating based on macroscopic and mesoscopic metrics. It would require many more simulations to use both microscopic and mesoscopic and/or macroscopic metrics and due to time limits this was not considered to be viable within this study. Secondly, the current approaches for calibrating based on trajectories do not deal with the stochastic nature of the model. Lastly, since pedestrian simulation models are mostly used to approximate the macroscopic properties of the infrastructure (e.g., capacity, density distribution) [21] and given that calibrating based on microscopic metrics does not necessarily result in a macroscopically valid model [11], macroscopic and mesoscopic metrics take priority over microscopic metrics. The four metrics adopted in this research to calibrate PD are discussed in more detail below.

Flow. The flow is chosen as a macroscopic metric to check to what extent the model can reproduce the throughput in different situations. In all seven scenarios the average flow is measured along a certain cross-section (see Figure 4) during a certain measurement period. The average flow is calculated as follows:

$$\overline{q}_i = \frac{N_i}{\Delta t \times l} \quad [\text{ped/s/m}] \tag{4}$$

where N_i is the number of unique pedestrians with main travel direction i that passed the line in the direction equal to the main travel direction and during the measurement period (Δt). The flow is normalized to a flow per meter of measurement line, whereby l is the length of the measurement line, in order to allow for comparisons between scenarios.

Distribution over Space. Reference [14] showed that microscopic models might not always be able to accurately reproduce the spatial distribution patterns. Hence, it is essential to check whether a model performs well with respect to this property. The distribution over space measures how the pedestrians are distributed over the measurement area. A grid of 0.4 x 0.4 m, which is approximately the size of one pedestrian during a high density situation, overlays the

Figure 4: Overview of the layout of the four movement base cases used during the calibration. (a) Bidirectional flow. (b) Unidirectional corner flow. (c) Merging t-junction flow. (d) Bottleneck. In the figure the hatched areas indicate the measurement areas; the dashed lines the location where the flow is measured and in the case of the bottleneck the grey area indicates the waiting area at the start of the simulation.

measurement area and for every cell the percentage of the time it is occupied is determined by (5).

$$F_j = \frac{N_{\text{occ};j}}{N_{\text{steps}}} \quad [-] \tag{5}$$

where $N_{\text{occ};j}$ is the number of time steps cell j is occupied by one or more pedestrians (based on the centre point of the pedestrians) and N_{steps} is the number of time steps taken into account.

Travel Time. The travel time is the time it takes a pedestrian to traverse the measurement area as determined by (5).

$$TT_k = \frac{t_{\text{end}} - t_{\text{start}}}{l_{\text{ref}}} \quad [\text{s/m}] \tag{6}$$

where t_{start} and t_{end} are, respectively, the time pedestrian k first which entered the measurement area and time pedestrian k which left the area. l_{ref} is the average length of the path in the measurement area, as obtained from the reference data. The travel time is normalized in order to simplify the comparison of the goodness-of-fit of different scenarios with different average path lengths. Note that this metric approximates the realized pace of each individual. That is, if an individual makes a detour at a very high speed it will not affect its travel time, but it will influence the effort required to get to its destination.

Only the travel times of those pedestrians who successfully traversed the whole measurement area during the measurement period are included in the distribution of the travel times.

Effort. Several studies have identified the difficulty of smooth interactions between simulated pedestrians in bidirectional flows. In order to ensure realistic interaction behaviour the effort metric is introduced, which captures how much effort it takes a pedestrian to traverse the measurement area. The effort for pedestrian k is defined as the average change in velocity per time step (see (7)).

$$e_k = \frac{\sum_{n-1} \left(\left| v_x(t) - v_x(t-1) \right| + \left| v_y(t) - v_y(t-1) \right| \right)}{n-1}, \quad [\text{m/s}] \tag{7}$$

$$\begin{aligned} v_x(t) &= \frac{x(t) - x(t-1)}{\Delta t}, \quad [\text{m/s}] \\ v_y(t) &= \frac{y(t) - y(t-1)}{\Delta t}, \quad [\text{m/s}] \end{aligned} \tag{8}$$

Table 2: Normalization values.

	M_{norm}
Flow	1.0
Spatial distribution	0.18994
Travel time-mean	0.99107
Travel time-std	0.20728
Effort-mean	0.04345
Effort-std	0.00953

where $v_x(t)$ and $v_y(t)$ are, respectively, the speed in the x and y-direction at time step t and n the number of time steps. The speeds are obtained by differentiating the current and previous positions of pedestrian k (see (8)), where $x(t)$ and $y(t)$ are, respectively, the x and y-position at time step t and Δt is the duration of the time step. The effort measurements of all pedestrians are combined into one distribution.

4.3. Objectives. In this research multiple objectives are combined into a single objective using the weighted sum method [29]. This is in line with research by Duives [14]; the only example in literature using both multiple metrics and scenarios to calibrate a pedestrian model.

In order to make a fair comparison between objectives, normalization is necessary, as the metrics have different units and different orders of magnitude. Table 2 shows the normalization values used during calibration. The adopted normalization method is based on two main assumptions. Firstly, it is assumed that for a single metric a deviation of 1 unit (for example, 1 ped/m/s is case of the flow) in one scenario is equally wrong as a deviation of 1 unit in another scenario (i.e., an absolute error is used instead of a relative error). Secondly, it is assumed that, for every metric, a deviation of 1 ped/m/s in the flow is equal to a deviation equal to the average ratio between the values of flow and the respective metric in the reference data (i.e., $(1/S_n)\sum_{s\in S}(y_{m;s}/\overline{q}_s)$, where S is the set of scenarios, S_n is the number of scenarios, $\overline{q}_s$ is the average flow of scenario s, and $y_{m;s}$ is the value for metric m for scenario s). This method is chosen because it does not explicitly assume a bias towards any of the metrics or scenarios which is deemed appropriate for this study given its goal. However, this might not necessarily be the case if one intends to calibrate a model for a specific intended use. For a more detailed explanation of this method and an underpinning of the choice to specifically use this method, the reader is referred to [25].

The objective function for a given metric and scenario is given by the normalized Squared Error (SE) which for the macroscopic metrics is determined by (9) and for the mesoscopic metrics is determined by (10).

$$SE_{\text{norm}}(\theta) = \frac{1}{m}\sum_{j}\left(\frac{\sum_i M_{\text{sim};i;j}(\theta)/n - M_{\text{ref};j}}{M_{\text{norm}}}\right)^2 \quad (9)$$

$$SE_{\text{norm;meso}}(\theta) = \frac{1}{2}\left(\frac{M_{\text{sim};\mu}(\theta) - M_{\text{ref};\mu}}{M_{\text{norm};\mu}}\right)^2 + \frac{1}{2}\left(\frac{M_{\text{sim};\sigma}(\theta) - M_{\text{ref};\sigma}}{M_{\text{norm};\sigma}}\right)^2 \quad (10)$$

where M_{sim} is the metric's value according to the simulation, M_{ref} the reference value according to the data, M_{norm} the value used for the normalization, and θ the vector of model parameters. In the case of (9) n is the number of replications and m is the number of travel directions in case of the flow and the number of cells in case of the spatial distribution. In the case of the mesoscopic metrics (10) shows that the difference between the distributions is approximated by taking both the error in the mean (μ) and the standard deviation (σ). These distributions contain the measurements of all replications.

The objective functions for a given set of metrics and scenarios are combined into a single objective function as follows:

$$O(\theta) = \frac{1}{N_s * N_m}\sum_{s}\sum_{m} SE_{\text{norm};s;m}(\theta) \quad (11)$$

where $SE_{\text{norm};s;m}(\theta)$ is the value of the objective function of scenario s and metric m for the parameter set θ and N_s and N_m are, respectively, the number of scenarios and metrics in the set. A likelihood method, which multiplies probabilities, might not work in this case, as this method will always attempt to fix the worst parameter first. In an additive scheme weights can be applied to prioritize certain combinations of scenarios and metrics over other combinations. However, as this research studies the effects of the different choices of scenarios and metrics, in this research all combinations are considered to be of equal importance and hence equal weights are used.

4.4. Optimization Method. In this research a grid search is used to obtain the optimal parameter set, as it provides the researcher with more insight into the shape of the surface of objective space. The disadvantage of using a grid search is that other optimization methods, e.g., Greedy and Genetic algorithms, can potentially be faster. However, these methods do run the risk of getting stuck in a local minimum and do not necessarily give a good insight into the shape of surface of the objective space. As can be derived from (11), smaller values of the objective function represent a better goodness-of-fit (GoF) and hence the goal of the optimization is to minimize the objective value.

4.5. Search Space Definition. Rudimentary calibration of PD has already been performed by the company. Thus, instead of calibrating all model parameters, the presented calibration method will be used in this research to identify the correctness of the variables with respect to which this model is most sensitive, namely the relaxation time and the viewing angle. Even though the model is less sensitive with respect to the radius, this parameter will also be included in the calibration as initial tests of the implementation of the scenarios illustrated that in the case of the bidirectional high density scenario the default radius of this model produced problematic results. The search space is defined as follows:

(i) The upper and lower boundaries of the relaxation time and viewing angle are determined by a deviation of $-0.24 * \theta_{\text{def}} < \theta < 0.24 * \theta_{\text{def}}$ with respect to the

default parameters. The step size is 3% of the default value. The resulting ranges are [0.380s^{-1}-0.620s^{-1}] for the relaxation time and [57.00°-92.00°] for the viewing angle.

(ii) For the radius the upper boundary is equal to the default value, the lower bound has a deviation of $-0.40 * \theta_{\text{def}}$ and the step size is 4% of the default value. This results in a range of [0.14340m-0.23900m].

As this research focuses on the effect of density levels, the metrics that are part of the objective function and movement base cases, the search space is not continuous and has been restricted in order to create reasonable computation times and a reasonably good insight into the shape of the objective function.

4.6. Dealing with Stochasticity in Pedestrian Simulation Models. Similar to most pedestrian simulation models, PD is stochastic in nature. Therefore, it is essential to determine the minimum amount of replications one would need in order to assure that statistical differences are due to differences in model parameters instead of stochasticity in the model realization.

In this research the required number of replications is determined using a convergence method similar to [30] whereby the distribution of speeds is used as the sole metric. To determine if two subsequent distributions can be considered to be samples drawn from the same distribution the Anderson-Darling test is used [24]. Equation (12) shows that if b subsequent distributions are considered to be similar according to the Anderson-Darling test (i.e., the test return a p-value greater than $p_{\text{threshold}}$ indicating that the null hypothesis that the two samples come from the same distribution can be rejected at the $p_{\text{threshold}}$ significance level) the distribution has converged.

$$AD\left(S_n, S_{n-1}\right) > p_{\text{threshold}} \quad \forall\, n \in [m-b+1, m-b+2, \ldots, m] \tag{12}$$

whereby S_n is the speed distribution containing all instantaneous speed measurements of all pedestrians for all time steps they spent within the infrastructure for all n subsequent replications.

Tests showed that regardless of the chosen values for b and $p_{\text{threshold}}$ the required number of replications depends on the exact seeds that are used and their order. Therefore, a predefined seed set was used during the calibration of PD to ensure that any differences between simulations using different parameter sets were not caused by the stochastic nature of the model. Using this predefined set, a value of 10 for b and a value of 0.25 for $p_{\text{threshold}}$, it was determined that the required number of replications was a 100 for the bidirectional scenarios, 50 for the corner high density scenarios, 40 for the t-junctions and corner low density scenarios, and 30 for the bottleneck scenario. For a more detailed discussion of the method and the choice for the values of b and $p_{\text{threshold}}$, the reader is referred to [25].

5. Calibration Results Based on Single Objectives

In this section the results of the individual objectives (a combination of a single scenario and a single metric) are discussed. Figures 5(a)–5(d) show boxplots of the objective values, determined by (11), per individual objective containing the objective values of all 3179 points of the search space. These plots provide insight into the distribution of the objective values. More importantly, these figures show the order of magnitude of the minimal objective value if the model would be calibrated using a single metric/objective. Here, smaller objective values represent a better fit of the model results to the reference data.

These plots provide insight into how the objective values are distributed but primarily show the order of magnitude of the minimal objective value if the model would be calibrated using only a single objective. The smaller the objective values the better the model results fit the reference data. By using a logarithmic scale the figure clearly illustrates how well the model fits to the data (when the optimal parameter set is used) and how this differs between the different scenarios and metrics.

Figures 5(e)–5(j) show boxplots of the nonnormalized, nonsquared errors and these provide insight into the size of the errors and how they are distributed. Here it is the case, the closer to zero the values are, the smaller the error between the simulation and the reference data is. Due to the linear scale these plot provide a better insight into how the value of the parameters influences the error and therefore the objective value.

Figures 5(a) and 5(e) show that for all scenarios the model can reproduce the flows well given both the small errors and the low minimal objective values. Furthermore, one can observe that on average the low density scenarios have a lower objective value but that the minimal objective value is smaller for the high density scenarios.

Figures 5(b) and 5(f) show that the model cannot reproduce the spatial patterns very well given the high errors and the large minimal objective values. The low density scenarios both have a lower objective value on average and a lower minimal objective value. Furthermore, especially for the high density case of the t-junction scenario the performance is relatively bad compared to the other scenarios.

Figures 5(d), 5(h), and 5(j) show that, except for the bidirectional high and t-junction high density scenarios, the travel time distribution can be reproduced well by the model. In the case of the bidirectional high and t-junction high density scenarios the figures show that the model can reproduce the mean and the standard deviation of the travel time distribution well individually but apparently not when they are combined. Also, similar to the spatial distribution, the low density scenarios have a lower objective value on average as well as a lower minimum objective value.

In the case of the effort metric Figures 5(c), 5(g), and 5(i) show that for most scenario the model cannot reproduce the effort distribution very well. The two exceptions are the bottleneck and t-junction high density scenarios. In these cases the model can reproduce the effort distributions well.

Figure 5: Results of calibrating the model using a single objective. Graphs (a)-(d) show, per combination of metric and scenario, how the objective values (calculated according to (11)) are distributed. Graphs (e)-(j) show the nonnormalized, nonsquared errors (i.e., $M_{\text{sim}}(\theta) - M_{\text{ref}}$) which give insight into size and the distribution of the errors. The flow scenarios are identified by their acronyms (i.e., B-H = bidirectional high, B-L = bidirectional low, B = bottleneck, C-H = corner high, C-L = corner low, T –H = T-junction high, and T-L = T-junction low).

Generally, the same pattern can be observed as the flow regarding the difference between the high and low density scenarios. That is, the high density scenarios generally have a lower minimum objective value but the low density scenarios generally have a lower objective value on average.

All figures show that both the size of the minimal objective value and the distribution of the errors depend on the particular combination of scenario and metric. Furthermore, the figure illustrates that the model can generally reproduce the metrics related to the performance of the infrastructure (the flow and travel time) better than those more related to the underlying microscopic and macroscopic pedestrian dynamics (spatial distribution and the effort). However, regarding the difference between the performances of the

model on the different metrics, three things have to be noted.

Firstly, as Liao, Zhang, Zheng, and Zhao [31] show, even though the flow of their calibrated model is similar to the flow in the data, the underlying fundamental diagrams differ slightly. Regarding the results of this study, a quick review of the average velocities and average densities illustrates that differences exist between the reference data and the data obtained during the calibration. This finding suggests that the model and the data have slightly different underlying fundamental diagrams. Furthermore, it also suggests that, within the given search space, there does not seem to exist a parameter set that aligns the model's fundamental diagram to the data. This may in part explain why especially for the spatial distribution and effort metrics the model fit is worse than compared to the flow.

Secondly, as pointed out by Benner, Kretz, Lohmiller, and Sukennik [32], also a lack of detailed information about the boundary conditions (e.g., the exact distribution of the desired speeds and the order in which pedestrians enter the infrastructure) might negatively influence a model's capability to fit the data. Again, this lack of detailed information is likely to have the smallest impact on the flow as this is the most aggregated metrics of the four.

Lastly, some metrics might be more sensitive to changes in parameters of the pedestrian simulation model that are not taken into account in this study than the parameters included in the search space of the calibration. The sensitivity to these 'other' parameters is due to two things. First, the sensitivity analysis was performed before the choice of metrics for this calibration. Second, the speed distribution was used in the sensitivity analysis to determine significant differences in model result. Thus, this suggests that it is not only important to include multiple scenarios in the sensitivity analysis but also multiple metrics. This would ensure enhanced insight into the model's sensitivity and hence also better insight into which are the most important parameters to include in the search space during calibration.

This research aims to determine how different choices regarding scenarios and metrics influence the calibration and not calibration of the InControl model. Therefore, differences between the simulation model results and the data are not investigated in more detail in this paper.

6. Differences in Performance between Calibration Strategies

In this section the results of different calibration strategies are discussed. First, a general analysis of the results is performed based on the obtained optimal parameter sets for all of the 16 combinations. Afterwards, the results of different strategies are compared to determine the influence of movement base cases, density levels and metrics. Table 3 identifies 16 different calibration strategies whereby the table indicates which scenarios and metrics are included during the calibration according to a certain strategy.

Table 4 presents the optimal parameter sets for all 16 strategies. The results in the table show three notable things. Firstly, given the large variance in optimal parameter sets, it is clear that the choice of scenarios and metrics does affect the results of the calibration. Secondly, the optimal objective values in Table 4 are notably higher than those found in Figure 5 which indicates that a combination of objectives decreases the fit of the model with respect to the data. Next to that, for all 16 strategies, the optimal viewing angle is smaller than the default and in many cases equal to the lower limit (57 degrees). Given that PD only takes into account the four closest pedestrians, the results of the calibration indicate that it is more important to take those pedestrians into account who are in front rather than those who are more to the side. Furthermore, in the case of the relaxation time the parameter value also frequently lies on the boundary of the search space. Due to time constraints it was not possible to extent the search space. However, an analysis is performed to ascertain the likely effects changing the search space, this includes both extending it and increasing the precision, would have on the location of the optimal parameter sets.

6.1. Precision of the Grid Search and the Values on the Search Space Boundaries. The search space is limited both by its boundaries and by its precision. To obtain insight into the likelihood that the results would change significantly (i.e., the location of the optimal parameter set changes significantly) an analysis is performed. The analysis is based on visual inspection of two types of graphs.

Figure 6 provides insight into how likely it is that the location of the optimal parameter changes significantly if the precision of the search space in increased. It is considered likely that the location of the optimal parameter set can change significantly if the search space contains points with a very similar objective value, compared to the minimal objective value, which are located in a significant different part of the search space. The graphs show the relation between the decrease in GoF and the distance from the optimal parameter set. The decrease in GoF is calculated by (14), whereby a small decrease in the GoF equals a small difference between the objective value of a given parameter set and the minimal objective value. The distance is calculated by

$$D(\theta, \theta^*) = \sqrt{N_\tau(\theta, \theta^*)^2 + N_\phi(\theta, \theta^*)^2 + N_r(\theta, \theta^*)^2} \quad (13)$$

where $N_\tau(\theta, \theta^*)$, $N_\phi(\theta, \theta^*)$ and $N_r(\theta, \theta^*)$ are, respectively, the number of step-sizes between the optimal parameter set θ^* and the parameter set θ for the relaxation time, the viewing angle, and the radius. So $N_\tau(\theta, \theta^*) = 2$ means that the relaxation time of parameter set θ is 2 step-sizes removed from the relaxation time of the optimal parameter set. The maximum distance is 24.74 ($\sqrt{16^2 + 16^2 + 10^2}$) which is the distance between one corner of the search space to the opposite corner of the search space.

Figure 6(a) shows that for the bidirectional low case there are many points that have a fairly similar GoF and that many of them are in significantly different parts of the search space (i.e., are at a large distance from the optimal parameter set). Hence, it could be likely that a change in the precision of the search space would lead to a significant different location of the optimal parameter set.

Table 3: Tested combination of scenarios and metrics, where the acronyms identify the metrics (i.e., Q = flow, SD = spatial distribution, Eff = effort, and TT = travel time) and the scenarios (i.e., B-H = bidirectional high, B-L = bidirectional low, B = bottleneck, C-H = corner high, C-L = corner low, T-H = T-junction high, and T-L = T-junction low).

Combination	Metrics				Scenarios						
	Q	SD	TT	Eff	B-H	B-L	C-H	C-L	T-H	T-L	B
1. Bidirectional high (B-H)	x	x	x	x	x						
2. Bidirectional low (B-L)	x	x	x	x		x					
3. Corner high (C-H)	x	x	x	x			x				
4. Corner low (C-L)	x	x	x	x				x			
5. T-junction high (T-H)	x	x	x	x					x		
6. T-junction low (T-L)	x	x	x	x						x	
7. Bottleneck (B)	x	x	x	x							x
8. Flow (Q)	x				x	x	x	x	x	x	x
9. Spatial distribution (SD)		x			x	x	x	x	x	x	x
10. Travel time (TT)			x		x	x	x	x	x	x	x
11. Effort (Eff)				x	x	x	x	x	x	x	x
12. High density scenarios (HD)	x	x	x	x	x		x		x		x
13. Low density scenarios (LD)	x	x	x	x		x		x		x	
14. All scenarios - Macro (Macro)	x	x			x	x	x	x	x	x	x
15. All scenarios - Meso (Meso)			x	x	x	x	x	x	x	x	x
16. All combined (All)	x	x	x	x	x	x	x	x	x	x	x

Table 4: Calibration results, where $O(\theta)$ represents the optimal value of the objective function. The cells in italic font indicate that the value is at the upper or lower boundary of the search space.

Combination	O(θ) [-]	Relaxation time [1/s]	Viewing angle [degree]	Radius [m]
1. Bidirectional high	0.1329	*0.620*	*57.00*	0.15296
2. Bidirectional low	0.0588	*0.620*	*57.00*	0.19120
3. Corner high	0.0561	0.395	*57.00*	0.23900
4. Corner low	0.0742	*0.380*	61.50	0.23900
5. T-junction high	0.1190	0.590	*57.00*	0.21998
6. T-junction low	0.0468	*0.380*	68.25	0.23900
7. Bottleneck	0.1093	0.395	68.25	0.20076
8. Flow	0.0146	*0.380*	59.25	0.20076
9. Spatial distribution	0.2015	0.575	59.25	0.21988
10. Travel time	0.1814	*0.620*	59.25	0.15296
11. Effort	0.1798	0.500	*57.00*	0.23900
12. High density scenarios	0.2647	0.575	*57.00*	0.21032
13. Low density scenarios	0.0722	0.500	*57.00*	0.23900
14. All scenarios - Macro	0.1444	0.545	59.25	0.21988
15. All scenarios - Meso	0.2012	*0.620*	59.25	0.15296
16. All combined	0.1814	0.575	*57.00*	0.21032

Figure 6(b) shows that this is not the case for the bottleneck case. Figures 6(c) and 6(d) show a few points whose GoF is similar to that of the optimal point but whose distance to the optimal point is rather large (see the red rectangles). For these cases it is determined which parameter(s) is/are the main contributor to this large distance. In both examples here, it is found that primarily the viewing angle changes. So, in these cases it is likely that, even if the precision of the search space is increased, the location of the optimal parameter set will not change significantly in relation to both the relaxation time and the radius. The location regarding the viewing angle is less certain though.

The main conclusion of the visual inspection of these graphs for all 16 combinations is that for most of the low density cases, the exception is the T-junction low case, and the flow case it is likely that the location of the optimal parameter set could change significantly if the precision of the search space in increased. For all other cases this is not the case.

Figure 6: The deviation from optimal GoF versus the distance to the optimal parameter set.

Figure 7 shows how the objective value changes over the search space for two examples. These graphs provide insight into the question if it is likely that an extension of the search space would cause the optimal parameter to be located in a significantly different part of the search space in relation to the parameter whose value is on the search space boundary.

For example, Figures 7(a)–7(c) show no discernible pattern. Hence one cannot state with a high degree of certainty that if the search space is extended the relaxation time will be equal to or larger than the current value and that the viewing angle will be equal to or smaller than its current value.

Figures 7(d)–7(f), on the other hand, do show a clear pattern. In this case it is likely that an extension of the search space will result in an optimal parameter set whose viewing angle is equal to or smaller than the current optimal viewing angle. The patterns shown in the graphs also make it likely that the optimal radius and relaxation time will be fairly similar to the current optimal values.

Performing this analysis for all 16 combinations yields the conclusion that, for all cases where the previous analysis did conclude that an increase in the precision is unlikely to change the results, an extension of the search space is likely to increase the differences between the cases instead of decreasing it.

Overall, the analysis shows that for some cases the location of the optimal parameter set could change significantly if the search space if changed. However, it also shows that the large differences between the optimal parameter sets, currently found, are also likely to be found if the search space is adapted. Hence, the authors expect that an extension of the search space results in even larger differences in the optimal parameter sets than the differences identified in this paper.

6.2. Identification of Differences in Performance between Calibration Procedures. In order to illustrate the differences between the optimal parameter sets a cross-comparison of the goodness-of-fit is performed. These comparisons are based on the difference between the optimal GoF of combination A and the GoF of combination A when the optimal parameter set of combination B is used (see (14)).

$$\Delta GoF_{\mathrm{A;B}} = -\left(O_{\mathrm{A}}\left(\theta_{\mathrm{B}}^{*}\right) - O_{\mathrm{A}}\left(\theta_{\mathrm{A}}^{*}\right)\right) \tag{14}$$

where $O_{\mathrm{A}}(\theta_{\mathrm{A}}^{*})$ is the value of the objective function of combination A when its optimal parameter set θ_{A}^{*} is used. $O_{\mathrm{A}}(\theta_{\mathrm{B}}^{*})$ is the value of the objective function of combination A if the optimal parameter set of combination B is used. As stated in the methodology section, an increase in the value of the objective function equals a decrease in the GoF, hence the minus value equation (14). Thus, the larger the decrease in GoF, the worse the fit of the model to the data is if the given parameter set is used instead of the optimal parameter set. In the remainder of this section the effects the choice of movement base case, the density level and metrics on the GoF are discussed in more detail.

6.3. Effect of Movement Base Case on Multiple-Objective Calibration Results. Figure 8 presents the results of a comparison

(a) $\phi = 57.00$ (b) $\phi = 75.00$ (c) $\phi = 93.00$

(d) $\phi = 57.00$ (e) $\phi = 75.00$ (f) $\phi = 93.00$

Figure 7: Examples of surface plots showing how the objective value changes over the search space. The green dot identifies the location of the optimal parameter set.

Figure 8: The distribution of the objective values per movement base case combination is displayed by the boxplots. The markers indicate, per used parameter set, how much the objective value would deviate from its optimum if the optimal parameter set, obtained using another (combination of) movement base case(s), would be used. The combinations are identified by their acronyms as found in Table 3.

Figure 9: The distribution of the objective values per density level combination is displayed by the boxplots. The markers indicate, per used parameter set, how much the objective value would deviate from its optimum if the optimal parameter set, obtained using the same (combination of) movement base case(s) but a different density level, would be used. The combinations are identified by their acronyms as found in Table 3.

between different calibration strategies, in which the difference in goodness-of-fit is depicted. All comparisons are made between (combinations of) scenarios of the same density level, in order to exclude the possibility that differences are caused by a difference in the level of density and not by a difference in movement base case.

The figure shows the distribution of the objective values for the different movement base cases. The markers depict the objective value if the optimal parameter set obtained using another movement base case is used. The difference between the location of the marker and the minimal objective value, as indicated by the boxplot, indicates the difference in GoF.

The boxplots show that, generally, the low density cases have a higher GoF and that they are less sensitive to changes in the parameter set regarding their fit to the data. Furthermore, for both the low and high density cases the corner scenarios seem least sensitive to changes in the parameter set. The data, moreover, illustrates that in all cases the GoF of the individual movement base cases decreases when the parameter set based on another movement base case or a set of movement base cases is used. However, the size of the decrease clearly depends on the scenario as well as which scenario's optimal parameter set is used. A few notable observations can be made regarding the decreases in GoF.

Firstly, in the case of the high density bidirectional scenario (B-H) all other optimal parameter sets from the other high density combinations lead to a similar decrease in GoF. This is also the case for the low density bidirectional scenario (B-L). However, in this case the optimal parameter set obtained when combining all three low density scenarios results in a far smaller decrease in GoF indicating that the bidirectional scenario has a strong influence on the objective function of this combination. Overall, both observations indicate that the bidirectional movement base case contains behaviours which are not well captured by other movement base cases.

Secondly, the high density t-junction scenario (T-H) also seems to contain behaviours which are not captured well by other high density movement base cases. Furthermore, as the decrease of GoF is clearly smallest for the optimal parameter set obtained using a combination of all four high density scenarios, it is clear that the objective function of this combination is strongly influenced by the t-junction scenario.

Thirdly, in the cases of the low density corner (C-L) and t-junction scenarios (T-H, T-L) the decrease in GoF is very small when the optimal parameter set of the other scenario is used. Table 4 furthermore identifies that the optimal parameter sets for these two scenarios are very similar. This indicates that at low densities the t-junction movement base case effectively reduces to a corner movement base case as the densities are so low that there is probably little merging behaviour.

Overall, based on this analysis we conclude that different movement base cases contain different behaviours which are not necessarily captured when the model is calibrated using other movement base cases. The exceptions are the corner and t-junction base cases at low densities (C-L, T-L). Using an optimal parameter set obtained by combining multiple movement base cases mitigates this problem somewhat. However, this still results in clear decreases in the GoF for all movement base cases.

6.4. Effect of Density Level on Multiple-Objective Calibration Results. In Figure 9 the results of the comparison between the GoF's for different density levels are presented. The data shows that in all three cases the decrease in the GoF is smaller when the optimal parameter set of the high density case is used in the low density case than vice versa. However, there are clear differences to be observed between the movement base cases. In the case of the corner movement base case the level of density does not have a clear effect as using the optimal parameter set of the other density level only leads to

Figure 10: The distribution of the objective values per metric combination is displayed by the boxplots. The markers indicate, per used parameter set, how much the objective value would deviate from its optimum if the optimal parameter set, obtained using another (combination of) metrics(s), would be used. The combinations are identified by their acronyms as found in Table 3.

a very small decrease in the GoF. This is also the case when the optimal parameter set of the high density bidirectional scenario is used for the low density bidirectional scenario. However, vice versa it is not the case. For the t-junction scenarios, the figure clearly shows that in both cases using the optimal parameter set of the other density level results in a large decrease in the GoF.

The data also illustrates that the decrease in GoF of the combination of high density scenarios is larger when the optimal parameter set of the combination of low density is used than vice versa. This remains the case even if the bottleneck scenario is omitted from the high density set, such that the high density set contains exactly the same movement base case as the low density set. In this case the decrease in GoF for the high density set becomes even larger.

Overall, it can be concluded that the level of density of the scenario does influence the calibration results. Therefore, it is concluded that it is more important to include the high density scenarios than the low density scenarios. Furthermore, depending on the movement base case, it can even be the case that the low density variant can be omitted as it will not add any value.

6.5. Effect of the Metrics on the Multiple-Objective Calibration Results. In Figure 10 a comparison is visualised between the influences of the different parameter sets on the performance of the metrics. There seems to be a correlation between the distribution of the effort and the spatial distribution (i.e., SD, Eff, Meso, and all). When the model is calibrated using only one of them, the decrease in the GoF of the other is small. Besides that, both the use of the spatial distribution and the use of the distribution of the effort result in a far worse prediction of the flow compared to the distribution of the travel times. That is, the decrease in GoF of the flow is far larger in case the optimal parameter set of the spatial distribution or the use of the distribution of the effort is used. Lastly, the optimal parameter sets obtained using combinations of metrics are more heavily influenced by certain metrics. When only the macroscopic metrics are applied, the spatial distribution clearly has a larger impact on the location of the optimal parameter set given the lower decrease in GoF. When solely using the mesoscopic metrics, the distribution of the travel time has a larger impact compared to the distribution of the effort.

These results show that the choice of metrics does influence the results of the calibration. Depending on the choice of metric or combination of metrics, different optimal parameter sets are found which in turn lead to different results regarding the GoF.

7. Conclusions, Discussion, and Implications for Practice

The findings of this research regarding the influence of the movement base cases are found to be consistent with both [13, 14]. Similar to those studies, this research finds that (1) it is necessary to use multiple movement base cases, when calibrating a model, to capture all relevant behaviours and (2) the GoF of the individual movement base cases decreases when the parameter set based on multiple movement base cases is used.

