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Exploring occupant exit choices during fire drills and false alarm evacuations in a library

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ABSTRACT

Effective disaster management and public safety rely heavily on understanding human behaviour during evacuations. This study investigates 497 occupant exit choices in real-world evacuation scenarios including two evacuation drills and two false alarm evacuations in a university library building. These authentic settings offer a unique opportunity to examine real-world decision-making processes during evacuations. Employing a multinomial logit model, we quantitatively assess the impact of essential factors on human decision-making. Statistical analysis reveals that participants tend to choose the exits chosen by the majority, closer exits, exits indicated by staff, or exits they are familiar with. We found that participants on the ground floor showed a greater preference for familiar exits compared to those on other floors. Most importantly, we found that in fire drills the effect of crowding and familiarity on exit choices was reduced compared to false alarm evacuations. These findings underscore the critical implications for the conduct of drills and emphasise the importance of studying the contextual dependency of human behaviour during evacuations. Our work also contributes a novel exit choice dataset collected in a naturalistic setting and highlights the importance of the context in influencing pedestrian decision-making during evacuations.

1. Introduction

Evacuation, recognised as one of the most effective measures for safeguarding lives during disasters, has been extensively studied across diverse disciplines, from theoretical insights to practical applications (Trainor et al., 2013; Schadschneider et al., 2008; Tong & Bode, 2022). A profound comprehension of evacuation behaviour not only enhances our understanding of human decision-making during emergencies but also enables predictions of evacuation behaviour. Such insights are important for crowd management and safety assessments, especially in densely populated urban areas with high-rise structures (Ronchi & Nilsson, 2013; Ding et al., 2021).

Crowd behaviour during evacuations can be categorised into a hierarchical structure, consisting of strategic (highest), tactical (medium), and operational (lowest) levels (Davidich & Köster, 2012). At the strategic level, pedestrians make decisions regarding their trip before it begins, including selecting their destination and planning their reaction timing. At the operational level individuals continually make short-term movement decisions along their route in response to their immediate environment, such as manoeuvring around obstacles and other people. The tactical level describes exit choice as well as adaptation of exit choice (Haghani & Sarvi, 2024), which is the primary focus of this study.

Previous research has examined various factors influencing pedestrian exit choice in evacuations. These factors can be categorised as the characteristics of individuals and the properties of exits. Individual characteristics are the factors associated with an individual (e.g., age (Shi et al., 2022b; Bode & Codling, 2013; Lovreglio et al., 2016b), gender (Wang et al., 2024; Golshani et al., 2019; Shi et al., 2022b), and cultural background (Haghani & Sarvi, 2016; Lin et al., 2020b)), indicating that exit choice may depend on the characteristics of people. For instance, studies suggest that men tend to have higher levels of risk tolerance leading them to favour bolder actions during evacuations, perhaps due to a belief in their ability to navigate hazardous situations safely. Conversely, women typically lean towards risk aversion, prioritising safety over speed and consequently, they are more likely to choose exit routes that minimise potential danger (Shiwakoti et al., 2018). In

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contrast, exit properties encompass a range of characteristics linked to exits, including how far away they are from the current position of individuals (Duives & Mahmassani, 2012; Kinateder et al., 2018), how busy they are relative to other exits (Lovreglio et al., 2016a; Kinateder & Warren, 2021; Tong & Bode, 2023), their width (Haghani & Sarvi, 2019b; Cai et al., 2022), and signage features such as colour, shape and angle of interaction (Shi et al., 2022a; Kinateder et al., 2019; Kubota et al., 2024). In this study, we selected essential factors relevant to our dataset and provide detailed explanations about them in the literature review section.

The previous discussion highlights the varying factors potentially influencing pedestrian exit choice in evacuations. However, some studies operate under the assumption that individuals select routes based on simple rules to reduce cognitive effort (cognitive heuristics; (Gigerenzer & Gaissmaier, 2011)). For instance, many models assume people prefer the shortest route, and algorithms have been devised to find such paths, (e.g., Dijkstra's Algorithm (Ojekudo & Akpan, 2017) and a genetic algorithm (Ahn & Ramakrishna, 2002)). In addition, some other simple rules have been summarised for explaining pedestrian exit choice in a specific context such as the least-decision-load heuristic where pedestrians tend to choose the route with the least number of possible decision points (Jamshidi et al., 2020) and the least-angle heuristic where pedestrians tend to choose the path at an intersection which is most in line with the target direction (Hochmair & Frank, 2000). While these assumptions are usually used for optimising route selection in ideal scenarios, human behaviour often proves to be more complicated. Participants may, for example, choose to follow a crowd even if it leads to a route that isn't the closest (Kinateder et al., 2018). Therefore, some other studies focus on using models incorporating various factors to better interpret and predict human decision-making during evacuations. For instance, the logit model (Hensher & Greene, 2003), utilised to predict the probability of events based on independent variables, offers flexibility in quantitatively assessing the influence of specific factors. Consequently, it has been extensively employed in evacuation studies to model exit choice behaviour (Ren-Yong & Hai-Jun 2010; Haghani et al., 2015; Lovreglio et al., 2016a).

