Hindawi
Journal of Advanced Transportation
Volume 2019, Article ID 2380348, 20 pages
https://doi.org/10.1155/2019/2380348

Research Article

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

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Received 4 April 2019; Revised 19 May 2019; Accepted 12 June 2019; Published 20 August 2019

Academic Editor: Richard S. Tay

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

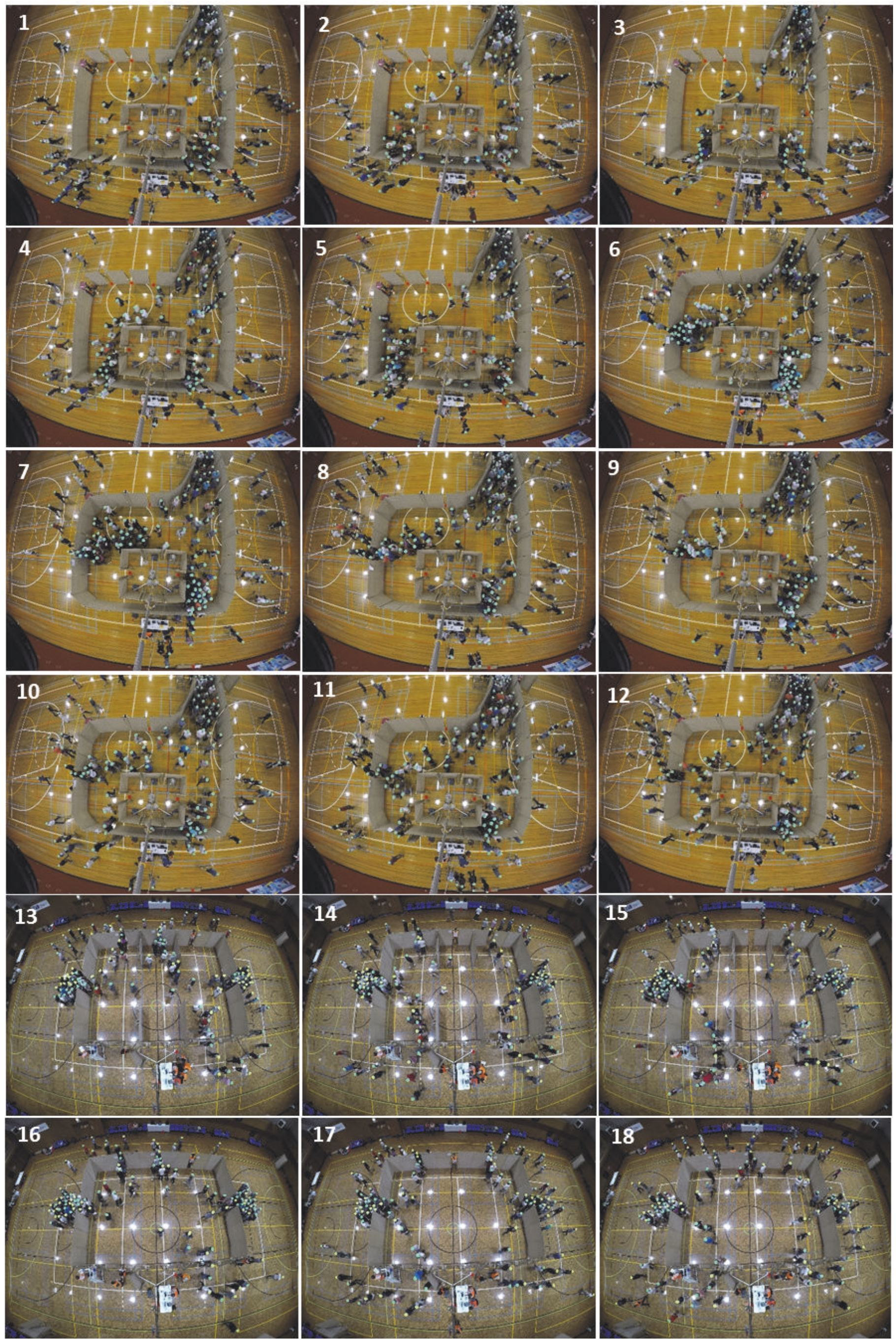
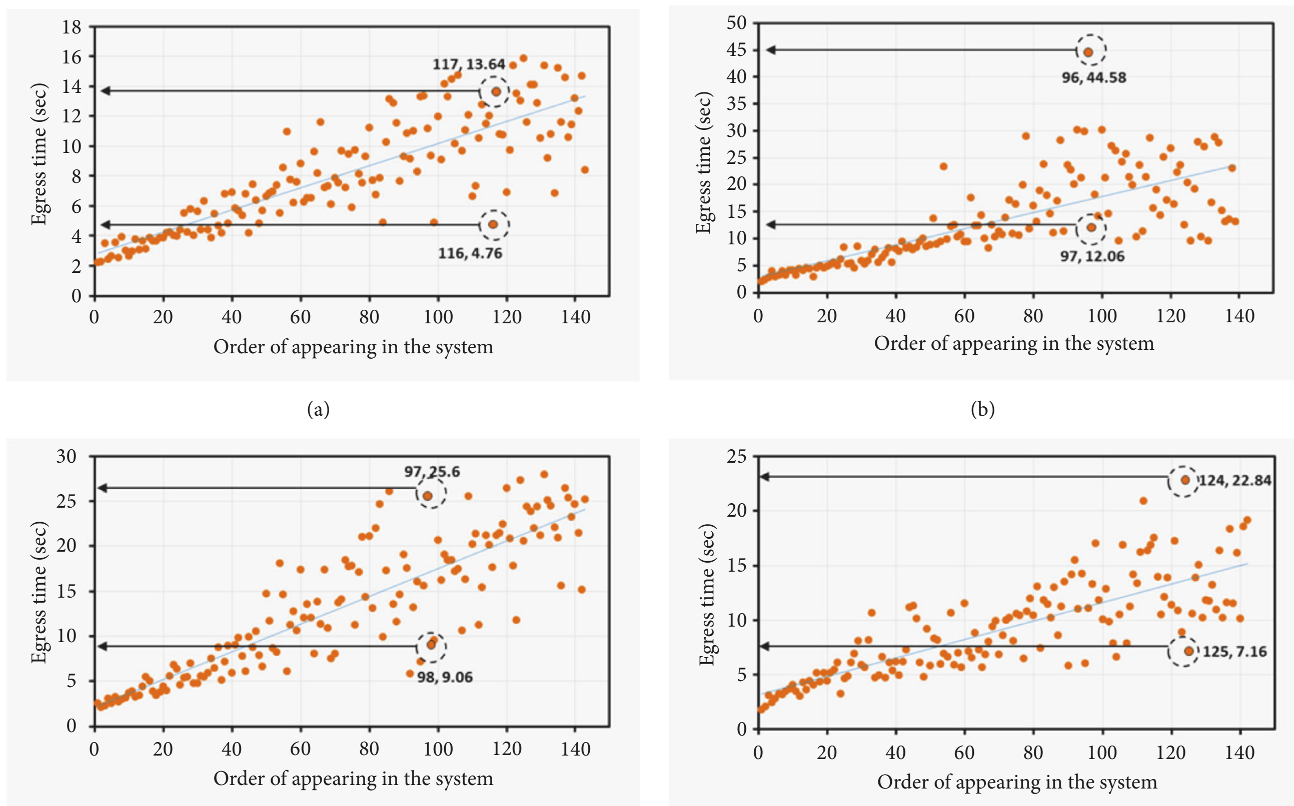