Hence, this research confirms that one needs to use multiple movement base cases when calibrating a model intended for general usage. However, when the intended use of the model is more limited (i.e., it does not need to accurately replicate all movement base cases and or metrics), it might be preferred to use a limited set of movement base cases during the calibration, in particular, given the fact that the GoF of the individual movement base case decreases when multiple movement base cases are used during the calibration.

The level of density also influences the calibration results. Thus, depending on the intended use of the model different density levels should be taken into account during the calibration. Furthermore, this study concludes that it is more

important to incorporate high density scenarios. As a result, one can omit some of low density scenarios, in particular the bidirectional and corner low density scenarios.

This study also finds that the calibration results depend on the choice of metric or combinations of metrics. Depending on the combination of metrics, also the choice of objective function and normalization method influences the results. Consequently, depending on the usage of the model, one should decide which metric or metrics are most important and how to reflect the difference in importance of these metrics when combining multiple objectives into one.

The results also show that the relaxation time is the only parameter to which the model is sensitive to in all scenarios. Its exact value thus has a large impact on how well the simulations fit the data. Reference [33] found similar results for a different model, though they only studied a bottleneck. Furthermore, it is also the only parameter where the optimal value can lie on both sides of the search space depending on the used combination of scenarios and metrics. This can possibly be explained by the fact that the relaxation parameter has multiple roles as is described in [34]. As Johansson et al. [34] conclude, this indicates that the models may be too simplistic.

A number of things have to be noted when reflecting on the method of handling the multiple objectives. In light of the goal of this study, the method presented in this study was chosen to assure as little as possible bias towards any of the metrics or scenarios. However, if one calibrates a model given a certain type of model usage, one might use different weights or even different optimization method. For example, one can search for the Pareto optimal solution [29] or combine multiple objectives using the ϵ-constraint method [29]. Both the choice of the optimization method and its influence on the calibration results are relevant topics for future research.

Though this study is more extensive than previous studies, it still has a number of limitations. Firstly, due to limitations of the available dataset, this study did not include a crossing movement base case. So, it is unclear whether and to what extent the crossing movement base case contains behaviours which are not captured by other movement base cases. More research, in which also effects of the intersecting movement base cases are included, is needed to create a comprehensive overview of the effect the choice of movement base cases has on the calibration. Secondly, only one microscopic model was used in this study. Therefore, as such, it is unclear to what extent the current findings can be generalized and whether the conclusions of this study also hold for other microscopic models. The fact that the results are consistent with [13, 14] and the fact that these studies used another microscopic model does indicate that this is the case. Lastly, as already reflected upon, this study did not look into the effects of the chosen calibration methodology. Insights into these effects could be relevant when deciding on the calibration methodology for a microscopic model with a certain intended use.

All in all, the results show two important things. Firstly, the optimal parameter set obtained using a single or limited amount of objectives does not always provide an accurate fit of the model to the data for other combinations of scenarios and metrics. Besides that, using multiple objectives (e.g., using multiple high density scenarios) to calibrate the model decreases the GoF of the model to the data for all the individual objectives. These two conclusions imply that the intended use of the model should be taken into account when deciding which scenarios, metrics, objective functions and method for combining multiple objectives one should use. These results also raise an important question. Is the implicit assumption that the behaviour of the pedestrians is independent of the flow situation, which is at the foundation of most pedestrian simulation models, valid? This research cannot answer this question because of, among other, its limitations on the number of parameters included in the search space. Hence it is an interesting topic for future research.

Lastly, these results show that a model only provides accurate results for scenarios and metrics that the model has been calibrated and validated on. Using the model for predictions of other scenarios and metrics is likely to result in large inaccuracies. Hence, it is essential that calibration or validation attempts include multiple scenarios and multiple metrics.

Data Availability

The empirical data used in this study can be found at http://ped.fz-juelich.de/da/.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

Understanding Pedestrian Interactive Behaviors under the Different Level of Services on Stairways

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Stairways serve as important walking facilities for pedestrians, especially in metro stations, but researches of pedestrian traffic on stairways are not sufficient. This paper investigates pedestrian interactive behaviors (PIBs) under the different level of services (LOS) on stairways, including overtaking behavior and evasive behavior on stairways. Macro and micro indicators are proposed and calculated based on field observation collected from two stairway flights in a certain metro station in Shanghai, China. Results of macro indicators reveal that the characteristics of overtaking behavior and evasive behavior have both similarities and differences. As for similarities, neither of these two types of behaviors would occur under extremely low or high densities, representing LOS A or LOS F. Under other ranges of density, occurrence intensities of pedestrian interactive behaviors on stairways are different. Overtaking behavior intensity shows a rapid increase trend with the density from low to medium, while evasive behavior intensity keeps a certain value. Results of micro indictors show that the available space for overtaking behavior and evasive behavior is the main factor contributing to the above similarities and differences. Characteristics of PIBs under the different LOS present in highway capacity manual are discussed based on field observations. Findings of this research are helpful to understand the knowledge of PIBs on stairways for a better stairway traffic design and level of service evaluation.

1. Introduction

Pedestrian stairway is one of the most common and important walking facilities. It is widely used in transportation buildings (such as metro stations) and other pedestrian traffic areas. Pedestrian interactive behaviors (PIBs), including overtaking behavior and evasive behavior, always occur when pedestrians move in cluster on stairways, which have significant impacts on the comfort and safety of pedestrian traffic on stairways. Thus, it is important to understand the characteristics of PIBs under the different level of service (LOS) on stairways.

Previous studies mainly focused on pedestrian walking features and the analysis of factors affecting walking speed on stairways [1–6]. For example, Templer [1] found that pedestrians have preference to walk right-hand side on stairs. Yi et al. [2] conducted an experimental study about walking characteristics on U-shaped stairways. They pointed out that pedestrians concentrated in the middle part of the stair when the facility was narrow but had preference to walk along the stair edge when it became wider. Yang [3] analyzed the behavior characteristics of young students when they were walking on stairs. Phenomena of queuing on platforms, confluences at entrances, and subgroup behavior have been observed. And results showed that pedestrians have higher possibility of overtaking in emergency conditions. Fujiyama and Tyler [4, 5] analyzed the factors that can affect walking speed and established a model to estimate pedestrian walking

(a) Ascending flow on stairway A (b) Descending flow on stairway B (c) Bidirectional flow on stairway A (d) Bidirectional flow on stairway B (e) Physical parameters of a stairway

Figure 1: Two stairways observed with different flow patterns.

speed on stairways. Results revealed that the speed of pedestrians became slower when they are surrounded by the other persons.

As for the analysis of PIBs, many researchers have conducted studies on level walkways [7–14]; studies about PIBs on stairways were relatively inadequate. Pauls [15] pointed that the lateral oscillation of pedestrians walking on stairways would increase when their speed become slower. Fujiyama and Tyler [16] observed the avoidance behavior of pedestrians on bidirectional stairways. Furthermore, in Highway Capacity Manual (HCM) 2010, the LOS criteria for stairway traffic are developed based on the analysis of probability of conflict among pedestrians when PIBs occur at different density levels [17]. However, it should be admitted that quantitative studies on pedestrian behavior on stairways are still insufficient, and the descriptions of these behavior characteristics at different LOS presented in HCM 2010 are quite vague. For example, at LOS B, it states the following: "Occasional need to adjust path to avoid conflicts" and "Frequent need to adjust path to avoid conflicts" for LOS C. However, how to quantify the degree of such needs and give more explicit description for stairway traffic status at different LOS is not fully supported by current available knowledge.

From previous studies, we can find that quantitative studies on PIBs on stairways are quite scarce. There is a gap between the research on individual walking behavior features and the traditional research on pedestrian flow characteristics. These lead to no comprehensive understanding of stairway traffic. Therefore, the main objective of this paper is to strengthen the knowledge of PIB characteristics on stairways and to provide a theoretical support for the planning and design of stairway facilities as well as the evaluation of stairway traffic flow.

This paper aims to extend the understanding of PIBs on stairways to quantitatively investigate the stairway pedestrian flow characteristics, including overtaking behavior and evasive behavior. On one hand, macro indicators describing the frequency of events of PIBs events are analyzed with the variation of pedestrian traffic density. On the other hand, micro indicators describing the characteristics of PIBs are developed to reveal how pedestrians interacted with each other. Connections between macro and micro indicators are also built up to give a full picture of pedestrian traffic flow phenomena and rules on stairways. The description of PIBs under the different LOS on stairways is discussed according to HCM 2010. The paper is organized as follows. Data collection is introduced firstly in Section 2. Section 3 analyzes the characteristics of overtaking behavior on unidirectional stairways. And evasive behavior on bidirectional stairways is presented in Section 4. Descriptions of PIBs under the different LOS on stairways are discussed in Section 5. This paper ends with a brief conclusion and discussion on future studies in Section 6.

2. Data

2.1. Observation Sites. To analyze the characteristics of PIBs on stairways, the observation sites should be isolated from other transportation modes. And the sites could be bidirectional to observe pedestrian evasive behavior. Meanwhile, pedestrian traffic is expected to vary with density range to cover pedestrian flow of low, middle, and high densities. According to filed observation, Zhong-Shan Park Station is selected as the observation site, which is a metro station in Shanghai with large amounts of pedestrian flow and three metro lines interchanging. In 2016, daily passenger flow volumes including transfer volumes in this station were 570,000 ride trips. During peak hours, passenger flow volumes make up nearly 20 percent of the total daily volumes. Thus, the various pedestrian flow densities could be observed in this site.

As can be seen in Figure 1, two flights of stairways in the metro station are selected for field observation. Physical characteristics of the observed stairways are given in Table 1, illustrated in Figure 1(e). Bidirectional flow is allowed in these two stairways all the time in a day. Stairway A serves ascending pedestrian flow (see Figure 1(a)), and Stairway B serves descending flow (see Figure 1(b)). For peak hours, bidirectional pedestrian flows are observed on such two stairways (see Figures 1(c) and 1(d)). The average grades of these two stairways are about 25°, and the tread width and riser height are 0.30 m and 0.15 m, respectively.

Table 1: Physical parameters of the two observed stairways.

Facility	Width (m)	Pitch line (m)	Grade (°)	Tread Width (m)	Step Riser Height (m)
Stairway A	1.77	4.82	25.8	0.30	0.15
Stairway B	2.10	4.71	24.4	0.30	0.15

(a) The observed ascending stairway (b) A landing area upstream of the observed stairway (c) A landing area downstream of the observed stairway

Figure 2: Details of connected landings of the observed ascending stairway.

With consideration of the impact of connection with other spaces on PIBs, Figure 2 shows the details of the connected landings and other flights of the observed ascending stairway. There are four flights for the ascending stairway. The second flight is selected as the observed object; see Figure 2(a). There is a landing area to connect with the third flight upstream of the second flight; see Figure 2(b). There is also a landing area to connect with the first flight downstream of the second flight; see Figure 2(c). Similarly, as for the descending stairway, the top flight is selected as the field observation; see Figure 3(a). There is a station hall upstream of the observed stairway; see Figure 3(b). And there is a landing area to connect with another flight; see Figure 3(c). Furthermore, the outlined ellipses are set with the red lines to associate with the location of the observed flight.

Field observation is conducted by recording the videos of pedestrian traffic on the two stairways during peak commuting hours, which are 7:00~10:00 in the morning and 16:00~19:00 in the evening. The reason for selecting peak hours as observation time is twofold. One is to obtain more high-density traffic flow data, and the other is to facilitate observing interactive behavior of pedestrians, since pedestrians usually walk in a hurry during peak hours, which will cause high possibility of pedestrian overtaking behavior and evasive behavior.

2.2. Indicator Definition. Two different categories of indicators are introduced for describing the characteristics of PIBs. A person who needs to overtake the slow pedestrians in unidirectional pedestrian flow on stairways represents overtaking behavior; and a person who needs to avoid the opposite pedestrians in bidirectional pedestrian flow on stairways represents evasive behavior. Shan et al. defined these two types of indictors on the walkway characteristics of PIBs, named macro and micro indicators [11]. Similarly, the macro indicators, representing the occurrence frequencies of PIBs, and micro indicators, representing the space necessary for taking PIBs for this research, are listed in Table 2.

A brief description of the meaning of these indicators is given as follows:

(i) The occurrence intensity of PIBs (ρ_o, ρ_e). They are defined as the number of PIB events occurring per unit time at a certain density level. They are the balanced outcome of PIB demand and available space supply, which can represent the possibilities of PIBs occurrence at different pedestrian flow densities.

(ii) The proportion of sideways (R_o, R_e). They are defined as the proportion of sideways PIB events to the total PIB events at a certain density to illustrate the difficulty of taking behaviors.

(iii) The initial longitudinal distances of interactive behaviors (L_o, L_e). These indicators are defined as the longitudinal distances between the two pedestrians when the PIB event starts; see Figure 4. Such indicators reflect the pedestrians' available longitudinal space during the interactive behavior process.

(iv) The final lateral distances of interactive behaviors (H_o, H_e). They are defined as the lateral distances between the two pedestrians at the moment when the interactive behavior events are over. The indicators reflect the pedestrians' available lateral space during the interactive behavior process.

2.3. Indicator Calculation. As for data extraction, a manual counting method is adopted with the help of a video player software, which can play (including playing frame by frame, a frame equals 0.04 seconds) and replay the recorded videos.

(a) The observed descending stairway (b) A station hall upstream of the observed stairway (c) A landing area downstream of the observed stairway

Figure 3: Details of connected landings of the observed descending stairway.

(a) Pedestrian overtaking behavior (b) Pedestrian evasive behavior

Figure 4: Schematic drawing of PIBs.

Table 2: Macro and micro indicators of PIB characteristics.

Behavior Type	Macro Indicators	Micro Indicators
Overtaking behavior	Occurrence intensity (ρ_o)	The initial longitudinal distance of overtaking behavior (L_o)
	Proportion of sideways (R_o)	The final lateral distance of overtaking behavior (H_o)
Evasive behavior	Occurrence intensity (ρ_e)	The initial longitudinal distance of evasive behavior (L_e)
	Proportion of sideways (R_e)	The final lateral distance of evasive behavior (H_e)

For macro indicators of PIB occurrence intensities, each overtaking behavior or evasive behavior can be recorded, as well as the density, when PIBs are happening. Thus, we can calculate the total number of PIBs events (with the symbol of N_{oi} and N_{ei}, resp.) that happened at a certain density. We divided the observed time period into more than 4000 portions with the unit of 5 s for each portion. And density of each portion is also recorded to sum the total time length (T_i) for a certain density i. The occurrence intensities (ρ_o, ρ_e) can be calculated using the following formulas:

$$\rho_{oi} = \frac{N_{oi}}{T_i}$$
$$\rho_{ei} = \frac{N_{ei}}{T_i} \quad (1)$$

(a) Starting point of overtaking behavior (b) Ending point of overtaking behavior (c) Starting point of evasive behavior (d) Ending point of evasive behavior

Figure 5: Illustration of the starting point and ending point of PIBs.

Meanwhile, at the ending point of PIBs, we can determine whether the behavior is a sideways behavior or not; thus the total of sideways behavior at a certain density could be summed (S_{oi}, S_{ei}). And the proportions of sideways behavior to the total events at a certain density could be calculated with the following formulas:

$$R_{oi} = \frac{S_{oi}}{N_{oi}}$$
$$R_{ei} = \frac{S_{ei}}{N_{ei}} \quad (2)$$

It should be noted that theoretically the density is the instant number of pedestrians on stairways divided by the observed area. But, in practice, the statistical interval for density calculation is 5 seconds because it could be regarded that the average density will mostly remain the same in five seconds [11].

For micro distance indicators, the horizontal and vertical coordinates of the key points are recorded with the consideration of the feet positions of pedestrians and physical characteristics of stairways. The key points of PIBs include the starting point and end point, as can be seen in Figure 3. The starting points of PIBs are defined as the positions where the pedestrians start to change their walking directions; see Figures 5(a) and 5(c). The ending points of PIBs are defined as the positions where two pedestrians are paralleled to the lateral; see Figures 5(b) and 5(d). The tread width and the equidistant tapes pasted on stairways can be helpful to estimate such distances. Then the micro indicators can be computed using the following formulas:

$$L_o = |y_{o3} - y_{o1}|$$
$$H_o = |x_{o4} - x_{o2}|$$
$$L_e = |y_{e3} - y_{e1}| \quad (3)$$
$$H_e = |x_{e4} - x_{e2}|$$

Figure 6: Macro characteristics of pedestrian overtaking behavior on stairways.

3. Pedestrian Overtaking Behavior On Stairways

3.1. Occurrence Intensities on Ascending and Descending Stairways. During the time period of field observation, a total number of 120 pedestrian overtaking behavior events on ascending stairway are observed, with the density ranging from 0.15 to 2.7 p/m^2. Similarly, 63 pedestrian overtaking behavior events are collected on descending stairway, with the density ranging from 0.15 to 3.0 p/m^2. Through classifying available density values into sequential subgroups with the unit of 0.15 p/m^2 interval to aggregate behavior samples in the same density group, the distribution characteristics of occurrence intensity of pedestrian overtaking behavior on stairways under varying densities are captured with the different pedestrian flow LOS presented in HCM 2010, as shown in Figure 6. Overall, with the continuous increase of pedestrian flow density, both of the occurrence intensities of

(a) Extremely low density (b) Less than a critical value (c) Larger than the critical value (d) High density (e) Extremely high density

Figure 7: Illustrations of unidirectional stairway traffic at different density levels.

pedestrian overtaking behavior on ascending stairway and on descending stairway first increase and then show a decreasing trend.

As can be seen in Figure 6, at extremely low density with the density less than 0.15 p/m^2 or extremely high density with the density greater than 2.4 p/m^2 on ascending stairway and greater than 3.0 p/m^2 on descending stairway, there is no pedestrian overtaking behavior. This is because, at extremely low density, there is no interaction among pedestrians; thus there is no need to take overtaking behavior; see Figure 7(a). On the contrary, at extremely high density, all pedestrian movements are severely restricted, resulting in no available space for overtaking behavior; see Figure 7(e).

When pedestrian density increases from a low value to a critical value, the occurrence intensity raises dramatically up to the peak value. The density range is about 0.15~0.9 p/m^2 on ascending stairway, and the density range is from 0.15 to 0.6 p/m^2 on descending stairway, as shown in Figure 6. This may be interpreted as follows: interaction among pedestrians accrues with density increasing, leading to the demand for overtaking behavior growing up quickly. On the other hand, the space supply on stairways is still enough for pedestrians to overtake other pedestrians; see Figure 7(b). Fast growing overtaking demand and abundant space supply lead the occurrence intensity of overtaking to increase rapidly.

With the continuous increase of pedestrian flow density, larger than the critical value, the occurrence intensity shows a decreasing trend. And the range of density is from 0.9 to 1.65 p/m^2 on ascending stairway, with the range from 0.6 to 1.35 p/m^2 on descending stairway. The reason for this feature is that although the demand for overtaking still grows up, the space supply on stairways decreases rapidly, which restricts the occurrence of pedestrian overtaking behavior; see Figure 7(c).

As the density increases further, the intensity of pedestrian overtaking behavior keeps a declining tendency with a relatively low rate. The density range on ascending stairway is about 1.65~2.4 p/m^2, and the range of density is from 1.35 to 3.0 p/m^2 on descending stairway. The continuing decrease of the occurrence intensity shows much intensive constraints of overtaking ability with the little available space for pedestrians; see Figure 7(d).

Figure 8: Fitting curves between occurrence intensity and pedestrian flow density.

Furthermore, from the aspect of pedestrian flow LOS, the largest intensity of pedestrian overtaking behavior on ascending stairway is the LOS D, while the largest intensity on descending stairway is the LOS B. There are no pedestrian overtaking events on LOS F. And both the intensities on ascending stairway and descending stairway show very low values on LOS E. Meanwhile, the intensity on ascending stairway at a certain density is always larger than the intensity on descending stairway. The reason may be that pedestrians should focus their mind when they walk on descending stairway.

To fit the functions between pedestrian flow density and occurrence intensity, SPSS software is used with the module of nonlinear regression. Results are shown in Figure 8. The regression functions are as follows:

Table 3: Description of distance indicators on ascending and descending stairways.

Descriptive indexes	On ascending stairway		On descending stairway	
	L_{oa}	H_{oa}	L_{od}	H_{od}
Sample size	98	98	54	54
Min (cm)	30	30	25	30
Mean (cm)	91.3	74.3	88.3	62.3
Max (cm)	205	135	185	115
Key density (p/m^2)	1.05	0.9	1.05	0.75
Average value (cm)	81.1	62.7	73.5	57.2
Range of density (p/m^2)	0.26-2.21	0.26-2.21	0.22-2.12	0.22-2.12

Figure 9: Proportion of sideways pedestrian overtaking behavior with the increase of density.

$$\begin{gathered}\text{For ascending stairway,}\\ \rho_{oa} = 386.89 \times D^4 \times e^{-4.408\times D},\\ R^2 = 0.877;\\ \text{For descending stairway,}\\ \rho_{od} = 477.71 \times D^4 \times e^{-5.723\times D},\\ R^2 = 0.912,\end{gathered} \tag{4}$$

where D means the pedestrian flow density, ρ_{oa} is the occurrence intensity on the ascending stairway, and ρ_{od} is the occurrence intensity on the descending stairway. Both of the values of R-square are larger than 0.85, showing a good regression.

3.2. Proportion of Sideways Pedestrian Overtaking Behavior. As can be seen in Figures 6 and 8, for a certain occurrence intensity, two density values could be obtained. For example, when the occurrence intensity is about 1.4 times/min on ascending stairway, the density may be 0.37 p/m^2 or 1.81 p/m^2 based on the fitted function. However, the difficulty of implementing overtaking behavior at such densities is different, which can be illustrated based on the indicator of proportion of sideways behavior, as shown in Figure 9.

As can be seen in Figure 9, with the increase of density, proportion of sideways behavior shows an increasing trend. When the density is less than 0.9 p/m^2, the proportion is less than 10%, at LOS of A, B, and C. Based on field observation, when the density is larger than 1.6 p/m^2, all the pedestrian overtaking behavior events are sideways behaviors with the LOS of E. When the density is from 0.9 p/m^2 to 1.6 p/m^2, the proportion of sideways behavior shows a linear increasing trend from 4% to 100%, with the LOS of D.

3.3. Microscopic Characteristics of Distance Indicators. For the purpose of deeply understanding the macroscopic characteristics of pedestrian overtaking behavior, most of the behavior events are selected for micro indicators analysis with the 98 samples on ascending stairway and 54 samples on descending stairway. The distance indicators include the initial longitudinal distance (L_o) and the final lateral distance (H_o). Table 3 shows the descriptive results of such distance indicators on ascending and descending stairways. And the scatter diagrams between such indicators and density are shown in Figure 10.

The method of one by one to calculate the correlations between these two distance indicators and density has been adopted to identify the key densities [11]. As for the ascending stairway, when the density is less than the key density (1.05 p/m^2), the longitudinal distance shows a decreasing trend; see Figure 10(a). When the density is larger than 1.05 p/m^2, there is no significant relationship between longitudinal distance and density, with the average value of 81.1 cm. For the horizontal distance, in contrast, when the density is less than 0.9 p/m^2, we find that there is no significant relationship between horizontal distance and density, with the average value of 62.7 cm; see Figure 10(b). After that, the horizontal distance decreases with the increase of density.

Similarly, the key density of longitudinal distance on descending stairway is also 1.05 p/m^2 (see Figure 10(c)), while the density of horizontal distance is 0.75 p/m^2 (see Figure 10(d)). The average values on descending stairway are 73.5 cm and 57.2 cm.

Thus, the occurrence of overtaking behavior is more dependent on the longitudinal distance rather than horizontal distance. Within a low-density range, the horizontal distance remains almost constant with the increasing density, meaning that available space for pedestrians to overtake is not deducted notably even though the longitudinal distance keeps decreasing. Meanwhile, the space for implementing overtaking behavior is about 75 cm for longitudinal distance

(a) Longitudinal distance on ascending stairway

(b) Horizontal distance on ascending stairway

(c) Longitudinal distance on descending stairway

(d) Horizontal distance on descending stairway

Figure 10: Microscopic distance indicators of pedestrian overtaking behavior.

and 60 cm for horizontal distance, which also reflects the space demand for a person walking on stairways. The reason for the differences of micro distances between these two different stairways may be that descending people have already changed their lateral positions before they got the first stair due to the top flight selected as the field observation [18].

The above rules of space supply change for pedestrian overtaking behavior are in line with and support the characteristics of occurrence intensity change with pedestrian flow density. At low-density range, the increasing density leads to much interaction among pedestrians and the overtaking demand rises up. At the same time, the available space for taking behaviors is maintained at a high level. Therefore, the occurrence intensity increases rapidly. As the density goes up further, the interference among pedestrians is intensified and the overtaking demand increases continuously, but unfortunately the available space for overtaking declines sharply (mainly because the micro distances decrease quickly, see Figure 10). Therefore, the occurrence intensity decreases rapidly. Finally, there is no available space at extremely high density, resulting in none of pedestrian overtaking behavior events.

4. Pedestrian Evasive Behavior on Stairways

4.1. Occurrence Intensity on Bidirectional Stairways. A total number of 122 samples of pedestrian evasive behavior events on bidirectional stairways are collected, with the density ranging from 0 to 3.45p/m^2. The available density values are also classified into subgroups with 0.15 p/m^2 interval to aggregate behavior samples in the same density group. The distribution characteristics of occurrence intensity of evasive behavior under different LOS defined in HCM 2010 are shown in Figure 11.

Figure 11: Occurrence intensity distribution of pedestrian evasive behavior.

As can be seen in Figure 9, at extremely low density (less than 0.15 p/m^2) or extremely high density (greater than

(a) Extremely low density (b) Less than a critical value (c) Larger than the critical value (d) High density (e) Extremely high density

Figure 12: Illustrations of bidirectional stairway pedestrian flow at different density levels.

3.15 p/m^2), there are no pedestrian evasive behavior events. The reason is that pedestrians are not influenced by others at extremely low-density level and there is no need to take behavior; see Figure 12(a). On the contrary, at extremely high density, all pedestrian movements are severely restricted; see Figure 12(e). There is no available space for taking evasive behaviors.

As the density increases, pedestrian evasive behavior can be observed and the occurrence intensity remains relatively stable, with the average value of 2.28 times/min. The range of density is from 0.15 p/m^2 to 1.4 p/m^2. The reason is that, with the increase of density, the interaction among pedestrians accrues and the demand for taking evasive behaviors grows up quickly. Meanwhile, the space supply for pedestrians to avoid others decreases simultaneously from more pedestrians crowding; see Figure 12(b).

As the density increased over the critical value (1.4 p/m^2), the occurrence intensity declined sharply. The reason is that the space supply for pedestrians to avoid others on bidirectional stairway decreases rapidly, which restricts the occurrence of pedestrian evasive behavior events in spite of the increasing demand of taking evasive behaviors; see Figure 12(c).

As the density increases further larger than 1.8 p/m^2, the intensity of avoidance behavior keeps the declining tendency but with a relatively lower rate. The continuing decrease of the occurrence intensity is mainly the result of more intensive constraints among pedestrians, which severely restricted the occurrence possibility of pedestrian evasive behavior; see Figure 12(d).

Furthermore, from the aspect of pedestrian flow LOS, the occurrence intensity shows a stable trend when the LOS is B, C, and D. At LOS E, the intensity shows a decreasing trend. In LOS F, there are few pedestrian evasive behavior events.

The fitted function for the occurrence intensity when the density is larger than 1.4 p/m^2 is as follows:

Figure 13: Proportion of sideways pedestrian evasive behavior with the increase of density.

$$\rho_e = -0.7964 \times D^3 + 6.6796 \times D^2 - 18.654 \times D + 17.519, \quad R^2 = 0.9094, \tag{5}$$

where D means the pedestrian flow density and ρ_e is the occurrence intensity of pedestrian evasive behavior.

4.2. Proportion of Sideways Pedestrian Evasive Behavior. To show the difficulty of pedestrian evasive behavior at different densities, almost 70% of evasive behaviors are sideways behaviors. Figure 13 illustrates the proportion of sideways evasive behavior at the different LOS. The proportion of sideways behavior shows an increasing trend from LOS A to LOS D. The evasive behavior events are totally the sideways behaviors when the density is larger than 1.5 p/m^2 at LOS E. Compared with the characteristics of proportion of sideways overtaking behavior, evasive behavior needs more space to take behavior, which will be discussed in Section 4.3.

(a) Longitudinal distance indicator

(b) Horizontal distance indicator

Figure 14: Microscopic distance indicators of pedestrian evasive behavior.

Table 4: Description of distance indicators on bidirectional stairways.

Descriptive indexes	L_e	H_e
Sample size	96	96
Min (cm)	85	20
Mean (cm)	188.4	61.2
Max (cm)	370	115
Key density (p/m^2)	1.45	1.45
Average value (cm)	144.2	46.4
Range of density (p/m^2)	0.19-2.22	0.19-2.22

4.3. Microscopic Characteristics of Distance Indicators. To analyze the microscopic characteristics of distance indicators, 96 samples of the pedestrian evasive behavior events on bidirectional stairway are selected. The description of such indicators including the initial longitudinal distance (L_e) and the final horizontal distance (H_e) is shown in Table 4. Figure 14 shows the relationship between these two distance indicators and density.

As can be seen in Figure 14, both L_e and H_e show a decreasing trend when the density increases from 0.19 p/m^2 to 1.45 p/m^2, as well as the LOS A, B, C, and D. This finding indicates that the increasing density leads to the reduction of available longitudinal and horizontal space, and the total space for taking evasive behaviors becomes smaller and smaller. Therefore, the ability of taking evasive behaviors is restricted severely.

When the density is larger than 1.45 p/m^2, there is no significant relationship between L_e or H_e and density at LOS E. The average value of L_e is about 145 cm when density is larger than 1.45 p/m^2, almost two times compared with the average value of L_o with the density larger than 1.05 p/m^2, while the value of H_e is about 45 cm.

The microscopic characteristics also support the occurrence intensity features, of which first remains stable and then decreases. At low density, the increase of density leads to much interaction among pedestrians and much demand for taking evasive behaviors, but the available space reduces synchronously. Therefore, the occurrence intensity maintains a stable level due to the trade-off between demand and space supply. As the density increases further, the interference among pedestrians intensifies continuously, while the space supply becomes decreasing, resulting in the rapid decrease of occurrence intensity. Finally, the basic space requirement for evasive behavior is not large enough, leading to none of pedestrian evasive behavior events. In this case, pedestrians walk forward by following the lanes of their own directions.

Compared with the results of two such behaviors, we find that there are similarities and differences between pedestrian overtaking behavior and pedestrian evasive behavior in terms of the macro and micro characteristics. As for similarities, neither the overtaking behavior events nor the evasive behavior events can be observed at extremely low- or high-density level. Meanwhile, when the density increases from the extremely low level, the occurrence intensity of overtaking behavior increases rapidly, but that of evasive behaviors remains relatively stable. This is mainly due to the different change rules of space supply for different PIBs with the continuous increase of density. Meanwhile, it may also be attributed to the different natures of the two types of behavior. If the space allows, all individual pedestrians have probability to overtake others, while pedestrian evasive behavior mainly occurs at the interface of two flows in different directions. As for the distance indicators, the average value of L_e (188 cm) shows two times larger than the value of L_o (90 cm) due to the more space demand of pedestrian evasive behavior. The value of H_e (60 cm) is similar to the value of H_o (65 cm) because of the width demand of a person walking alone.

5. Discussions

Based on the macro and micro characteristics of PIBs on stairways, Table 5 shows the critical densities with the descriptions found in our research. For example, when the density is less than 0.15 p/m^2 or the space is larger than 71.8 ft^2/p, none of PIBs could be observed. For LOS B, the largest intensity of pedestrian overtaking behavior on descending stairway is observed with the density of 0.65 p/m^2. The horizontal distance of overtaking behavior on descending

Table 5: Critical densities observed in this study.