One of the main methods to calibrate and validate exit choice models uses data from controlled experiments. For example, Haghani & Sarvi (2017b) compared different types of mixed logit models based on stated and revealed exit choices of pedestrian crowd evacuees obtained from controlled experiments, revealing that factors such as spatial distance, congestion level, exit visibility, and flow size significantly influence evacuees' exit choices. Additionally, Kinateder & Warren (2021) established binary mixed models based on experi- mental data from virtual reality experiment to investigate how various factors (e.g., crowd majority, crowd size, and exit width) impact exit choice. Furthermore, Lovreglio et al. (2022) employed a multinomial logit model using data from virtual reality experiments, demonstrating that decisions are influenced by multiple factors, including social in- fluence, exit distance, smoke presence, and familiarity. However, one limitation of these experimental methods is their limited ecological validity (Falk & Heckman, 2009; Haghani, 2023). Pedestrian behavioural data is typically gathered within a specific context. Participants may alter their behaviour when aware of the artificial nature of the experiment, recognising that a real emergency is not imminent. This raises doubts about whether the collected data can accurately reflect pedestrian behaviour in real-life scenarios or be extended to different situations (Feng et al., 2021).

In this study, we investigate the factors influencing pedestrian exit choice in fire drills and false alarm evacuations in a university library. This unique resource closely mirrors real-world decision-making processes. We introduce a multinomial logit model to quantitatively assess how each factor and their interaction impact human decision-making, providing valuable insights into people's behaviour during emergencies.

2. Literature review

2.1. Distance

Distance is an essential factor influencing pedestrian exit choice. Two commonly employed heuristic approaches, the shortest path heuristic, assuming participants prefer the nearest exit (Ibrahim et al., 2022; Wang et al., 2011), and the quickest path heuristic (Sin et al., 2007; Hamacher & Tjandra, 2001), estimating the time taken to reach the exit based on both the distance to the exit and the anticipated congestion level, considers distance as one of the most important components. This preference for shorter routes is understandable, as participants strive to evacuate disaster zones swiftly. In terms of practice, the distance also plays an essential role in evacuation planning and building design guidelines, such as the regulation on travel distance to the emergency exit in Approved Document B, the building regulation in England covering fire safety matters within and around buildings.[1] However, in many instances, distance alone does not dictate exit choice, even though it might be of utmost importance. Research indicates that while route length plays a significant role, can only explaining over half of route choice decisions (Al-Widyan et al., 2017; Gim & Ko, 2017).

2.2. Crowd

In pedestrian dynamic models, it is often assumed that individuals tend to follow others (Low, 2000; Helbing et al., 2000). This tendency potentially leads to uneven exit usage and compromises evacuation efficiency (Haghani & Sarvi, 2019a) while some modelling work suggests that moderate levels of following behaviour can optimise evacuation systems and reduce evacuation times (Kirchner & Schadschneider, 2002). Conversely, certain studies propose that pedestrians exhibit behaviour contrary to following; they may actively avoid others when selecting exits (Liu et al., 2009; Zia & Ferscha, 2009; Haghani & Sarvi, 2017a). Empirical findings on how pedestrians respond to others' movements are varied. Some studies suggest that the direction favoured by the majority does not significantly impact exit choice in isolation but may become relevant when combined with other factors (Bode et al., 2014; Kinateder et al., 2018). Other studies indicate that pedestrians often spontaneously follow others, a tendency that may intensify under heightened stress levels (Moussaïd et al., 2016; Tong & Bode, 2021). In contrast, other work found that pedestrians may be more inclined to follow the minority, particularly under stressful or crowded conditions (Haghani & Sarvi, 2019c). The following the minority might be a strategy adopted by pedestrians to minimise their evacuation time (Lovreglio et al., 2016b; Haghani & Yazdani, 2024). Moreover, Tong & Bode (2023) attempt to explain the diverse findings by considering various contextual factors including spatial information, the size of crowds and the distribution of individuals across exits. In summary, where other evacuees are going is likely relevant for individual route choice but the specific mechanisms depend on the context.