Figure 1: Still images from each experimental scenario. Subplots 1-12 represent the scenarios from the experiment performed in 2015 (with 145 participants) and subplots 13-18 represent the experimental scenarios performed in 2017 (with 114 participants). Within each set of experiments, each scenario 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



(a) (b) (c) (d)

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

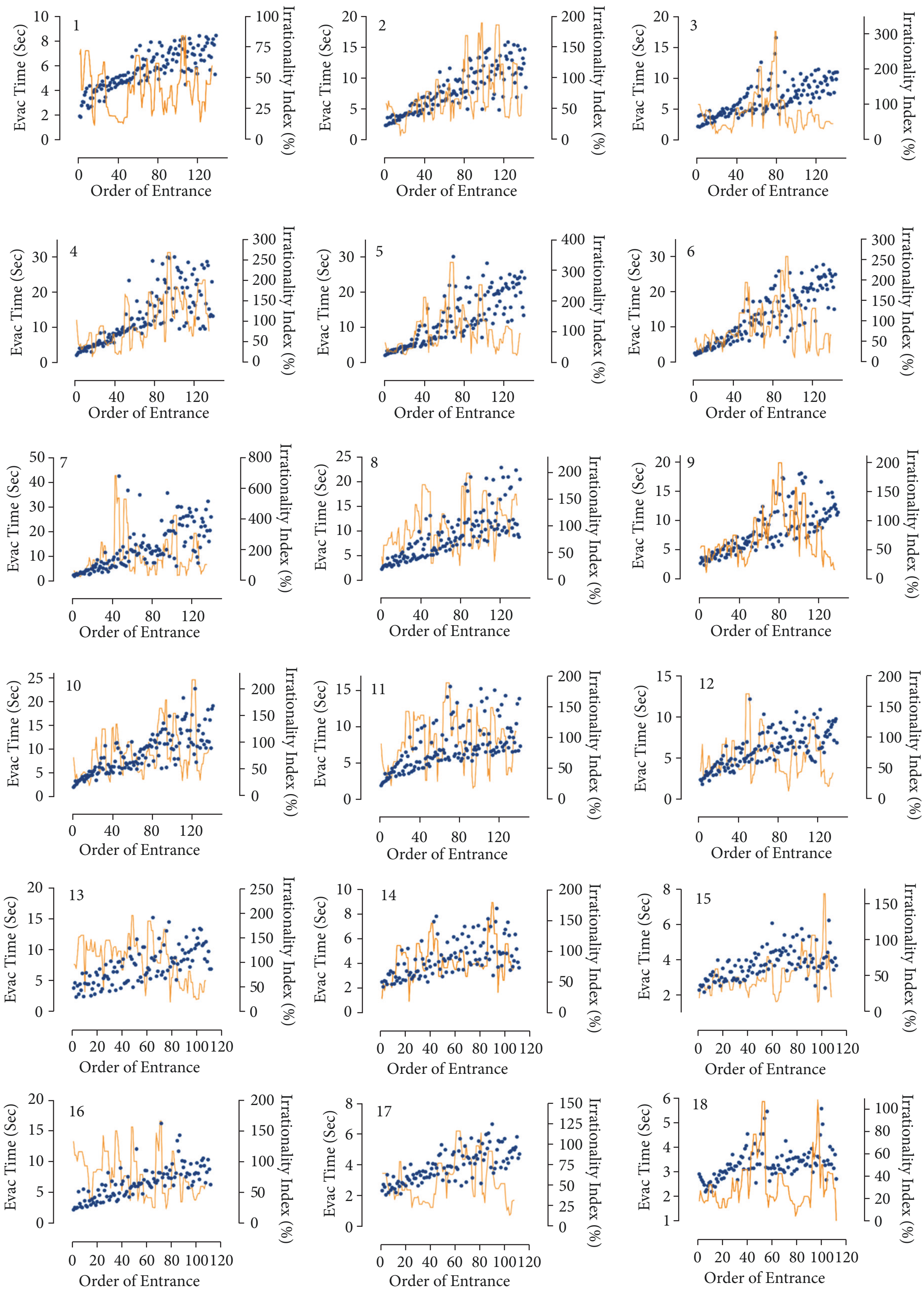


Figure 3: Scatterplots of the individual evacuation times for all 18 experimental scenarios, along with the "irrationality index" visualised at each point in time, shown by the orange fluctuating lines and represented by the right vertical axes of each plot.

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

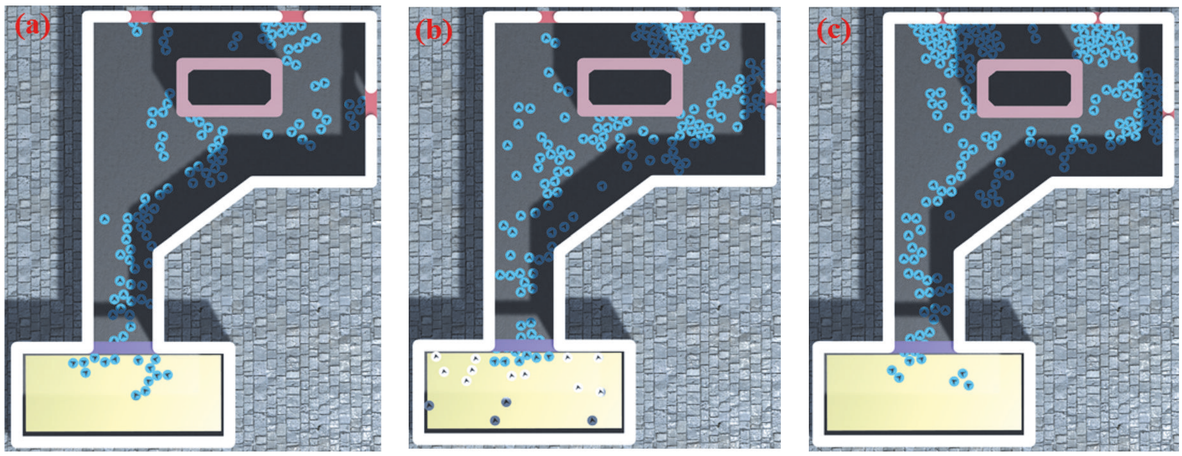
4.1. Simulated Experiments Setup. For the analyses of optimum behaviour from a system perspective, we computer-simulated a variety of systems (or evacuation setups) while varying the behavioural tendencies of simulated agents in terms of their exit decision-making behaviour. We devised two general physical 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.