Density (p/m^2 and ft^2/p)	LOS based on HCM	Description of the critical density
0.15 (71.8)	A	None of PIBs
0.225 (47.8)	A	Pedestrian overtaking behavior events could be observed
0.65 (16.6)	B	The largest intensity of overtaking behavior on descending stairway
0.75 (14.3)	C	Key density of horizontal distance on descending stairway
0.975 (11.0)	D	The largest intensity of overtaking behavior on ascending stairway
1.05 (10.2)	D	Key density of longitudinal distance for overtaking behavior
1.45 (7.4)	E	Key density of longitudinal distance for evasive behavior
1.6 (6.7)	E	All the overtaking behavior events are the sideways behaviors
1.875 (5.7)	E	None of pedestrian overtaking behavior on descending stairway
2.325 (4.6)	F	None of pedestrian overtaking behavior on ascending stairway
3.15 (3.4)	F	None of pedestrian evasive behavior

Figure 15: Descriptions of PIBs in HCM 2010 and critical densities identified in this study.

stairway becomes decreasing when the density is larger than 0.75 p/m^2 at LOS C. Meanwhile, the longitudinal distance for overtaking behavior keeps a stable value, when the density is larger than 1.05 p/m^2 at LOS D. All the PIB events are the sideways behaviors at LOS E. None of pedestrian evasive behaviors could be observed when the density is larger than 3.15 p/m^2 at LOS F.

The left part of Figure 15 shows the description of PIBs presented in HCM 2010, while the right part of Figure 15 shows the critical densities identified in this study. There are some differences between the two different descriptions, compared with the description of the critical density presented in Table 5 and the description presented in the left part of Figure 15. For example, the largest intensity of overtaking behavior on ascending stairway is at LOS D, while the description of HCM 2010 is "limited ability to pass lower pedestrians." And none of pedestrian overtaking behaviors on descending stairway could be found in LOS E, while the description of LOS E is very limited ability to pass slower pedestrians. It is reasonable for such differences due to the differences of the observation environment and the different walking directions.

6. Conclusions

Pedestrian interactive behaviors, such as overtaking behavior and evasive behavior, are crucial elements for better understanding pedestrian flow on stairways. This paper aims to explore the characteristics of PIBs under the different LOS on stairways. Related indicators are proposed and calculated based on field observation, including occurrence intensity, proportion of sideways behavior, longitudinal distance, and horizontal distance. Then, pedestrian overtaking behavior and evasive behavior features are analyzed, with the consideration of different pedestrian flow densities. The relationship between macro indicators and micro indicators are discussed. Lastly, the description of PIBs on stairways presented in HCM 2010 is discussed and revised based on the characteristics of PIBs.

Results show that the occurrence intensities of PIBs first increase and then show a decreasing trend with the increasing density. Neither of the two types of behavior occurs at extremely low or high density. At extremely low density, pedestrians walk individually with no need to take PIBs. At extremely high density, there is no enough available space for taking overtaking behavior or evasive behaviors, resulting in none of PIBs. At the other ranges of density, the occurrence intensity of interactive behavior presented the tendency of first increasing and then decreasing. This is mainly due to the change of available space for PIBs with the increase of density. As for sideways behavior, the proportion of sideways behavior shows a rapid increasing trend from LOS A to LOS D. At LOS E, all the observed PIB events are sideways behaviors.

The longitudinal distance indicator of pedestrian overtaking behavior first shows a decreasing trend and then keeps a stable value with the key density of 1.05 p/m^2, while the horizontal distance indicator first shows no significant relationship with density and then decreases with the continuous increase of density. As for pedestrian evasive behavior, the micro distance indicators first decrease and then keep a certain value with the increase of density. The key density is 1.45 p/m^2.

Based on the findings of our research, there are some differences compared with the descriptions presented in HCM 2010 and the descriptions of critical densities identified in this study. The findings of our research are helpful to understand the knowledge of pedestrian behavior on stairways for a better stairway traffic design and level of service evaluation.

One of the limitations of this study is that only the second flight of the ascending stairway and the top flight of the descending stairway are selected as the observed objects. More field observations should be conducted to analyze the characteristics of PIBs on stairways. Meanwhile, more researches should be done to propose a local level of service criteria of pedestrian stairways. And other factors such as gender, age, walking speed, and luggage-carrying also need to investigate their impacts on the PIBs. In addition, comparative analysis between level passageway and stairway is also helpful to comprehensively grasp the characteristics of PIBs on stairways.

Data Availability

The data used to support the findings of this study are included within the supplementary information file.

Disclosure

The contents of this paper reflect the views of the authors who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views. This paper does not constitute a standard, specification, or regulation. The manuscript is based on a Poster Paper that was presented at Transportation Research Board 94th Annual Meeting "https://trid.trb.org/view/1336821".

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Supplementary Materials

Data of macro and micro characteristics of pedestrian overtaking behavior and evasive behavior have been supplied. *(Supplementary Materials)*

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Research Article

The Influence of Wheelchair Users on Movement in a Bottleneck and a Corridor

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Emergency exits as bottlenecks in escape routes are important for designing traffic facilities. Particularly, the capacity estimation is a crucial performance criterion for assessment of pedestrians' safety in built environments. For this reason, several studies were performed during the last decades which focus on the quantification of movement through corridors and bottlenecks. These studies were usually conducted with populations of homogeneous characteristics to reduce influencing variables and for reasons of practicability. Studies which consider heterogeneous characteristics in performance parameters are rarely available. In response and to reduce this lack of data a series of well-controlled large-scale movement studies considering pedestrians using different types of wheelchairs was carried out. As a result it is shown that the empirical relations $\overline{\rho}(\overline{v})$ and $\overline{J_s}(\overline{\rho})$ are strongly affected by the presence of participants with visible disabilities (such as wheelchair users). We observed an adaption of the overall movement speeds to the movement speeds of participants using a wheelchair, even for low densities and free flow scenarios. Flow and movement speed are in a complex relation and do not depend on density only. In our studies, the concept of specific flow fits for the nondisabled subpopulation but it is not valid for scenario considering wheelchair users in the population.

1. Introduction

Experimental investigations of pedestrian movements and dynamics have been widely improved during the last decades. Many studies under laboratory or field conditions have been performed to address movement characteristics, improve tracking methods, or investigate behavioural insights [1]. In particular fundamental diagrams are of strong interest to assess the performance of a facility. Frequently fundamental diagrams have been determined for experiments under laboratory conditions with a homogeneous (Homogeneous means in this case a comparative characteristic in attributes, e.g., similar range of age, soldiers, or students as participants, well-abled participants. In contrast, heterogeneous means a state of being diverse in skills and competencies relevant for movement (e.g., movement with vision loss, impeded movement, and using a wheelchair in *one* group)) configuration of the participating groups in terms of complexity of the type of movement (e.g., single-file movement [2–11], bidirectional movement [12–17], movement through corridors [5, 18–22], considering bottleneck situations [5, 19, 20, 23–43], or multidirectional movement [5, 13, 44–54]).

The findings of this research were recently collected and comparatively prepared by extended reviews focussing on different flow types and geometries [55], empirical data collection with regard to complexity of movement [56], and movement dynamics [57]. In addition Haghani et al. [58] have compiled a detailed discussion on empirical methods on crowd behaviour and motion. Even these controlled boundary conditions result in significant differences in scope, shape, and characteristics [59]. It is debatable whether those data are still representative in terms of transferability to diverse, inhomogeneous, and more realistic populations. Given the fact that the demographic transformation process is already in progress ([60–63]) movement characteristics and functional relationships may be out of date [64]. To summarise, social-demographics in western societies are changing as the way of living and the kind of dwellings are. Particularly

in the context of these developments and the associated lack of data, it is necessary to improve the understanding of movement behaviour of heterogeneous pedestrian groups.

Until now, only a few studies considered a more heterogeneous characterisation of participants. This challenge is addressed by a review of Geoerg et al. [65] who discussed the influence of reduced mobility on characteristics of movement. Daamen et al. [25, 26] have performed movement studies with bottleneck configuration considering participants with disabilities. A significant decrease of the bottleneck capacity for disabled participants is reported. The influence of age (elderly or younger subpopulations) on fundamental diagrams was investigated by [25, 26, 66–73]. A difference in characteristics of the fundamental diagrams was observed and stop-and-go waves are more probably to occur, if the population consists of a broader ageing range [70]. Contrary to this, Kolshevnikov et al. found that general characteristics of fundamental diagram considering elderly participants are comparable to younger populations [67]. An overall reduction of movement speed and flow for the elderly compared to younger adults in the studies under the same density situation is reported. The impact of vision loss, reduced visibility, or blindness in subpopulations was analysed by [74–78]. A slightly higher tendency to walk in groups or close to boundaries is reported by [76]. Furthermore, a reduction of flow rate and significantly more unstable flow conditions were reported by [77]. The importance of individual space requirements on flow and density was investigated by [78, 79] (presence of wheelchair users) or [80] (impact of luggage). An important influence by the presence of wheelchair users on flow characteristics is reported which is related to the required space of an individual. Additionally, research on several impacts like fatigue (decrease of movement speed with longer walking distance [81]), stress (higher urgency leads to a higher capacity [82]), or distraction (higher stopping duration with background music [83]) was published.

Concluding, little is known about the influence of heterogeneity on pedestrian movement characteristics which calls into the question of transferability for existing data to heterogeneous population settings. Therefore, this work is developed to analyse a series of well-controlled movement studies with focus on characteristics of pedestrians' movement and assessment of performance of a facility. The structure is organised as follows: in Section 2 the setting of the movement studies, the data extraction techniques, and the used calculation methods are introduced. The data analysis is subjected to Section 3. First, we present a comparison of unimpeded (unrestricted, free) movement speed in different subpopulations (Section 3.1). Second, the impact of the presence of wheelchair users in group movement is presented. Particularly the effect on fundamental diagrams ($\overline{v}(\overline{\rho})$, $\overline{J}(\overline{\rho}) = \overline{\rho} \cdot \overline{v}$) is focused on (Section 3.2). Afterwards, the analysis of individual time gaps (Section 3.3) and the consequences on the specific flow (Section 3.4) are analysed. The conclusion will be made in the last section (Section 4).

2. Methods

2.1. Study Setup. The movement studies were conducted as a part of the interdisciplinary research project SiME (SiME is an acronym for the German meaning of "safety for all people" and is funded by the German Ministry of Education and Research) on two days in an industrial hall in Wermelskirchen-Dabringhausen (Germany) in June 2017. Twelve studies with more than 145 single runs and overall 252 participants with populations composed of people with and without disabilities were performed. In addition studies without any people with disabilities have been conducted.

Non-disabled participants (NDP) were recruited by public call while participants with disabilities (PWD) were recruited from a sheltered workshop. For defining the type of disability and to consider and select participants with disabilities, we used the Score RNA-approach, which is a method to weight potentially critical indicators for egress (for details we refer to [84, 85]). The Score RNA considers disabilities in reception (blindness, deafness), perception (cognition), and realisation of movement (walking impairments, requirement on assistance devices) and in addition a cross-section variable (age) and evaluates the influence of the individual ability to evacuate autonomously.

The consideration of an appropriate proportion of people with disabilities in the overall population is oriented towards the prevalence of disability (approximately 10 % in Germany [86], 15 % for EU-27 [87], and 19 % for the US [88]). In real scenarios pedestrians with disabilities do not occur in homogeneous groups. Their appearance in real situations is characterised by individual requirement on special aids, equipment, personal help, or assistance in the given situations. In this study, we focus on the impact of presence of wheelchair users as representatives of a heterogeneity (persona (for details of applying a persona we kindly refer to [89])), because the subpopulation deals with a variation in individual space requirements and movement characteristics (e.g., inertia, amplitude of swaying, and viewing height). Wheelchair users are therefore a necessary simplification for the design of persona "participants with disability."

We differentiate the population of a study into two subpopulations: on the one hand the participants with disabilities (disabled subpopulation) and on the other hand the participants without any disabilities (non-disabled subpopulation). In accordance with the reported ratio of inhabitants with disabilities, it has been tried to configure the populations in a similar ratio. In addition, we did reference studies for all geometrical settings with a reference population without any disabilities. The mean age of the disabled participants was 47.57 ± 6.99, and the mean age of nondisabled participants was 35.93 ± 16.26. The mean age of the reference population was 32.07 ± 15.50. The heights of all participants range from 1.45 m to 2.04 m with a mean of 1.74 ± 0.1 m.

Participation was absolutely voluntary for everybody and a cancellation of participation without any negative consequences was possible at any time. All participants have been paid 25 € per half a day of participation. Only anonymous data were used for the studies and the methodological design, data storage process, and the access authorisation for data

(a) Sketch of the bottleneck study

(b) Sketch of the corridor study

(c) Snapshot of the bottleneck study

(d) Snapshot of the corridor study

Figure 1: Sketch of the study setup. The width w is varied between 0.9 and 1.2 m in steps of 0.1 m. Green rectangle: measurement area.

were approved by the ethics committee of the Bergische Universität Wuppertal. No ethical concerns were mentioned.

The aim of the studies was to investigate the impact of presence of wheelchair users on performance criteria for movement in built environments under laboratory conditions. Following the classification of complex movements by Shi et al. [56], we focused on investigations of internal driven movements in multilane pedestrian traffic. This includes effects like self-slowing, grouping queuing and is represented in corridors and egress situations (bottlenecks). To control the possibility of overtaking (corridor) and the density/queuing in front of the bottleneck (as a representative for a limited flow), the passage width w was varied from $w = (0.9, 1.0, 1.1, 1.2)$ m. The minimum width for doors in public accessible buildings in Germany is 0.9 m, which is the reason to set the minimum width to a clear width of 0.9 m [90]. Expecting approximately 120 participants during the studies, it was estimated that a steady state concerning densities of approximately $3\,\mathrm{m}^{-2}$ will hardly be reached at large widths. Thus, the width was increased in steps of 0.1 m up to a maximum width of 1.20 m (which is in line with [37]). The length of the bottleneck was constant ($l = 2.4$ m, see Figure 1). The geometry was built from wooden three-layer panels with a height of 2.0 m. A waiting zone of $\approx 30\,\mathrm{m}^2$ was located at $x = [-18, -12]$ with an initial density of $\approx 3.0\,\mathrm{m}^{-2}$. The distance was meant to buffer starting conditions and minimize effects of entering the geometry. Wheelchair users were placed randomly over the entire space. The participants were advised to move through the bottleneck without haste. It was emphasized not to push and to walk with the preferred movement speed. A run was started on instruction of the experiment leader. When a participant leaves the geometry, he or she returns to the waiting zone for the next run. In order to avoid outliers, every run was repeated twice. Table 1 summarises the configuration and characteristics of the analysed runs in this article. The characteristics were measured in a measurement area of $4.0\,\mathrm{m}^2$ located four meters in front of the bottleneck entrance (see Figures 2 and 4).

Every experimental design is characterized by research pragmatic decisions, priorities, and a focus on complexity reduction. The authors are aware that this results in limitations for transferability to real scenarios. In particular, such narrow and long corridors are rarely found in real geometries. The decision for the geometric boundary conditions was made against the background of investigating the transition from single-file movement to group movement (corridor). On the other hand, bottlenecks are defined by their temporal and/or local limitation. The influence of the output from the bottleneck and the empirically observed capacity-increasing effect of very short bottlenecks [32] should be excluded to reduce complexity (bottleneck situation). In summary, the geometric configuration does not represent a real situation in a building. It focuses on creating the spatial boundary conditions: preventing and later enabling lane formation (corridor) and regulating the outflow given constant inflow (bottleneck).

2.2. Data Extraction. The passageway through the study setting was captured by nine high-definition cameras attached to the ceiling of the hall (height ≈ 6.34 m). Each participant wore a coloured cap according to their individual body height. We used the PeTrack-Framework to determine the

Table 1: Controlled boundary conditions and characteristic of each run. Note that some participants have to rest after a run due to their disability and that volunteers without tasks participated run-wise.

Bot_whe	Run	01	02	03	04	05	06	07	08
	Width	0.9 m		1.0 m		1.1 m		1.2 m	
	N (non-disabled)	81	81	80	80	83	83	85	83
	N (disabled)	7							
Bot_ref	Run	01	02	03	04	05	06	07	08
	Width	0.9 m		1.0 m		1.1 m		1.2 m	
	N (non-disabled)	67	67	66	66	69	69	69	69
	N (disabled)	–							
Cor_whe	Run	01	02	03	04	05	06	07	08
	Width	0.9 m		1.0 m		1.1 m		1.2 m	
	N (non-disabled)	85	83	85	85	84	83	85	86
	N (disabled)	7							
Cor_ref	Run	01	02	03	04	05	06	07	08
	Width	0.9 m		1.0 m		1.1 m		1.2 m	
	N (non-disabled)	68	68	69	69	70	69	68	69
	N (disabled)	–							

automatic extraction of positions at every time step (frame) from the video recordings [91]. PeTrack detects the center of the coloured cap and tracks the position in the next time step. The transformation from pixel coordinates into physical (world) coordinates was autocorrected by taking the height according to the colour of the caps into account [92]. We assume a coherent area of pixels in the middle of the coloured caps as body centre of a participant, so the resulting trajectories represent positions of the head projected on the ground. All resulting trajectories were checked and corrected manually. The trajectories are precise with a maximum error of ≈ 0.092 m in the perspective of the centred camera (for details of the error calculation we refer to [92]). Figure 2 displays the trajectories corresponding to the runs Bot_whe_01, Bot_ref_01, Cor_whe_01, and Cor_ref_01. Participants with disabilities (in this case using a wheelchair) are coloured in orange. For summarised configuration details see Table 1.

2.3. Calculation of Characteristics. Calculation of characteristics is separated into different approaches: (a) values of a fixed time interval (space-time-mean, according to [13]) to calculate the fundamental diagram, (b) the flow J through the bottleneck at a fixed distance (time-mean, according to method A in [22]), and (c) values based on the Voronoi method (space-mean, according to [93]) to analyse the instantaneous movement speed along a given trajectory.

Method (a). We used a method to calculate the characteristics of the fundamental diagram which is able to provide mean values for density and movement speed at the same space and time. The mean density $\overline{\rho}(A, \Delta t)$ is the individual share of a participant i at the total density in context of their effective time $[t_0, t_1]$ in the measurement surface A during the measurement interval $\Delta t_i(A)$ and the length of the time interval (see (1)). The density within the measurement area is defined as the sum of the individual shares of the density [13].

$$\overline{\rho}(A, \Delta t) = \sum_{i=1}^{n} \frac{t_i(A)}{\Delta t} \cdot \frac{1}{A} \tag{1}$$

The mean movement speed $\overline{v}(A, \Delta t)$ is defined as the ratio of the sum of all covered distances $e_i(\Delta t)$ during the sampling interval $[t_0, t_1]$ to the sum of the time spent $\Delta t_i(A)$ on the measurement area A (see (2)).

$$\overline{v}(A, \Delta t) = \frac{\sum_{i=1}^{n} e_i(\Delta t)}{\sum_{i=1}^{n} \Delta t(A)} \tag{2}$$

Method (b). The flow rate J based on the time gaps of the participants is similar to the number of participants crossing the fixed location at $x = 0$ [57]. Therefore, the time gaps $\Delta t_i = t_{i+1} - t_i$ are calculated between the consecutive participants i and $i+1$. The sum of the individual time gaps is directly related to the flow (see (3) and (4)).

$$J = \frac{1}{\Delta t_i} \quad \text{with } \Delta t_i = \frac{1}{N} \sum_{i=1}^{N} (t_{i+1} - t_i) \tag{3}$$

$$= \frac{N}{\sum_{i=1}^{N} (t_{i+1} - t_i)} \tag{4}$$

The specific flow J_s giving the flow per unit width is defined as the normalised flow J related to the width (see (5)).

$$J_s = \frac{J}{w} \tag{5}$$

Method (c). The Voronoi tessellation assigns an individual required space $A_i(t)$ to each person (called Voronoi cell) which includes all coordinates of the Euclidean plane closer to

(a) Trajectories for run Bot_whe_01 with ≈ 10% participants using wheelchairs

(b) Trajectories for run Bot_ref_01 without participants using wheelchairs

(c) Trajectories for run Cor_whe_01 with ≈ 10% participants using wheelchairs

(d) Trajectories for run Cor_ref_01 without participants using wheelchairs

Figure 2: Individual trajectories of movement through a bottleneck and a corridor with a width of 0.9 m considering participants using a wheelchair (left) and without participants with disabilities (right). Participants using a wheelchair are coloured in orange. Black rectangles represent the measurement surface (coordinates are given in the legend).

Table 2: Unimpeded movement speeds in ms^{-1} for different subpopulations. For a comprehensive description of the characteristics we kindly refer to [84]. Data is presented in the following format: mean [standard deviation, minimum - maximum].

Study	N (PWD)	v_0 (PWD) /ms^{-1}	N (NDP)	v_0 (NDP) /ms^{-1}
Elderly[a]	4	1.30 [0.20, 1.08 - 1.58]	81	1.42 [0.14, 1.02 - 1.75]
Cognition[b]	9	1.20 [0.09, 1.04 - 1.31]	88	1.47 [0.14, 1.09 - 1.81]
Wheelchair[c]	7	0.96 [0.35, 0.45 - 1.41]	77	1.45 [0.17, 0.63 - 1.82]
Walk[c]	5	1.28 [0.12, 1.07 - 1.41]	70	1.44 [0.17, 0.88 - 2.08]
Mixed[d]	5	0.71 [0.26, 0.41 - 1.15]	74	1.43 [0.20, 0.39 - 1.87]
Hetero[e]	12	1.33 [0.29, 0.29 - 1.65]	71	1.47 [0.18, 0.65 - 1.89]
Reference			68	1.47 [0.17, 1.08 - 1.86]

[a] Participants with an age ≥ 60 years without any other disability.
[b] Participants with a cognition impairment (MELBA SL Score ≤ 0.5. MELBA-SL is a profile to assess the work participation of people with impairments in Germany (see [96], available only in German; for an English summary, see [97]). MELBA-SL measures and classifies 29 different characteristics to evaluate the work ability of impaired persons. The MELBA-approach evaluates individual abilities with regard to requirements to a concrete work. Attributes are rated in MELBA are for instance attention, resolving problems, degree of empowerment, carefulness, reading, writing and so on.
[c] Participants with marking in the severely handicapped pass.
[d] Mixed participants with different single disabilities.
[e] Mixed participants with different multiple disabilities.

the participant i than to the neighbours ([8, 93, 94]). Density inside a Voronoi cell of a participant is equal to the reciprocal of its area ($\rho_{x,y,t}(i) = 1/A_i$). The Voronoi density and velocity for the measurement area are then defined as

$$\rho_v(x, y, t, \Delta x, \Delta y) = \frac{\int\int \rho(x, y, t)\, dx\, dy}{\Delta x \cdot \Delta y} \quad \text{with } \Delta y = w \tag{6}$$

$$v_v(x, y, t, \Delta x, \Delta y) = \frac{\int\int v(x, y, t)\, dx\, dy}{\Delta x \cdot \Delta y} \quad \text{with } \Delta y = w \tag{7}$$

3. Analysis and Results

3.1. Unimpeded Movement Speed. The unimpeded (free) movement speed v_0 for each participant was measured before starting the studies (Table 2). The participants were ask to move alone through the bottleneck setting with a width of $w = 0.9$ m. The movement start of each individual was controlled and we considered a distance of ≈ 5 s between each start. This leads to an interpersonal distance of ≈ 6 m, if we suppose a free movement speed of ≈ 1.2 ms^{-1}.

Overall, the observed unimpeded movement speeds of nondisabled participants are comparable with literature findings (see [1]), which indicates a working experimental setting. On the other hand, unimpeded movement speeds of the

(a) $v(\rho)$ (b) $J_s(\rho)$

Figure 3: Schematic representation of the fundamental diagram $v(\rho)$ and $J_s(\rho)$ (visualisation according to [95]).

participants with disabilities depend strongly on individual characteristics such as the kind of movement ability which leads to high standard deviations. For this reason, it is difficult to derive general statements about movement characterisation [84]. Due to the small sample size for the disabled participants, the results represent in particular the relation of the individuals in this study and the results should be verified in further experiments.

3.2. Influence on the Fundamental Diagram. In general, a fundamental diagram describes the relation between density and movement speed or density and flow. It indicates the importance for calculation methods for dimensioning pedestrian facilities [57]. Quantities for characterisation of the fundamental diagrams are the capacity $J_{s,max}$, the density ρ_c where $J_{s,max}$ is reached, and ρ_0 where the overcrowding results in impossibility of movement [39]. A fundamental diagram consists of three branches [95] (see Figure 3):

(i) a free-flow branch at low density, where the flow increases with density and the movement speeds are similar to the desired (unimpeded) movement speeds

(ii) a branch where interactions between pedestrians occur with needs for changes of velocity and directions but still a stable flow

(iii) a congested branch at higher densities where the flow decreases with increasing density due to the distance to neighbours and which in consequence leads to the formation of jams

The obtained trajectory data enable analysing the movement through the geometries in relation of space and time. Figure 4 shows the movement of each participant through the bottleneck with different widths. Sequences of the trajectories with a slow instantaneous movement speed ($\leq 0.1\,\mathrm{ms}^{-1}$ as calculated by method (c), described in Section 2.3) are coloured in red. Data for the subpopulation with wheelchair users (left) and the reference population (right) are shown.

It can be seen that the movement through the bottleneck for the reference population is uniform and homogeneous for all widths. All participants overcame the same distances by a similar time and without overtaking and clogging effects. The overall passage time decreases with increasing bottleneck width (from top to down). In contrast, the data for a population with wheelchair users are presented on the left side in Figure 4. Significant changes of uniformity in movement were observed in front of the bottleneck. Waiting phases (lower increase of the trajectory in y-direction) and overtaking situations (crossing of trajectories) result in an inhomogeneous movement characteristic (situational change of instantaneous movement speed). This phenomenon is called shockwave and it is well known from incidents or bottlenecks on road traffic and pedestrian dynamics [98, 99]. Shockwaves occur in case of transition between two traffic states (e.g., free flow to congested) [100]. The individual (Voronoi) movement speed is depending on time and x-position and is presented in two colours in Figure 4:

$$\text{colour} = red, \quad \text{if } v_v \leq 0.1\,\mathrm{ms}^{-1} \tag{8}$$

$$\text{colour} = grey, \quad \text{otherwise} \tag{9}$$

They occur more likely in case of presence of wheelchair users and propagate with certain speed upwards the flow (v_{jam}) and clearly related to the entrance of the person with disability at the bottleneck.

We focus on the fundamental diagrams to analyse the characteristics of movement depending on population characteristics (Figures 6 and 7). The presented fundamental diagrams show the mean values and the standard deviations over all runs (and different widths). The relation between movement speed and density and flow and density is based on time-space-mean calculations (method (a), described in Section 2.3) introduced by Eddie [101] and generalised by [13]. A time interval of $\Delta t = 2\,\mathrm{s}$ (which is corresponding to 50 frames) was used to calculate the moving averages of the characteristics.

To determine the fundamental diagram only data from stable conditions are used (see the grey coloured area in Figure 5). This is particularly important since pedestrian dynamics experiments usually have significantly shorter running times due to limited personnel and financial factors which is unlike in field studies of vehicle traffic. While in field studies of car traffic periods of three to five minutes are not uncommon for the determination of moving averages [102], pedestrian experiments are often shorter than two minutes due to limited resources. Thus, a significant part of

(a) Bot_whe_01 (w = 0.9 m)
(b) Bot_ref_01 (w = 0.9 m)
(c) Bot_whe_03 (w = 1.0 m)
(d) Bot_ref_03 (w = 1.0 m)
(e) Bot_whe_05 (w = 1.1 m)
(f) Bot_ref_05 (w = 1.1 m)
(g) Bot_whe_07 (w = 1.2 m)
(h) Bot_ref_07 (w = 1.2 m)

Figure 4: Time-space plots of movement through a bottleneck with different widths considering participants using a wheelchair (left) and without participants with disabilities (right). Black rectangle: measurement surface in space and time (steady states). The threshold for visualisation was defined by 0.1 ms^{-1}.

the time period depends on (random distributed) start and end conditions. Since a central objective of the investigation was the analysis of the influence of heterogeneous movement properties on the stability of the values of interest, an automatic detection, as, for example, the Cumulative Sum Control Chart algorithm [31], did not lead to the consideration of the desired time periods. For this reason steady states are defined by the relative stable condition of the time development [30]. In this work, the steady state conditions were detected and manually selected by analysing the time series for movement

(a) Time development with wheelchair subpopulation (Bot_whe_01)

(b) Time development with reference population (Bot_ref_01)

Figure 5: Time series of $\overline{\rho}(t)$, $\overline{v}(t)$, and $\overline{J}(t)$ for a bottleneck with a subpopulation of wheelchair users (left) and a reference population (right) in a width of 0.9 m and calculated by method (a). The manually detected steady state is coloured in light grey. The entrance of participants in wheelchairs into the measurement surface is emphasised by the vertical lines.

speed, density, and flow (in accordance with the work by [10, 13, 30, 52, 94, 103]).

In result the shape of the measurement surface depends on space and time. In constant space-dimension we took the measurement in a rectangular area in a distance of 4 m to the bottleneck entrance (Figures 1 and 2). In variable time-dimension, the spread of the measurement surface was adapted by the steady state definition (see black rectangles in Figure 4).

The steady state for the configuration with wheelchair users takes the significant fluctuations and multiple local maxima in density and flow (caused by the inhomogeneous movement in space and time) into account. For the bottleneck configuration the density increases within 25 s from initial density up to a local maximum for bottleneck and remains steady (but fluctuating) for ≈ 40 s (Figure 5(a)). In consequence, the process of obtaining the fundamental diagram is in balances between considering the data of disabled participants (fluctuating data) and the need for stable conditions (steady states). In contrast, characteristics for the reference run without any wheelchair users (Figure 5(b)) are marked by a strong increase of density to a plateau of 2.8 m^{-2} which is only steady for ≈ 10 s.

Because of the limited number of participants, a polite and considerate behaviour, and the motivation of the participants, we only observed mean density values between 1.0 m^{-2} and 3.0 m^{-2}. As a consequence, we did not reach the congested state of the fundamental diagrams in our studies (see Figure 3). The maximum density of ≈ 3 m^{-2} without participants in wheelchairs and ≈ 3.8 m^{-2} in the bottleneck studies was observed (Figure 6). Also the maximum density for the corridor studies differs for the presence of wheelchair users: if wheelchair users attend, the maximum density $\overline{\rho}_{max}$ is ≈ 3 m^{-2}. In the reference studies without presence of wheelchair users, we observed maximum densities of $\overline{\rho}_{max} \approx 2.3\,\mathrm{m}^{-2}$. Due to the lower movement ability, flexibility, and higher requirement in (static) space, participants in wheelchairs reside more likely in lower density regions than the participants without disabilities.

It is noticeable that the observed mean movement speed is remarkably slow and—in case of the bottleneck situation—independent of the density (Figure 6). This is in contrast to the expected behaviour and to data from previous studies with homogeneous populations (e.g., [2, 37, 57]) and the classic understanding of the fundamental diagram. However, movement speed in the corridor shows a slight dependency on the density for both population settings (Figure 7). The variation in observed movement speeds is much higher in case of presence of wheelchair users.

A dependency of the (hydrodynamic) flow on density was observed for both geometries and is independent of the population configuration. In both presented studies, the capacity $J_{s,max}$ was presented where $\overline{\rho}_c$ was not fully reached. In case of the bottleneck geometry, the flow slightly increases with the density but reaches a plateau of ≈ 1.1 m^{-1}s^{-1} in case of presence of wheelchair users. A monotonically increased flow without reaching the capacity limit ($J_{s,max}$) was observed for the reference population. The flow increases monotonously with the density in the corridor studies and reaches the capacity where the flow will turn into congested state (and decrease) at $\overline{\rho} \approx 2.5\,\mathrm{m}^{-2}$ in case of the participation of wheelchair users or $\overline{\rho} \approx 2.0\,\mathrm{m}^{-2}$ otherwise. This is because of the low density region of the studies and because of an anticipation of movement speed to the slower wheelchair users (compare similar colours which represent the instantaneous movement speed of each attendee in Figure 4). Because of the latter and due to width of maximum 1.2 m overtaking of wheelchair users was not possible which has as consequence

(a) Fundamental diagram $\overline{v}(\overline{\rho})$

(b) Fundamental diagram $\overline{v}(\overline{\rho})$

(c) Fundamental diagram $J_s(\overline{\rho}) = \overline{\rho} \cdot \overline{v}$

(c) Fundamental diagram $J_s(\overline{\rho}) = \overline{\rho} \cdot \overline{v}$

Figure 6: Fundamental diagrams for bottleneck studies. The mean values are presented as scattered bins in density intervals of 0.1 m^{-2} and as mean values with standard deviation in a continuously coloured area over all runs. The point cloud coloured in grey consists of continuous data gathered from all runs. Top: fundamental diagram $\overline{v}(\overline{\rho})$ for different widths. Bottom: fundamental diagram $J_s(\overline{\rho}) = \overline{\rho} \cdot \overline{v}$ for different widths and the grey dotted nomogram lines for associated movement speeds v. Left: population consists of ≈ 10 % wheelchair users, right: population without wheelchair users.

that the movement speed of the slower ones determines the movement speed of the following people.