2.3. Familiarity

Familiarity refers to pedestrians' spatial knowledge about the environment they are in, usually acquired through experience, and is widely acknowledged as a crucial factor influencing exit choice (Gwynne et al., 2019; Kinateder et al., 2018). Research consistently indicates that individuals are more likely to choose the exits they are familiar with (Shields & Boyce, 2000; Sime, 1985), even if they are not the closest ones (Kinateder et al., 2018), as they may lack preparedness to navigate

[1] Fire Safety: Approved Document B, Department for Levelling Up, Housing and Communities and Ministry of Housing, Communities and Local Government, Building regulation in England covering fire safety matters within and around buildings, published on December 7, 2010.

an unfamiliar route (Proulx, 2001). Some studies have shown that pedestrians tend to choose exits they have previously entered, suggesting a preference for familiar routes (Benthorn & Frantzich, 1999; Graham & Roberts, 2000). However, measuring spatial knowledge and familiarity is challenging, and researchers may have varying interpretations. The knowledge of pedestrians about the environment can be categorised as route knowledge and point-and-survey knowledge (Andresen et al., 2018). Route knowledge enables pedestrians to navigate between landmarks without an understanding of the overall spatial layout, while point-and-survey knowledge involves a more comprehensive understanding of spatial relationships. Some studies distinguish "building familiarity," referring to familiarity with the overall spatial layout, and "exit familiarity," focusing specifically on familiarity with exits and exit routes, which occupants may not necessarily be familiar with (Song et al., 2019). However, current research does not delve into the subtle differences between different types of spatial knowledge and familiarity. In experimental settings, occupants are typically assumed to have a high degree of familiarity with the building (Fu et al., 2024; Chen et al., 2020), while controlled experiments sometimes provide additional environmental information, such as maps, to manipulate levels of familiarity (Tong & Bode, 2023; Lin et al., 2020a).

2.4. Guidance

Guidance is a fundamental concept in evacuation procedures, encompassing various approaches developed to assist people in evacuating to safety. These approaches can be categorised into signage, leaders, auxiliary equipment, and evacuation guidance systems (Zhou et al., 2019).

Signage systems are extensively used in large structures like commercial office buildings, subway stations, and hotels, serving as crucial wayfinding tools. They offer general guidance, including pathfinding and exit directions, to occupants during normal circumstances. In emergencies, they provide safety instructions to evacuees who may be unfamiliar with the building layout (Galea et al., 2014). These signage systems can be categorised into static and dynamic signage (Filippidis et al., 2021). Static signage conveys fixed, passive information, while dynamic signage adjusts evacuation guidance based on factors such as occupant distribution and the evolving situation. The design elements of evacuation signs can significantly impact the evacuation process. For instance, larger signs improve the evacuation efficiency of participants by delivering better visibility of exit signs to evacuees (Ronchi et al., 2016; Jeon et al., 2019) and green exit signs are the most effective way to aid evacuees' recognition compared to other colours (Wong & Lo, 2007).

Leaders play a crucial role in evacuations, possessing the ability to influence the behaviour of others and comprising diverse types of individuals. One category of leaders comprises those with spatial knowledge about the environment and a willingness to aid others during evacuations, such as guides in complex buildings (Zhou et al., 2018). Another type of leader spontaneously emerges, such as individuals with stronger relationships in social networks (Ding & Sun, 2020), in a specific position in the group (Nagy et al., 2010) or exhibit superior stress management skills, even if they lack spatial knowledge (Zhou et al., 2019). During evacuations, the leader–follower dynamic is important, and leaders have a significant influence on crowd behaviour, especially in high-risk emergency scenarios (Low, 2000; Ding & Sun, 2020).

Regarding auxiliary equipment, various tools are employed to facilitate crowd evacuation. These include mobile devices, robots (Hara et al., 2019; Inoue et al., 2008), wireless sensor networks (Chen et al., 2015; Ma et al., 2020; Lopez-Carmona & Garcia, 2021) and laser aids (Liao & Shaw, 2013). In contrast, evacuation guidance systems use advanced technologies such as monitoring techniques, and artificial intelligence, in order to systematically offer occupants suitable evacuation routes and exits through visual, auditory, or tactile means (Zhao et al., 2022; Hajjem et al., 2017).

3. Material and methods

This section provides information about the building where the exit choice data was collected, and its occupancy (Section 3.1). Section 3.2 provides insights into the evacuation events while Section 3.3 details how the data was collected. Finally, the statistical methods are described in Section 3.4.

3.1. Building and occupancy

This study focuses on how people made evacuation exit decisions during fire drills and false alarms in the Massey Library Building at the Albany Campus in Auckland, New Zealand. The library building is mainly used by Massey University students. However, external visitors can also enter and use the library. The demographics of Massey University students in 2019 are shown in Table 1. However, there are no records of visitors who were in the library during the fire drills or unplanned events as such the data in Table 1 represents a proxy of the occupancy of the library at the time of the evacuations.