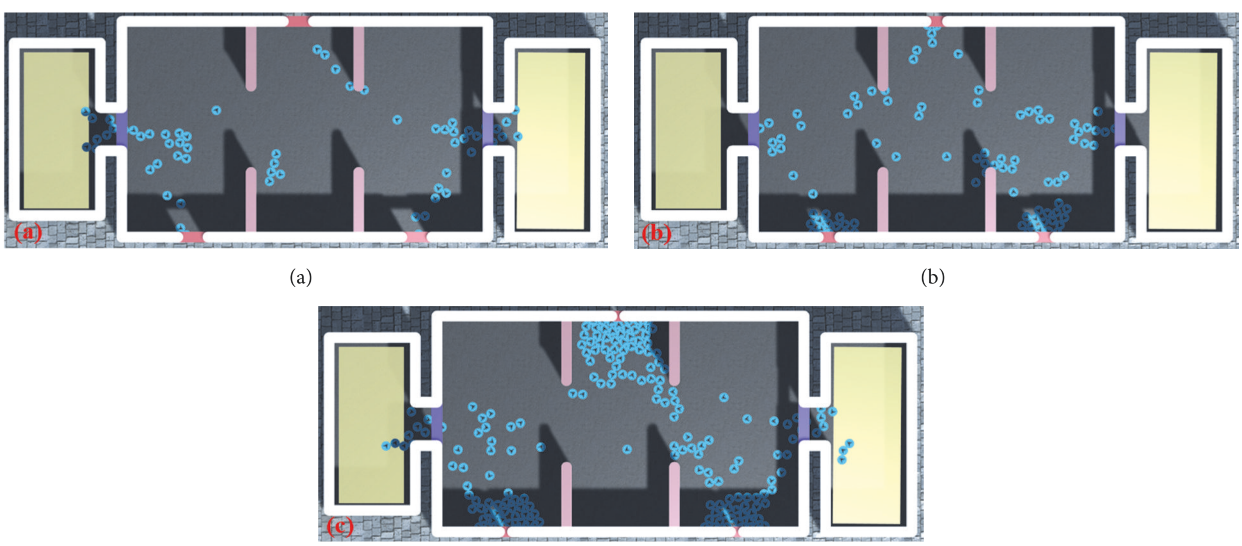
$(DIST)_{in}$ The spatial distance (in meters) from the position of agent n to the centre of exit i.

$(CONG)_{in}$ 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.



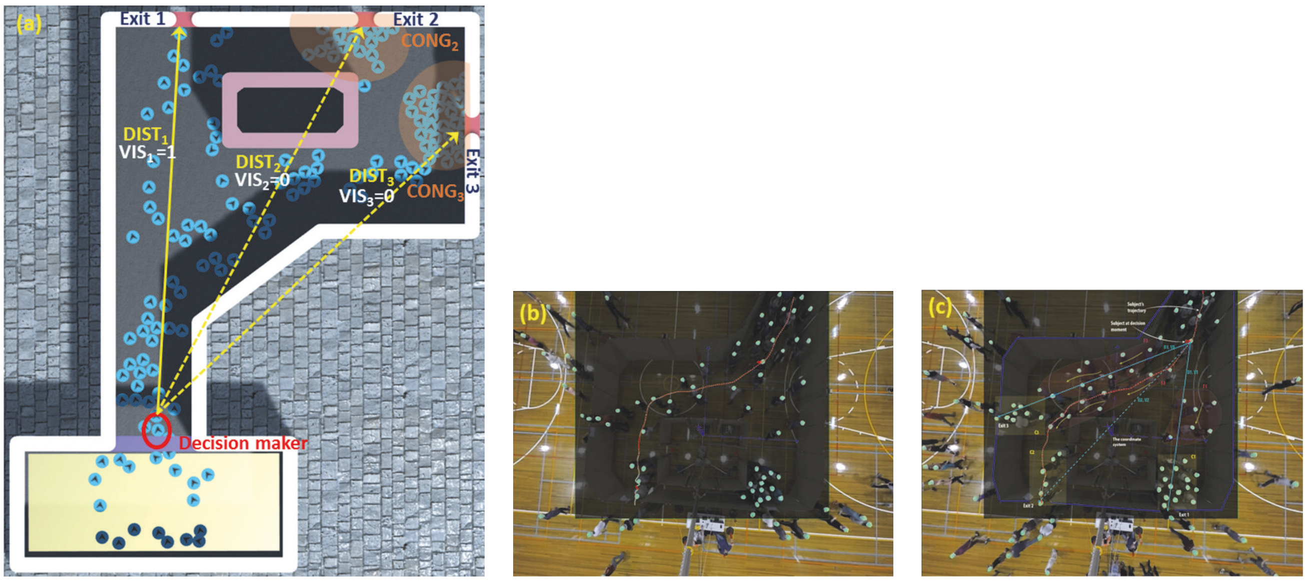
(a) (b) (c)

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.

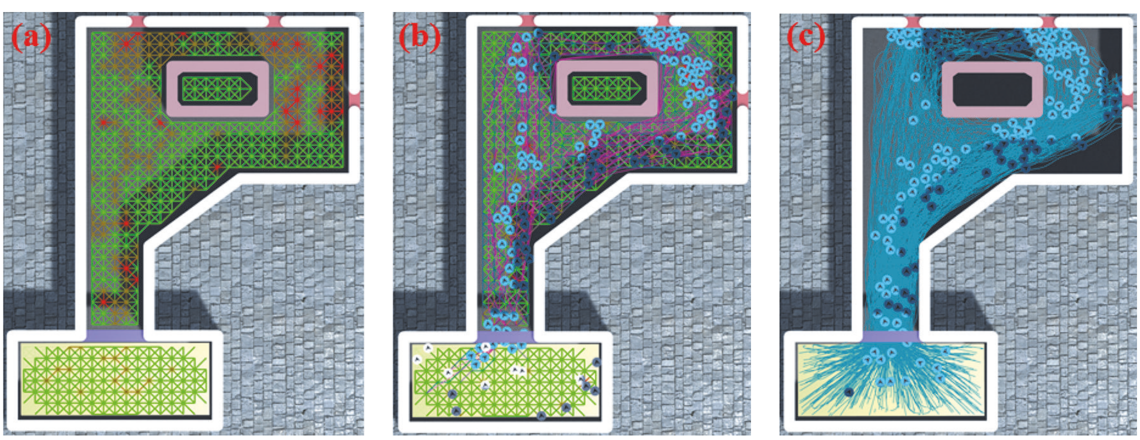
$(VIS)_{in}$ The visibility status of exit i from the position of agent n, equating 1 if visible and 0 otherwise.