3.3. Individual Time Gap. The individual time gap for the passage of a line between a participant and the person moving ahead of him (preceding person) is analysed to quantify the individual distance headway. The headway of a pedestrian is used to maintain the distance of an individual to a predecessor because of additional space to adopt movement speed, avoid collisions, or take a step [104]. Therefore, time gaps are an important parameter to describe the movement of a crowd and it is the basis to quantify the specific flow (see Section 3.4).

The mean time gaps for the disabled and nondisabled subpopulations and the reference population in the bottleneck and a corridor situation of different widths are presented in Table 3. A noticeable difference between the time gaps of the disabled and the nondisabled subpopulations in both geometrical settings is remarkable. Because of the spatial boundary, wheelchair users tend to be slower and increase the distance to the predecessors over time. This leads to higher time gaps between the passage of a participant without disabilities and a wheelchair user (see the orange scatter in Figure 8(a)). Whilst the time gap for participants without disabilities depends on the width (for both geometries) and decreases with increasing width, the time gap of the participants in wheelchairs is constant. In our studies, the width was expanded in steps of 0.1 m. Assuming that a wheelchair user has a minimum width of 0.8 m, the additional cross-section has no effect for a faster movement (through the corridor).

In case of a bottleneck situation, an increased interaction and communication between participants in wheelchairs and nondisabled participants was noticed. Even if a wheelchair user reaches the entrance to the bottleneck, their neighbours anticipate individual movement speed and stop passing. They

(a) Fundamental diagram $\overline{v}(\overline{\rho})$

(b) Fundamental diagram $\overline{v}(\overline{\rho})$

(c) Fundamental diagram $J_s(\overline{\rho}) = \overline{\rho} \cdot \overline{v}$

(c) Fundamental diagram $J_s(\overline{\rho}) = \overline{\rho} \cdot \overline{v}$

Figure 7: Fundamental diagrams for corridor studies. The mean values are presented as scattered bins in density intervals of 0.1 m^{-2} and as mean values with standard deviation in a continuously coloured area over all runs. The point cloud coloured in grey consists of continuous data gathered from all runs. Top: fundamental diagram $\overline{v}(\overline{\rho})$ for different widths. Bottom: fundamental diagram $J_s(\overline{\rho}) = \overline{\rho} \cdot \overline{v}$ for different widths and the grey dotted nomogram lines for associated movement speeds v. Left: population consists of ≈ 10 % wheelchair users, right: population without wheelchair users.

interact and solve priority of movement by communication. Social norms, individual behaviour, and degrees of freedom in movement and the influence of technical assistance devices and accompanying persons may affect the passageway [105]. As a result, the time between passage of a wheelchair user and his predecessors increases.

3.4. Validity of Specific Flow Concept. One of the most important questions while assessing the performance of a facility is to quantify the capacity of a bottleneck and how the capacity increases with the width [106]. According to a common approach (method (b)) the flow here is obtained for a cumulative number of passed participants over a passage line where the time gaps were measured. The flow rate is then the derivative in time of the cumulative flow [57, p. 4] and the specific flow is the flow per unit width. The specific flow for the subpopulations wheelchair users and nondisabled participants for the bottleneck and the corridor settings is presented in Figures 9 and 10. We found high flows for studies without a disabled subpopulation which is in accordance with previous finding (e.g., [26]). As indicated by the strong difference in time gap analysis, the specific flow of the subpopulation in wheelchairs is much less than the specific flow of the nondisabled participants (Figures 9(a) and 10(a)).

It is generally assumed that the specific flow is a linear (e.g., [29, 37, 38]) or a stepping function (e.g., [28]) of the width. This behaviour was reproduced in the presented studies with the reference population but not in the case of a subpopulation using a wheelchair (compare the difference between the left and the right in Figures 9 and 10). The presence of wheelchair users has a noticeable impact: the specific flow (green dots) for the cumulative population (wheelchair users and participants without disabilities) is nearly constant in both geometries. Due to the high space requirements of wheelchair users the extended space for additional widths of

Table 3: Individual passage time gap (mean + standard deviation) in s^{-1} for disabled and non-disabled participants in heterogeneous and homogeneous crowds.

	Run	width / m	Time gap Δt_i /s^{-1}	
			disabled population	non-disabled population
Bot_whe	01	0.9	2.51 ± 0.88	0.93 ± 0.44
	02	0.9	2.83 ± 1.00	0.97 ± 0.54
Bot_whe	03	1.0	2.69 ± 1.08	0.84 ± 0.51
	04	1.0	2.38 ± 1.08	0.74± 0.40
Bot_whe	05	1.1	2.45 ± 0.88	0.74 ± 0.45
	06	1.1	2.75 ± 0.73	0.68 ± 0.36
Bot_whe	07	1.2	1.39 ± 0.80	0.77 ± 0.68
	08	1.2	2.23 ± 0.45	0.62 ± 0.36
Bot_ref	01	0.9	–	0.77 ± 0.31
	02	0.9	–	0.76 ± 0.34
Bot_ref	03	1.0	–	0.69 ± 0.34
	04	1.0	–	0.67 ± 0.39
Bot_ref	05	1.1	–	0.61 ± 0.40
	06	1.1	–	0.62 ± 0.31
Bot_ref	07	1.2	–	0.56 ± 0.40
	08	1.2	–	0.54 ± 0.37
Cor_whe	01	0.9	5.21 ± 6.87	1.07 ± 0.46
	02	0.9	3.03 ± 2.26	0.99 ± 0.49
Cor_whe	03	1.0	4.47 ± 5.24	0.91 ± 0.51
	04	1.0	3.76 ± 2.67	0.87 ± 0.40
Cor_whe	05	1.1	3.27 ± 3.24	0.79 ± 0.42
	06	1.1	3.00 ± 3.26	0.79 ± 0.41
Cor_whe	07	1.2	3.51 ± 4.21	0.77 ± 0.40
	08	1.2	3.10 ± 2.54	0.76 ± 0.47
Cor_ref	01	0.9	–	0.95 ± 0.38
	02	0.9	–	0.87 ± 0.33
Cor_ref	03	1.0	–	0.75 ± 0.31
	04	1.0	–	0.72 ± 0.31
Cor_ref	05	1.1	–	0.72 ± 0.43
	06	1.1	–	0.69 ± 0.39
Cor_ref	07	1.2	–	0.63 ± 0.36
	08	1.2	–	0.59 ± 0.29

0.1 m to 0.3 m is only usable for agile, flexible participants without disabilities. This leads to no remarkable change in flow when wheelchair users are attending.

4. Conclusions and Outlook

A series of well-controlled studies on movement through a bottleneck and a corridor was performed. We compared the influence of different populations (with and without wheelchair users) on movement characteristics. Individual trajectories of ≈ 80 participants per run were used for calculation; ≈ 10 % of the heterogeneous crowds were participants in wheelchairs. The width of both geometries has been varied to archive different densities and to investigate the possibilities of overtaking actions.

Unimpeded movement speed of all participants was measured and analysed with respect to the individual abilities. Expected unimpeded movement speeds (1.47 ± 0.17 ms^{-1}) were observed with the nondisabled reference population which is consistent with the literature [65]. Even slower unimpeded movement speeds were observed for the disabled populations, especially for the wheelchair users (0.96 ± 0.35 ms^{-1}) and the mixed population (0.71 ± 0.26 ms^{-1}).

Further on, the speed-density and flow-density relation (fundamental diagram) was studied. It was found that the basic shape of the flow-density relation is similar to previous research, but the shape of the speed-density relation is different in case of the bottleneck configuration. Because of a polite and considerate (social) behaviour, participants anticipate their movement speed to the slower wheelchair users and

(a) Individual time gaps for run Bot_whe_01 with ≈ 10 % participants using wheelchairs

(b) Individual time gaps for run Bot_ref_01 without participants using wheelchairs

Figure 8: Comparison of passage time gaps for bottleneck studies (width w = 0.9 m) considering different subpopulations.

renounced overtaking actions. This results in density regions of the fundamental diagram of 3.0 m^{-2} where the maximum flow is not reached.

It is found that the participants using wheelchairs keep larger distances to their predecessors, which is caused by the slower movement speeds in corridors and as a consequence of communication process in front of the bottleneck. Furthermore, additional space in case of larger widths has no effects on the time gaps of wheelchair users because the additional space is to leak for overtaking or passing the line simultaneously.

As a consequence, the specific flow concept is only approved for the reference study without disabled participants. Because of significantly lower specific flow for disabled subpopulations, the cumulative specific flow of heterogeneous group is constant and depend not on the width. It is worth mentioning that the number of data for the wheelchair users is limited and that usage of larger steps of additional widths (e.g., a multiple of a wheelchair width) may have an impact on the flow.

As a first step, the presented results may be used to improve the capacity calculations for different configurations of populations in design and planning process of facilities. Further research, especially on the comparison between different process in movement and different ratios of populations, is required.

Abbreviations

A: Measurement surface /m^2
Bot: Bottleneck
Cor: Corridor
e_i: Effective length of the covered distance during the sampling interval $[t_0, t_1]$ / m
J: Flow rate / s^{-1}
J_s: Specific flow / m^{-1}s^{-1}
$J_{s,max}$: Capacity of a facility / m^{-1}s^{-1}
l: Length of the bottleneck / m
MA: Measurement area
N: Numbers of participants
persID: Unique identification number of a participant
ref: Study with a reference population without any disabled participants
SiME: Safety for pedestrians with disabilities
t: Time / s
t_0, t_1: Lower and upper limit of the time interval / s
v: Movement speed / ms^{-1}
v_0: Unimpeded (free) movement speed / ms^{-1}
v_{jam}: Propagation speed of a congestion / ms^{-1}
v_v: Voronoi movement speed / ms^{-1}
$\overline{v}$: Mean movement speed / ms^{-1}
w: Width / m
whe: Study with a subpopulation using a wheelchair
x: Horizontal axis in the Cartesian coordinate system / m
y: Vertical axis in the Cartesian coordinate system / m
μ: Mean value
Δt_i: Sampling interval / s
ρ_c: Density where the flow reaches the maximum / m^{-2}
ρ_v: Voronoi density / m^{-2}
$\overline{\rho}$: Mean density / m^{-2}
ρ_0: Density, where the velocity is close to zero due to overcrowding / m^{-2}
σ: Standard deviation

(a) Specific flow for study Bot_whe with ≈ 10 % participants using wheelchairs

(b) Specific flow for study Bot_ref without participants using wheelchairs

Figure 9: Comparison of specific flows for bottleneck studies considering different subpopulations in a bottleneck. Reference data is obtained from [37].

(a) Specific flow for study Cor_whe with ≈ 10 % participants using wheelchairs

(b) Specific flow for study Cor_ref without participants using wheelchairs

Figure 10: Comparison of specific flows for studies considering different subpopulations in a corridor. Reference data is obtained from [37].

Data Availability

Trajectory data will be published with DOI at the Juelich database about data in pedestrian dynamics (http://ped.fz-juelich.de/db/) with the latest six months after publication of this research article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Paul Geoerg, Jette Schumann, Stefan Holl, and Anja Hofmann carried out the problem identification and developed the method for the selection and evaluation of relevant material for the contribution. Paul Geoerg, Jette Schumann, and Stefan Holl carried out the movement studies. Paul Geoerg and Jette Schumann carried out the analysis and drafted the manuscript. Stefan Holl and Anja Hofmann suggested modifications in the manuscript critically revising its content. All authors read and approved the final manuscript.

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Supplementary Materials

This section contains supplementary data for the fundamental diagrams $\overline{v}(\overline{\rho})$ and $J_s(\overline{\rho}) = \overline{\rho}\cdot\overline{v}$ presented in Figures 6 and 7. Here the results are presented for all runs in different widths (w = (0.9, 1.0, 1.1, 1.2) m) considering a population with 10% of wheelchair users in comparison to a population without participation of disabled pedestrians in a bottleneck (Figure S1) and a corridor (Figure S2). The runs are represented in different colours. According to the specific features in the boundaries, the results of the individual runs are similar and not influenced by the width of the bottleneck or corridor. *(Supplementary Materials)*

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Research Article

Identifying High-Risk Intersections for Walking and Bicycling Using Multiple Data Sources in the City of San Diego

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Over the last decade, demand for active transportation modes such as walking and bicycling has increased. While it is desirable to provide high levels of safety for these eco-friendly modes of travel, unfortunately, the overall percentage of pedestrian and bicycle fatalities increased from 13% to 18% of total road-related fatalities in the last decade. In San Diego County, although the total number of pedestrian and bicyclist fatalities decreased over the same period of time, a similar trend with a more drastic change is observed; the overall percentage of pedestrian and bicycle fatalities increased from 19.5% to 31.8%. This study aims to estimate pedestrian and bicyclist exposure and identify signalized intersections with highest risk for walking and bicycling within the city of San Diego, California, USA. Multiple data sources such as automated pedestrian and bicycle counters, video cameras, and crash data were utilized. Data mining techniques, a new sampling strategy, and automated video processing methods were adopted to demonstrate a holistic approach that can be applied to identify facilities with highest need of improvement. Cluster analysis coupled with stratification was employed to select a representative sample of intersections for data collection. Automated pedestrian and bicycle counting models utilized in this study reached a high accuracy, provided certain conditions exist in video data. Results from exposure modeling showed that pedestrian and bicyclist volume was characterized by transportation network, population, traffic generators, and land use variables. There were both similarities and differences between pedestrian and bicycle models, including different spatial scales of influence by mode. Additionally, the study quantified risk incorporating injury severity levels, frequency of victims, distance crossed, and exposure into a single equation. It was found that not all intersections with the highest number of pedestrian and bicyclist victims were identified as high-risk after exposure and other factors such as crash severity were taken into account.

1. Introduction

According to the fatality analysis reporting system (FARS) encyclopedia, in 2016, 818 cyclists and 5987 pedestrians were killed in traffic accidents, making up 18.2 percent of all crash fatalities. After some reduction between 2005 and 2009, pedestrian and cyclist fatalities have seen an increasing trend since 2009. The overall percentage of pedestrian and bicycle fatalities, as a percentage of total road-related fatalities, increased from 13% to 18% in the last decade [1]. In San Diego County, although the total number of pedestrian and cyclist fatalities decreased over the same period of time, a similar trend with a more drastic change is observed; the overall percentage of pedestrian and bicycle fatalities increased from 19.5% to 31.8%. Statistics also shows more Americans are walking and bicycling for commuting and recreation over that last decade [2]. Bicycle and pedestrian volume, known as exposure data, is an essential part of safety assessment. However, most existing bicycle and pedestrian networks are not equipped to routinely collect count data,

such as typical count data collection undertaken for vehicular networks (e.g., via loop detectors). Given this lack of bicycle and pedestrian data, local agencies are not able to accurately assess which facilities are in highest need of improvement. Technological advancements in transportation are creating new opportunities to investigate new sources of data to more accurately measure pedestrian and bicycle activity and risk exposure, thereby improving our safety modeling and planning.

Average annual daily pedestrian volume (AADP) and average annual daily bicyclist volume (AADB) are common metrics used in nonmotorized transportation studies. These metrics can be used as a measure of exposure in crash risk analyses. Due to limited resources and time, it is not possible to collect data for a whole year at many locations. Thus, a common practice is to collect short-term counts at several locations and apply an extrapolation method to convert short-term counts into yearly counts [3–9], which can be expressed in AADP or AADB forms. Exposure modeling can then be applied to estimate AADP or AADB for all other locations that were not originally selected. Direct-demand models have been the most popular approach for exposure estimation. Several studies have used the direct-demand model approach to develop demand models based on observed pedestrian or bicycle traffic volume and associated socioeconomic and land use variables in specific areas [10–13]. The estimated exposure can be used in risk quantification for normalization; risk is generally calculated by dividing the number of safety events by the estimated exposure derived from pedestrian and bicycle counts. Depending on how safety events (number of crashes, victims, etc.) and exposure (populations, traffic volume, AADP, etc.) are defined, different crash risk values can result for the same location. Some studies have focused on pedestrian and bicyclist crash risk modeling to investigate the factors that increase or decrease crash risk as well as selecting or developing a metric to quantify risks at specific locations [14–19].

While exposure—or the amount of pedestrian, bicyclist, or motorist activity occurring within a certain timeframe within a certain area—is highly correlated with pedestrian and bicycle crashes [20], there is a well-acknowledged dearth of data on walking and bicycling behaviors and activity levels, and researchers globally are working to address this gap [21]. This study contributed to the field by utilizing data from multiple sources, including automated pedestrian and bicycle counters, video cameras, crash databases, and other sources (e.g., GIS), to identify high-risk signalized intersections within the city of San Diego, California, USA. Data mining techniques, a modern sampling strategy, and automated video processing methods were adopted to demonstrate a holistic approach that can be applied to identify facilities with highest need of improvement. The study was conducted in four major steps: (1) Identifying the intersections for short-term video data collection. (2) Developing a vision-based intersection monitoring system to automatically detect, track, and count pedestrians and bicyclists. (3) Converting short-term counts to long-term counts collected at the selected intersections. (4) Conducting exposure modeling and risk quantification for walking and bicycling at signalized intersections. The remainder of the paper is organized as follows. Background on exposure modeling, risk quantification, and data needs are presented next, followed by a data description section. Subsequently, the methodology and results sections discuss the four major steps mentioned above. Finally, conclusions and future direction are provided.

2. Background

Exposure and roadway crash risk studies have been conducted for different levels of the geographic area. These studies can be divided into two categories [22]: (1) area-wide approaches in which wide areas such as traffic analysis zones and census tracts are considered as units of analysis [23, 24], and (2) facility-specific approaches that take roadway segments or intersections as units of analysis [25–30]. The present study focuses on identifying high-risk signalized intersections in the city of San Diego, and therefore signalized intersections are the units of analysis for this study. Out of all these intersections, a sampling strategy is required to identify a subset of intersections for collecting short-term counts that are utilized to develop an exposure model. The exposure model can then be applied to estimate the volumes at other locations that were not part of the sample. Two general groups of sampling methods for site selection include probabilistic and nonprobabilistic sampling [22, 31]. Nonprobabilistic sampling techniques are mostly based on nonrandom factors such as engineering judgment [31]. In contrast, probabilistic sampling techniques involve some random selection in the process and thus result in better generalization. Other probabilistic sampling techniques include cluster analysis, stratified sampling, and multistage random which is basically the combination of clustering and stratification [22, 31].

2.1. Short-Term and Long-Term Data Collection. Most studies and agencies have used a manual approach [14, 32] that includes having people collect count data in the field or having them extract count data by watching video data collected at the selected intersections. To facilitate manual work, advanced video processing algorithms [33–35] can be applied to automatically count pedestrians and bicyclists. Different methods and technologies for collecting vulnerable road users are extensively discussed in [36]. Three steps can be identified when conducting video data analysis: object detection, object tracking, and behavior analysis. Object detection is the process of identifying different objects in images or video frames. Once the objects are detected, they need to be tracked frame by frame to monitor the spatial and temporal characterization of the objects. Finally, behavior analysis of the object trajectories could be carried out to obtain a desired outcome, such as speed of moving objects [37, 38], object counts [35, 38–40], waiting time [35, 40], lane keeping data [41], traffic violations [37, 42], and overtaking information [43].

As it is not feasible to collect count data for a whole year at the selected sites, even automatically, a common practice is to collect data for shorter periods of time and apply an extrapolation method to convert short-term count data to yearly data. Extrapolation has been used in several studies

for estimating Annual Average Daily Pedestrian (AADP) and Annual Average Daily Bicyclist (AADB) [4, 6, 25, 44, 45]. When collecting short-term counts, several factors such as counting period length, time of day, month, and year could potentially impact the accuracy of yearly count estimation [3, 4, 6, 45–47]. In addition to collecting short-term data, long-term count data at several locations are also required to perform the extrapolation. The long-term counts could provide daily, weekly, and monthly count patterns that are used for calculating adjustment factors to perform extrapolation.

Several extrapolation methods have been used in previous studies such as traditional or standard method, Day-by-month, day-of-year, and weather model [4, 6, 9, 45, 47]. The selection of the method depends on the geographic location and weather variation of the study area as well as the availability and duration of short-term and long-term counts. For example, the variation in temperature has a great impact on the number of pedestrian and bicyclists in certain areas. Therefore, some methods were proposed to incorporate the influence of weather on AADP and AADP [7, 9]. Another consideration in the extrapolation process is to apply a suitable method for matching short-term counters to appropriate long-term counters [6, 7, 9, 30, 47–50].

2.2. Exposure Modeling and Risk Quantification. Crash risk is generally estimated by dividing the number of safety events such as crashes by a total number of people who were likely to be involved in the safety events (i.e., exposure). Hence, crash risk is the probability of crash occurrence per unit of exposure. Focusing on pedestrians and bicyclists, the exposure has been defined in different ways such as pedestrian or bicyclist volume and estimated number of streets or travel lanes crossed [51]. At a theoretical level, it has been suggested that exposure may be defined as a measure of the number of potential opportunities for a crash to occur [14]. In most studies, the number of pedestrian/bicyclist crashes has been divided by a single exposure variable in order to calculate the crash risk. However, exposure can also be defined using multiple variables simultaneously. For example, the number of pedestrians and vehicles were used in [14]; average daily pedestrians, average daily traffic, and distance crossed were used in [52]; and hundred million pedestrian/bicycle miles of roadway traveled were used in a study conducted in Washington, D.C. [51].

When investigating intersection-related crash risk, it is important to consider the roles that different transportation modalities including pedestrians, bicyclists, motorcyclists, and low-speed mobility vehicles play in traffic and the differential risks that are faced by people traveling in these modalities. In a large-scale study, crash risks were investigated by travel mode, gender, and age groups [53]. In a study in Washington, D.C., it was found that although the number of crashes involved with pedestrians was more than two times the number of bicycle-involved crashes, the crash risks were similar after taking exposure (per 100M miles traveled) into account [32]. Also, in a tendency known as the "safety in numbers" phenomenon, areas with higher bicycle traffic flow have been found to be less risky for individual bicyclists in some cases [54].

3. Data Description

The unit of analysis in the present study is signalized intersections in the city of San Diego. A total of 1522 signalized intersection was identified using an ArcGIS shapefile. Short-term video data were collected by National Data and Surveying Services (NDS) at a sample of 45 intersections (selection of 45 intersections will be discussed in the site selection section below). These intersections were equipped with cameras, and the videos were recorded for 12 hours (7:00 am to 7:00 pm) in a workday (Tuesday, Wednesday, or Thursday) in May, June, or July 2018. Short-term data collection can be conducted for different lengths from a few hours to a few weeks, and generally, more data leads to smaller extrapolation errors. In this study, data collection length of 12 hours was used for two reasons. First, data collection for longer periods was not feasible due to budget constraints. Second, according to Nordback et al.'s study, it was found that extrapolation error rates do not decrease significantly from 12 to 24 hours [6]. Subsequently, pedestrian and bicycle short-term counts were automatically obtained through machine-vision modeling. In addition to the short-term counters (of selected intersections), 43 automated counters were also utilized among all automated counters in the county of San Diego. These counters are not located at intersections, but they continuously collect pedestrian and bicyclists counts since 2012. Data have been collected for several years from these counters. However, due to the equipment being vandalized and some issues with battery counters, data from 2015 were used, which is believed to contain the most reliable data. For every intersection, demographic characteristics, socioeconomic, and built environment variables were obtained by buffer analysis in ArcGIS. In addition, crash data involving pedestrians and bicyclists were obtained from the Statewide Integrated Traffic Records System (SWITRS) through the Transportation Injury Mapping System (TIMS). Crash data per victim for each intersection was extracted from 2006 to 2016. For all data sets, missing values and outliers were identified and dealt with by comparing saturation flow rate of bicyclists and pedestrians with actual observations, manually reviewing the data, and imputing data (e.g., using interpolation).

4. Methodology

4.1. Site Selection. A sampling strategy entailing cluster analysis and stratified sampling was utilized to identify a representative subset of intersections based on several variables. Cluster analysis is a classification technique that can be used to classify observations (intersections in our case) into distinct categories with similar characteristics. The algorithms used for data clustering can be categorized into several groups, such as partitional, hierarchical, density-based, grid-based, and model-based algorithms [55, 56]. In the present study, partitional algorithms were considered as they are the most widely used approaches. To select the best number of clusters, the Silhouette metric, Elbow, and gap statistics method can be employed [57, 58].

In stratified sampling, a few variables with different levels or thresholds are typically used to create strata, and each

analysis unit can then be associated with a stratum [26]. Stratified sampling is effective in that it ensures the sample contains observations with different levels for the variables used. However, as the number of variables increases the number of strata grows rapidly, and thus selecting one intersection per stratum could make the sample too large. Therefore, stratified sampling could reduce flexibility in selecting many variables in the site selection process. Many factors could potentially impact pedestrian and bicyclist volume at intersections, which are typically used in site selection. A number of variables have been used in similar studies for selecting count locations such as population density, median income, and proximity to commercial properties [4, 26, 32, 45, 59–61].

In this study, a multistage random approach was adopted to benefit from both stratification and clustering. The data in this study contains both numerical and categorical variables and thus Gower coefficient [62] was used to calculate distances (i.e., similarities) between two observations. After determination of pairwise distance among observations, a partitional clustering algorithm, Partitioning Around Medoids (PAM) [57], was employed to identify the clusters. The most popular partitional algorithm is K-means due to its efficiency and simplicity [63, 64]. However, K-means is more sensitive to outliers compared to PAM, since K-means employs centroids as the center of clusters and PAM employs the actual observations to define clusters. In the stratification step, depending on the number of clusters used, a stratified sampling method can be applied using one or more intersection characteristics to ensure that intersections with different levels for these characteristics are included in the sample. If the number of clusters turns out to be very high or very low, then the number of variables and/or levels of variables used for stratification could be adjusted to obtain the desired sample size.

4.2. Vision-Based Pedestrian and Bicylist Monitoring. A vision-based monitoring system was used to count the number of pedestrians and bicyclists crossing the intersections from short-term video data. The system used consists of three steps: object detection, object tracking, and object counting. Object detection was performed by utilizing Faster R-CNN [33] to detect pedestrians and bicyclists in video frames. Faster R-CNN is a state-of-the-art real-time object detection method that has reached a high performance when applied to the PASCAL VOC 2007 test data. Subsequently, detection results were used to perform object tracking implemented by using Intersection-Over-Union (IOU) [65] tracker. The main idea of this tracker is to associate each detection result with the highest IOU to the last detection result in the previous frame. The tracker starts a new trajectory and ends the old trajectories if all detections are not associated with any trajectories. Finally, pedestrian and bicyclist counts were obtained from regions of interest which were defined as areas typically used by pedestrians and bicyclists to cross intersections. To obtain the counts, any trajectory that entered the regions of interest was counted as a crossing pedestrian or bicyclist.

4.3. Extrapolation. To estimate AADP and AADB from short-term counts, similar pedestrian and bicyclist volume patterns for each short-term data collection site need to be identified. These volume patterns are utilized for extrapolating long-term counts from short-term counts. Permanent counters, even at a different location from the short-term counters, are typically used to identify similar demand patterns. In this study, the matching process was performed in two steps as proposed in [30]: in the first step, the PAM clustering method was applied to classify long-term counters into different clusters based on traffic distribution indexes including AMI, WWI, and PPI for bicycle counters and AMI and WWI for pedestrian counters. In the second step, the classified long-term counters were used as the training data for developing a K-nearest neighbor (KNN) [57] model to match short-term counters to appropriate clusters.

Several variables have been calculated and utilized in the extrapolation process. These variables include population density, employment density, and land use density (commercial, residential, government, industrial, park and recreational) within a given counter buffer (0.25-mile buffer), as well as traffic distribution indices such as AMI, WWI, and PPI introduced in [7, 9]. These indices reflect bicyclist volume in morning peak hour over midday peak hour, weekend over weekday, and monthly variations, respectively.

Several extrapolation methods have been used in previous studies and a few -such as day-of-year [4], day-by-month [9], and weather model- have been shown to produce lower AADP and AADB estimation errors. The day-of-year method was not applicable in this study as it required the short-term and long-term data to be collected in the same year. However, short-term data collection was conducted in 2018 while long-term data used were collected in 2015. In addition, the weather model was not deemed to be beneficial due to San Diego's year-round mild weather. Thus, the day-by-month method was applied with minor modification as described below.

First, 12-hour counts were converted to 24-hour counts using (1). Equation (2) shows how day-by-month factor was calculated for every day d of the week and month m. Subsequently, AADP and AADB counts were estimated by applying day-by-month adjustment factors to the 24-hour counts using (3). The long-term counter data in the following equations refer to a counter that has been matched with the short-term counter of interest. However, it should be noted that if two or more permanent counters are matched to a short-term counter, the mean of adjustment factors across all matched counters was used.

$$P^s_{dm} = \sum_{h=7}^{18} P^s_{hdm} \times \frac{\sum_{h=1}^{24} P^l_{hdm}}{\sum_{h=7}^{18} P^l_{hdm}} \tag{1}$$

$$PF_{dm} = \frac{AADP^l}{ADP^l_{dm}} \tag{2}$$

$$AADP^s = P^s_{dm} \times PF_{dm} \tag{3}$$

where

P^s_{dm} (*or* B^s_{dm} *for bicyclists*): pedestrian (bicyclists) count on day d of a week, in month m estimated for short-term counter s;

P^s_{hdm} (*or* B^s_{hdm} *for bicyclists*): pedestrian (bicyclist) count in hour h of day d of a week, in month m from short-term counter s;

P^l_{hdm} (*or* B^l_{hdm} *for bicyclists*): pedestrian (bicyclist) count in hour h of day d of a week, in month m from matched long-term counters;

PF_{dm} (*or* BF_{dm} *for bicyclists*): pedestrian (bicyclists) day-by-month factor for day d of a week, in month m;

$AADP^l$ (*or* $AADB^l$ *for bicyclists*): average annual daily pedestrian (bicyclist) count obtained from matched long-term counters;

ADP^l_{dm} (*or* ADB^l_{dm} *for bicyclists*): average daily pedestrian (bicyclist) volume on day d, in month m from matched long-term counters;

$AADP^s$ (*or* $AADB^s$ *for bicyclists*): average annual daily pedestrian (bicyclist) count estimated for short-term counter s.

4.4. Exposure Modeling and Risk Quantification. A wide variety of approaches and methods have been used in predicting nonmotorized activity using direct-demand models. Given the nature of the dependent variable, which is discrete in nature, and the variance was greater than the mean, the negative binomial model was selected as the exposure model of this study. As discussed earlier, several variables were considered in the analysis. Univariate and bivariate correlation analyses were first conducted to explore variables' distribution or pattern and to investigate the relationship between the dependent and independent variables. Several variable forms and functions were examined to get the best data fit.

After several model trials with different combinations of the key variables, the best models were evaluated based on the predictive accuracy of the models in terms of mean absolute error (MAE) and root mean squared error (RMSE). Cross-validation technique was employed for performance evaluation. Cross-validation is a resampling technique that helps identify a parameter value, ensuring a proper balance between bias and variance [66]. For cross-validation, a subset of the data, known as the training set, is used to train the model, and the remaining data points serve as a test set or validation set. While fitting a model on a training set, it is desirable to have minimum MSE, which minimizes the difference between the prediction and the actual observation. This research used a 10-fold cross-validation method to evaluate and compare the performance of the developed models. This method split the feature vector sets into ten approximately equally sized distinct partitions. While one set was used for testing, the other sets were used for training. Then, the procedure was repeated ten times, and all accuracy rates over these ten runs were averaged to improve the estimate. The performance evaluation criterion was the average accuracy. The final models were identified based on statistical, predictive, and intuitive considerations as well as insights from the literature.

