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A Virtual Reality Exit Choice Experiment to Assess the Impact of Social Influence and Fire Wardens in a Metro Station Evacuation

S. Lu[1,3] · M. Rodriguez[1,2] · Z. Feng[1] · D. Paes[1] · A. B. Daemei[1] · R. Vancetti[2] · S. Mander[1] · T. Mandal[4] · K. R. Rao[5] · R. Lovreglio[1]

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Abstract
Assessing evacuation time is a fundamental task in fire engineering. One of the key decisions made in evacuation dynamics is exit choice. In this work, we propose a new immersive virtual reality (VR) experiment to assess the effects of social influence and fire wardens' instructions on the exit chosen. We also investigate if and how the perceived level of authority of the fire wardens (i.e., metro staff members or firefighters) can affect these decisions. The proposed immersive VR experiment includes 12 different scenarios during a fire evacuation in an underground metro station. A sample of 131 participants took part in the experiment, making 1048 choices. We estimate a discrete choice model to quantify if and how these factors affect the participants' decisions. The results show that both instructions by fire wardens and social influence significantly affect exit choice and that the impact of fire wardens can change depending on their perceived level of authority.

Keywords Discrete choice model · Evacuation · Exit choice · Fire safety engineering · Human behaviour in fire · Virtual reality

1 Introduction

Accounting for evacuation while designing the built environment can be complex, and evacuation assessments represent a crucial aspect of Fire Safety Engineering. Over the past few decades, studies on pedestrian evacuation dynamics have increased and become a key research topic to support fire safety engineering [1–4]. These studies are driven

✉ S. Lu
lu-s19@tsinghua.org.cn

1 School of Built Environment, Massey University, Auckland, New Zealand

2 Politecnico di Torino, Turin, Italy

3 Tsinghua University, Beijing, China

4 Mallabhum Institute of Technology, Bishnupur, West Bengal, India

5 Indian Institute of Technology Delhi, New Delhi, India

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by the need for new data, which is necessary to evaluate the safety of a given built environment design when using a performance-based approach.

Performance-based design focuses on comparing the Available Safe Egress Time (ASET) with the Required Safe Egress Time (RSET) [5]. ASET is the time that can pass before the environment becomes too dangerous to escape, while RSET is the time required for all evacuees to exit safely [6]. There are many methods and models in the current state of the art that simulate the evacuation process to evaluate RSET [7–9]. Quantifying evacuation time with these existing methods and models can be a challenging task for fire safety engineers, especially for complex built environment scenarios.

To accurately determine RSET, it is essential to consider the various factors. These factors encompass individual characteristics such as physique, age, gender, and cognitive capabilities, as well as environmental and behavioural elements like route and exit choices, visibility of guidance signs, familiarity with the environment, and the suitability of emergency lighting [10]. Among these, exit choice behaviour plays a pivotal role in shaping the overall evacuation dynamics and, consequently, the RSET. Therefore, the study of human behaviour in fire emergencies must be at the core of all life safety projects, examining how people respond to emergencies, including their awareness, attitudes, behaviours, motivations, beliefs, coping strategies, and decisions [11].

Several existing datasets on human behavior in fire and pedestrian dynamics have been proposed using data from field-based experimental studies, such as evacuation drills and real incidents [10–13]. In these cases, researchers can reach a high level of ecological data validity. However, a downside of these data is that researchers have limited experimental control over the variables under examination [14]. For instance, in the cinema experiment published in [15], the only variable under control was the alarm type. In many other case studies, researchers had no control over the factors affecting evacuee behavior. Moreover, the involvement of human subjects in evacuation experiments carries a risk of grievous injury. An alternative is to collect data through laboratory experiments. In a laboratory setting, data can be collected by presenting participants with hypothetical scenarios and asking how they would respond in those situations. For this purpose, different methods can be employed. Virtual Reality (VR) is one of the emerging tools in the field [16–18].

In recent years, VR has gained popularity in the safety research community [19]. VR has been defined as a "real or simulated environment in which the perceiver experiences telepresence" (the feeling of being present in a virtual environment) [20]. Therefore, VR is not limited to computer-generated environments or any specific technology but can include different immersive and non-immersive solutions [21]. VR is a research tool that balances ecological validity with the ability to control experiments [18]. If this balance is reached, VR can serve as an effective, versatile, and affordable platform for safety-related scenarios. Several existing studies have explored the use of VR to understand human behavior and train individuals for emergency scenarios [22–24].