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.

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

$$\begin{aligned} V_{in} = {} & \beta_1 (DIST)_{in} + \beta_2 (CONG)_{in} + \beta_3 (FLTOVIS)_{in} \\ & + \beta_4 (FLTOINVIS)_{in} + \beta_5 (VIS)_{in} \end{aligned} \quad (2)$$

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

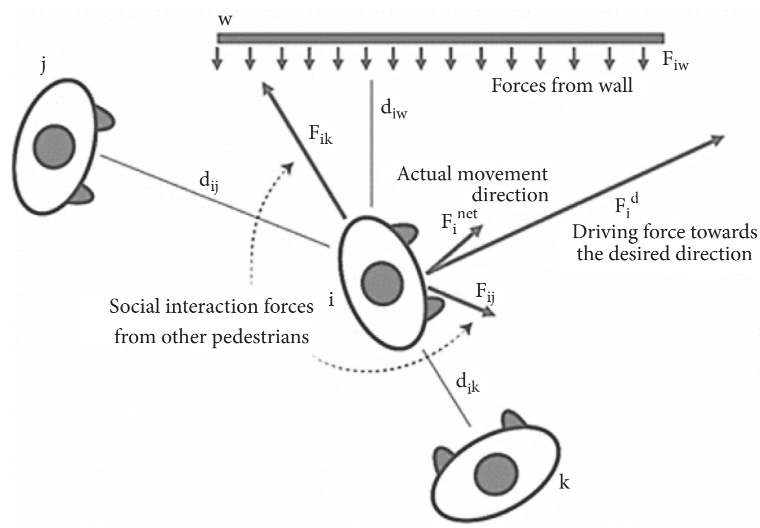


Figure 8: Visual illustration of the final modelling step of the simulation process, the step-taking model. This layer of simulation is a calibrated social-force module. The virtual forces from other agents and the walls as well as the driving force of the agent (determined by the local pathfinding algorithm 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