Utilizing the estimated pedestrian and bicycle activity (i.e., exposure), risks associated with walking and bicycling at signalized intersections can be calculated. A general equation to quantify risk is shown in (4).

$$Risk = \frac{Number\ of\ safety\ events}{Exposure} \tag{4}$$

Several studies have used the number of crashes in the risk equation as the number of safety events. As a result, two different locations with the same number of crashes and exposure would lead to the same level of risk, while different number of victims might be involved at one location from the other. Taking number of victims into consideration (instead of number of crashes), a crash with multiple victims should be associated with a higher risk comparing to a crash with only one victim. In addition, crashes with higher levels of severity should be attributed to higher risks. Also, the number of fatalities (instead of crashes) could be used to provide an estimate of the relative lethality of intersections. Therefore, a combination of fatalities and injuries was utilized to provide a more holistic estimate of the risk. Crash severity was incorporated in risk quantification by utilizing crash costs associated with severity levels. Other factors, AADP (AADB) as the exposure and distance crossed, were also included in the risk equation as presented in (5). In addition to the crash cost, the equation numerator includes a term, N^k, to produce more weight (i.e., importance) on the locations with higher frequency of victims. Since crashes are rare events, it is important to magnify the number of occasions that led to fatalities and injuries. The tuning parameter, k, can also be used to provide the extent of the weight. For example, if zero is selected for this parameter, N^k becomes one, which means zero weight is given to the victim frequency. As k increases, it provides more weight on the victim frequency and consequently higher risks are resulted.

Crash cost has been used for different purposes, such as analyzing the effectiveness of a specific roadway enhancement and measuring the effect of seatbelt, and it has been estimated based on injury severity in several studies [67–71]. In the very beginning, Miller estimated motor-vehicle crash comprehensive costs by injury severity and body region [67]. Another study estimated crash costs of medium and heavy trucks by seven injury severity levels [68]. Miller et al. broke down pedestrian and pedalcyclist crash costs by age, injury severity, and body region in the United States [69]. Federal Highway Administration (FHWA 2005) also presented an estimation of crash cost based on maximum police-reported injury severity.

In crash cost studies, maximum abbreviated injury severity (MAIS) is defined as the maximum threat of a crash to a victim's life [72]. Crash cost generally results from a combination of different cost categories, including medical, emergency service, lost productivity, the monetized value of the pain and suffering, and lost quality of life costs. Collectively, these costs have been called comprehensive costs. Monetary or economic cost value of a crash can be obtained by subtracting lost quality of life from the comprehensive cost

Figure 1: Identifying the best number of clusters: Silhouette method on the left and Elbow method on the right.

[67]. In this study, lifetime costs were used which includes medical, work loss, and quality of life costs [69].

$$Quantified\ Risk = \frac{C \times N^k}{AADP\,(AADB) \times D}$$
$$C = \sum_s N_s \times C_s \tag{5}$$

where

C: total crash cost weighted by severity;

N_s: number of pedestrians or bicycle victims with injury severity level s;

C_s: cost per victim with injury severity level s;

s: severity level = {fatal, severe injury, other visible injury, and complaint of pain};

N: total number of victims;

k: exponent of N, a tuning parameter to magnify the frequency of victims;

$AADP(AADB)$: average annual daily pedestrian (bicyclist) count;

D: distance a pedestrian or bicyclist crossed.

5. Results and Discussion

5.1. Site Selection. Any variable that is expected to affect pedestrian and bicycle activity at intersections could potentially be included in the site selection process. A total of 18 variables were examined and after several trials with different subsets of variables and excluding variables with high correlation with other variables, a subset of 12 variables were selected to perform site selection as follows: population density, land use (parks and recreational; residential), presence of college, presence of school, transit stops density, mean traffic volume, pedestrian victims, bicyclist victims, proximity to Balboa Park, proximity to beaches, sidewalk density, and bikeway density.

Using all selected variables, signalized intersections were grouped into clusters by applying PAM clustering method. The Silhouette metric and Elbow method were applied to identify the best number of clusters. The highest Silhouette value -that shows the highest clustering performance- was obtained when using 5 clusters, as shown in Figure 1. Based on the Elbow plot in this figure, as the number of clusters increases, the total sum of squares decreases. However, no clear elbow point is visible, and thus the best number of clusters was selected to be five based on the Silhouette method only. The geographic distribution of these 5 clusters is shown in Figure 2.

Within each cluster, stratified sampling was performed using two variables, namely the number of pedestrian victims and the number of bicyclist victims. The purpose was to ensure that the sample includes intersections with a high, moderate, and low number of victims. The number of pedestrian victims, ranging from 0 to 13, was divided into three levels (low: 0, 1, 2; moderate: 3, 4, 5; high: >=6). Similarly, the number of bicyclist victims was divided into three levels (low: 0, 1; moderate: 2, 3, 4; high: >=5). Consequently, nine strata for each cluster (3∗3=9) resulted. Subsequently, a sample of 45 intersections was identified as shown in Figure 2 by selecting one intersection per stratum (5∗9=45). It should be pointed out that most adjacent intersections are assigned to the same cluster unless their characteristics are very different from their adjacent intersections. In addition, the selected sample was carefully reviewed to ensure adjacent intersections are not in the sample. This was considered to avoid variable correlation of intersections sharing the same area of influence.

5.2. Vision-Based Pedestrian and Bicylist Monitoring. Utilizing video data, machine-vision models were trained to detect and track pedestrians and bicyclists. Several pedestrians and bicyclists were labeled to perform the training task. The vision-based monitoring system was tested in several scenarios and system performance was assessed using real-world video data from stationary cameras at several signalized intersections. Figure 3 shows an example in which two pedestrians and a bicyclist were successfully detected, tracked, and counted as they crossed the intersection within the region of interest (transparent blue region). The average pedestrian and bicycle counting accuracies were 85% and 81%, respectively. Several factors impacted the model performance, including the number of pedestrians and

Figure 2: Site selection results by cluster analysis and stratification: triangular shapes are the 45 selected intersections.

bicyclists labeled, intersection shape and size, lighting condition, occluded objects, and video quality. The best counting accuracy of 95% was achieved for both pedestrians and bicyclists in scenarios in which many objects were labeled, good lighting condition was present, video quality was decent, and pedestrians/bicyclists were not crossing in groups.

As expected, more labeled pedestrians and bicyclists led to better model performance as the models were provided with more information in terms of positioning, angles, and lighting conditions. For example, the detection accuracy increased by 68% when the number of labeled pedestrians increased from 15 to 32. Model transferability was examined by using data from one intersection to train models and testing these models on other intersections. The benefit was that the manual work of labeling was reduced, but the models performed poorly since different intersections have different shapes and sizes. Focusing on one intersection for both training and testing, the way people cross the intersection (as individual vs. in groups), lighting conditions due to time day significantly affected model generalizability. For instance, the models had difficulty detecting and tracking pedestrians and bicyclists crossing the intersection in groups since some of them were occluded by others in multiple video frames. In addition, the quality of the video and object distances to the camera impacted the results. Cameras used in this study were set at a corner of each intersection. Detecting objects crossing the two farther intersection approaches from the camera was challenging, especially in large intersections where pedestrians and bicyclists were too small to distinguish.

5.3. Extrapolation. Pedestrian and bicycle volume patterns at permanent counters were identified by PAM clustering method. Figures 4 and 5 illustrate clusters of pedestrian counters classified into three clusters (Recreational, Mixed, and Utilitarian) based on AMI and WWI. As shown in Figures 6 and 7, bicycle counters were grouped into four clusters (Utilitarian, Recreational, Mixed Recreational, and Mixed Utilitarian) based on AMI, WWI, and PPI calculated for every counter. Pattern classification into three and four clusters have been used in past studies [46, 49, 73] and the only reason three clusters were used (instead of four) for pedestrian counters was the limited number of counters which would have led to having only one counter in a cluster, which is not recommended [6, 50].

Utilitarian counters have two distinct peak hours in mornings and evenings on weekdays. They also have a relatively uniform distribution throughout the week as shown by daily pattern. Recreational counters have higher weekend peaks than weekday peaks as expected. The daily patterns also show the highest volume on Saturdays and Sundays compared to the other days of the week. Mixed, mixed recreational, or mixed utilitarian counters represent different combination variations of utilitarian and recreational demand. These classifications for bicycle and pedestrian counters were consistent with the literature as discussed in [49]. Finally, each short-term counter was matched to one of the specified clusters, and the mean of the adjustment factors across all counters within that cluster was used to extrapolate the short-term counts (12-hour counts) to yearly counts (AADP or AADB).

5.4. Exposure Modeling and Risk Quantification. After the estimation of AADP and AADB for the sample intersections, exposure modeling was applied to calculate AADP and AADB for the remainder of intersections as discussed below. Tables 1 and 2 show the results of the negative binomial regression models of pedestrian and bicycle annual average daily volume, respectively. The tables present the explanatory variables and their estimates. The variables such as transit stop density for which buffer analysis was conducted were tested in exposure models with three different areas of influence (0.1 miles, 0.25 miles, and 0.5 miles). The number following each variable represents the buffer area of influence.

As shown in Table 1, the pedestrian model has seven variables, and all of them were statistically significant at the 90 percent confidence level. As shown in Table 2, the bicycle model also has seven variables, and all variables except one (transit stop density at 0.1 miles) were statistically significant at the 95 percent confidence level. The R-squared values for the pedestrian and bicycle models were 0.7 and 0.67, respectively, which assert that the models have decent goodness of fit. The MAE and RMSE of the models also

Figure 3: Pedestrians (right) and a bicyclist (left) detected while crossing an intersection within the region of interest.

Table 1: Negative binomial regression model for pedestrians.

Variable	Estimates	t-stat	Sig.
(Intercept)	4.865	23.24	0.000
Transit stop density (0.5 miles)	8.782	3.81	0.000
Percentage of regular transit rider, pedestrian, or bicyclist population (0.25 miles)	3.717	1.95	0.051
Employment density (0.25 miles)	0.051	2.41	0.016
Maximum speed limit within the intersection less than 40 mph	1.135	5.37	0.000
Percentage of vacant housing units (0.5 miles)	−3.517	−2.99	0.003
Total commercial or mixed-use land area (0.1 mile)	0.190	5.01	0.000
If the area contains a higher crime count than the average crime counts among the buffers (0.25 miles)	−0.292	−1.65	0.098
N		45	
R-squared		0.70	
RMSE		1633.24	
MAE		1147.41	

Figure 4: Clusters identified for long-term pedestrian counters (each circle in the plot represents a long-term pedestrian counter).

indicated that the models provide a good estimate of the annual average pedestrian and bicycle volume at locations without counts.

The model results revealed important insights. The pedestrian volume was characterized by transportation network (transit stop density and speed limit), population (employment density, and regular transit rider, pedestrian, or bicyclist population), and land use (vacant housing units, commercial or mixed-use land area, and high-crime area). The best model was obtained with variables of different spatial scales. This finding is consistent with previous studies [26, 74, 75] that suggested it is unlikely to have all the variables significant at the same buffer scale. The direct-demand model for bicycle traffic included variables that represent characteristics of the transportation network (density of bicycle facility, maximum posted speed within an intersection, and transit stops density), population (total regular bicyclist population), traffic generator (presence of a school and proximity to the beach), and land use (total commercial or mixed-use area).

Interestingly, some variables, such as commercial or mixed-use land area and transit stop density, influence both pedestrian and bicycle traffic for the study area, but the spatial scale of influence varies. The commercial or mixed-use land area influences pedestrian and bicycle volume within 0.1 miles and 0.25 miles, respectively. This indicates that the commercial and mixed-use land area attracts bicyclist traffic for a larger catchment area than pedestrian traffic does. Previous studies have also indicated that commercial areas attract pedestrian [12, 75] and bicycle [11, 12, 28] activity. However, the study by Tabeshian and Kattan (2014), conducted in Canada, found a significant impact of commercial areas on pedestrian and bicycle traffic within 0.25 miles and 0.1 miles, respectively, which is contrary to this study's findings [12]. Two separate studies in Alameda

Figure 5: Clustering result of long-term pedestrian counters classified into three groups (Recreational, Mixed, and Utilitarian).

Table 2: Negative binomial regression model for bicyclists.

Variable	Estimates	t-stat	Sig.
(Intercept)	4.265	12.56	0.000
Regular bicyclist population (0.25 miles)	0.015	3.90	0.000
Transit stop density (0.1 miles)	0.852	1.55	0.121
Maximum speed limit within the intersection less than 40 mph	0.457	2.90	0.004
Distance between the intersection and beachfront access point less than or equal to 10 miles	0.379	2.33	0.020
Presence of a school (0.5 miles)	−0.483	−2.40	0.016
Bike facility density (0.5 miles)	1.371	2.00	0.045
Total commercial or mixed-use land area (0.25 miles)	0.021	2.18	0.030
N		45	
R-squared		0.67	
RMSE		105.93	
MAE		87.68	

Figure 6: Clusters identified for long-term bicycle counters.

County, California, have also found a significant influence on commercial areas on pedestrians within 0.25 miles [26] and bicyclists within 0.1 miles [28]. The comparison suggests that not only the explanatory variables but also their influence areas for nonmotorized traffic activity vary with location and community.

Similarly, transit stop density influences pedestrians within 0.5 miles, which is larger than the bicycle buffer of 0.1 miles. The results indicate that pedestrians are likely to travel more to ride a transit facility than bicyclists are. Previous studies have also observed a significant association of transit facilities with pedestrians within 0.5 miles [76] and bicyclists within 0.5 miles [11]. Given that mass transit facilities are bicycle-friendly in San Diego [77], transit riders probably make up a large proportion of pedestrians and bicyclists in the city.

Pedestrian and bicycle volumes decrease when the maximum intersection speed limit exceeds 40 mph. The finding confirms that pedestrians and bicyclists are more likely to avoid high-speed intersections and find an alternative route. Fagnant, D. J., and K. Kockelman [10] also observed a similar relationship for bicycle traffic in the Seattle, Washington, area. The finding is not surprising given the rise of traffic fatalities. A report [78] indicated that around 1,000 pedestrians and bicyclists are hit and seriously injured annually in San Diego, and in 2012, pedestrian collisions increased 20 percent compared to previous years. In 2017, there were 12 deaths and 71 serious injuries involving pedestrians and bicyclist [79]. The high crash risk could discourage pedestrians and bicyclists from using high-speed intersections.

The pedestrian model had a strong positive association between the pedestrian volume and the percentage of regular transit rider, pedestrian, or bicyclist population within 0.25 miles. As expected, the population inclined to use active modes and public transportation was more likely to contribute to the walking volume within their neighborhood. The pedestrian volume also increased with increasing employment density within 0.25 miles. Previous studies also observed similar influence in San Francisco [13] and San Diego, California [59]. The results suggest that with more people working in a neighborhood, intersections are more likely to observe higher pedestrian volume. Similarly, the negative association between pedestrian volume and total vacant housing units indicates that pedestrians are less likely to generate from neighborhoods with many vacant properties. The negative influence of crime on pedestrian volume, but not on bicyclists was also observed, which shows that people are more likely to avoid high-crime locations and conforms with previous research [80, 81].

As expected, the bicycle model indicated higher bicycle volume in areas with a larger population of regular bicyclists. The model also indicated that the intersections near beach access points (less than 10 miles) were more likely to observe high bicycle traffic. The density of bike facilities also had a positive influence on daily bicycle volume. The finding can be attributed to the recent surge of dockless bicycles in the city [82] as well as the 16 miles of separated bike paths around San Diego Bay, completed in February 2018 [83]. The Bay Shore bikeway was built with a vision to provide a scenic and convenient way for bicyclists to travel in the San Diego area. The dockless bike sharing facilities were first launched in February 2018 and added the convenience of using bicycles. The combined influence may contribute to a higher bicycle volume in locations near beach areas and with better bicycle facilities. Surprisingly, the model revealed a negative association between the presence of a school and bicyclist volume, which contradicts previous studies conducted in Canada [11, 84]. However, a study conducted in the United States suggested that the number of students (ages 5 to 18) who walk or bike to school decreased sharply in recent years due to increased traffic collisions, lack of sidewalks, and urban sprawl [85]. Perhaps the increasing collision rate in the city discouraged children from bicycling to schools, and adult bicyclists tend to avoid locations near schools.

After estimating pedestrian and bicycle volumes (i.e., AADP and AADB) as the exposure measure, the risk was quantified by applying the proposed quantified risk equation presented in (5). In this equation, number of victims and crash severity levels were obtained from the SWITRS data, distance pedestrians or bicyclists crossed at the intersection was calculated by multiplying the average number of lanes (across all approaches) by the lane width (12 ft was assumed), cost per victim was obtained based on the victim's age and injury severity as estimated by Miller et al. [69]. After experimenting several values for the tuning parameter k, a value of three was chosen for the final model. Models with smaller values of k, identified some intersections as high-risk (i.e., top 50) with only one or two victims in the past ten years. While other factors such as a small AADP (AADB) and/or a

Figure 7: Clustering result of long-term bicycle counters classified into four groups (Utilitarian, Recreational, Mixed Recreational, and Mixed Utilitarian).

high crash cost could lead to high-risk values, it may not be practical to recognize an intersection with only one victim in the past ten years as a high-risk intersection even if the AADP is small. High values of k led to extreme values of risk especially when the number of victims was high, and thus the value of three was selected as it provided a reasonable outcome. The risk for all signalized intersections was calculated to identify high-risk intersections for walking and bicycling as mapped in Figure 8. Previously, 15 intersections, known as "fatal 15", were identified as the deadliest intersections for pedestrians in the city of San Diego [86]. As expected, it was found that these intersections had more number of victims than other intersections. However, when exposure and other factors were taken into account using the quantified risk equation, not all intersections with the highest number of pedestrian and bicyclist victims were identified as high-risk. For example, out of 39 intersections with the highest number of pedestrian victims (Victims >= 8), only 22 were made it to the top 39 high-risk intersections based on the quantified risk. Similarly, out of 36 intersections with the highest number of bicyclist victims (Victims >= 5), 26 remained in the top 36 high-risk intersections.

Figure 8: High-risk intersections for walking (left side) and bicycling (right side).

6. Conclusion

While it is accepted that pedestrian and bicyclist volume is positively correlated with the number of pedestrian and bicyclist crashes, there is a renowned lack of pedestrian and bicycle data that can negatively impact accurate risk quantification and safety evaluations. This study leveraged a combination of available data sources including automated pedestrian and bicycle counters, video cameras, crash databases, and other sources (e.g., GIS), to identify high-risk intersections for walking and bicycling. Cluster analysis and stratification were applied to identify a representative sample of locations to collect short-term video data that were used to develop a vision-based monitoring system for automatic detection, tracking, and counting of pedestrians and bicyclists. When sufficient number of pedestrians and bicyclists were annotated, pedestrians and bicyclists were not too far from the camera, they did not cross the intersection in groups, and good lighting condition was present, a high counting accuracy of 95% was obtained. Utilizing permanent counters, an extrapolation method along with a novel matching method was employed to estimate yearly counts that were used for estimating exposure by direct-demand models. Exposure analysis identified transportation network, population, traffic generator, and land use variables as statistically significant in estimating pedestrian and bicyclist volume. Accounting exposure as a normalization factor and other factors such as frequency of victims and crash severity in quantifying risk had a significant impact on the selection of high-risk intersections; not all intersections with the highest number of pedestrian and bicyclist victims were identified as high-risk. The variables were found to be influential at multiple buffer area and showed differences across pedestrian and bicycle activity. The results underscored the importance of location and community in characterizing nonmotorized demand and targeted improvements to encourage nonmotorized activities.

The modeling framework and data sources used in this study are beneficial to conduct future analyses for other facility types such as roadway segments and also at more aggregate levels such as traffic analysis zones. The approach is also beneficial to public agencies, which can help identify high-risk facilities and prioritize them for countermeasure implementation. Since crashes are rare events, the identification

of high-risk facilities would take a long time, and thus a potential future direction is to proactively assess safety by discovering near-crash situations in video analysis. This enables researchers and practitioners to quantify risk and evaluate safety in a much shorter period of time. Another future research topic is to investigate advanced spatial modeling methodologies with direct-demand models to better understand the impact of intersections sharing the same area of influence (e.g., adjacent intersections).

Data Availability

Except the video data that may include personally identifiable information, other data may be made available. However, at this point, since the project has not been finalized yet, it is not possible to make them available within any supplementary files or any other forms. The data may be released after finalizing the project and obtaining any required permissions from the project sponsor if any.

Disclosure

The contents of this paper reflect the views of the authors, who are responsible for the facts and the accuracy of the information presented herein. This document is disseminated in the interest of information exchange.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Identifying the Indoor Space Characteristics of an Urban Railway Station Based on Pedestrian Trajectory Data

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Stations are being converted into various living spaces that can be used for public transportation, work, commerce, and leisure. To satisfy the various requirements and expectations for functional extension, it is necessary to investigate and understand the phenomena caused by users. A methodology to cluster the characteristics of pedestrian space of a railway station through the pedestrian trajectory data collected from an actual operating station is proposed in this paper. Then the spatial usability of the movement and stay of pedestrians were defined through the results of the clustering. The procedure to cluster the indoor space characteristics of an urban railway station in this study consists of four steps: data collection, feature vector extraction, K-means clustering, and cluster characteristics analysis. A case study was conducted for the Samseong station. The results of the proposed spatial clustering analysis showed that there are several types of spaces depending on the space occupancy characteristics of pedestrians. The proposed methodology could be applied to indoor space diagnosis from the perspective of station monitoring and management. In addition, the station operator could respond flexibly to unexpected events by monitoring the indoor spaces according to whether the flow is normal or suggestive of an emergency.

1. Introduction

The urban railway station consists of various spaces: a platform, passage, concourse, complementary, and urban spaces [1]. Rather than being spaces used solely for the public transportation, these spaces are transformed into complex living spaces with various functionalities, including spaces of work, commerce, and leisure. The multi-business district centered on the railway station has a positive effect, leading to an improvement in the urban traffic environment in conjunction with transit-oriented development, unlike large-scale traffic inducing facilities such as marts and department stores. To support the various requirements and expectations of this expansion, it is necessary to investigate and understand various types of spatial utilization patterns generated by users.

Traditionally, evaluations of station facilities have been conducted through levels of service. The Transportation Research Board [2] proposed a method for evaluating the service of space and facilities through measures such as density, speed, and space. The space was divided into concourse, platform, stairs, and passage, with evaluation criteria presented for each facility. However, this evaluation method is limited in that it does not reflect the many phenomena of increasingly various spaces. In addition, the existing approach for designing stations has focused on efficiency for reducing the cost and scale of buildings without considerations of pedestrian flow. Accordingly, a novel strategy based on scientific analysis techniques is required to ensure the service quality provided to pedestrians. You et al. [3] proposed the pedestrian movement-based assessment toolkit for simulation (PATS), utilizing a comprehensive analytic framework that incorporates Big Data platforms such as individual travel records and demographic statistics corresponding to building information. By defining the space with increasingly diverse characteristics, this paper proposes a systematic space management and operation method.

This study classifies the characteristics of indoor spaces using the pedestrian travel information collected by advanced sensor technology. A method is presented for clustering the pedestrian space of railway stations using the pedestrian trajectory data collected from an actual operating station. Additionally, the method defines the spatial usability of

movement and static tendencies through the results of the clustering. The spatial clustering procedure comprises four steps. First, a field experiment was conducted in the present study to collect actual pedestrian trajectory data using 2D-LiDAR sensors. Second, the cell-based feature vectors related to the utilization efficiency, mobility, and comfortability were extracted from the pedestrian trajectories. These feature vectors were used to input variables for clustering the spatial characteristics. Third, a K-means clustering algorithm was used for spatial clustering. The K-means clustering method derives optimized spatial classification results using three feature vectors. Finally, analyses of the case study on the Samseong station were conducted. The characteristics of patterns were identified by clusters associated with the feature vectors to demonstrate whether the spatial pattern differentiated by the feature vectors.

The remainder of this paper is organized as follows. In Section 2, the proposed procedure for spatial clustering is explained while Section 3 introduces the pedestrian trajectory collection systems and presents an overview of data collection. Section 4 presents the analysis results along with a discussion. Finally, Section 5 presents the conclusion with a summary of this study and future research directions based on the identification of limitations involved in this study.

2. Literature Review

A literature review was conducted to identify valuable research opportunities that would differentiate this study from existing studies. This literature review is focused on existing studies in two major fields that are closely associated with the objective of this study. The first looks at the approaches used to obtain pedestrian trajectories and the applications of this. The second investigates pedestrian movements in indoor spaces to model pedestrian behavior.

Recently, advanced sensor and communication technologies have been widely applied to collect the data not only of vehicles but also of pedestrians. Significant efforts have been made to detect and to track pedestrians [4–6]. These studies proposed the algorithm for detecting and tracking the vehicles and pedestrians using advanced methodologies such as LiDAR and VISION sensors. In addition, several studies were performed to assess the congestion of the indoor spaces using pedestrian characteristics data collected from various sensors, video, and Bluetooth [7–10]. In this study, the pedestrian trajectory collection system based on the LiDAR sensor was used to collect pedestrian trajectory data. Rather than proposing a pedestrian trajectory detection and tracking method, this study suggests a method to utilize the collected pedestrian trajectories. The pedestrian detection technologies developed in the previous studies can be combined with the methodology developed in this study to inform the service evaluation and operation plan.

A few existing studies have developed an extended model of pedestrian behavior based on cellular automata and demonstrated the model through simulation analysis [11–13]. Ji et al. [14] presented the cell-based model for aggressive pedestrians weaving their way through a crowd in a corridor. Relevant lines of literature proposed methodologies surrounding the concept that existing pedestrian models could better reflect real-world pedestrian behavior. Ma et al. [15] demonstrated that the movement of pedestrian counter flow is caused by the interaction of K-nearest-neighbor. It also conducted a validation analysis by comparing the lane formation pattern and the fundamental diagram with real pedestrian counter flow. The results indicate that the proposed modeling method therein provides a more efficient and accurate traffic condition. These studies can be applied to the pedestrian simulation model for evaluating facilities and services in regard to pedestrian movement in the subway stations. The purpose of this study is not to simulate the pedestrian behavior model, but to present the characteristics of the space by aggregating the movement of the pedestrian. Thus, a systematic framework for future space management and operation can be suggested.

Many efforts have been conducted for collecting pedestrian data and investigating the pedestrian behavior model. Although several related studies involved pedestrians, we are unaware of any study that incorporates pedestrian movement characteristics into a spatial pattern analysis in a subway station. With this perspective, this study proposes a method to monitor the station, juxtaposing this with pedestrian detection and tracking technologies of existing studies. The systematic framework for classifying the spatial patterns using pedestrian trajectory data is proposed in this study.

3. Methodology

3.1. Overall Procedure of Spatial Clustering Analysis. In the past, the railway station has been defined as a waiting space for pedestrians to use public transportation. More recently, stations have rapidly changed into spaces where pedestrians engage in mobile, sedentary, and commerce-driven behaviors. Because the space impacts the nature of the users' activity occurring within it, there is a need for systematic analysis of the diversified space.

In this study, spatial clustering was conducted to establish the basis for ensuring the safety and efficiency of railway stations. This was done through the classification of space characteristics for the indoor station. Feature vectors for spatial clustering were extracted using pedestrian trajectory data collected through the pedestrian trajectory collection system (PTCS), and the indoor space was classified using the K-means clustering method. To identify the spatial characteristics, a sequential procedure for clustering the indoor space has been developed, as shown in Figure 1. These steps were applied in a case study at Samseong station.

(i) Step 1: For the study area, the pedestrian trajectory data was collected and used for clustering the spatial characteristics. Samseong station in Seoul, Korea, was selected for the study area, as it is connected to the large complex shopping center, COEX mall. This study used the commercialized pedestrian trajectory collection system based on LiDAR sensors. The pedestrian trajectory data includes the two-axis coordinates, speed, acceleration, and the direction angle of an individual pedestrian. The pedestrian trajectory data comprise calculated values by the

Figure 1: Overall framework of this study outlining the procedure's four sequential steps: (1) pedestrian trajectory data collection, (2) feature vector extraction, (3) spatial clustering, and (4) spatial characteristics analysis.

internal algorithm. The algorithm is provided by the commercialized system based on the raw data collected from the LiDAR sensors.

(ii) Step 2: The cell-based feature vectors were extracted for spatial clustering. The feature vector is an aggregated value by 1 m × 1 m cells from the individual pedestrian trajectory data. Features related to utilization efficiency, mobility, and comfortability of pedestrians were considered. These three feature vectors, utilization efficiency, mobility, and comfortability, were represented as the number of trajectory points, average speed, and standard deviation of direction angle, respectively.

(iii) Step 3: The spatial clustering using a K-means clustering method was conducted. Because the K-means clustering method is an unsupervised learning method, it is necessary to determine the optimal number of clusters. In this step, the silhouette method was used to derive the optimal number of clusters. Then, the cluster results were assigned to minimize the objective function, which is the Euclidean distance based on the predefined number of clusters.

(iv) Step 4: Finally, the cluster results were applied to Samseong station, including the analysis of the characteristics according to clusters and time of day. Based on the clustering results, space characteristics were defined to include moving space, waiting space, and crowded space. Further discussion of Step 4 includes explanations of methods used in spatial characteristics identification.

3.2. Pedestrian Trajectory Collection System (PTCS). Recently, advanced sensor and communication technologies have been widely applied to provide various services for transportation users and operators. In this study, the PTCS, based on a 2D-LiDAR sensor, was used to collect individual pedestrian trajectory data in a public facility.

Table 1: Collected data list and descriptions for pedestrian trajectory data.

No.	Output data	Description
1	Trajectory ID	Randomly assigned ID by each object. If same object continues to be detected, the same ID will be maintained.
2	Time	The duration in which the information of the trajectory ID is recorded in a 0.2 second cycle.
3	Two-axis coordinate	Position at the time of the trajectory ID (x and y coordinates)
4	Speed	Speed at the time of the trajectory ID (m/s)
5	Acceleration	Acceleration at the time of the trajectory ID (m/s^2)
6	Direction angle	Direction(vector) at the trajectory ID viewpoint (degrees)

The LiDAR (Light Detection And Ranging) sensor, which was recently used as a core component of autonomous vehicles, is easy to install and expand, with a fast data acquisition process. Consisting of a transmitter and a receiver, a LiDAR sensor detects the distance, direction, and speed from the object by calculating the duration of the returning short light pulse laser. The sensor has an excellent range and spatial resolution in weather conditions of various lighting and temperatures. The LiDAR sensor has the advantage to precisely track objects and process data quickly, enabling it to smoothly track a pedestrian's movement, even in a complex room such as a subway station. More technical details of the LiDAR sensor can be found in the referenced literature [16].

In this study, commercially developed PTCS based on the LiDAR sensor was used for data collection. The PTCS affords customized communication, with the maximum sensing range of a LiDAR sensor approximately 15 m and 270°, with a 5-Hz band. Continuous pedestrian trajectories can be collected by overlapping the detection areas between LiDAR sensors. Collected and recorded every 0.2 s on a server computer connected to the sensors, the pedestrian trajectory data include the two-axis coordinates, walking speed, and the direction angle. Based on tracking results, the PTCS also provides visualization solutions, such as real-time pedestrian tracking systems and a heat-map. Further information regarding the PTCS can be found in the referenced literature [17].

4. Analysis and Results

4.1. Data Collection. Samseong station in Seoul, Korea, which has a development plan to establish additional six-railway lines, was selected for the study area. According to the development of Samseong station, the space will be changed into the complex space where pedestrians will use it for various purposes. The high-density waiting room connected to the ticket gate in Samseong station was selected as the data collection space. Five LiDAR sensors were used to collect the pedestrian trajectory data, with the sensing range in the red area shown in Figure 2.

The field experiment for collecting the pedestrian trajectories was conducted from 7 AM to 10 PM on July 12, 2017, in Samseong station. The individual pedestrian trajectory data is collected in 0.2 second increments via the PTCS and includes two-axis coordinate, speed, acceleration, and direction angle. Table 1 presents a description of the trajectory information collected by PTCS.

Samseong station is a commercial and business-oriented district, so the pedestrian flow patterns vary according to the time of day, as presented in Figure 3. At the morning peak hours (dotted box ①), there is significant pedestrian flow from the ticket gate to concourse; on the other hand, the opposite pattern appears in the afternoon peak hours (dotted box ③). In addition, the inflow and outflow patterns are similar during nonpeak hours (dotted box ②). In total, 11,007 pedestrian trajectories were collected and used to establish a dataset for indoor spatial clustering. The dataset comprises 5,729; 747; and 4,531 pedestrians in the morning peak hours, nonpeak hours, and afternoon peak hours, respectively [18].