The building has five floors, including a semi-underground floor (F −1), a ground floor (GF), and three floors above it (F1, F2 and F3). Fig. 1 shows the layout of these floors and the location of the available exits available to evacuate each single floor. The exits in green are the ones allowing getting out of the building while the exits in yellow are the ones allowing evacuees to leave the floor using internal stairs leading to other floors. Some of these exits (i.e. the exits in red in Fig. 1) are not available during evacuations as fire curtains drop from the ceiling making the stairs connecting the ground floor with the semi-underground floor and F1 floor not usable. These curtains get activated when the alarm goes off. There are two elevators (which cannot be used during an evacuation) and several staircases connecting all floors which are instead usable to evacuate the building. Most of the building is open to the public, who can enter through the main entrance on the ground floor. Only two areas on the ground floor and the F1 floor are offlimits to the public and available only for the Massey University staff. Both the ground floor and the semi-underground floor have evacuation doors leading outside to safe spaces away from the building in case of emergencies.

3.2. Evacuation events

This article analyses data from four evacuations that happened in 2019. Two were unannounced fire drills, and the other two were unplanned evacuations due to false alarms. In these false alarm events the building's fire alarm was initiated; however, there was no real fire danger in the building. As such the building occupants had little way of knowing the level of threat posed by the incident. According to New Zealand health and safety rules, the library conducts one or two fire drills every year, usually during the first (February-June) and second (July-November) semesters. Only the library manager knows about the drills a few days in advance; the rest of the staff and students do not. However, staff and students might still guess when a drill is coming because they happen regularly and often follow drills in other campus buildings. Additionally, before a drill starts, facility management staff in high-visibility jackets enter the building to activate a smoke detector on the ground floor, which can tip off the library staff and students that a drill is about to begin. Table 2 provides general information about these

Table 1
Demographic data for the students of the Massey Auckland Campus in 2019 (Massey University Student Registry, 2021).

Demographics	Measurement
Gender	53 % Female; 47 % Male
Age (years)	Mean value: 26.7; Standard Deviation: 8.4
Student Origin	52 % New Zealander; 48 % International
Ethnicity	11 % Maori; 5 % Pacific People, 84 % Others