Current evacuation models often rely heavily on user input to predict fire evacuation scenarios, which can lead to inaccuracies and inconsistencies [25]. This dependence on ad-hoc user input limits the models'ability to accurately capture individual and group behaviours under various situations. There is a clear need for next-generation models that can autonomously predict evacuation behaviours based on real-time situational data rather than manual inputs. Gwynne et al. [26] have identified this gap, emphasizing the necessity for data-driven approaches that integrate comprehensive behavioural data to enhance the predictive accuracy of evacuation models. In this context, Virtual Reality (VR) represents a suitable approach to study human behaviour in fires and to develop the next generation of data-driven models for potential integration within existing or new evacuation software tools.

However, several studies have identified specific limitations of VR in replicating real-world evacuation scenarios [27, 28]. Technologically, VR systems may suffer from a limited field of view, latency-induced motion sickness, and insufficient environmental realism due to computational constraints. As an experience, VR may lack scenario authenticity and fail to evoke genuine psychological and physiological responses, which can influence evacuee decision-making. To mitigate these issues, careful experimental design and appropriate hardware selection are essential to enhance the ecological validity of VR systems and reliability of VR-based evacuation studies.

The present study utilises a new VR experiment to investigate exit choice, an important behavior affecting fire-related evacuations in an underground built environment [29]. This work assesses how both social influence and fire wardens' (metro staff or firefighter) instructions can affect evacuees' exit choices, especially when these two factors conflict. To achieve this aim, we developed an immersive VR experiment to investigate exit choices during a fire evacuation in a metro station using 12 different scenarios. The 12 scenarios differ in the presence or absence of a fire warden to guide the participants, the level of authority of the fire wardens, and the presence or absence of other evacuees. This experiment involved 131 participants who were asked to choose between two possible exits for 8 of the 12 scenarios. Finally, we estimate a discrete choice model to quantify if and how these factors affect the participants' decisions.

2 Background

This section provides an overview of exit choices and the factors affecting them, including social influence and role-rule model factors. Additionally, it summarises relevant studies that use VR technologies to investigate exit choice. Exit and route choices can significantly affect evacuation performance [29, 30]. Numerous studies have investigated exit choices during fires [31–34]. These studies have identified several elements that can affect evacuee exit choices, such as social influence, evacuation systems' affordances, familiarity with the environment, the geometry of the building, and harmful conditions within the environment itself (i.e., smoke) [35, 36]. Research by Lin et al. [37] demonstrated that when a crowd was split unevenly, participants were influenced to follow the majority. This trend was observed across multiple cultural contexts. Other studies indicate that people tend to evacuate via familiar routes and exits, most often the main entrances [38, 39]. This is an example of affiliative behavior, which occurs when people move towards "familiar persons and places". In some cases, people prefer not to adopt a new route or an exit previously unknown, even if they are available and/or closer. Lovreglio et al. [40] found that in VR simulations of building fires, participants were less likely to use exits obscured by smoke unless they observed others successfully navigating through those areas.

Social influence describes the actors accounting for how an individual's beliefs, thoughts, emotions, opinions, or behaviours are affected by others in their social network [41]. During emergencies, occupants must decide their destination (i.e., where they want to move to) and their route (i.e., how they want to reach their destination). In unfamiliar situations, such as those that occur in emergencies, a useful source of information can be the behaviour of other occupants [42]. Therefore, the presence of others in emergencies can influence an individual's behaviour. Nilsson and Johansson [15] demonstrate that when fire cues are ambiguous (e.g. an alarm bell rather than a pre-recorded message), social influence is more significant and increases when people are closer to each other. An important aspect of social influence has been highlighted by Templeton et al. [43]. This study investigated the behavioural effects of shared social identity on crowd movement at a pedestrian level. By analysing the behaviour of a psychological crowd (where the entire crowd perceives themselves as part of the same group through a shared social identity) and a physical crowd (where members are in the same place at the same time), they demonstrated that the differences in speed, distance and proximity are crucial factors to consider when planning the egress of a crowd in the event of an emergency. Latané and Darley [44] found that social inhibition effects are common across different types of emergencies. In four separate experiments, bystanders were less likely to step in when others were present. The type of bystander made a difference: a non-responsive confederate caused the greatest inhibition, a stranger had a moderate effect, and a friend had the least. These findings support a multi-process model of intervention, showing that the presence of others influences both how a bystander will interpret the situation and their decision to act.