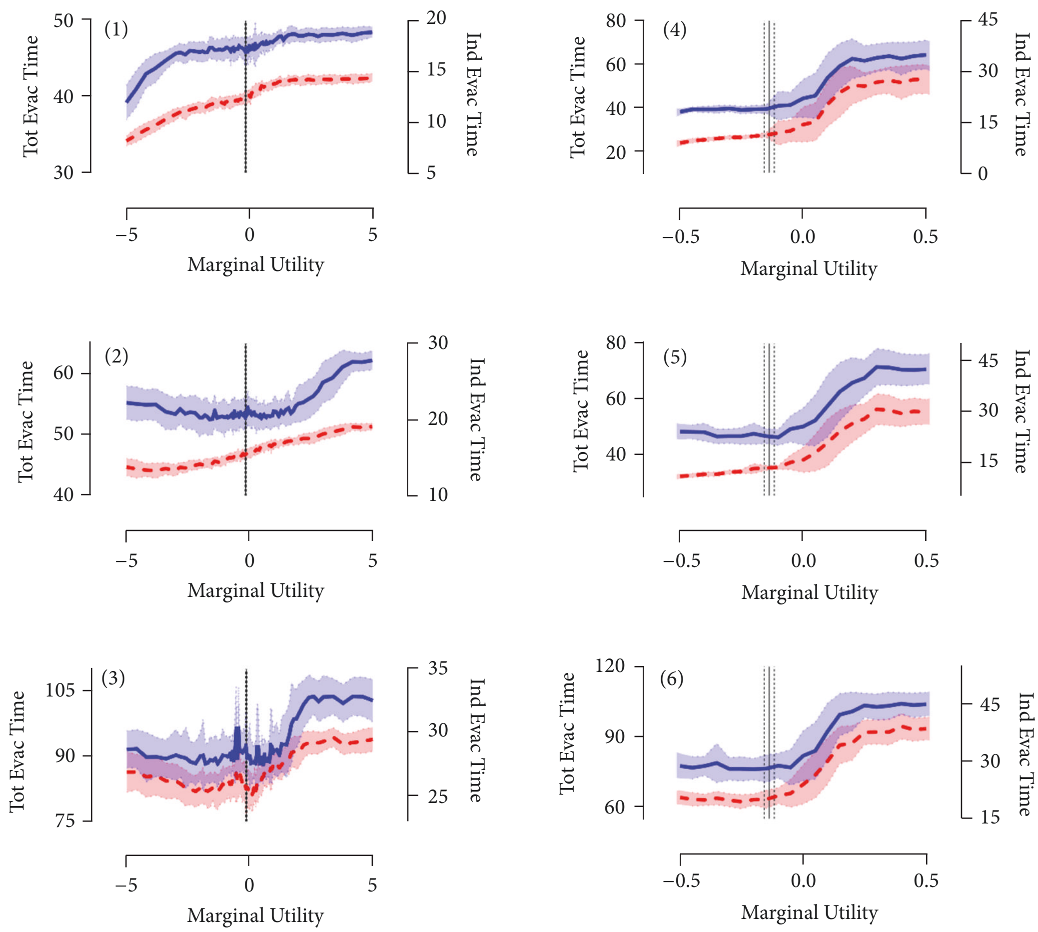


FIGURE 9: Variations of the simulated total evacuation times (blue solid lines; left vertical axis) and simulated average individual evacuation times (red dashed lines; right vertical axis) as a result of changes in the marginal utility of DIST attribute in exit decision-making of the simulated evacuees. 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

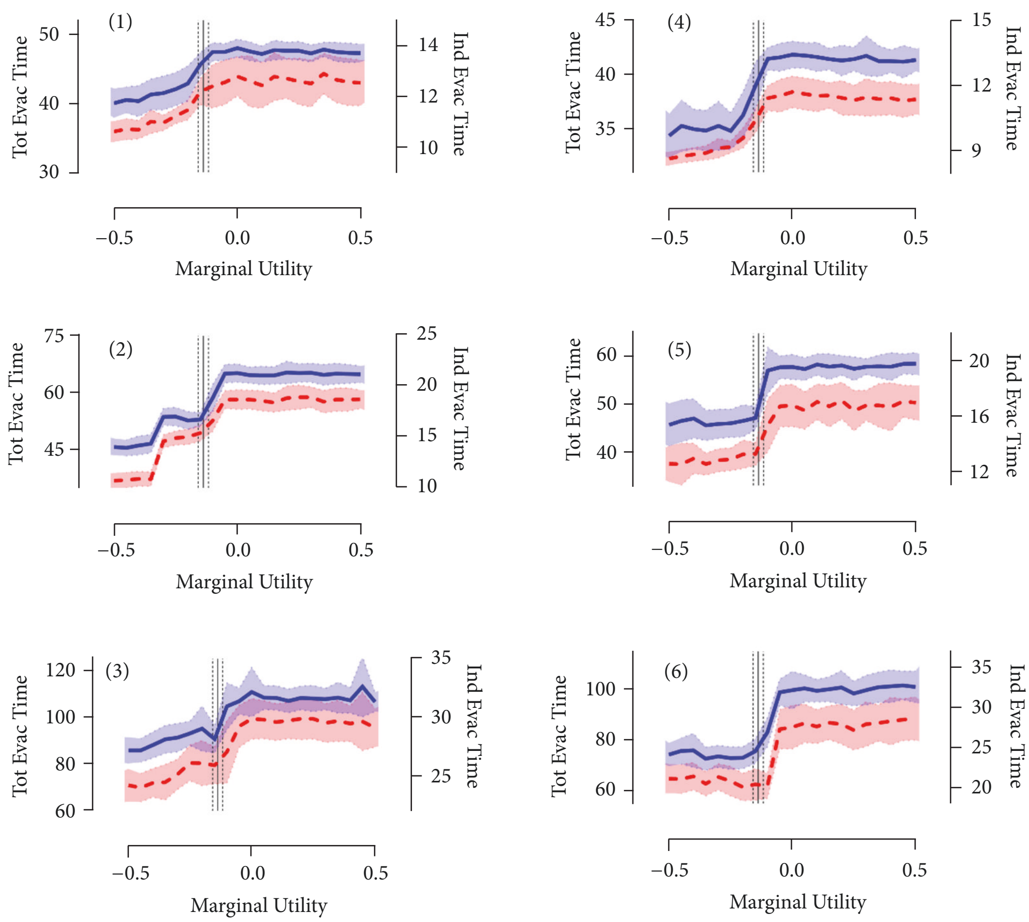


Figure 10: Variations of the simulated total evacuation times (blue solid lines; left vertical axis) and simulated average individual evacuation times (red dashed lines; right vertical axis) as a result of changes in the marginal utility of CONG attribute in exit decision-making of the simulated evacuees. 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