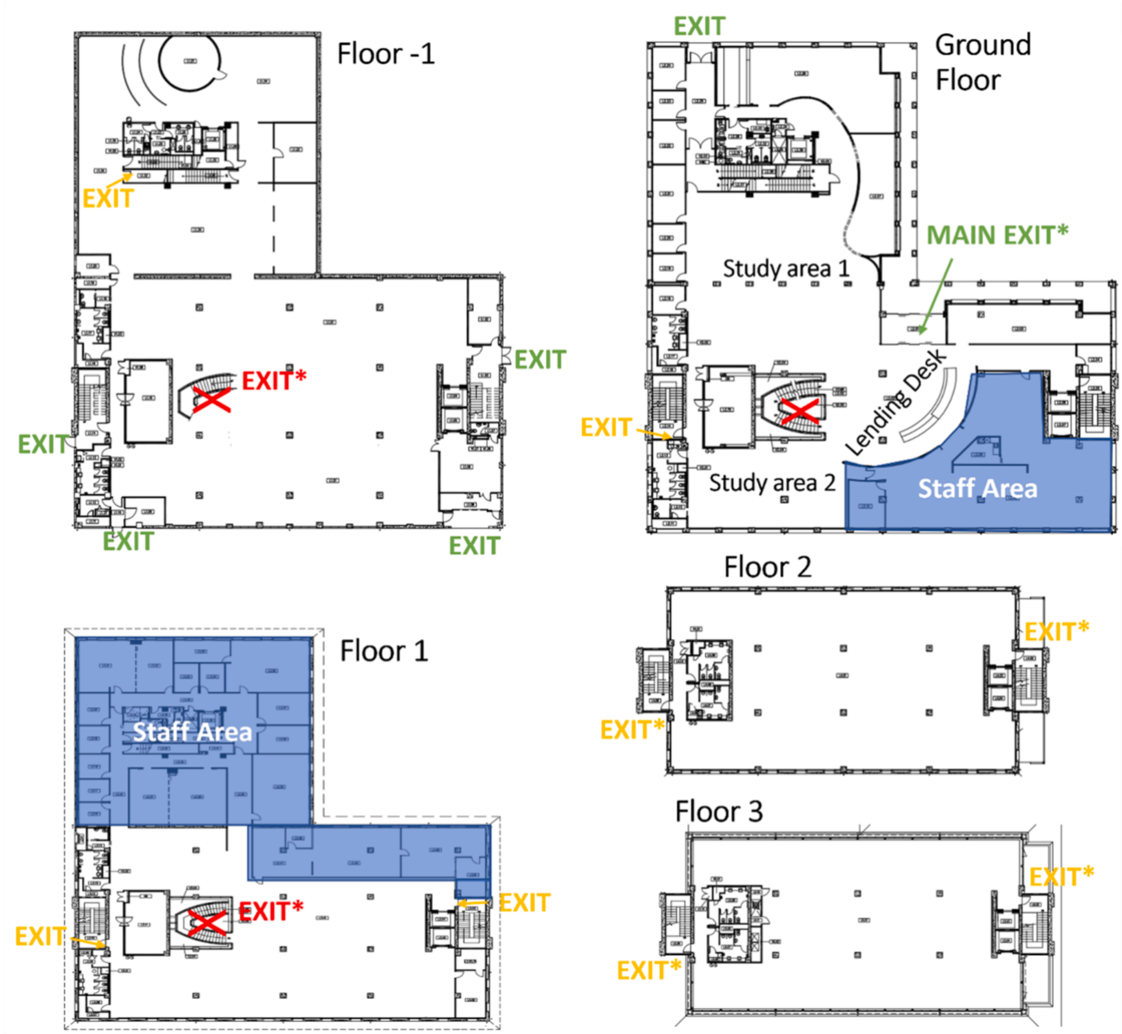

Fig. 1. Floor plan of the five floors of the library building. The exits in green allow evacuees to leave the building; the exits in yellow allow the evacuation from the floor using internal stairs; the exits in red are not usable to evacuate the floor because fire curtains block their access. The * symbol indicate the exit commonly used in normal conditions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Summary of the four evacuations.

	Evacuation 1	Evacuation 2	Evacuation 3	Evacuation 4
Date	March 02, 2019	March 06, 2019	Sept. 11, 2019	October 31, 2019
Alarm time	1:19 pm	10:08 am	9:52 am	7:59 pm
Day of the week	Saturday	Wednesday	Tuesday	Thursday
Season	Autumn	Autumn	Spring	Spring
Floor in use	F-1 and GF	All	All	All
Type of event	False Alarm	Drill	Drill	False Alarm

four evacuations. The data shows that in three evacuations all the floors were occupied while in Evacuation 1 only two floors were occupied as the library was partially open during the weekend, allowing access only to F-1 and GF. Table 3 shows that both false alarm evacuations happened in the afternoon or evening, while the two planned drills were in the morning.

In all the evacuation events studied in this article, the same type of alarm was used to alert the people in the building. The alarm consists of a voice message telling the occupants to leave the building immediately through the nearest exit. Each time the alarm went off, a library staff member began telling people and other staff to evacuate, starting with the ground floor (GF) and first floor (F1) where they were initially located, and then moving to the other floors of the library. This

Table 3
Sample size and number of observations on each floor for the four evacuation events.

Type of events	Date	Floor	Number of Exit	Observed exit choices
Evacuation 1	False Alarm	F-1	6	25
		GF	3	19
Evacuation 2	Drill	F-1	6	33
		GF	3	37
		1	3	18
		2	2	9
		3	2	22
Evacuation 3	Drill	F-1	6	40
		GF	3	21
		1	2	23
		2	3	11
		3	2	31
Evacuation 4	False Alarm	F-1	6	56
		GF	3	44
		1	3	32
		2	2	40
		3	2	36

procedure was the same for all four evacuations.

The dataset employed in this study has been used in prior research, focusing on pre-evacuation time (Lovreglio & Kuligowski, 2022). Here, we examine participant exit choices to provide new insights.

3.3. Data collection

In this study, we used video from the 33 CCTV cameras already installed in the library to collect data on exit choices. These cameras covered most of the public areas in the library. We analysed the recorded videos to identify which exit was selected by each evacuee and if they were changing their decision during the evacuation. The selected exit was defined by looking at the direction in which the evacuees were moving. As such, it was possible to identify 497 exit decision choices for a sample of 497 evacuees (excluding the staff who was managing the evacuation). Table 3 shows a summary of the location of the evacuees investigated in this study and the number of observed exit choices for each floor for the four evacuation events.

The dataset used for this study includes both variables defining the exit conditions (Exit variables) and variables defining aspects of the overall evacuation scenarios (Scenario variables) as shown in Table 4. For each exit choice, we identified the approximate Euclidean distance of the evacuees from all the available exits on the floor (*Dis*). We also counted the number of other evacuees who had already selected each available exit at the time when an evacuee started moving toward an exit such as the chosen exit (*Crowd*). As these numbers changed over time, not all exit choices were associated with the same levels of exit usage, meaning that participants may have different crowd measures for the same exit compared to participants a little while later. For each exit we assign a binary value indicating the familiarity of the evacuees with that exit (*Fam*). In this case we assumed that the participants were familiar with all the exits which are commonly used in normal conditions in the library and they are marked with a * symbol in Fig. 1. Finally, for each occupant we indicate if there was a library staff member directing evacuees towards the exit using a binary value (*Guide*). The variables used in the developed dataset are summarised in Table 4. The scenario variables included in this work are two binary variables. The first one identifies if the exit choice was made during a drill (*Drill*) and the second is if the evacuee was located at the ground floor when they made their choices (*Ground_Floor*).