Many traditional findings from research on social influence have been duplicated effectively in virtual environments, as demonstrated in certain studies [45–47]. These studies indicate that VR can be an effective platform for studying social influence [48]. However, a potential drawback in VR studies related to social influence is that virtual agents might be perceived differently from real people, as participants may not recognise animated agents as humans [49].

The role-rule model represents the relationship between roles, rules and behaviour and is a crucial aspect of human behaviour in fire emergencies. To analyse this important factor, Fridolf et al. [29] discussed an excellent example of human behaviour during an emergency at an underground station: the King's Cross fire. They observed that the recognition, interpretation, and response to the first fire cues correlated with the role of an individual in everyday life. For example, underground staff members and police officers assumed positions of authority while, in contrast, tunnel users waited for authoritative instruction. This example highlights the significance of preparedness and training in handling emergency situations and the need for fire wardens capable of directing evacuees toward safe exits. Fridolf et al. [29] also observed that passengers responded more readily to instructions provided by the police than those from staff members. The role-rule model could explain this phenomenon, as people see the police as having more authority than underground staff members in a non-fire situation. Two further studies on policing and public order show that people's response is influenced not only by how clear and useful the guidance is but also by their perception of the organisation delivering it [50, 51]. Templeton et al.[52] observed that trust in fire safety guidance is an essential factor that should be incorporated into evacuation models.

Various scientific observation and simulation techniques have been developed to assist in the evacuation of buildings threatened by disasters, such as fires. In recent years, VR and AR (Augmented Reality) have gained popularity in the safety research community [19]. Different combinations of hardware and software allow the public to access these technologies. In this work, only VR will be discussed. VR technologies are divided into immersive and non-immersive solutions. Non-immersive VR relies on displaying virtual content on a computer screen, while immersive VR uses technologies such as head-mounted displays or Cave Automatic Virtual Environments to create more immersive experiences [53–55]. Several studies explore the wide range of VR hardware options for studying human behaviour during disasters [27, 28, 47], such as the review by Lovreglio [56]. This review notes that the most suitable hardware configuration is influenced by the research budget and objectives. The review also emphasises the extensive use of VR solutions in studying human behaviour during disasters, with a particular focus on fires in buildings. However, a concern about these studies is whether data collected using VR has ecological validity (i.e. whether people behave similarly in real disasters and VR) [18]. While some studies have attempted to explain this crucial issue [49, 57, 58], more studies comparing real and virtual scenarios are necessary to evaluate the ecological validity of VR investigations quantitatively. Kinateder et al. [18] claim that the most significant advantage of VR is its ability to generate experimental set-ups that are highly immersive, externally valid, highly controlled, and safe. The major drawback is the reduced ecological validity compared to field and case studies. However, several recent studies have provided evidence of the validity of this tool in investigating human behaviour in fires [27].

In the previous paragraphs, some studies regarding factors affecting exit choice have been discussed. A considerable number of studies examined the impact of these factors to independently influence exit or route selection, but only a limited number considered multiple factors simultaneously [40, 59]. No study was identified that analysed the combined effect of social influence and the presence of fire wardens on exit choices.

3 Methods and Materials

This section presents the materials and methods used to perform the experiment. Section 3.1 provides a detailed description of the VR experiment designed in this work. Section 3.2 explains the experimental procedure, while Section 3.3 describes the participants involved. Finally, the statistical analysis tools used to investigate the factors that influence participants' choices are outlined in Section 3.4.

3.1 VR Experiment Design

Throughout the VR experiment, the participants are situated within a hypothetical virtual metro station where they are asked to choose an exit to evacuate the station during a fire emergency. The 3D model of the metro station was purchased and downloaded from Sketchfab [60], a platform that allows users to share, buy, and sell 3D models.