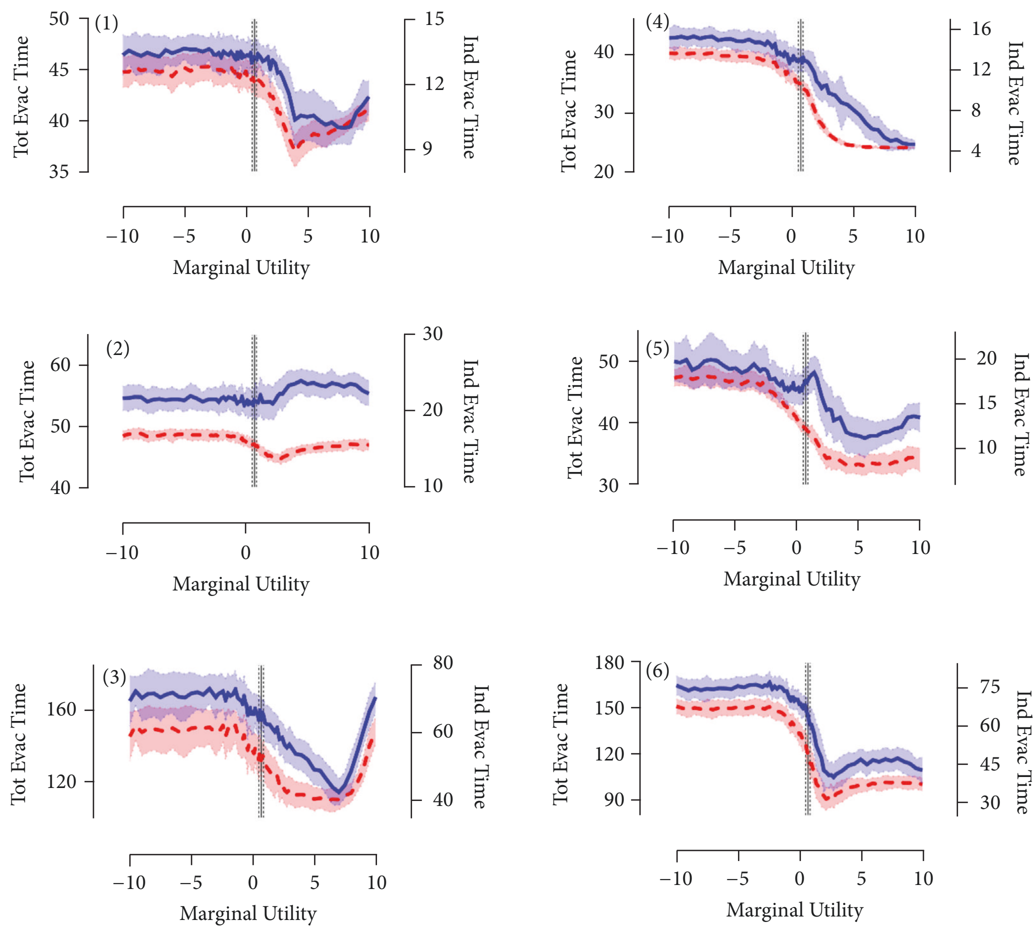


FIGURE 11: Variations of the simulated total evacuation times (blue solid lines; left vertical axis) and simulated average individual evacuation times (red dashed lines; right vertical axis) as a result of changes in the marginal utility of FLTOVIS attribute in exit decision-making of the simulated evacuees. 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