3.4. Model specification

First, we use multinomial logit models to describe pedestrian route choices between a set of alternatives (Hensher & Greene, 2003; Lovreglio et al., 2016a; Ren-Yong & Hai-Jun 2010). In accordance with the multinomial logit model, The utility associated with exit j for individual i can be calculated as shown in Eq. (1), which comprises a deterministic part V_{ij} and a random unobserved factor ϵ_{ij}. The latter is assumed to be distributed identically and independently as Extreme Value Type 1.

$$U_{ij} = V_{ij} + \epsilon_{ij} \tag{1}$$

The deterministic part V_{ij} can be calculated using Eq. (2), which includes β_{jm} as a weighting vector of coefficients for option j and factor m that contributes to the utility of each exit, and X_{ijm} which represents the combination of m factors for alternative j and individual i, and its calculation is defined by Eq. (3).

$$V_{ij} = \sum\nolimits_{m} \beta'_{jm} X_{ijm} \tag{2}$$

where m is the m^{th} factor that contributes the individual choice and β'_{jm} is the transpose of the β_{jm}.

X_{ijm} comprises the exit variables and scenario variables. The descriptions of each variable are shown in Table 2.

$$X_{ij} = \{Dis_{ij}, Crowd_{ij}, Guide_{ij}, Fam_{ij}, Drill, Ground\_Floor\} \tag{3}$$

The probabilities (denoted as P_{ij}) of an individual i selecting a specific exit j can be computed by considering the utility associated with that exit relative to the total utility of all available options. This relationship is described in Eq. (4), ensuring the probabilities for all alternatives sum up to 1.

$$P_{ij} = \frac{Exp(V_{ik})}{\sum_1^n Exp(V_{ik})} (k = 1, 2 \ldots n) \tag{4}$$

where n is the number of available exits.

Based on the collected data, the model parameters and relevant statistical metrics were computed through the following steps:

1. Normalise the variables associated with each alternative by dividing the variable of an alternative by the total sum of corresponding variables across all alternatives. It aims to ensure that variables with different scales contribute equally to the analysis, preventing any single variable from dominating the results due to its scale.
2. Use Maximum Likelihood Estimate to obtain model parameters, which is achieved by maximising a likelihood of the observed data to ensure that it aligns most favourably with the model, as shown in Eq. (5).

$$L(\beta) = \sum_{i=1}^{Q} \frac{Exp\,(V_{ik})}{\sum_1^n Exp(V_{ik})} \tag{5}$$

where $L(\beta)$ is the likelihood function of β, aiming to find the value of β that maximises it. Q is the number of choices participants made.

3. Use the Likelihood-ratio tests to calculate test statistics and p-values, which is achieved by assessing the goodness of-fit of the model under different conditions.

Additionally, we used 5-fold cross-validation to further evaluate the established model (Wong & Yeh, 2019). The dataset is randomly divided into five equally sized subsets, or "folds." Each fold represents roughly 20 % of the data, ensuring that every data point is used for both training and testing across multiple iterations. The model is trained on four of these five folds (80 % of the data) and tested on the remaining fold (20 % of the data). This process is repeated five times, with each fold serving as the test set once. After all iterations are complete, the prediction accuracies from each iteration are averaged to provide an overall estimate of the model's performance, and the standard deviation of the prediction accuracies across the five folds is calculated to assess the model's consistency and robustness.

Table 4
Details on exit and scenario variables in the model.

Category	Variable	Format	Description
Exit variables	*Dis*	Numeric	The Euclidean distance from the participant's location to a specific available exit.
	Crowd	Numeric	The number of other evacuees who selected the exit. It was measured at the time when an evacuee started moving toward an exit.
	Fam	Binary	1 if the evacuee is familiar with the exit; 0 otherwise.
	Guide	Binary	1 if a staff member directed evacuees towards the exit; 0 otherwise.
	Drill	Binary	1 if the exit choice was made during a drill; 0 otherwise.
	Ground_Floor	Binary	1 if the evacuee was located at ground floor; 0 otherwise.

4. Results

4.1. Model selection

We perform a statistical model selection process as follows (see Fig. 2 for a detailed workflow):

1. Initiate the model with the variables *Dis, Crowd, Guide*, and *Fam* without interaction terms.
2. Construct pairwise interactions between *Dis, Crowd, Guide*, and *Fam*.
3. Assess whether the inclusion of an interaction improves the model goodness using a likelihood-ratio test.
4. Include the interaction terms in the original model if they improve the model goodness.
5. Construct pairwise interactions between *Dis, Crowd, Guide, Fam* and *Drill, Ground_Floor*.
6. Repeat steps 4–5.
7. Arrive at the final model.