The geometry of the final layout is shown in Figure 1. Utilising a hypothetical building means that all participants are free from any familiarity bias related to prior knowledge of the environment when making decisions. The participants can choose between two exits

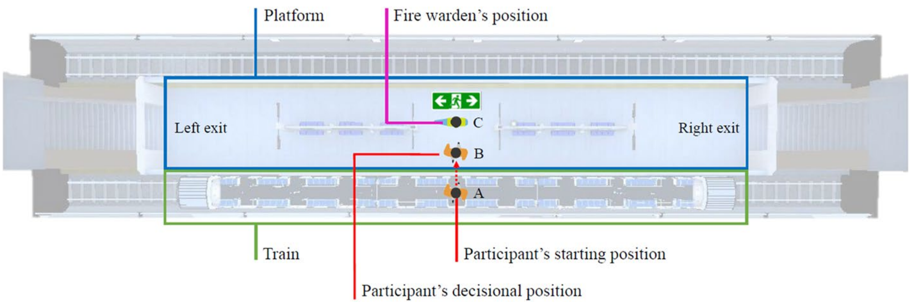

Fig. 1 Geometry of the virtual environment and position of people involved

Fig. 2 Screenshots of the virtual experience showing the virtual evacuees (left) and fire warden (right) in the metro station

(i.e., Left Exit and Right Exit), as illustrated in Figure 1. The virtual metro station has exit signs indicating two available evacuation paths (see Figure 3).

Figure 1 also highlights the positions of the participant (starting at position “A” and moving to position “B” where they make the decision) and fire warden (position “C”). The participant is initially located inside the train (position “A”) and is either alone or accompanied by virtual evacuees (non-player characters). After receiving an alarm signal and watching all of the virtual evacuees (when present) get out of the train, the participant moves automatically to position “B”, which is where they have to make the exit choice. The participant’s movement is managed by a C# script, ensuring a smooth transition automatically occurs from position “A” to “B” with no physical effort. The participant may choose to exit to the left or right, as indicated by the exit signs in Figure 1.

Fig. 3 Screenshots of the virtual experience showing the presence of a fire warden (left: a metro staff member; right: a firefighter) and the conflicting information provided to the participant

The experiment includes 12 different scenarios for which the geometry is kept constant. The scenarios differ by (a) the number of virtual evacuees (from 0 to 20) (see Figure 2), (b) the presence of a fire warden who directs the participant toward one of the exits and (c) the authority level of this fire warden (see Figure 3). Therefore, it is possible to define the following variables:

- NPC: the number of virtual evacuees using the exit;
- I: the presence of a fire warden who indicates the other exit;
- FF: the authority level of the fire warden (i.e., a metro staff member wearing a hi-vis vest and hard hat or a firefighter wearing a full firefighting kit).

These independent variables were introduced to study the influence of two factors on the exit choice: social factor and role-rule factor. In addition, the presence of fire wardens with differing levels of authority allows us to determine whether people's trust levels can vary and how that can change their consequent behaviour. To investigate the influence of all variables, conflicting information was provided to the participants in the experiment: the fire warden (when present) always indicates the Left Exit, while the virtual evacuees (when present) always go to the Right Exit (Figure 3).

All variables have multiple dimensions that can differ within the experiment. Table 1 summarises the dimensions of each independent variable (i.e. how many different values the variable can assume) and the values themselves. The number of NPCs leaving the metro station can be equal to 0, 1, 10 or 20. Therefore, the NPCs dimension is equal to 4, and the values are 0, 1, 10, 20. These NPC values were chosen in line with previous experiments [43]. In this experiment, NPCs only move towards the right exit. The variable related to the fire warden (I) is Boolean, and therefore, it can be equal to 0 (the fire warden is not present) or 1 (the fire warden is present). The dimension of the independent variable I is equal to 2 because the variable can assume only two values. Suppose the I variable is equal to 1. In that case, it is possible to introduce another Boolean variable (FF) equal to 1 if the fire warden looks like a firefighter or equal to 0 if the fire warden looks like a metro staff. The fire warden consistently advises evacuees to choose the left exit, creating a scenario where conflicting information is presented (NPCs moving right while the fire warden suggests moving left). The summary of the dimensions and values for each variable is provided in Table 1.