4.2. Extract the Feature Vector. Currently, performance measures for evaluating the level of service provided to pedestrians include pedestrian space, flow rate, density, and travel time [2, 19]. Additionally, significant effort has been made in many countries to develop a novel method for evaluating pedestrian environments [20–23]. In this study, feature vectors were extracted based on the index for evaluating pedestrian environments related to utilization efficiency, mobility, and comfortability. To identify the characteristics of indoor space for an urban railway station, this study used three feature vectors derived from the individual pedestrian trajectory data collected by PTCS: sum of the trajectory point, the average speed, and the standard deviation of the direction angle. The study area was divided into 1 m × 1 m cells, to reflect spatial characteristics, as shown in Figure 4. The definition of the feature vectors is as follows.

(i) Sum of the trajectory points (STP, number of points/m^2): The STP represents the utilization efficiency for the space. That is, it indicates how many pedestrians used the space in a given time interval. The value can be calculated by aggregating the number of trajectory points existing in 1 m^2 to the given time interval, which is defined as 1-hour in this study.

(ii) Average speed (AS, m/s): The AS represents the variable indicating the mobility of pedestrians in the station. This feature vector is used to evaluate the mobility of the cell. Each pedestrian trajectory point has a speed value. Speed is the measured value from the PTCS based on the coordinates between two consecutive cells. The cell-based aggregation AS value

Figure 2: Data collection area. The area represents the first basement of the Samseong station. The five overlaid photos show the installation of the LiDAR sensors.

Figure 3: Pedestrian counts from ticket gate to concourse by time of day on July 12, 2017, in Samseong station. The dotted boxes designate the morning peak hours (1), nonpeak hours (2), and afternoon peak hours (3).

Figure 4: Example of pedestrian trajectories and overlay of cells from 8 AM to 9 AM.

Figure 5: Concept and equation of the direction angle. The range of the SDD, or comfortability value, is from −180° to +180° depending on quadrant location.

of the speed collected from the PTCS is used as the feature vector for mobility.

(iii) Standard deviation of direction angle (SDD, degrees^2): The SDD is used as the surrogate measure reflecting how comfortable the pedestrians can move in the corresponding cell. When the presence of pedestrians moving in various directions in the same cell is large, many conflicts occur between pedestrians in the corresponding cell. The direction angle is the numerical value for the movement direction of the pedestrian. It is calculated using the vector values of the coordinate of time "T-1" and "T," with reference points. The value ranges from −180° to +180°. The direction angle concept is illustrated in Figure 5.

4.3. Spatial Clustering Results. The K-means clustering algorithm used in this study is a simple method to partition n observations into K clusters in which each observation belongs to the cluster with the nearest mean. The objective function serves to minimize the variance of distance between each cluster. The steps for clustering the given data are described below. A more detailed theoretical background can be found in the referenced literatures [24, 25].

(i) Step 1: Select the number of clusters, K, and then randomly assign K points to be centered on the cluster.

(ii) Step 2: Calculate the distances between individual data and the centers of K, and assign the individual data to the closest cluster to which the corresponding data belongs.

(iii) Step 3: Set the average data value belonging to the cluster as the center of the new cluster.

(iv) Step 4: Repeat steps 2-3 until the objective function converges to the predefined threshold.

(a) Silhouette value by cluster number

(b) Silhouette value for optimal cluster (K=6)

(c) Distribution of similarity value

(d) K-means clustering (K=6)

Figure 6: Results of the optimal cluster number and K-means clustering. (a) and (b) indicate optimal number of clusters using the silhouette method. (c) and (d) represent the clustering result with the optimal clustering number K=6. Each point represents the feature vectors for a spatial 1 m × 1 m cell in 1 h.

The cell-based STP, AS, and SDD were used as input variables of the K-means clustering algorithm. Because K-means clustering is an unsupervised learning method, it is necessary to decide the optimal number of clusters. In this study, the optimal number of clusters is determined by the silhouette method.

The silhouette method interprets and validates consistency within clusters of data. The technique provides a concise graphical representation of how well an object lies within the cluster [26]. The silhouette value is a measure of cohesion and separation within its own cluster compared with other clusters, as shown in

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \cdots \quad (1)$$

Here, i is each object, s(i) is the silhouette value, a(i) is the average distance between i and all other data within the same cluster, and b(i) is the lowest average distance from i to all points in any other cluster, of which i is not a member.

The silhouette value ranges from -1 to +1, where a high value indicates that the data are appropriately clustered. As presented in Figures 6(a) and 6(b), the optimal number of clusters was 6. Figures 6(c) and 6(d) show the distribution of three input variables clustered to six groups, with the minimum distance between the center point and each object.

4.4. Characteristic Analysis by Clusters for Samseong Station. To identify that the results of the cluster indicate the characteristics of indoor space, a characteristic analysis of the feature vectors was conducted for each of the six clusters. The STP was defined as the utilization efficiency for space, AS was represented by the mobility of pedestrians, and the SDD was used as a surrogate measure for comfortability of the space. Table 2 represents the descriptions of feature vectors for each cluster.

Table 2: Descriptions of feature vector by clusters and the meaning of the range of feature vector values.

Cluster	Sum of the trajectory point (# of point/m^2, 1-hour)	Average speed (m/s)	Std. direction angle (degree^2)
1	117	1.31	24
2	377	1.20	87
3	381	1.08	142
4	1488	1.20	53
5	2379	1.00	146
6	3283	1.13	51
Feature vector	High value	⟷	Low value
Sum of the trajectory point	High frequency to use		Low frequency to use
Average speed	Good mobility		Poor mobility
Std. direction angle	More conflicts (or less comfortability)		Less conflicts (or more comfortability)

Table 3: Definition of the indoor space at Samseong station based on clustering results.

Cluster	Definition	Example of space
1	Low level of utilization, but secured the freedom of passage	Close to pillars and walls
2	Low level of utilization, and medium level of mobility and comfortability	Waiting room of station
3	Low level of mobility and comfortability	Corridor, near the ticket gate
4	Middle level of utilization, high level of mobility	Moving space
5	High level of utilization, low level of mobility and comfortability	Bottleneck caused by train arrival
6	High level of utilization and mobility	Moving space (high pedestrian flow)

The spaces of Samseong station were characterized into six groups, as illustrated in Figure 7. *Cluster 1* has the smallest STP, which indicates a lesser space utilization frequency, with less conflicts, and a higher AS related to mobility. *Cluster 1* could be defined as the space through which pedestrians move with more varying speeds because the SDD is higher compared to that in other clusters. According to the results of spatial matching, *cluster 1* appears to be a region close to pillars and walls. It has a low utilization rate and few conflicts; thus, it can be identified as a space suitable to high-speed movement. *Clusters 2 and 3* have a similar STP value; however, the AS of *cluster 2* is higher and the SDD lower, characterizing *cluster 2* as a space where pedestrians can move stably. In *cluster 3*, the SDD was high, thus confirming the heightened conflict involved in walking. For *clusters 4-6*, the occupancy rate of pedestrians was high. This coincided with the main purpose of these spaces, which was to pass by the station in morning-peak and afternoon-peak hours. In particular, *cluster 5* had more conflicts than *clusters 4 and 6*, which could be explained by the bottleneck caused by passengers getting off the train at peak hours in the morning. The definition of space based on the description of feature vectors is presented in Table 3.

Additionally, the results showed that the characteristics of the Samseong station had different patterns depending on the time of the day. Figure 8 presents the number of cells depending on clusters and the time of day. *Cluster 1*, located near the pillar or wall, showed that the characteristics of the space did not change regardless of time. The space connected to both sides of the ticket gate is mainly used as a movement space for pedestrians, with the type of movement changing according to the morning-peak and afternoon-peak hours. In the corridor and the vicinity of the ticket gate of *cluster 3*, conflicts occur constantly. This mandates additional services such as moving line separation and real-time control of the gateway in order to secure pedestrians comfortability.

5. Discussion and Conclusion

With the expansion of complex business centers in urban railway stations, a comprehensive and systematic analytical framework is required to inform the complicated procedures of design and operational planning. For this purpose, it is necessary to manage the space according to differentiated spatial characteristics through analysis of movement patterns of pedestrians. This study proposed a spatial clustering methodology based on the complex walking patterns of railway pedestrians.

This study used the pedestrian trajectory data to classify the spatial characteristics of the station by patterns of pedestrian usage of space. The pedestrian trajectory data were collected from the PTCS based on 2D LiDAR sensors. Cell-based surrogate measures, including the sum of the trajectory point, the average speed, and the standard deviation of the direction angle, were used to represent utilization efficiency, mobility, and comfortability, respectively. These were then derived as feature vectors. The K-means clustering algorithm was used to classify the characteristics of the indoor space; by using the silhouette method, the optimal cluster number was determined to be six. A case study was

Figure 7: Spatial clustering results of Samseong station. The pedestrian volume was 6,965 in morning peak hours, 3,186 in nonpeak hours, and 8,343 in afternoon peak hours (unit: ped/h).

	8:00-9:00	14:00-15:00	18:00-19:00
Cluster 1	37	33	41
Cluster 2	108	199	130
Cluster 3	70	66	55
Cluster 4	53	19	70
Cluster 5	29	0	0
Cluster 6	36	0	44

Figure 8: Clustering results for the number of cells by various times of day.

conducted in the Samseong station, and the results showed that the characteristics of the Samseong station had different patterns depending on the time of day. Additionally, it was demonstrated that there are various space types according to the space occupation characteristics of pedestrians. In particular, this emphasized the importance of spatial analysis as a reflection of pedestrian travel behavior.

In the related studies, the service level of a station was evaluated using measures such as density, flow rate, space, etc. In this evaluation method, the investigator directly investigated the number of pedestrians at various times. Advanced sensor technologies were used to collect more accurate pedestrian data. Through this, a systematic process was suggested to analyze the usage status and the diagnosis of indoor space characterizations. Although useful insights were derived from this study, further research must be conducted to achieve more reliable and widely applicable results. First, to analyze the diversity of indoor space, various clustering techniques and feature vectors are needed. Furthermore, it is possible to optimize an indoor space through repetitive learning methods such as deep neural networks. Additionally, spatial analysis using various cell sizes is necessary to investigate the effects of cell sizes on the results. Second, an integrated evaluation study that incorporates methodologies such as space syntax should be conducted, as such methodology is already being used for building design and assessment. Finally, system extensions and a real-time monitoring framework should be developed to improve practical usability of the proposed methodology. To do this, the methodology proposed in this study should be applied to various stations and the resulting characteristics compared and analyzed. Thus, a novel evaluation criterion for spatial analysis of indoor spaces could be established and utilized in the management and operation of the station.

Through spatial diagnosis of pedestrians' movement patterns, the proposed methodology can be applied to space management and monitoring. In particular, its application can be expanded to include real time situations involving changes in pedestrian flow caused by the arrival and departure of trains. Furthermore, it can support flexible responses for unexpected events by proactively monitoring the occupation pattern of an indoor space according to the type of flow, whether normal or emergent. Stations' interest in using such advanced technology is increasing. Thus, the proposed methodology could be extended to other applications: it could be applied not only as a space management technique, but also as an underlying technology for providing various services to users and operators.

Data Availability

The pedestrian trajectory data used to support the findings of this study were supplied by LG Hitachi under license and so cannot be made freely available.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

Exploring the Effect of Boarding and Alighting Ratio on Passengers' Behaviour at Metro Stations by Laboratory Experiments

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The objective of this work was to study the effect of the ratio between passengers boarding and alighting on the passengers' behaviour at metro stations. A mock-up of a vehicle and the relevant portion of the platform was built to run a series of simulation experiments at University College London's Pedestrian Accessibility and Movement Environment Laboratory (PAMELA). Different scenarios were tested based on the next generation London Underground trains. The scenarios were classified according to different load conditions. Four types of behaviour are described. In most cases boarding is first, and passengers compete for space to enter the train. In the case of alighting, first passengers are faster than the rest of alighters due to the space available on the platform as boarding passengers give way to those who are getting off the train. In addition, alighters form lanes of flow depending on the number of passengers waiting to board the train on the platform. With respect to the train, if the density inside the train is higher than 4 passengers per square metre, then the flow at the doors starts to decrease. More experiments are needed to study the relationship between platform density and boarding and alighting time.

1. Introduction

The platform train interface (PTI) is a very complex space where most interactions occur between passengers boarding and alighting [1]. The way (e.g., movement) that passengers go from the platform to the train (boarding) or from the train to the platform (alighting) is a very important issue that affects the efficiency and safety of metro systems. In the case of London Underground (LU) [2], the total network provides around 4.69 million trips per day with a high peak of demand between 8 and 9 a.m., requiring one train every 2 or 3 minutes at metro stations such as Green Park (77,242 trips/weekday) on the Jubilee Line.

One of the main problems at the PTI is that passengers stay too long in the process of boarding and alighting. When the number of passengers boarding and alighting increases, crowding situations can be reached at stations. Crowding influences the dwell time, which is the time each vehicle remains stopped at the station when transferring passengers [3]. The dynamic part is defined as the boarding and alighting time (BAT), whilst the static part includes the time of opening and closing of doors. The dwell time depends on the number of passengers boarding and alighting and their speed. The speed of passengers depends on different design variables such as height and distance between the train and the platform, the number and width of doors, and the layout inside the train. In addition, the speed of passengers is influenced by operation variables such as the density of passengers on the platform and inside the train, the behaviour of passengers (e.g., interactions), etc. Therefore, the dwell time affects the capacity of stations, delays and queues of trains, which in turn impacts on the frequency and regularity of the services, and therefore on the delays of passengers.

To reduce crowding, manuals and recommendations are needed. In the case of the United Kingdom, the London Underground (LU) [4] proposes different recommendations which can be modelled and then compared to design thresholds. One of the most common indicators to represent the degree of congestion is the Level of Service or LOS [5], which represent walkways, stairs, and queues from a Level A (free flow) to a Level F (over the capacity). However, the LOS is based on average values in existing stations (e.g., number of passengers divided by the total platform area), and therefore it is difficult to identify which factors affect the passengers' behaviour and which part of the circulation space is more congested when the train design or station layout is changed.

To solve this problem a line of research has been developed based on laboratory experiments and observations. Some experiences have been started at University College London's Pedestrian Accessibility and Movement Environment Laboratory (PAMELA) and continue in other laboratories worldwide. Laboratories such as PAMELA are considered as an ideal opportunity to study different layout and load conditions such as the effect of different demand levels on the behaviour of passengers boarding and alighting, which is exactly the main objective of this research.

The main question of this research is how the boarding and alighting ratio (R) affects the passengers' behaviour at the PTI. At stations with low demand level (i.e., noncrowded situations), train doors are opened for a fixed period of time; however when crowding increases train doors need to be opened for a longer period, and therefore the BAT increases. The hypothesis is that the behaviour would be the same under the same value of R no matter what the number of passengers boarding and alighting is.

The specific objectives are to (a) review the literature related to the variables that affect the passengers' behaviour and their effect on BAT, (b) simulate the boarding and alighting process at PAMELA for different values of R, and (c) identify the type of behaviour according to each value of R at the PTI.

This paper is composed of five sections. The next section describes existing studies that measured the passengers' behaviour and their effect on the BAT, followed by a section that explains the methods of this work. The fourth section presents the laboratory results. Finally, the discussion and further work are presented.

2. Literature Review

According to RSSB [6], four types of factors can affect the behaviour of pedestrians in public transport environments: presence of other people (e.g., density on the platform or personal space), physical design of the train carriage (e.g., width of the platform, number of train doors, or position of the seats), information provided to pedestrians (e.g., maps, on-board displays, and on-train announcements), and environment (e.g., weather). In the case of railway and metro systems, the presence of other people is considered the most important factor that influences the passengers' behaviour. When passengers are walking with a density of more than 2 passengers per square metre, or more than 5 pass/m^2 in a waiting area (e.g., queuing) [4], then a crowded situation is reached.

However, according to Cox et al. [7] there is a difference between density (physical characteristics of the environment) and crowding (psychological phenomenon) because a high-density situation is not always perceived as crowded with a high level of stress. The authors [7] proposed a model with a high level of density and perception of crowding and stress level and also identified the relationship between crowding and risk safety. Similarly, Evans and Wener [8] studied high density and stress while commuting in trains where passengers have to sit next to others. The authors found that when the density increased, passengers perceived a high stress level. For Still [9], crowding is also related to the perception of risk and safety. The author states that the use of typical manuals and standards is not an ideal method to measure the risk and safety of passengers as they are "cut and paste" solutions from other realities. Therefore, the space of passengers is related to situations in terms of physical measurements, i.e., as a function of density and capacity on the platform and train, but also as a psychological dimension which is more about the perception of crowding.

To capture crowding in railway and metro systems Lam et al. [10] proposed a binary logit model to represent discomfort of passengers. The authors used interviews as a physical measurement based on the LOS of Fruin [5] and degree of crowding on the platform and inside the train. Similarly, to study the effect on the level of stress and feeling of exhaustion, Mahudin et al. [11] proposed a model to measure crowds based on psychological aspects of crowds (dense, disorderly, confining, chaotic, disturbing, cluttered, and unpleasant), evaluation of the environment where the crowd is situated (stuffy, smelly, noisy, and hot), and how crowds react in specific situations (squashed, tense, uncomfortable, distracted, frustrated, restricted, hindered, stressful, and irritable). Recently, Kim et al. [12] identified that people avoid delays caused by crowding and the stress caused by crowding, such as lack of availability of seats, and avoid other passengers or worry about sexual harassment. To measure delays, the authors used the dwell time (e.g., delay inside train and transferring), to measure stress they used the passenger load, and to collect the path choice of passengers they used "smart card" data. However, according to Preston et al. [13], in short commuter journeys crowding is based on stress and physical discomfort, while in long distance services the space to relax and use the journey productively is much more important for passengers. Other authors [14] have studied the concentration of passengers boarding at railway platforms, in which bigger clusters are not necessarily related to a higher density due to crowding at the station (e.g., passengers move along the platform to avoid contact with other passengers). Passengers tend to wait for the train near the entrance of the platform, especially closer to staircases and ramps [15]. Moreover, Oliveira et al. [16] found that the distribution of passengers on the platform is related to crowding, in which an evenly distribution of boarding can reduce the dwell time. The authors studied the behaviour in rail stations using video footage.

Crowding is also related to the dynamic part of the dwell time, i.e., the boarding and alighting time (BAT). In the case of linear models, the Transit Capacity and Quality of Service Manual [3] states that the t_d is influenced by the time needed to open and close the doors, the number of passengers boarding and alighting, and the average time each passenger takes to board and alight. In the case of nonlinear models, Lin and Wilson [17] studied the dwell time in light trains of one-car and two-car vehicles as a function of the number of boarding, alighting, and on-board passengers. Similarly, Fernadez et al. [18] calibrated the dwell time for the case of Transantiago in Chile, in which the average boarding time was 40% higher than the alighting time in the metro system. In the case of LU some authors [19, 20] have used the well-known LU Train Service Model to describe the BAT as part of the station stop time (SS). The SS depends on the number of passengers boarding and alighting, number of doors per car, peak door/average door factor, number of seats per car, number of through passengers, and door width factor. Recently, Tang et al. [21] modelled the behaviour of passengers at the PTI of high speed railway stations. The authors reported that the efficiency of the boarding process is influenced by the passengers' inflow rate and the entrance choice behaviour.

Different field studies have been done by Li et al. [22] to support the different models in order to study the BAT. In relation to the width of doors, Wiggenraad [23] found that wider doors decreased the BAT by 10%. The author studied five door widths in existing Dutch trains: 800 mm, 900 mm, 1100 mm, 1300 mm, and 1900 mm. In addition, Heinz [24] reported that the BAT can be increased when the number of vertical steps is increased. The author studied 18 different entrance designs at Swedish trains with level access, 2 steps, and 3 steps. The same author [24] found that a horizontal gap of 150 mm or more increased the BAT. Harris et al. [25] studied that the relationship between door width and capacity is not linear. The authors analysed a range of door widths, from 0.80 m to 1.80 m, in which the flow rate at doors is influenced by the available space on the platform and inside the train. Recently, Barron et al. [26] compared 33 metro systems worldwide to study the effect of platform doors (e.g., platform edge doors). The authors found that these elements had a negative impact on the dwell time, reaching an extra time between 4 and 15 s at the station.

However, field studies are limited to the type of vehicles and stations existing at the time of study. Therefore, it could be difficult to change the layout of the station or buy new vehicles to calibrate the dwell time and identify their effect on the passengers' behaviour. In addition, it is impossible to control all the factors that influence the boarding and alighting for each observation which are classified according to RSSB [6].

To solve this, a line of researches based on laboratory experiments and observation have been started at PAMELA and continued in other laboratories worldwide. These experiments have been very useful to single out the influence of a particular variable because only a certain variable could be changed while keeping the other variables the same. One of the first laboratory studies was reported by Fernandez et al. [27], in which a simulated experiment represented the boarding and alighting process. In the experiment two door widths (0.80 m and 1.60 m) were tested. The authors found that wider doors (1.60 m) reduced the alighting time by 40%. That study was followed at the Universidad de los Andes's Human Dynamic Laboratory (HDL) [28], in which the BAT was influenced by the vertical handrails, waiting areas on the platform, and the use of one-way doors. Recently, de Ana Rodriguez et al. [29] reported that the use of platform edge doors has no relevant impact on the BAT; however passengers change their behaviour by queuing at the side of the doors rather than waiting in front of the doors. Following this study Seriani et al. [30, 31] studied the interaction and passenger space at PAMELA, in which passengers reached a high interaction near the doors and it decreased as the distance from the doors increased because of the availability of space to board or alight.

In relation to the height between the train and the platform, laboratory experiments at PAMELA have shown that the use of steps can be considered an obstacle for passengers boarding and alighting. In this case Holloway et al. [32] simulated 60 passengers boarding and alighting with one single door and three different steps: 20 mm (zero step), 350 mm (2 steps), and 510 mm (3 steps). The authors [32] found that boarding passengers spent more time (4.13s on average) than those who were alighting (3.68s on average), in which 40% of them felt it difficult to use steps. Similarly, Daamen et al. [33] performed different experiments at Delft University, in which small vertical gaps increased the capacity of doors. At HDL Fernandez et al. [34] presented the relationship between door width and discharge rate. The authors [34] found that for a door width of 1.65 m the best vertical may be 150 mm. In such a case, the alighting rate is 1.6 pass/s. Nonetheless, [34] only considered passenger alighting, and Fujiyama et al. [35] stated that for a bidirectional flow (boarding and alighting) the station and vehicle should be designed with a vertical gap of 50 mm, reaching a maximum flow of 1.42 passengers per second. Moreover, Karekla and Tyler [36] proposed a model to predict the dwell time based on laboratory experiments, in which a small vertical gap can reduce the dwell time by 8%. When accessibility is not achieved over the complete platform, Tyler et al. [37] proposed to build platform humps, in which only a part of the platform is raised to be level with the train. The authors tested different slopes and cross-fall gradients at PAMELA, in which the trains should not stop in front of the ramp.

In addition, laboratory experiments can be used to calibrate pedestrian models. For example, Rudloff et al. [38] presented a social force model to predict the BAT in which parameters were calibrated using experiments. The authors found that the BAT decreased as the door width increased, reaching a minimum overall value of 24.93 s for a door 1.85-cm wide. To represent similar situations, Kretz et al. [39] studied 10 different widths of bottlenecks (in a range of 40 cm to 160 cm), in which a 90 cm width allowed to pass two or more pedestrians. Hoogendoorn and Daamen [40] found that the capacity of a bottleneck did not increase linearly with a gradual increase in the width of the doors but increased in stepwise fashion. When pedestrians are formed into lanes of flow, the capacity will be increased only if a new lane is

Figure 1: Drawing, dimensions (mm), and areas calculations (m^2) for the simulated experiments at PAMELA.

formed. The authors defined the "zipper effect" when two lanes of pedestrians overlapped, reaching a distance between pedestrians of about 45 cm, which is less than the body breadth (50 or 60 cm). This is caused because pedestrians need more space to move forward than to move laterally. Similar to [39], Seyfried et al. [41] simulated experiments using unidirectional flow in a corridor with a bottleneck cantered. The authors reported that density in front of the bottleneck has a major impact on the flow and around 70 cm width the zipper effect is formed. More recent studies [42] reported that a linear dependency is between the flow and the bottleneck width up to 5 m. In addition, the same authors [42] identified that the density inside the bottleneck keeps the same as the width of the bottleneck increased, but the density in front of bottleneck decreased. Moreover, Adrian et al. [43] studied five bottlenecks widths: 1.2 m, 2.3 m, 3.4 m, 4.5 m, and 5.6 m. The authors used the Voronoi density using the location of the head of each participant, in which the corridor width and the motivation of participants are important factors to determine if pedestrians start queuing or pushing.

In spite of different research being done, more detailed research is needed to identify the effect of the boarding and alighting ratio on the passengers' behaviour, and therefore on the BAT. The observations made from the results of the experiments presented in this paper would fill gaps and reconfirm important points in relation to existing studies.

3. Method

3.1. Geometrical Layout and Variables. The method used in this research was based on real-scale laboratory experiments at PAMELA. The main variables used in these methods were selected according to the classification proposed by [1]. The authors used three types of variables: physical (i.e., vertical and horizontal gap, width of doors, and width and length of platforms), spatial (i.e., number of seats and setback), and operational (i.e., density of passengers, BAT, and time for each passenger to board and alight).

In relation to physical and spatial variables, the laboratory (or the experimental setting) consisted of a simulated experiment of a carriage and the relevant portion of the platform in front of the doors (see Figures 1 and 2). The carriage was configured with a set of parameters representative of a next generation LU train: 2 double 1.60 m wide doors, 12 fixed seats (4 in the centre and 4 at each end), 8 tip-up seats (2 on each side of the fixed central seating), a setback of 200 mm between the door and the end seats, and a setback of 300 mm between the door and the centre seats. The horizontal gap between the train and the platform was 90 mm and the vertical gap was 170 mm.

With respect to operational variables, different loading conditions were tested at PAMELA (see Table 1), because demand is considered the main driver of passenger behaviour. The experiments were completed in four days in November 2014. The first two conditions (LC 0 and LC 1)

PTI

Figure 2: Different views of the simulated experiments at PAMELA.

Table 1: Load condition descriptions at PAMELA.

Load Condition code	Boarding per door	Alighting per door	On-board	R = Boarding/Alighting Ratio	Number of runs per scenario
LC 0	55	0	0	-	2
LC 1	0	55	0	-	2
LC 2	40	10	10	4	20
LC 3	10	40	10	0.25	20
LC 4	20	20	30	1	20
LC 5	20	5	60	4	20
LC 6	5	20	60	0.25	20
LC 7	10	10	70	1	20
LC 8	55 +crush	0	0	-	10

Note: All passengers on-board remain inside the train in each run.

were used to make participants feel familiarized with the experiments, while the last condition (LC 8) was performed to calculate the capacity of the carriage. The load conditions LC 2, LC 3, and LC 4 were classified as crowded situations at the PTI, while the noncrowded situations at the PTI are grouped in LC 5, LC 6, and LC 7. The values of boarding to alighting ratios R = 4, R = 1, and R = 0.25 were chosen in consultation with London Underground based on previous laboratory experiments at PAMELA and current demand levels at existing stations such as Green Park station in Jubilee Line. Using the definition in LUL [4] a crowded situation could reach a density of more than 5 passengers per square metre at the PTI, while the noncrowded situation presented less than 2 passengers per square metre at the PTI. In Table 1 the number of passengers boarding and alighting is considered for each double door, and on-board passengers remain inside the train while the boarding and alighting take place.

The experiments were recorded and then analysed with semiautomatic video analytics software. The cameras at PAMELA were located in the ceiling (4 m height), which enabled the recording of a space on the platform of only 3 m width by 5 m length in front of each train door (which produced an observed area on the platform $A_p = 15\,\mathrm{m}^2$). The software Observer X11 [44] was used with a bespoke coding template. Two types of codes were used (to establish the time and to register an event) and 6 types of events were processed (train arrival, first passenger entering PTI, door opening, boarding or alighting, last passenger exiting PTI, and door closing), in which the period of analysis was between the times of the doors being opened and closed. The PTI was defined in consultation with Transport for London (TfL) as the space between the yellow line on the platform edge and the train doors.

The average boarding time per passenger j was defined at PAMELA following Equation (1). In Equation (1), the total boarding time for passenger j is obtained as the difference in time between the passenger boarding j (t_{bj}) and the first passenger boarding (t_{b1}). Therefore, the number of passengers boarding is obtained from the opening to the closing of the doors minus the first passenger boarding. The same calculation is obtained for the average alighting time per passenger i (see Equation (2)). In Equation (2), t_{ai} is the time registered when the passenger i alights and t_{a1} is the time registered when the first passenger alights.

$$\overline{t_{bj}} = \frac{\left(t_{bj} - t_{b1}\right)}{j-1} \tag{1}$$

$$\overline{t_{ai}} = \frac{\left(t_{ai} - t_{a1}\right)}{i-1} \tag{2}$$

In Equation (1), $i = 2, \ldots n$, in which n is the total number of passengers boarding. Similarly, in the case of Equation (2) $j = 2, \ldots m$, in which m is defined as the total number of passengers alighting. The values of n and m varied depending

on the load condition defined in Table 1. For example, in the case of R = 4 (LC 2) the value n is equal to 40 passengers and m is equal to 10 passengers. The total average boarding time per passenger ($\overline{t_{bn}}$) can be obtained when $j = n$. The same calculation can be obtained for the total average alighting time per passenger ($\overline{t_{am}}$) when $i = m$.

In addition, the behaviour was observed according to RSSB [6]. In this study we only considered the factor related to people, i.e., the effect of the ratio between passengers boarding and alighting. Three variables were defined to study the behaviour. Firstly, the sequence of movement was analysed, i.e., when alighting and boarding started and its relationship with t_{bj} and t_{ai}. Secondly, the formation of lanes of flow was identified each time a passenger alighted. If two passengers alight simultaneously, then two lanes of flow are reached. A single lane of flow was defined as one passenger alighting throughout the train doors. The last variable measured was the density inside the train each time a passenger boards and its relationship with the flow at the train doors. The density (k) was defined as the ratio between the total number of passengers inside the train (p_v) and the total floor area (A_f). The variable p_v is the sum of the number of passengers on-board (which remained constant in each run), the number of passengers waiting to alight, and the number of passengers who already board the train. From Figure 1, $A_f = 17.46\,\mathrm{m}^2$; i.e., the floor area for each door is equal to $A_f/2 = 8.73\,\mathrm{m}^2$. The flow of passengers boarding j (q_{bj}) is obtained as the inverse of the average boarding time per passenger j (i.e., $q_{bj}=1/\overline{t_{bj}}$).

To compare the mean between $\overline{t_{bn}}$ and $\overline{t_{am}}$ for each value of R, a Student's t-Test was performed in which the data were normally distributed with independent observations. The null hypothesis (Ho) indicates that the 2 samples have the same mean. An $\alpha = 0.05$ (significance level) or 95% of confidence level was chosen for the statistical test. In addition, an ANOVA test single factor (significance level of 5%) was done to compare if there were significant differences in $\overline{t_{bn}}$ and $\overline{t_{am}}$ over the different values of R. The null hypothesis was defined as the samples having the same mean.

3.2. Participants. The 110 participants recruited at PAMELA represented the boarding (red hats) and alighting (white hats) at the PTI. Each participant had a number and they formed 11 groups with different colour bibs. Participants were asked to complete a form to register for the experiments, which included the following details: name, email, gender, age, height, weight, and if he/she is a regular commuter or has any mobility impairments.

From the total of passengers at the experiments (110 passengers), 46% (50 passengers) were men and 54% (60 passengers) were women. Most of them (78%) were regular users of the London Underground (LU). With respect to their age, most of them were under 45 years old (15% under 24 years old, 26% between 25 and 34 years old, 19% between 35 and 44 years old, 27% between 45 and 59 years old, 7% between 60 and 64 years old, and 7% more than 65 years old). The total passenger load tested in the scenarios LC 0 and LC 1 (defined in Table 1) was 8221 kg (including seated passengers). The average height of passengers was 170 cm with a deviation standard of 8 cm.

Participants at the experiment were instructed to walk "naturally" as if they were boarding and alighting a train in the LU. All boarding passengers were instructed to enter the platform area and wait to board the train. After all passengers entered the platform area then the process of boarding and alighting began. Due to restrictions of space at PAMELA we did not consider passengers arriving at a specific distribution rate before or after the train arrived. To make sure that this behaviour was represented over time, random groups were chosen to board, alight, or remain inside the carriage. In addition, a complete sound system was provided in order to make the experiment feel real for the participants. The sound included the train arriving, braking, door opening alarm, door closing alarm, and departure.