The results indicated that the interactions between *Drill* and *Crowd*, *Drill* and *Fam*, *Fam* and *Crowd*, and *Fam* and *Ground_Floor* should be included. The final model is presented in Eq. (6), and the statistics information is shown in Table 4.

$$V_{ij} = \beta_{ij}\{Dis + Crowd + Guide + Fam + Drill \times Crowd + Drill \times Fam + Fam \times Crowd + Fam \times Ground\_Floor\} \quad (6)$$

Our datasets encompassed various sets with different numbers of available exits. Different numbers of available exits across scenarios or building floors could introduce biases in our analysis, as the likelihood of selecting a particular exit may systematically decrease in situations with more exits compared to those with fewer exits. To address this, we employed weighted regression to balance the choice probability across varying numbers of alternatives, as shown in Eq. (7). This approach allowed us to investigate whether the number of exits had a significant impact on the probability of selecting a specific exit. The results did not reveal any differences compared to the original model.

$$P_{ij} = \frac{n}{N}\frac{Exp(V_{ik})}{\sum_1^n Exp(V_{ik})}(k = 1, 2 \ldots n) \quad (7)$$

where n is the number of exits in the current situation and N is the maximum number of available exits across all datasets.

The results of 5-fold cross-validation to our model showed that the average accuracy is 85.11 %, indicating that the model correctly predicted outcomes 85.11 % of the time, on average, and the standard deviation across the folds was 3.34 %, suggesting low variability and consistent model performance across different subsets of the data.

4.2. Statistical results

Table 5 presents the statistical results of the simple model with the four essential variables, and the improved model with scenario variables and interactions between variables. The simple model reveals that participants were more likely to choose the nearest exit, avoid the busy exit, and prefer to follow the guide's instructions. However, the analysis uncovers an unexpected trend regarding the impact of familiarity on exit selection: participants preferred unfamiliar routes. This suggests that there may be interactions or other unobserved factors influencing their exit choices. In contrast, for the improved model, all four exit variables were observed to have a significant influence on human decision-making. More specifically, participated tended to choose a closer exit, a trend that aligns with the substantiated observations from numerous previous investigations on pedestrian exit choice behaviour in evacuations. Furthermore, the presence of a guide was found to increase the likelihood of participants choosing the guided exit, highlighting the importance of the guidance in directing pedestrian exit choice. Our results reveal that participants tended to choose the exit selected by the majority of the crowd, and preferred exits they were familiar with. However, the crowd effect was reduced for familiar exits ($Fam \times Crowd$ term in Table 5). In addition, we estimated the effect sizes via Cohen's d and found that in the simple model, the influence of crowd presence exhibited the largest effect size, indicating a substantial impact on the participant exit choice. Conversely, familiarity demonstrated the smallest effect size, suggesting a minimal influence. In the improved model, while the effect size of crowd presence diminished, it remained the most influential factor. Meanwhile, the effect size of the guide emerged as the least significant, highlighting a reduced impact on the participant exit choice.

Regarding scenario variables, we found they individually had no significant influence but collectively had an effect as their interactions

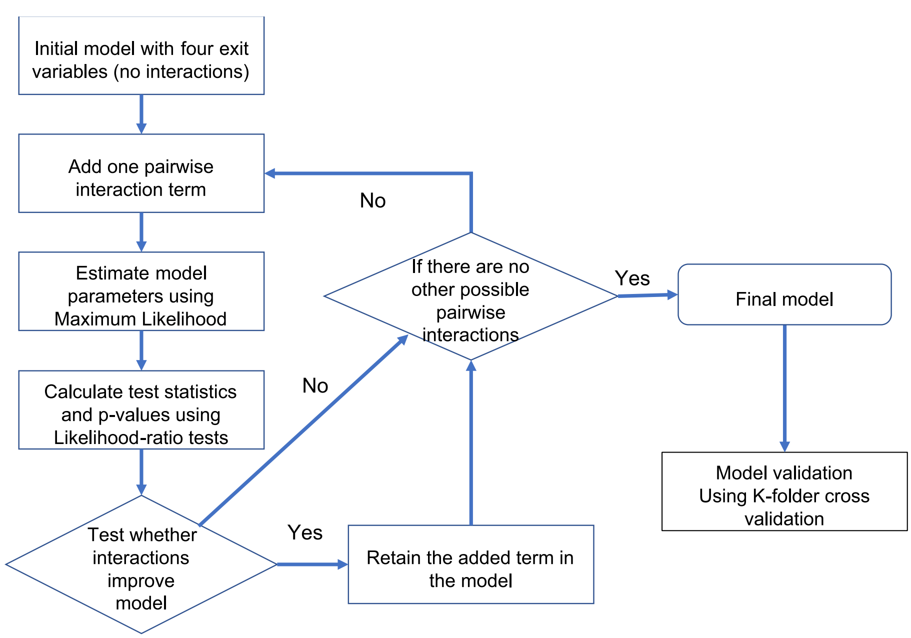

Fig. 2. Workflow for model specification and selection.

Table 5
Results of statistical analysis conducted for the simple multinomial logit model U = Dis + Crowd + Guide + Fam and the improved model as shown in Equation (6). P-values equal to zero are smaller than the numerical precision of the software used. Positive parameter estimates correspond to an increased probability for choosing an exit for increases in the corresponding variable.