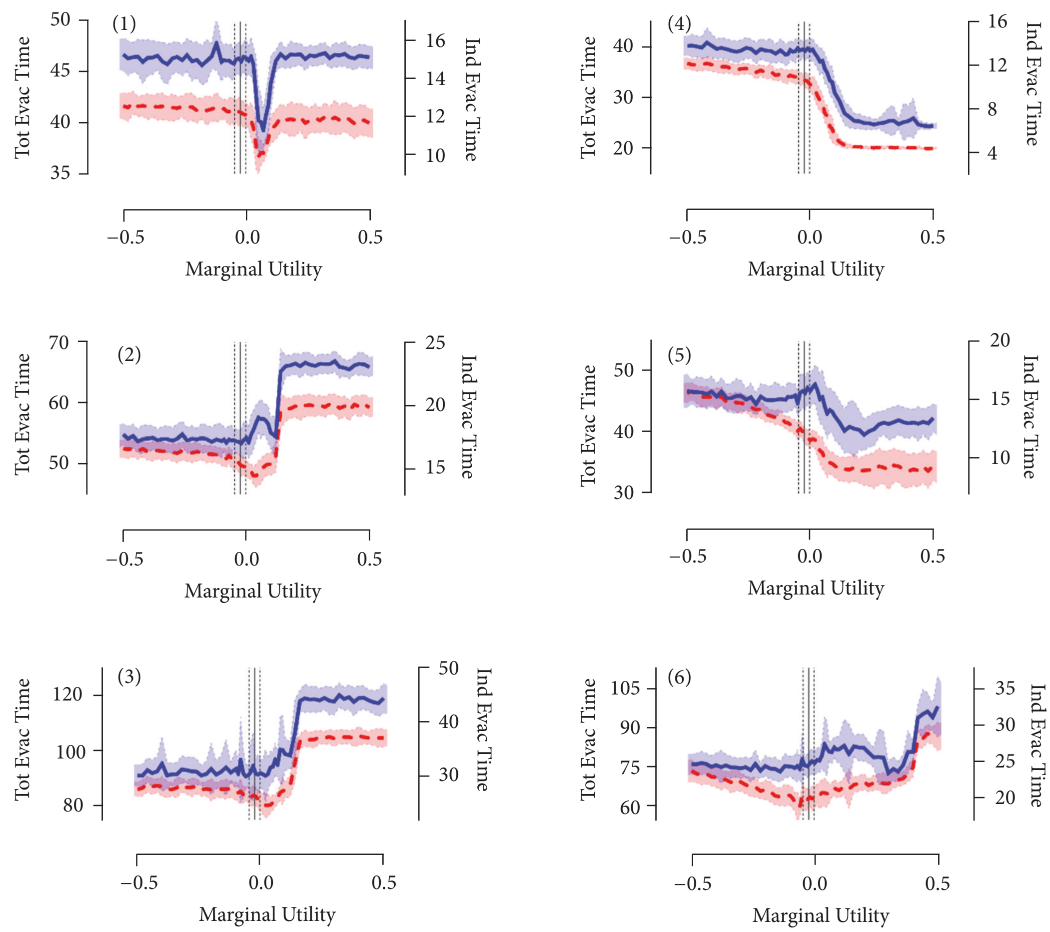


Figure 12: Variations of the simulated total evacuation times (blue solid lines; left vertical axis) and simulated average individual evacuation times (red dashed lines; right vertical axis) as a result of changes in the marginal utility of FLTOINVIS attribute in exit decision-making of the simulated 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

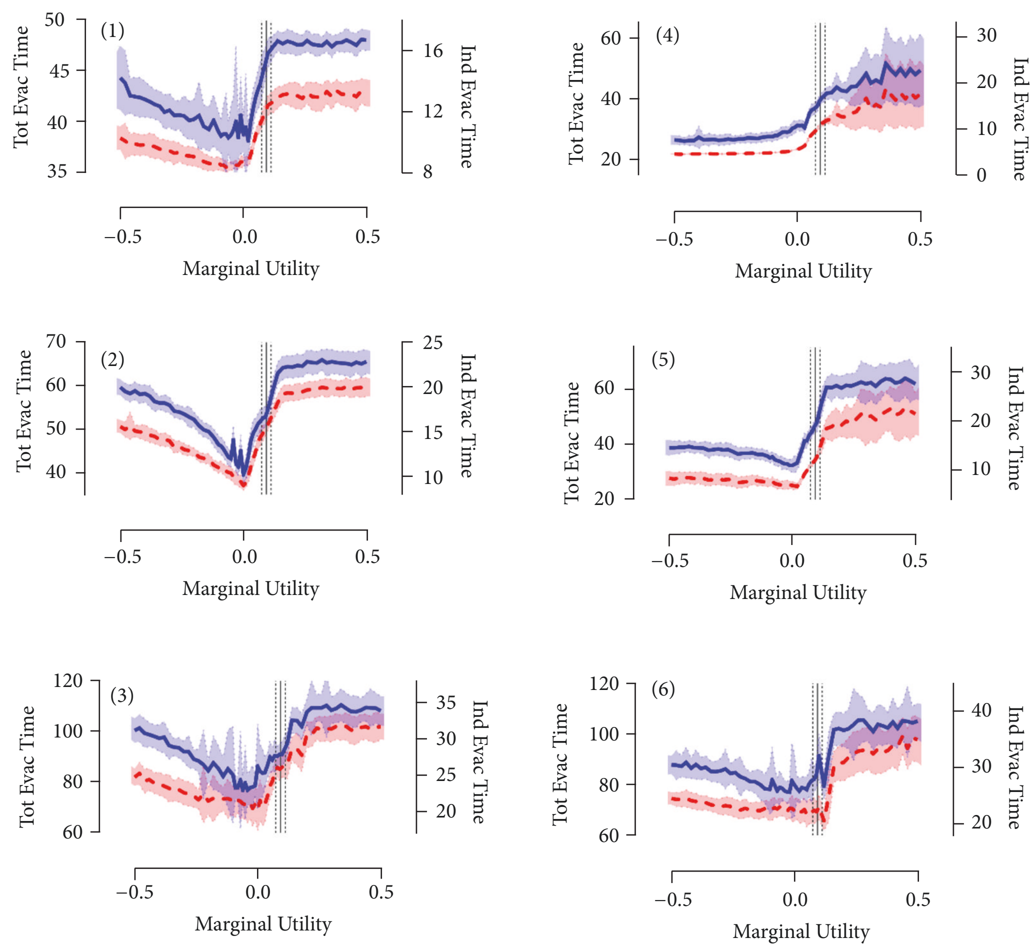


Figure 13: Variations of the simulated total evacuation times (blue solid lines; left vertical axis) and simulated average individual evacuation times (red dashed lines; right vertical axis) as a result of changes in the marginal utility of VIS attribute in exit decision-making of the simulated evacuees. 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.

Acknowledgments

This study was financially supported by the Discovery Project research grant DP160103291 awarded by the Australian Research Council.

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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