The complete procedure (74 seconds approximately) was based on LU metro stations and started with an announcement: "Participants with colour xx: when the door opens, please alight the train. Participants with colour yy: when the door opens, please board the train." After this announcement, the sound effect starts (0 seconds), in which the sound of the train approaching is heard from the speakers (20 seconds). When the sound stops, then the door alert starts, and door starts opening (21 seconds). After 2 seconds the doors are full open. Next, another announcement is made (25 seconds): "let the costumer off the train first." Consequently, the last announcement is made (58 seconds): "please move right down inside the carriage and make use of all the available space." Ten seconds later door alter starts. Finally, door starts closing (72 seconds), and doors are fully closed (74 seconds).

The use of laboratory experiments could help to separate the effect of external factors that influence the movement of passengers such as social interactions, activities, and safety constraints. In addition, the laboratory environment is an ideal space to change one variable and keep the rest fixed. Therefore, PAMELA represents an ideal opportunity for researchers to test "what if" scenarios. However, this does not mean that the behaviour of passengers during the experiments is the same as the behaviour of passengers at existing stations. Thus, the experiments help to identify relative differences between scenarios, which would then be tested afterwards in existing stations. In previous experiments, Ana Rodriguez et al. [29] simulated the boarding and alighting when platform edge doors were installed at PAMELA and then compared to two existing stations in the LU. The authors [29] found that similar profiles of boarding and alighting were obtained between the experiments and the stations.

4. Experiments at PAMELA

4.1. Average Boarding and Alighting Time. Figure 3 shows the results of the experiments in the case of crowded situations at the PTI (load conditions LC 2, LC 3, and LC 4 in Table 1). The figure presents the total average boarding time per passenger ($\overline{t_{bn}}$) and the total average alighting time per passenger ($\overline{t_{am}}$) for different values of R. The $\overline{t_{bn}}$ and $\overline{t_{am}}$

Figure 3: Total average boarding time per passenger ($\overline{t_{bn}}$) and total average alighting time per passenger ($\overline{t_{am}}$) in crowded situations at the PTI.

Figure 4: Total average boarding time per passenger ($\overline{t_{bn}}$) and total average alighting time per passenger ($\overline{t_{am}}$) in noncrowded situations at the PTI.

are obtained according to Equations (1) and (2) defined in Section 3 for each of the 20 runs in each case of R, respectively. In the case of R = 4 (i.e., 4 times more passengers boarding than alighting), $\overline{t_{am}}$ reached 1.48 s/pass which is 70% higher than $\overline{t_{bn}}$. This is caused because the platform is crowded and passengers alighting have less available space to get off the train. As a consequence, a high interaction between passengers boarding and alighting is reached. On the other hand, when R = 0.25 (i.e., 4 times more passengers alighting than boarding), $\overline{t_{bn}}$ reached 1.15 s/pass which is 51% higher than $\overline{t_{am}}$. In this case (R = 0.25) passengers alighting have more space available to get off the train, and therefore less interaction is obtained with those passengers who are waiting to board the train. The case R = 1 presented no variation between $\overline{t_{bn}}$ and $\overline{t_{am}}$ on average due to similar level of demand between passengers boarding and alighting. All these differences are significant according to Student's t-Test (p value < 0.05). In Figure 3, ∗ shows that there are significant differences between $\overline{t_{bn}}$ and $\overline{t_{am}}$ for each value of R.

When comparing $\overline{t_{am}}$ over the different values of R, some relationship could be obtained in Figure 3. If R decreases (i.e., there are more passengers alighting than boarding), then $\overline{t_{am}}$ decreases on average. The case R = 4 (10 passengers alighting per door) reached the highest value (1.48 s/pass), which is 48% more than $\overline{t_{am}}$ in the case R = 1 (20 passengers alighting per door) and 94% more than $\overline{t_{am}}$ in the case R = 0.25 (40 passengers alighting per door). With respect to $\overline{t_{bn}}$, if R increases (i.e., there are more passengers boarding than alighting), then $\overline{t_{bn}}$ decreases on average. The case R = 0.25 (10 passengers boarding per door) presented the highest value (1.15 s/pass), which is 11% more than $\overline{t_{bn}}$ when R = 1 (20 passengers boarding per door) and 32% more than $\overline{t_{bn}}$ when R = 4 (40 passengers boarding per door). All these differences are significant according to the ANNOVA test single factor (p value < 0.05).

Similarly, Figure 4 presents $\overline{t_{bn}}$ and $\overline{t_{am}}$ for different values of R in noncrowded situations at the PTI (load conditions LC 5, LC 6, and LC 7 in Table 1). Due to the similar level of demand, $\overline{t_{am}}$ reached only a difference of 3% with respect to $\overline{t_{bn}}$ when R = 1. In fact this case (R = 1) presented no significant differences (p value = 0.147) according to Student's t-Test. It was expected to have the same differences observed in Figure 3 for the other two cases of R (R = 4 and R = 0.25). However, when R = 4, $\overline{t_{am}}$ is only 6% higher than $\overline{t_{bn}}$. This is caused because of the low number of passengers alighting (only 5) who are pressured to alight faster from those passengers who are waiting to board (20 passengers). When R = 0.25, this difference is much higher in which $\overline{t_{am}}$ reaches almost the half of $\overline{t_{bn}}$ but also presented a higher standard deviation (1.31 s/pass) compared to the other cases. These differences are significant according to Student's t-Test (p value < 0.05). However, the situation of R = 1 reached no significant differences (p value = 0.147) between $\overline{t_{bn}}$ and $\overline{t_{am}}$ due to the similar and low number of passengers boarding and alighting (only 10 passengers boarding and 10 passengers alighting). In Figure 4, ∗ shows that there are significant differences between $\overline{t_{bn}}$ and $\overline{t_{am}}$ for each value of R.

In addition, some relationship can be obtained when comparing $\overline{t_{am}}$ over the different values of R in Figure 4. When R = 4, $\overline{t_{am}}$ reached the highest which is 11% higher than $\overline{t_{am}}$ in the case of R = 1 and 33% more than $\overline{t_{am}}$ in the situation of R = 0.25. With respect to $\overline{t_{bn}}$, the case R = 0.25 presented the highest value (2.54 s/pass) which is 72% more than $\overline{t_{bn}}$ in the case of R = 1 and 70% higher than $\overline{t_{bn}}$ when R = 4. All these differences are significant according to the ANNOVA test single factor (p value < 0.05).

4.2. Sequence of Movement. From the laboratory experiments it was observed that alighting occurs first and then boarding; i.e., passengers on the platform give way to those who are alighting or wait for a gap in space to board the train. In the case of crowded situations at the PTI (load conditions LC 2, LC 3, and LC 4 in Table 1), Figure 5 shows the average boarding time per passenger j ($\overline{t_{bj}}$) and average alighting time per passenger i ($\overline{t_{ai}}$). In the figure it can be observed that boarding started earlier when R = 4 compared to the cases of R = 0.25 and R = 1. This is caused due to the few passengers alighting (10 passengers) compared to those who were waiting to board the train (40 passengers) when R = 4. Consequently, $\overline{t_{bj}}$ in R = 4 is smaller than the other two cases (R = 1 and R

Figure 5: Average boarding time per passenger j ($\overline{t_{bj}}$) and average alighting time per passenger i ($\overline{t_{ai}}$) at PAMELA when crowded situations are reached at the PTI.

= 0.25) even though there were more passengers boarding. On the other hand, when there were 4 times more passengers alighting than boarding (i.e., R = 0.25), passengers on the platform almost wait until alighting was finished to board the train, and therefore $\overline{t_{bj}}$ increased.

From Figure 5 it can be also observed that the first passengers alighting reached a lower $\overline{t_{ai}}$ compared to the last passengers alighting. For example, when R = 4 and R = 1 the first passengers alighting reached a value of $\overline{t_{ai}}$ in the ranges of 0.5 s/pass and 1.0 s/pass, while the last passengers alighting obtained a $\overline{t_{ai}}$ of 1.5 s/pass or more. In the case of R = 0.25, a smooth variation is presented between the first passengers alighting ($\overline{t_{ai}}$ is around 0.5 s/pass) and the last passengers alighting ($\overline{t_{ai}}$ is almost 0.9 s/pass). This could be caused because the first passengers alighting have more space at the PTI to move (as passengers boarding give way to those who are alighting) than the rest of passengers who need to follow the person in front of them to avoid collision with those passengers boarding. In addition, the case of R = 0.25 presented only 10 passengers waiting to board the train; therefore passengers alighting have less interaction with boarding passengers and they reach a lower value of $\overline{t_{ai}}$ compared to the other two cases of R (R = 4 and R = 1). Another reason is that first passengers alighting could be closer to the train doors (e.g., they accommodate their position to alight first) than the rest of alighters who need to avoid contact with those passengers on-board; however it was not possible to obtain the exact location inside the train due to the position of the cameras in which each passenger's head was obstructed by the structure of the carriage.

The same sequence of movement is observed in the case of noncrowded situations (see Figure 6); i.e., alighting is first and then boarding and first passengers alighting reached a lower $\overline{t_{ai}}$ compared to the last passengers alighting. Therefore, the sequence of movement is the same under the same value of R no matter the number of passengers boarding and alighting. However, the demand level affects the variability on the $\overline{t_{bj}}$ and $\overline{t_{ai}}$. For example, in the case of R = 0.25 the crowded situation (LC 3) reached a $\overline{t_{ai}}$ in a range between 0.4 s/pass and 1.5 s/pass, while the range in the noncrowded situation (LC 6) varied between 0.5 s/pass and 3.0 s/pass. A Student's t-Test (p value < 0.05) was performed to compare $\overline{t_{ai}}$ between the crowded and noncrowded situations for each value of R. The results show that all the cases presented significant differences. A similar comparison was done with respect to $\overline{t_{bj}}$, in which the differences are also significant between the crowded and noncrowded situations for each value of R.

4.3. Formation of Lanes of Flow. Another behaviour is observed with respect to the formation of lanes of flow in the alighting process. It was expected that the formation of lanes of flow will be the same under the same value of R no matter the number of passengers boarding and alighting. However, the formation of lanes of flow varied depending on the value of R and the number of passengers boarding and alighting. The only cases in which two lanes were formed were obtained in the crowded situations when R = 4 (LC 2) and R = 0.25 (LC 3). In the case of R = 4, 152 alighting passengers were registered, in which 12 of them formed two lanes of flow (i.e., 8% of the observed alighters) and the rest only formed

Figure 6: Average boarding time per passenger j ($\overline{t_{bj}}$) and average alighting time per passenger i ($\overline{t_{ai}}$) at PAMELA when noncrowded situations are reached at the PTI.

Figure 7: Example of formation of lanes of flow for alighting passengers. One narrow lane of flow when R = 4 (left) and two lanes of alighting flow when R = 0.25 (right) in crowded situations.

one narrow lane for alighting. For the situation of R = 0.25, 471 alighting passengers were recorded, in which 179 of them presented two lanes for alighting (i.e., 38% of the observed alighters), while the rest only formed one narrow lane.

Figure 7 shows an example of formation of lanes of flow in crowded situations. When R = 4, then only one narrow lane of flow is formed for those passengers alighting. This is caused because when R = 4, and there are four times more passengers boarding than those who are alighting; therefore the platform is crowded and alighters need to compete for space to get off the train. On the other hand, when R = 0.25 up to two lanes of flow are formed for those passengers alighting, due to the low number of passengers on the platform (there are four times more passengers alighting than boarding). In the case of R = 1, the formation of lanes of flow is between the two other cases of R = 4 and R = 0.25.

4.4. Density inside the Train. In the case of crowded situations (see Figure 5) the first passengers boarding reached a higher $\overline{t_{bj}}$ compared to the last passengers boarding due to the influence by those passengers alighting and the density inside the train. For example, when R = 4 the first passengers boarding reached a value of $\overline{t_{bj}}$ of 2.5 s/pass or more, while the last passengers boarding obtained a $\overline{t_{bj}}$ of around 1.0 s/pass.

Figure 8: Relationship between the flow of passengers boarding at the doors and the density inside the train at PAMELA in the case of LC 2 (R = 4).

The same situation is presented in the other two cases of R (R = 1 and R = 0.25). It was expected that this behaviour will be the same under the same value of R no matter the number of passengers boarding and alighting. However, in the noncrowded situations (see Figure 6) the first passengers boarding are not influenced by those passengers alighting or the density inside the train. In all the cases of R, the first passengers boarding presented a lower $\overline{t_{bj}}$ compared to the last passengers boarding. This could be caused due to the low level of demand in the noncrowded situation, in which less than 2 pass/m^2 are reached at the PTI.

When the alighting is finished the density inside the train starts to increase up to a point in which the boarding flow at the doors decreases. In the case when the platform is congested, i.e., R = 4 (LC 2), some similarities in behaviour were obtained. Figure 8 presents three stages to relate density inside the train and flow of boarding passengers when R = 4 (LC 2). A first stage is produced between the first passenger alighting and the last passenger alighting. At the end of this stage the density inside the train is 1.50 pass/m^2 on average (standard deviation of 0.64 pass/m^2) and the flow at the doors is 1.09 pass/s on average (standard deviation of 0.37 pass/s). A second stage is reached from the moment the alighting process is finished until the flow of passengers boarding at the doors started to decrease. At the end of this stage the density on the train is 4.03 pass/m^2 on average (standard deviation of 0.49 pass/m^2) and the flow at the doors is 1.38 pass/s on average (standard deviation of 0.19 pass/s). A third stage is obtained when the flow of passengers boarding at the doors started to decrease. This is caused because passengers boarding are influenced by the density inside the train. Because of this type of behaviour, it could be recommended to close the doors at the moment when the flow started to decrease, i.e., at the third stage. In this case (R = 4, LC 2), if the doors are closed at the third stage, then 78% of passengers will complete the process of boarding, while the rest (22% passengers) would need to wait for next train. This means that 10 passengers should wait for the next train on average from the total number of passengers boarding (40 passengers). Consequently, there is 26% boarding time saved (11.07 s on average), and therefore the dwell time will be reduced.

5. Discussion and Future Work

This work studied the effect of the ratio (R) between boarding and alighting on the behaviour of passengers, and therefore on the boarding and alighting time at the platform train interface (PTI). The approach used laboratory experiments at Pedestrian Accessibility and Movement Environment Laboratory (PAMELA, University College London) based on the next generation London Underground trains.

The results of the laboratory experiments showed the importance of R (ratio between passengers boarding and alighting) on the average boarding time per passenger ($\overline{t_{bj}}$) and the average alighting time per passenger ($\overline{t_{ai}}$). The hypothesis of our research could be refuted as the behaviour was not always the same for the same values of R due to the differences in the level of demand. Therefore, the number of passengers boarding and alighting is another influencing factor on passenger behaviour.

With respect to crowded situations, not always a high number of passengers boarding will increase the total average boarding time per passenger ($\overline{t_{bn}}$). The case R = 4 presented the lowest value of $\overline{t_{bn}}$ compared to the other two cases (R = 0.25 and R = 1). The same conclusion is obtained for the total average alighting time per passenger ($\overline{t_{am}}$), in which the lowest value was obtained when R = 0.25. These differences were statistical with a level of confidence of 0.05. In addition, when R = 4, $\overline{t_{am}}$ is bigger than $\overline{t_{bn}}$. This is caused due to the small available space to move for those 10 passengers alighting as there are 40 passengers waiting to board, reaching a high interaction between them. On the other hand, when R = 0.25, $\overline{t_{am}}$ is smaller than $\overline{t_{bn}}$, due to similar reasons. In this case (R = 0.25) those 10 passengers waiting to board need to look for a gap in space to board the train, which is difficult considering that 40 alighting passengers are getting off the train. The case R = 1 presented no major differences between $\overline{t_{am}}$ and $\overline{t_{bn}}$ due to the similar number of passengers boarding and alighting. To better represent the relationship between demand level and boarding/alighting time, this ratio R should be included in dwell time models presented in [3, 17–20, 22].

In the case of noncrowded situations at the PTI, it was not possible to establish major differences between $\overline{t_{am}}$ and $\overline{t_{bn}}$ when R = 4. It seems that the low number of passengers alighting did not affect the behaviour of those passengers waiting to board. The case R = 1 also presented no important differences between $\overline{t_{am}}$ and $\overline{t_{bn}}$ which is similar to the crowded situations for the same value of R. However, when R = 0.25 the difference between $\overline{t_{am}}$ and $\overline{t_{bn}}$ was much bigger. This could be caused because passengers boarding wait until alighting is almost finished to board, which is a similar behaviour in crowded situations. In these cases (noncrowded situations), the results are in concordance with different manuals [3], in which the train doors can be opened for a fixed period of time without problems of crowding at the PTI.

In relation to the sequence of movement, similar to the observation done at existing stations by Harris et al. [19, 20] the results from the laboratory experiments showed that alighting is first and passengers boarding compete for a space to board the train. In addition, the first passengers alighting reached a lower $\overline{t_{ai}}$ compared to the last passengers alighting. This can be caused because passengers boarding give way to those who are alighting; therefore the first passenger that gets off the train has more space available than the rest of passengers.

Different from the laboratory experiments done by Dameen et al. [33], Fernandez et al. [34], and Fujiyama et al. [35], another behaviour observed at PAMELA was that the capacity of the train doors will not only depend on the door widths but also on the ratio R. If the value of R increases, then the number of lanes of flow for those passengers alighting will decrease. This was only presented in the crowded situations, due to the high number of passengers boarding and alighting (reaching more than 4 pass/m^2).

The last type of behaviour is related to the density inside the train. When R = 4 (crowded situations), if the density is higher than 4 pass/m^2 the flow at the doors starts to decrease. Therefore, this could help to implement different crowd management measures such as to close the train doors before the boarding process finishes. In that case (R = 4), we could save up to 26% of the boarding time (i.e., about 11 s). This benefit can be very important to reduce dwell time at stations. In this sense, the results can complement other experimental studies related to crowd management measures such as that of Seriani and Fernandez [28].

The relationship between the flow of boarding passengers at the train doors and the density inside the train is not exactly the same as the relationship reported by different authors [39–43]. These authors used a confined space such as a corridor; however in our study the density is obtained inside the train, which is a separate place from the doors and platform. Considering the wide range of density inside the train there is little variation on the boarding flow at the doors. In addition, the statement that the flow decreases at high densities is only part of the results. In fact, the upper limit of flow decreases while the lower limit increases. In conclusion, the average boarding flow can be assumed to be independent of the on-board density, at least up to densities which were investigated. Further research will consider density classes to clarify this issue a bit better.

In conclusion, the use of laboratory experiments helped to test different situations (what if scenarios) in a controlled environment. This would be difficult to do in a real situation due to the different variables affecting the layout and vehicles of existing public transport systems. In addition, few laboratories such as PAMELA are built in the world, which has led us to be in a privileged position and to be able to perform new research. Further work is focused on new experiments to simulate the relationship between density and boarding and alighting time to identify which when to close the doors in more crowded situations (e.g., R = 5, R = 6, and R = 7 or more). This could be complemented with other measures such as the use of a waiting area or a "stay clear" to avoid alighting being blocked by passengers waiting in front of the doors.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

Hybrid Dynamic Route Planning Model for Pedestrian Microscopic Simulation at Subway Station

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To make agents' route decision-making behaviours as real as possible, this paper proposes a layered navigation algorithm, emphasizing the coordinating of the global route planning at strategic level and the local route planning at tactical level. Specifically, by an improved visibility graph method, the global route is firstly generated based on static environment map. Then, a new local route planning (LRP) based on dynamic local environment is activated for multipath selection to allow pedestrian to respond changes at a real-time sense. In particular, the LRP model is developed on the basis of a passenger's psychological motivation. The pedestrians' individual preferences and the uncertainties existing in the process of evaluation and choice are fully considered. The suitable local path can be generated according to an estimated passing time. The LRP model is applied to the choice of ticket gates at a subway station, and the behaviours of gate choosing and rechoosing are investigated. By utilizing C++, the layered navigation algorithm is implemented. The simulation results exhibit agents' tendency to avoid congestion, which is often observed in real crowds.

1. Introduction

Pedestrian simulation has engaged the attention of researchers over the past few decades. It is not only a simulation technology to reproduce the temporal and spatial changes of pedestrian flow in real scenes, but also an important application of computer technology in traffic studies. Different technical areas, such as architecture, urban planning, and transportation, can benefit from the simulation of groups of pedestrians. The simulation can help to improve the efficiency, comfort, and safety of pedestrian transport, to provide references for planning, design, and facility layout, or to optimize passenger flow organization and emergency evacuation plan.

The framework used for describing pedestrian traffic can be specified in a three-tier structure [1]. At the highest strategic level, the pedestrian agents generate the global route according to the activity planning and the topological network of building environment. The tactical level is performed in case of multipath choice. At the operational level, microscopic motions (e.g., walking in an area and moving in a queue) can be observed. To our knowledge, the development of behaviour models at the strategic level in the existing literature is fairly robust [2, 3] and a great deal of research has been dedicated towards modeling the operational-level movement of pedestrians [4, 5]. However, the intermediate tactical level is usually neglected. Generally, most global path planning (GRP) is static and cannot adjust to the changes of environment. Although some studies adopted a real-time global path planning [6], it always means a large amount of computing resources consumption. Though the operational-level navigation can take full account of the dynamic environment, but it is difficult to ensure an optimal route from an overall perspective due to the limited local information obtained by the agents. Therefore, to make a balance of efficiency and flexibility, this paper proposes a hybrid path planning model, which combines GRP at strategic level with local route planning (LRP) at tactical level. As shown in Figure 1, during the journey from starting point to destination, a pedestrian is guided by a series of target

Figure 1: The three levels of navigation algorithm.

points. These target points are generated by GRP based on the static building environment and dynamically modified by the LRP with the changing surroundings.

For the behaviour of multipath selection at tactical level, utility and probability are often used to solve this problem. Some researches defined the utility as time [7] or a function of some factors of the path such as distance, excitement, and density [8]. Reference [9] defined the utility as a sum of the relative values of distance and density. Paper [7] evaluated the exit choice by the maximum of the distance-based time and density-based time. In these studies, the route with most utility or least disutility will be definitely chosen. However, the choice of a pedestrian is not always sufficiently sensible. They cannot always make accurate estimations and optimal choices. To reflect the randomness of path choice, some researches introduced probability into this field. Reference [10] expressed the probability of selecting a certain path as a combination of the reliability probability and the cognitive probability. Paper [11] evaluated the probability of exit choice by a weighted sum of the distance-based probability and the density-based probability. The weights depend on the degree of deviation of the alternative paths. This model was also applied to the selection of ticket gates in subway stations. Reference [12] calculated the probability by an exponential function of distance and queue number. Among the studies attempting to model route choice behaviour, the Logit model based on the utility of each route [13] has been proved as a popular and practical approach. The mixed nested Logit model [14], multinomial Logit model [15], and other Logit models with complex forms have been proposed to estimate the behaviour of multipath choice. References [16, 17] constructed the utility of a path by a linear weighted sum of distance and time. In some studies, the time factor was replaced by density [18]. Paper [16] suggested that pedestrians' preferences for the factors are related to their speed. Reference [19] proposed a node selection model of ticket gates at metro stations and the linear weighting utility consists of multiple factors. Paper [14] evaluated the cost by a sum of distance-based time and density-based time. Unfortunately, the development of probability and generalized utility in these studies are usually the results of mathematical matching with multiple factors and lack of practical physical significance. This is not conducive to explaining the fundamental motivation of pedestrians to make choices and may lead to the deviation between the simulation results and the actual situation. Consequently, this paper aims to model the individual desires and interests of multipath choice to generate realistic community behaviours.

In the literature, the passenger simulation of multipath choice behaviour aims to achieve two purposes. One purpose is to explore the behaviour pattern of pedestrians in reality and then reproduce and estimate their selections. Some experiments have been made to explain the factors that affect pedestrians' choices, such as density, distance, visibility [20], and social influence [21, 22]. There are also data collected by stated-choice investigation [23, 24] and video [17] used to analyze passengers' selection behaviour. Another purpose is to find out the optimal guidance scheme of the pedestrians to each path to get a utility balance or to get the least evacuation time [25, 26]. This is often used in the layout design and evacuation organization. Paper [27] designed a class of variable guide sign systems based on the dynamic balance of each exit. Obviously, the former purpose is the foundation of the latter. Only by understanding the mechanism of pedestrian selection behaviour, the appropriate guidance management can be made. Therefore, this paper aims to reveal the mechanism of pedestrian choice behaviour in terms of psychology.

In design and operation stages of metro system, pedestrian simulation has become a necessary, low-cost, and effective method to improve facilities layout and passenger organization. It is of great significance to ensure the safety and good performance in operation. In order to achieve a reliable simulation result, the accuracy of simulation models and parameters are particularly important. At present, there are some commercial software aiming to simulate passenger behaviour, such as Pathfinder, Exodus, and PTV Viswalk. These tools have different characteristics and their own specific application range. Although some standardized verification and validation documents are published as a reference, these documents are directed at building environment, which is not necessarily used for subway scenes. This motivated the development of dedicated models and more accurate knowledge of pedestrian movement at different locations and facilities in subway. In particular, the multipath choice behaviour in subway stations at ticket gates [11, 19], stairs/escalator [28], and the waiting position on platform [29] is modeled in some researches. Similarly, the passengers'

motion during the check-in process in a high speed railway station is also studied in [30]. However, the whole process of ticket gate selection is not completely explored. This paper attempts to make up this gap. The behaviour of ticket gate selection is decomposed into several stages and embedded in the navigation model.

The multipath selection occurs when a pedestrian faces multiple paths [26], exits, and intermediate nodes. Nevertheless, the selection of multiple intermediate nodes, such as the ticket gates in a subway station, is different in some details from the other two kinds of multipath choices. Specifically, in order to avoid interference, the exits are usually dispersed in space. Differently, intermediate nodes such as service windows and ticket gates are usually centralized. As a result, all the nodes are visible to pedestrians in geometric space. Different from the exits, the intermediate nodes are not the end of trip. So, rather than just focusing on the condition before passing the nodes, the condition after passing, such as the distance between the nodes to the next target point, should also be taken into account. Furthermore, the node selection may involve some activities like queuing and ticket checking. Therefore, as pedestrians would adopt different behaviours to deal with these three kinds of multipath situations, it is inappropriate to model them by the same model. For example, there are some unreasonable assumptions when applied the exit-choice model to the selection of ticket gates [11]. For this reason, some necessary adjustments are made to the scalable LRP method proposed in this paper so as to apply it to the selection behaviour of ticket gates.

Uncertainty always exists in system components and processes, which are normally resulting from uncertain cost in nature and deviations in subjective judgments. Such a variety of uncertainties may become more compounded by combinations of uncertain information presented in multiple forms. Previously, a number of research works for uncertain methods in traffic simulation were undertaken. Reference [31] pointed out the effect of environmental uncertainty on cooperation of evacuation crowd and evacuation efficiency. Papers [32, 33] optimized the evacuation organization when the demand uncertainty and capacity uncertainty were taken into account. Actually, uncertainty also exists in many aspects of pedestrian path selection. For instance, since pedestrians have the characteristics of rational irrationality and randomness, they do not always make the best choice [34] and make the same decisions under the same circumstances. In addition, pedestrians have different preferences of choosing path. Their perceptions of the distance and the social influence factors are different [21]. Reference [35] pointed out that the evacuees could be divided into the patient and the impatient. The patient evacuees try to avoid physical contacts, but the impatient evacuees vie for the empty target cell by paying the effort. Similarly, [36] divided them into the active and the conservative. Reference [12] even considered four types of window choice strategies. It has been proved that the uncertainties will affect the results of path selection, but they have not been explicitly addressed in the existing literature. In this paper, the uncertainty underlying in route planning will be taken into account in three ways: the estimation of factors, the randomness of decision-making, and the subjective individual preference.

In this paper, a three-level navigation algorithm is proposed to capture passenger movement in subway station. Especially, the improved pedestrian route planning model balances the certainty of global route planning at the strategic level and the flexibility of local route planning at the tactical level. The local route planning model is developed based on a passenger's psychological motivation. The uncertainties and preferences within the process of path selection are fully considered. With this navigation algorithm, the most appropriate path will be activated according to real-time environment. The difference between simulation results and real situation can be minimized.

The study begins with the method of abstracting route planning network from realistic environment in Section 2.1 and generating a collision-free global route in Section 2.2. Following, a novel local route algorithm is described in Section 2.3. The field data collected in actual subway stations is given in Section 3.1. Then, an application to the selection of ticket gates is provided with some necessary adjustments in the following parts of Section 3. Furthermore, the advantages of the proposed models are demonstrated with examples in Section 4, and, last, Section 5 concludes with a summary and an outlook for future work.

2. Model

2.1. Environment Map Modeling. Before route planning, environment map should be established to mark the location of pedestrian and obstacles. Through expressing the obstacles as abstract geometric figures, the walking area in real world can be translated into perceivable environment information for pedestrians.

The common methods to model environment are obstacles polygon, barrier-free zone, hybrid space, and path diagram [37, 38]. Since pedestrians in subway station only need to recognize obstacles to avoid collision, this paper adopts obstacles polygon method to divide the station environment into two regions: walking area and obstacle area. Obstacle areas are abstracted as approximate polygons. All the other areas except obstacles are considered as walking areas on the basis of continuum space model.

2.2. Global Route Planning Model Based on Visibility Graph. Global route planning is indispensable in a pedestrian simulation. It can optimize the layout of guidance facilities, reduce calculating quantity, and decrease errors caused by manual operation, especially in an environment with lots of obstacles. The main route planning algorithms are visibility graph, free space and grids. The complexity of free space method increases with the amount of obstacles dramatically and this method cannot find the shortest path in any cases. The stored environment information of grids method is huge and the suitable grid size is difficult to determine. If gird size is too small, the calculated amount will be too large while the shortest path may not be got with too big grid. In the literature, most algorithms for global planning represent the

Figure 2: Obstacle expanding illustration.

connectivity of walkable space in the environment as a graph and perform search queries for each agent to determine a collision-free path. We do not diverge from previous work in this aspect and adopt visibility graph method to plan global route.

According to the method of visibility graph, the realistic environment is replaced by approximate polygon in proportion and the visible graph is composed by connecting all no-cross and unscreened lines. By using A∗ algorithm [39], the shortest path between origin and destination can be found on the visible graph, which is the global navigation route.

In global route, all of intermediate points except origin and destination are regarded as convex vertex of obstacles. In traditional visibility graph method, a pedestrian is considered as a point. While in fact, he occupies an area. As a result, a passenger overlaps with margin of obstacles when he walks on the global route [40]. To avoid collision, this paper makes a correction to the intermediate points using half of pedestrian maximum size as shown in Figure 2. The virtual obstacles are used to calculate a global route.

2.3. Local Route Planning Model Based on Estimated Travel Time. Global route planning is used to find out the whole route from origin to destination. If there are multiple routes, the shortest path in terms of Euclidean distance is searched. However, when the pedestrian density is large, it will cause unrealistic walking behaviour. For example, during pedestrian passing a ticket gate at a subway station, global route planning strategy will determine a fixed gate; therefore, pedestrians will wait in line at this gate and the other gates will be left unused. However, according to observation and video analysis of pedestrians' route choice behaviour at metro stations, pedestrians will choose a farther unoccupied gate to save travel time in practice. The local route planning model proposed in this paper is made in order to solve this problem.