	Effect	Estimate	Std	Test statistics	P	Effect size
Simple model	*Dis*	−1.880	0.464	94.857	< 0.001	0.093
	Crowd	2.946	0.539	290.608	< 0.001	0.886
	Guide	1.467	0.321	19.290	< 0.001	0.067
	Fam	−0.952	0.278	19.830	< 0.001	−0.020
Improved model	*Dis*	−2.356	0.701	122.743	< 0.001	0.053
	Crowd	5.213	1.135	151.431	< 0.001	0.409
	Guide	0.914	0.160	4.625	0.032	0.007
	Fam	0.879	0.159	3.906	0.048	0.008
	Drill × *Crowd*	−1.700	0.302	13.716	< 0.001	0.021
	Drill × Fam	−34.380	5.378	40.511	< 0.001	−0.018
	Fam × Crowd	−2.599	0.681	27.494	< 0.001	−0.001
	Fam × Ground_Floor	34.524	8.122	155.815	< 0.001	0.023

Note: The effect size is measured using Cohen's d by comparing the predicted probabilities obtained from the model with and without the inclusion of the variable (Ialongo, 2016).

with exit variables were found to enhance the model fit. More specifically, compared to unplanned (false alarm) evacuations, participants' inclination to select crowded and familiar exits decreased in pre-planned drill scenarios. Considering the corresponding effect sizes, which were larger than those of guide and familiarity, these results underscore the significant impact of evacuation scenario types on participant exit choices, indicating two distinct decision-making patterns observed during fire drills and false alarm evacuations. Furthermore, participants on the ground floor were more inclined to choose the familiar exit compared to other floors. Regarding effect size, the interaction between familiarity and the ground floor exhibited the second largest impact in this improved model.

5. Discussion

Our study provides empirical evidence regarding the impact of essential factors such as crowdedness, distance, guidance, and familiarity on participants' exit choices, based on data collected from library drills and false alarm evacuations over a period of time. The dataset offers an opportunity to examine human decision-making in both pre planned and spontaneous evacuations.

We found that participants exhibit different preferences for essential exit variables depending on the type of evacuation. Furthermore, our findings highlight the influence of scenario variables on pedestrian decision-making, including the interaction between participants' location on the ground floor and their familiarity with their chosen exit. Importantly, our findings reveal that individuals exhibit distinct decision-making patterns regarding exit preferences, suggesting that behaviours observed during drills may not accurately represent responses during real emergencies. For example, participants may prefer crowded exits during unplanned evacuations, possibly due to reduced expectations and heightened urgency compared to planned drills. This insight is crucial for optimising drill protocols and emphasises the importance of contextual factors in influencing human behaviour during evacuations.

While our research offers a thorough analysis based on a unique dataset, there are some limitations that deserve consideration. Firstly, the naturalistic occurrence of the data collection process is incapable of introducing control to investigate human decision-making further, and the conditions under which data are collected cannot be directly influenced by the researcher. The manual extraction of data may lack high precision, such as estimating the distance between participants and their preferred exits, which potentially influences model specification and accuracy. Moreover, our participant pool primarily consists of students from a university setting. Previous studies have found substantial and incoherent differences between students and the general public, stemming from various factors such as age and education level (Hanel & Vione, 2016). Consequently, we cannot generalise our findings from student samples to the general public, which may limit the unreliability of our results.

Our study employs quantitative analysis leveraging well-established statistical methods based on the collected data. However, extending our conclusions to broader scenarios and populations necessitates further empirical evidence, particularly from well-controlled experiments that systematically examine the influence of specific variables on pedestrian decision-making.

Furthermore, a significant challenge in human decision-making research lies in integrating subjective and objective data about participants for a deeper understanding of human decision-making. For example, while we attempt to consider the number of people around each available exit as a factor influencing individual exit choices, participants may be constrained by limited visibility and subjective perceptions of crowd density. To address this limitation, collecting participants' subjective views following the completion of experiments could provide valuable insights, although such data was unavailable in our naturalistic data collection process.

6. Conclusions

In conclusion, our study investigates the factors that influence human decision-making during evacuations, leveraging empirical evidence collected during library drills and false alarm evacuations. We identify significant factors such as crowdedness, distance, guide, and familiarity influencing pedestrian exit choices. Additionally, our findings underscore the impact of scenario variables such as the evacuation type and the floor they are on. While naturalistic data collection lacks experimental control, it provides realistic insights into human exit choices in natural settings. Future studies could enhance the reliability and generalizability of our conclusions by incorporating well-controlled experiments.

CRediT authorship contribution statement

Yunhe Tong: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Nikolai W. F. Bode:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Milad Haghani:** Writing – review & editing, Methodology. **Ruggiero Lovreglio:** Writing – review & editing, Methodology, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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