A pedestrian makes the route choice decision according to what has been seen in the surroundings and what has been formulated in his or her mind. Specifically, environmental factors include path distance or travel time, directness of path, capacity/width of exit, visibility and service level [16, 41]. The individual implicit factors include physical ability (walking speed), subjective preference, familiarity with the environment, and following behaviour [42]. From a review of the previous studies, three factors, namely, the route length, passing time, and density of pedestrian flow, are identified to have significant impacts on a pedestrian's behaviour of route choice [43]. The route length is the primary factor that affects route choice behaviour and the crowdedness is a measure to reflect discomfort [44]. What is more, it is found that a pedestrian tends to base his exit choice on time-dependent information rather than on time-independent information [9, 45]. Therefore, the local route planning model proposed in this paper allows pedestrians choose a path according to the estimated passing time, which is determined by the length and the crowdedness of each local path, shown as (1) and (2). The local route planning for each pedestrian is independent and dynamic. Namely, which path will be the optimal depends on the individual and the moment.

$$U_{i,\mathrm{j}} = V_{i,\mathrm{j}} + \varepsilon_{i,\mathrm{j}} \tag{1}$$

$$V_{i,\mathrm{j}} = \omega_{i,\mathrm{j}}^{N} \bullet V_{i,\mathrm{j}}^{N} + \omega_{i,\mathrm{j}}^{L} \bullet V_{i,\mathrm{j}}^{L} \tag{2}$$

where $U_{i,\mathrm{j}}$ is the utility for pedestrian i choosing path j, i=1,2,. . ., j=1,2,. . .. The random error $\varepsilon_{i,\mathrm{j}}$ is independent identically distributed and subject to a Gumbel distribution. $V_{i,\mathrm{j}}$ is a certain item, indicating the estimated passing time by pedestrian. It consists of waiting time and walking time. $V_{i,\mathrm{j}}^{N}$, $V_{i,\mathrm{j}}^{L}$ is the estimated waiting time and the estimated walking time, respectively. $\omega_{i,\mathrm{j}}^{T}$ and $\omega_{i,\mathrm{j}}^{L}$ are the perceived weights.

In real-world situations, passengers generally give a glance of the possible routes and make a rough estimation by hunch rather than by accurate calculations when making a route choice. Thus, uncertainty of decision variables should be introduced into the route choice model. To an appropriate level, the variability in time cost and uncertainty could help "blur" the agents' route choices. In this way, it can achieve simulation results that conform well to real situation.

2.3.1. Passengers' Perception of Time. During the process of a pedestrian's journey, on one hand, he needs to walk for a certain distance. The time spent on walking is called "walking time". On the other hand, if there are congestions on the way and the pedestrian need to queue for service, he would have to spend extra "waiting time". According to temperament and time urgency, pedestrians may have different values of time (VOT) on "walking time" and "waiting time". It is observed that there is a strong negative correlation between utility coefficients of distance and density, meaning that an individual who has a strong tendency to avoid congestion is likely to be more indifferent about walking for long distances to reach a further less-congested path, and vice versa [46].

2.3.2. Walking Time. Pedestrian i estimates the walking time of the j-th local path as

$$V_{i,j}^{L} = \frac{\sum L_{i,j}^{m\,\prime}}{v_i} \tag{3}$$

v_i is the desired walking speed of pedestrian i. $\sum L_{i,j}^{m\,\prime}$ is the estimated total length of local path j. If we divide path j into several segments, the real length of segment m is $L_{i,j}^{m}$.$L_{i,j}^{m\,\prime}$ is the estimated length and can be calculate as (4). The estimated error is limited within 10% and k is subject to a Gaussian distribution. As a result, $L_{i,j}^{m\,\prime}$ is also in a Gaussian distribution, with the average of $L_{i,j}^{m}$ and within range of $[0.9{\cdot}L_{i,j}^{m}, 1.1{\cdot}L_{i,j}^{m}]$.

$$\begin{aligned} L_{i,j}^{m\,\prime} &= L_{i,j}^{m} + \varepsilon\left(L_{i,j}^{m}\right) \\ \varepsilon\left(L_{i,j}^{m}\right) &= k \bullet L_{i,j}^{m} \\ k &\sim N\left(0, 0.001\right), \ |k| \le 10\% \end{aligned} \tag{4}$$

It is worth noting that although the value of the estimated length has an error, the order of local paths in length should not be changed. To ensure the right order of estimated distances, we should make a limit to the scope of estimated length. Before estimating the length of segment m for each local path, sort the actual distances from short to long. Then, compare every two adjacent distances. For $L_{i,p}^{m} < L_{i,q}^{m}$, if $1.1 \cdot L_{i,p}^{m} > 0.9 \cdot L_{i,q}^{m}$, the estimating range should be adjusted to

$$\begin{aligned} L_{i,p}^{m\,\prime} &\in \left[0.9 * L_{i,p}^{m}, \ \frac{\left(1.1 * L_{i,p}^{m} + 0.9 * L_{i,q}^{m}\right)}{2}\right] \\ L_{i,q}^{m\,\prime} &\in \left[\frac{\left(1.1 * L_{i,p}^{m} + 0.9 * L_{i,q}^{m}\right)}{2}, 1.1 * L_{i,q}^{m}\right] \end{aligned} \tag{5}$$

2.3.3. Waiting Time. Waiting time is estimated by the product of the estimated number of passengers in queue ($N_{i,j}^{\prime}$) and the average service time (t_0), as shown in (6).

$$V_{i,j}^{N} = N_{i,j}^{\prime} \bullet t_0 \tag{6}$$

Pedestrian i would estimate the number of passengers queuing at local path j as

$$\begin{aligned} N_{i,j}^{\prime} &= N_{i,j} + \varepsilon\left(N_{i,j}\right) \\ \varepsilon\left(N_{i,j}\right) &= \begin{cases} 0, & N_i \le 3 \\ \{0, \pm 1\}, & N_{i,j} \in [4, 5] \\ \{0, \pm 1, \pm 2\}, & N_{i,j} \ge 6 \end{cases} \\ P\left\{\varepsilon\left(N_{i,j}\right) = X_p\right\} &= \frac{1}{3}, \quad \left(X_p = -1, 0, 1\right) \\ P\left\{\varepsilon\left(N_{i,j}\right) = X_q\right\} &= \frac{1}{5}, \quad \left(X_q = -2, -1, 0, 1, 2\right) \end{aligned} \tag{7}$$

$N_{i,j}$ is the actual number of queuing at local path j when pedestrian i makes decision. $\varepsilon(N_{i,j})$ is estimation error and it would enlarge as the queuing passenger population increases. Specifically, in case of no more than three pedestrians queuing, pedestrian i can identify the number accurately. If the number is greater than 3, the estimated error would obey a Discrete Uniform Distribution.

2.3.4. Discrete Choice Model. After the walking time and the waiting time having been estimated, the final piece of the puzzle is how to decide which local path a passenger will pass through. As a problem of discrete choice, we adopt the Logit model. The probability of pedestrian i choosing local path j is

$$\begin{aligned} P_{i,j} &= \frac{\exp\left(-V_{i,j}\right)}{\sum_{j=1}^{M} \exp\left(-V_{i,j}\right)}, \\ \sum_{j=1}^{M} P_{i,j} &= 1 \end{aligned} \tag{8}$$

For a completely rational pedestrian, he would choose the most effective path to go through. While in practice, a pedestrian's decision is effected by some random factors, such as emotion and the pedestrians around him. For this reason, a pedestrian will not accurately evaluate the route options, and, as a result, the path with the smallest cost is not always chosen [47]. Therefore, the final decision is determined by a random number according to the probabilities $P_{i,j}$.

3. Model Application and Discussion

Utilizing MFC provided by Microsoft Visual Studio, we developed a pedestrian simulation tool to realize our navigation algorithm. Specifically, to enable agents to autonomously navigate in complex spaces and crowded environment, the tool combines the visibility graph at strategic level, multistage route choice scheme at tactical level, and a variant of Social Force Model at operational level. The local route planning is realized by a target converter and local route settings. A pedestrian can temporarily deviate from the global route, take reasonable detours to optimize his local route, and return to global route after passing the local route region. At the operational level, a pedestrian's movement towards the target point is driven by a resultant force, which is affected by the goal's attraction, barriers, and other agents. The framework of the layered navigation algorithm is shown in Figure 3.

Thanks to the developed simulation tool, the route choices and crowd characteristics estimated by the navigation algorithm can be favorably compared to the actual situations in practice. During simulation, all the agent movements are recorded to a database. Then, it can be analyzed to determine some key performance metrics such as crowd density, journey time, and flow rates. In addition, the simulation can be played back in real time (or faster) to provide a rich visual means for verifying and communicating. Though the proposed navigation algorithm and simulation tool are applicable in many scenarios, the automatic fare gate in subway stations is taken as an example in this work.

Figure 3: The framework of the layered navigation algorithm.

(a) (b)

Figure 4: The two simulation scenarios: (a) symmetric layout and (b) asymmetric layout.

3.1. Empirical Data and Simulation Settings. According to field survey in subway stations, it is found that there are different traffic lines because of the spatial layout of ticket gates. Roughly, the situation can be divided into two typical scenarios, i.e., the symmetry and the asymmetry scenario. As shown in Figure 4, in the symmetry scenario, passengers just move forward and pass through the gate directly. In the asymmetry scenario, passengers need to move towards the ticket gates firstly and then make a turn to pass through the gate. In the following sections, the gates are numbered as 1, 2, . . ., 5 in turn from top to bottom. At the strategic level, only a fixed one of these gates could be counted as a part of global route. But in practice, a pedestrian would choose the optimal path to replace the default one.

To trigger the local route plan, a virtual influence area is set in front of the ticket gate area where local route planning is needed, as shown in Figure 5. When a pedestrian walks into an influence zone, the local route plan will be activated to substitute global route. The pedestrian's destination will be temporarily reset to the local path's target point marked as D in Figure 5, which is normally the entrance of a stairway to platform or a turning point of path. Point O is the real-time location when pedestrians enter into the influence zone. It represents the origin of local path. Points A_j, B_j are the entrance and the exit of gate j. The concentration zones are set to count how many pedestrians are queuing at each gate. The polygonal line OA_jB_jD describes local path j. It can be divided into three segments in this scenario: OA_j, A_jB_j, and B_jD. Their lengths are $L^1_{i,j}$, $L^2_{i,j}$ and $L^3_{i,j}$, respectively. Here, $L^2_{i,j}$ has the same length for each local path, it can be ignored in calculation. Then, the estimated walking time can be simplified as

$$V^L_{i,j} = \frac{\left(L^{1\,\prime}_{i,j} + L^{3\,\prime}_{i,j}\right)}{v_i} \tag{9}$$

In order to get reliable simulation results, it is of great importance to assign the parameters of model with practical values. Generally, in the design of critical facilities, the performance under peak passenger flow is a vital indicator. Based on field data obtained in peak-15-minute of morning

Figure 5: Illustration of local route algorithm.

Figure 6: The service time of ticket gate based on field survey.

and evening rush hour, passengers' arriving rate at the gate area is subject to Poisson distribution (Equation (10)). The average number of passengers is 40 per minute. The desired speed ranges from 0.8 m/s to 1.5 m/s.

$$P(X = k) = \frac{\lambda^k}{k!} \bullet \exp(-\lambda), \quad k = 0, 1, \cdots \tag{10}$$

where X is the arrival interval, P is the probability, and λ is a parameter.

The value of service time t_0 in (6) can be measured by the interval between two passengers entering or leaving a certain ticket gate. Some investigations are carried out in subway stations at morning peak on weekdays. There is heavy passenger traffic during these periods and the passengers are always in a rush to go to work. In the investigation, we recorded the time interval between passengers leaving the end of the gate (point B_i in Figure 5) and the results are shown in Figure 6. It is observed that the service time for a pedestrian obeys a positive skewness distribution. It ranges from 0.8 s to 3.7 s and the mean value is 2.0 s. So the value of t_0 in (6) can be regard as 2 seconds.

The time for a passenger passing through the gate (from point A_i to B_i in Figure 5) is also observed in survey. The results are shown in Figure 7. More than 80% passengers can go through A_iB_i within 1.5 s ~ 2.9 s and the average is 2.4 s. The length of a gate is 1.4m. According to this, the average speed of a passenger passing through the gate can be obtained. As shown in Figure 7(a), the distribution of passing speed presents a normal distribution with an average of 0.65 m/s. Interestingly, there is a long tail of the distribution of the passing time (Figure 7(a)), and it disappears by transforming to speed (Figure 7(b)).

In terms of time perception, the passengers in a subway station can be summarized into three types. The first one is adventurous. They are active and more annoyed with time-waste of standing in a long queue than taking detour for a faster pass. So, their VOT of waiting time is greater. Indeed, commuters in morning peak and passengers who are pressed for time to catch a train or a flight are usually adventurous. In addition, passengers who have higher requirements for a comfortable walking environment are more willing to choose a far path to avoid crowd; they are also adventurous. The second type is the conservative, such as the elderly. Because of their difficulty in moving and other reasons, they prefer a path with shorter walking distance and without bypass. In their views, waiting is much more convenient than walking around. In this case, the VOT of walking time is 1.2 and of waiting time is 0.8 [48]. For some mild passengers, there is no preference of waiting and walking and both could be interpreted as "normal" time. Their perceived time is equivalent to the real time and the VOT is 1. The perceived weights in (2) can be valued as (11). These values are also referred to simulation experiments. It is the best scheme to keep the simulation results consistent with actual situation.

$$\begin{aligned}
&\omega_i^N = 1.2, \\
&\omega_i^L = 0.8, \\
&\qquad \text{if temperament is adventurous} \\
&\omega_i^N = 0.8, \\
&\omega_i^L = 1.2, \\
&\qquad \text{if temperament is conserved} \\
&\omega_i^N = 1.0, \\
&\omega_i^L = 1.0, \\
&\qquad \text{if temperament is mild}
\end{aligned} \tag{11}$$

Figure 7: (a) The time of passing through a gate based on field survey and (b) the calculated passing speed.

Figure 8: The feeding time based on field survey.

To pass through the ticket gate, a special activity must be performed—to check the card. Due to individual habit and the familiarity with subway, the card feeding time of each passenger would be different. In most cases, scanning time ranges from 0.5 s to 2.0 s and the average value is 1.1s, as shown in Figure 8. Occasionally, some greater feeding time can be observed because of a failure to prepare the smart card in advance and improper operation. The maximum value we observed during rush hour is 7.38 s.

The movement of passengers in subway stations and the situations of passing through the ticket gates are also recorded in field survey; the details will be mentioned in the following sections.

3.2. Multistage Route Choice Scheme. Local path selection is a dynamic process. The volume of passengers at each gate is time-varying and the utility value of each local path is also changing. When a pedestrian realizes that the utility value of his original choice obviously increased, or that another path is obviously superior to the original one, he will reevaluate the utility of each path and may change his choice. To solve the problem of reselection, some studies updated the selection choice at each time step [8]. However, this leads to a ping–pong effect [9]. This drawback can be corrected by using inertial system and relaxation processes. With the inertial system, a new selection will be adopted only when it gains a certain increment in contrast to the old selection [7]. With relaxation processes, the selection updates in a given time interval such as 10 seconds [14, 16]. These methods can achieve good results under certain conditions. However, in a subway system, it is difficult to determine an appropriate threshold for the inertial system and a time interval of reselection for the time-based relaxation processes. Fortunately, according to field studies, the selection process of passing through ticket gates can be abstracted into three stages (Figure 9). Firstly, a pedestrian generally begins to consider which gate is suitable and make a decision in front of the gates with a distance of 3.0 m. Then he moves towards the target gate and always pays attention to the surroundings. In most cases, if necessary, a selection change would be made in front of the gates with a distance of 1.7 m. Next, when he is close to the gate and prepares to check the card, in one case, he may change his choice for the third time. The case is that the passenger in front of him occupancies the gate for a long time and the next gate is unoccupied. The location for the third choice is set in front of the gates at a distance of 1.0m.

Unlike the first choice, as the pedestrian is considerable close to the gates when he makes the second-time and the third-time route choices, he would pay more attention to the distance between his current position and the gate (i.e., OA_j). So the estimated walking time can be simplified to (12). What is more, at that time, the estimations on distance and population size are relatively accurate. He would have more confidence in his judgment and will choose the fastest path, as indicated in (13).

$$V_{i,j}^{L} = \frac{L_{i,j}^{1\,\prime}}{v_i} \tag{12}$$

$$\begin{aligned} &\text{Optimal local path for ped } i \\ &= \left\{ Local\ Path_j \mid V_{i,j} = \min\left(V_{i,1}, V_{i,2}, \cdots V_{i,M}\right) \right\} \end{aligned} \tag{13}$$

As a passenger arrives at the gate, he will stop to press card and then pass through. When a passenger is scanning card,

Figure 9: The locations to make the multistage route choices.

Table 1: Algorithm of local route planning.

Input	(a) A set of local path, J (b) Preference of pedestrian i, $\omega_{i,j}^{N}$ and $\omega_{i,j}^{L}$ (c) Current speed v_i and position (x_i, y_i) of pedestrian i at time t
Output	A suitable local path for pedestrian i at time t
1	**For each** local path j in J, **do**
2	...estimate total walking distance $\sum L_{i,j}^{m\,\prime}$ by Equations ((4), (5)). (when pedestrian i is closed to the gates, $\sum L_{i,j}^{m\,\prime}$ can be simplified to $L_{i,j}^{1\,\prime}$ in Equation (12))
3	.....calculate walking time $V_{i,j}^{L}$ by Equation (3)
4	...estimate the number of passengers queueing $N_{i,j}^{\prime}$ at local path j by Equation (7)
5	.....calculate waiting time $V_{i,j}^{N}$ by Equation (6)
6	...calculate the estimated passing time of path j by Equation (2)
7	**End for**
8	**If** pedestrian i is closed enough to the ticket gates, **then**
9	...pass through the local path with minimum estimated passing time by Equation (13)
10	**else** calculate the probability $P_{i,j}$ of pedestrian i choose local path j by Equation (8)
11	...choose a suitable local path for pedestrian i based on $P_{i,j}$ and a random number
12	**End if**

the front edge of his body is almost tangent to the entrance of the gate. So the position of pressing card is set 0.25m ahead each gate, as shown in Figure 9.

3.3. Results of Local Route Choice. In order to test the proposed LRP model (the algorithm is summarized in Table 1), two experiments are carried out with the typical scenarios (shown in Figure 4). The ratio of pedestrians with different preferences is assumed as 1:1:1. The simulation lasts for 5 minutes with 200 passengers. In addition, the actual passenger flows of each gate in the two scenarios are also observed in Beijing Subway at peak hours. As shown in Figure 10, it indicates similar passenger distributions at each gate in field investigations and simulation results. Specifically, in the symmetric scenario, most passengers go through the three gates in the middle, which are the shortest paths. While there is less passenger flow of the farthest gates 1 and 5, all the 200 passengers continued to pass through the gates from 12 s to 342 s and the average service level of the gates is 36 person/min. Similarly, in the asymmetric scenario, the

Figure 10: Comparison of simulation results and survey data under symmetric layout (left) and asymmetric layout (right).

Figure 11: Measurement positions and travel time.

gates with the shortest distances (gate 4 and gate 5) have the largest passenger flows, accounting for 70%. Due to the long distance, the number of passengers passed through gate 1 and gate 2 is small; especially gate 1, only 4 persons passed. All passengers passed through the gates within 10 s to 343 s.

As shown in Figure 10, in the asymmetric scenario, the passenger flow of each gate exhibits a more nonuniform distribution. To gain an insight into the distribution of passengers with different preference, the simulation results of the asymmetric scenario is a good case to illustrate this issue. As shown in Table 2, the distribution of the adventurous is obviously different from the others. For the conserved and the mild, more than 40 percentage of the pedestrian volume pass through the nearest gate 5, and the total number of pedestrians passing through from the two nearest paths (gate 4 and 5) accounts for more than 70%. In contrast, most of the adventurous pass through gate 3 and 4, rather than the nearest gate 5. This is thanks to the fact that the nearest gate 5 is always occupied by the conserved and the mild. As a result, in order to avoid congestion, the adventurous have to pass through the farther gates. In addition, there are a few of adventurous pedestrians pass through gate 1, the farthest path. However, the conserved and the mild almost never choose gate 1. Therefore, in the condition of a large number of passengers passing through ticket gates, the adventurous would make an important contribution to the balance of facilities utilization.

3.4. Passing Time. To clarify the effects of passenger preference on local route decision-making, we set four positions to record the travel time for each pedestrian during simulation. As shown in Figure 11, the first position is the origin point. The second is 0.5-metre ahead to the gates. The third position is at the front edge of gates, where passengers are just walking into the gates. The last position is the destination of path. Then, four periods of time could be defined. Specifically, waiting time (t_2) is the period for a passenger walking from position 2 to position 3. It includes the time of walking,

Table 2: Results of local route choice for different passengers.

Temperament	gate1	gate 2	gate 3	gate 4	gate 5	Total
adventurous	4%	12%	28%	31%	24%	100% / 67 p
conserved	1%	9%	17%	31%	41%	100% / 70 p
mild	0%	5%	21%	32%	43%	100% / 63 p
Total	2%	9%	22%	32%	36%	100% / 200 p

Figure 12: The passing times for different passengers.

scanning card, and queuing up. "Prepassing walking time" (t_1) is the time taken to reach position 2 from the origin, and "postpassing walking time" (t_3) is the time spent from position 3 to the destination. The total time spent in the whole journey from origin to destination is defined as t.

As the expected speed and scan-card time of different pedestrians follow the same distribution, the walking distances and queuing time of pedestrians can be compared using the four time periods. In the same way, take the results of the asymmetric scenario for example. As shown in Figure 12, the conserved pedestrians who prefer to wait at a congested gate spend more time on waiting and less time on walking. And for the pedestrians avoiding congestion, the results are completely the opposite. For the mild, the time they spend and the distance they traveled at each stage are always at the middle level. In particular, the adventurous

Figure 13: Four simulation cases with different choice preferences under symmetric layout (left) and asymmetric layout (right).

Table 3: The values of MD for different passengers.

MD	adventurous	conserved	mild	Total
symmetric layout	4.0	5.6	3.0	3.6
asymmetric layout	2.8	4.8	3.6	2.8

passengers have the longest walking time (7.86 s before passing and 6.73 s after passing) and the shortest waiting time (1.86 s). This is in consistent with the hypothesis that they prefer to farther path to avoid queuing. On the contrary, the conserved passengers have the longest waiting time (1.94 s) but get to the destination faster by walking the shortest distance (total time is 15.26 s). Although the adventurous wait 0.08s less time than the conserved, they walk for 1.27s more than the conserved. As a consequence, the adventurous spend 0.90 s on the whole journey more than the conserved on average. This is a kind of "fast is slow" phenomenon. With the given population size and passenger's composition, from an individual's perspective, it seems that waiting and passing through the near paths is the most time-saving strategy.

3.5. Individual Preference. The three kinds of personality in this paper actually map different choice preferences. In order to further investigate the differences among them, four simulation cases are established. In the first three cases, all pedestrians have the same character. In this way, the performance of a kind of passengers can be revealed solely without interference from other types of passengers. As a comparison, each pedestrian in Case 4 would have one of the three choice preferences randomly, while the passenger volume stays the same. To highlight the impact of preferences, the passenger load in the four cases is triple as much as the normal situation. The passenger flow passed through each gate is shown in Figure 13. In the four cases of the symmetric scenario, there are small passenger flow of the two marginal gates (gate 1 and 5). Meanwhile, the adventurous display a better balance at the three middle gates and the mild achieve a suboptimal balance, whereas the passenger size of the conserved pass through the middle gate 3 is significantly higher than other cases. In the asymmetric scenario, Case 2 (only the conserved) and Case 3 (only the mild) have similar results: the shorter distance a path is, the more passengers pass through. However, Case 1 (only the adventurous) has a different performance: the passenger population of each gate is much better balanced. Except for the farthest gate 1, the proportions of the adventurous pass through each gate are almost the same.

To evaluate the passenger distribution, the mean deviation (MD, Equation (14)) is introduced as a coefficient of uniformity. The evaluation results are shown in Table 3. A larger value of MD means a more uneven distribution of passengers at each gate and a poorer utilization of the facilities. For instance, in the symmetric scenario, there is a seriously nonuniform distribution of the conserved passengers with the biggest value of MD (5.6). In the asymmetric scenario, the MD value of the adventurous is the smallest and the facilities

Figure 14: The survey data and simulation results under symmetric layout (left) and asymmetric layout (right).

are made best use in this case. Although the distributions of the mild and the conserved are similar, the mild present a better balance than the conserved. Actually, the MD values of the conserved are the biggest in the both scenarios and they are not conducive to make full utilization of facilities.

Interestingly, with mixed choice preferences, Case 4 is more in line with the practical condition. Both in the symmetric and asymmetric scenarios, Case 4 could achieve well balanced distributions. Furthermore, by a comparison with the simulation results in Section 3.3 (Figure 10), it can be found that, with the increased population size, the distribution of passenger flow of each gate is more balanced, and, as a result, the facility utilization is improved.

$$\mathrm{MD} = \frac{1}{N}\sum_{j=1}^{M}\left|x_j - \overline{x}\right| \tag{14}$$

where $(x_1, \ldots x_j, \ldots, x_M)$ is the proportion of passengers passing through each gate obtained in an experiment. $\overline{x}$ is the average value.

4. Simulation Experiment

In this section, some experiments are carried out to show the validity and stability of the model proposed in this paper. The techniques used to validate artificial pedestrian behaviours can be identified as three main streams [49]: the pedestrian dynamics descriptors, such as the fundamental diagram; the real data to validate the output of the models or simulation systems; and the visual realism and the way a human observer perceives in a simulation. Due to the fact that the main contributions of this paper focus on the mesolevel and macrolevel, we verified our model with the latter two techniques.

4.1. Simulation of LRP Model. As the core content of the layered navigation algorithm, the performance of the local route planning model determines the practical value of the navigation algorithm. As mentioned in the part of introduction, there are three kinds of alternative methods of node selection behaviour. They are based on utility, probability, and Logit model, respectively. Among each kind of method, a typical one with good performance is selected to compare with our LRP model and the field data. The compared methods were clearly stated in the literature and can be reproduced. Compared with the above models, the LRP model proposed in this paper makes further consideration of pedestrians' preferences, the process and motivation to make choice, and the uncertainties underlying in estimation and selection.

With the two typical layout scenarios of ticket gates, the simulation results are shown in Figure 14. In each experiment, the passenger size is the same as the survey. It can be seen that the results of the LRP model in this paper have better performance than the other methods, especially in the symmetric scenario. The simulation results can be evaluated by the mean relative error (MRE), expressed as Equation (15). The errors of different methods are indicated in Table 4. With the least values of MRE in both typical scenarios, the LRP model in this research is the best method to describe the node selection behaviour of ticket gates. By the LRP model

Table 4: The values of MRE by different algorithms.

MRE	This Research	Shuaib, M. M. 2018 [7]	Li, Y. et al. 2017 [16]	Zheng, X. et al. 2015 [11]
symmetric layout	0.33	0.63	0.63	0.51
asymmetric layout	0.29	0.38	0.43	0.35

Figure 15: A screenshot of the simulation process.

we proposed, the difference between the simulation results and the field data is reduced.

$$\mathrm{MRE} = \frac{1}{N}\sum_{j=1}^{N}\frac{\left|x_j - x_j^0\right|}{x_j^0} \tag{15}$$

where $(x_1, \ldots x_j, \ldots, x_N)$ is the proportion of passengers passing through each gate obtained by simulation. $(x_1^0, \ldots, x_j^0, \ldots, x_N^0)$ is the proportion of the field data.

4.2. Simulation of Layered Navigation Model. In the layered navigation algorithm of this paper, the global path can be modified by the local route planning in real time according to the dynamic environment. It performs well in simulating the self-optimizing path choice behaviour of passengers in real world. Firstly, in order to illustrate the optimization function of the LRP model in the layered navigation algorithm, two experiments are carried out to simulate the movements of passengers at the hall in a subway station. In the first experiment, agents are only guided by the global route. While in the other experiment, the local route planning can be activated according to dynamic environment.

Take Qianmen Station on Line 8 of the Beijing Subway as a case. Four groups of passengers are loaded into each experiment. Passengers could enter the station from the upper-left and the lower-right entrances. Their arrival rate is assumed to follow a Poisson distribution with an average of 50 persons per minute. The passengers getting off a train will leave from the two exits located in the upper-right and the lower-left corner of the station. Alighting passengers show a pulse distribution as the train arrives. The trains would arrive at an interval of 2 minutes. There are sixty alighting passengers who would continue to reach the ticket gates in one minute.

The experiments are carried out by the simulation tool we developed. According to the framework shown in Figure 3, the static global routes for each passenger group are firstly generated by an "initialization route" module. They are shown as the red polylines in Figure 15. Due to the similar activity planning of pedestrians in a subway station, it is reasonable to make the same global route for the pedestrians who have the same OD pair. In particular, the local route areas shown in Figure 5 should be set for the places needing local route choice. For example, when a pedestrian gets to the ticket gate, the local route plan will be activated. Figure 15 shows a screenshot after the simulation running for 54 seconds. The red ellipses represent agents.

The level of service (LOS) is an important criterion to evaluate a metro station. LOS is introduced by Fruin [50] to assess pedestrian facilities for the first time. Based on that, *Transit Capacity and Quality of Service Manual* takes the comfort and convenience of pedestrian into account and put forward a method to assessment the LOS, as shown in Table 5. By the "cluster display mode" of our simulation tool, the LOS of local area can be marked in the map during simulation. Figure 16 displays the screenshots of simulation. In Figure 16(a), passengers just walk along the global route and do not consider local congestion. This caused the crowdedness at the entrance of the ticket gates and escalators. At these places, the LOS is always at level E. In contrast, when the agents can respond to dynamic surroundings by the local route algorithm, the congestions at bottleneck locations are relieved effectively and the LOS is decreased in all local areas. In most cases, the LOS is not above level C. Level E only appears occasionally for a short time and could be adjusted by the self-organization of pedestrians quickly. In conclusion, the model just based on the global route generates unrealistic behaviour in the case of congestion. However, the model including the LRP allows describing the redistribution of the pedestrians over the gates.

In order to further demonstrate the effect of the hybrid navigation algorithm proposed in this paper, we also simulate the passenger movements in the above subway station by commercial software VISSIM. It is widely used in the research of pedestrian simulation. The settings of building

Table 5: Service level.

Service level	A	B	C	D	E	F
Personal space(m^2/p)	≥3.3	2.3-3.3	1.4-2.3	0.9-1.4	0.5-0.9	<0.5
Density (p/m^2)	≤0.3	0.3 - 0.4	0.4 - 0.7	0.7 - 1.1	1.1 -2.0	>2.0

Figure 16: Mapped LOS in a station (T=26s), (a) only global route planning and (b) two-level route planning.

Table 6: Comparison of local route simulation results.

Average value	Distance(m)	Travel time(s)	Speed (m/s)
VISSIM	19.171	53.449	0.359
the developed tool	27.891	30.275	0.922

environment and population size are the same as Figure 15. The experimental results of our tool and that of VISSIM are shown in Table 6. In our model, the local route planning based on the estimated time may increase the walking distance, but produce faster speed and less total travel time. In this respect, the model presented in this paper has better performances.

At the tactical level, our tool realizes a dynamic feedback and real-time planning, which could improve the utilization of facilities and reduce travel time. Passengers could choose the ticket gate rationally without crowding, as shown in Figure 17(a). However, although some commercial software has introduced local route planning into simulation algorithm, the effect on uniform use of facilities is not very ideal. Its route planning tends to be very mechanical and leads to distorted behaviour (Figure 17(b)).

5. Conclusion

We presented a novel approach to deal with the problem of route planning in dynamic environments. The method is based on a seamlessly transition between global planning and local planning. In order to generate a no-collision global route, we made a correction to the visibility graph method by expanding the obstacles to avoid the overlap of pedestrian's body with obstacles. We have further introduced a new and effective local route planning model based on estimated passing time. This approach results in smoother crowd movement and exhibits an agent's tendency to avoid congestion that is often observed in real crowds. The uncertainties existing in the process of node selection, such as the estimation of factors, the randomness of decision-making, and the subjective preferences of different passengers are fully integrated into the model. In its application to the selection of ticket gates in subway stations, the activity of card feeding is embedded. The whole process of selection and reselection is simplified into three stages and the differences of passengers' focuses during them are captured. Compared to previous navigation algorithms, it is demonstrated that our approach has better performances in multipath choices during trip. The agents in our simulation could produce faster speed and less travel time. Furthermore, our model is founded on cognitive science work on human locomotion, which can be combined with various classical methods for navigation in dynamic environments and open interesting perspectives for realistic simulation purposes.

In this paper, the route planning model is proposed based on the ticket gates in subway station. It can be extended

(a) (b)

Figure 17: A simulation snapshot by (a) our tool and (b) VISSIM.

to other similar scenarios of exit selection and multipath planning. In the future, the route planning model can be integrated with other strategic and operational methods to simulate the movement of pedestrians. Moreover, the route planning model will have potential to be applied to many other simulation cases, such as emergency evacuation and disaster response systems.

Data Availability

The empirical data used to support the findings of this study can be found in the section of "Model Application and Discussion". The "simulation results" data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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