Given the limited number of variables and possible values they can have, we used this factorial design [61]. It is worth noticing that, as shown in Table 1, we did not consider symmetric scenarios between left and right exits. As such, the number of scenarios includes 4 conditions for the right exit (i.e., different value if NPC) and 3 conditions for

Table 1 Levels and values of each independent variable

Independent Variables	Left Exit Possible Values	Right Exit Possible Values
NPC – Number of virtual evacuees using the exit	0	0, 1, 10, 20
I – Presence of a fire warden*	1 OR 0	0
FF – The fire warden looks like a firefighter*	1 OR 0	0

*These variables are treated as binary, where 1 indicates Yes and 0 indicates No.

the left exit (note: the conditions I=0 AND FF = 0 and I=0 AND FF = 1 are equivalent, and they count as single conditions). As such, it is possible to define 12 (4x3) final scenarios by combining the conditions of the two exits. Table 2 presents the 12 immersive VR scenarios, categorised into three classes based on I and FF values: Class A involves scenarios where variables I and FF are equal to zero, so the fire warden is not present; Class B involves scenarios where I is equal to 1 and FF is equal to 0, so the fire warden is present and they are a metro staff member; Class C involves scenarios where variables I and FF are equal to 1, so the fire warden is present and they are a firefighter. 66 participants experienced Class A and Class B, and the rest of the sample (65 participants) experienced Class A and Class C. As such, each participant was asked to make only eight choices in total. The sequence of the eight scenarios changed randomly for each participant. This experiment choice was made to reduce experimental fatigue for the participants.

The VR experience was developed using Unity, a popular gaming engine used for creating VR applications. We used the long-term support version 2021.3.16f1. The 3D model of the virtual metro station from Sketchfab (see Section 3.1) was imported into Unity and modified to enhance realism and alter the geometry for this work. The architectural structure and representation were symmetrised, and the model underwent extensive optimisation within the Unity Editor. These modifications involved refining rendering settings such as adjusting mesh features, optimising texture, implementing Level of Detail (LOD) techniques, static batching, and striking to find a balance between visual fidelity and computational performance. A low-cost and high-quality human body model generation algorithm named Skinned Multi-Person Linear (SMPL) algorithm was used to generate virtual evacuees [62]. Within the framework of the XR Interaction Toolkit, the comprehensive interaction mechanism (e.g., movement and animation of the virtual evacuees and fire wardens, movement of the participant, randomisation of the scenarios, data storage, and audio management) was programmed in C#. Participants interacted with the virtual environment using the Oculus Meta Quest 2, a head-mounted display with two controllers. This headset is characterised by six degrees of freedom. It tracks the movement of both head and body and then translates them into VR with realistic precision. Meta Quest 2 features a

Table 2 Experimental scenarios (I and FF are treated as binary variables where Yes is coded as 1 and No as 0. See Table 1 for definitions)

Class	Scenario	Possible values			Possible values		
		Left Exit			Right Exit		
		NPC	I	FF	NPC	I	FF
A	1	0	0	0	0	0	0
	2	0	0	0	1	0	0
	3	0	0	0	10	0	0
	4	0	0	0	20	0	0
B	5	0	1	0	0	0	0
	6	0	1	0	1	0	0
	7	0	1	0	10	0	0
	8	0	1	0	20	0	0
C	9	0	1	1	0	0	0
	10	0	1	1	1	0	0
	11	0	1	1	10	0	0
	12	0	1	1	20	0	0

resolution of 1832 x 1920 pixels per eye, a field of view (FOV) of 97 degrees, and a refresh rate of up to 90 Hz, providing a clear and immersive visual experience.

The VR experiment took place in an office of Massey University's Auckland campus. The participants were allowed to stand anywhere in the room. A representation of the physical space where the experiment took place is shown in Figure 4.

3.2 Experimental Procedure

The experiment was conducted between July and September 2023 following review and approval by Massey University's Ethics Committee (Ethics notification number: 4000027646). The experiment took around 15 minutes per participant and involved the following steps:

1. Before undertaking the experiment, participants were required to read an information sheet and sign a consent form. This document outlined their right to discontinue their involvement in the experiment at any point and to request the deletion of their data if desired. Additionally, it provided information about medical conditions that would make them ineligible to participate in the experiment.
2. After a brief introduction to the VR system, participants were asked to stand up and wear the VR headset. The participants could stand anywhere in the room and only needed to hold and use one controller.
3. Upon wearing the VR headset, participants were immersed inside a train that was stopping at a metro station. They were either alone or with virtual evacuees. The evacuation exercise started a few seconds later. Initially, the participants were situated in the train (position "A" in Figure 1), where they heard an evacuation message from the metro public address system asking them to evacuate. The participants then watched the virtual evacuees (if present) evacuate the train. The participants were then automatically moved outside the train to the second position (position "B" in Figure 1). In this position,

Fig. 4 Physical space used to carry out the VR experiment

they observed exit signs indicating the Left and Right Exit choices. When present, the virtual evacuees could be seen moving to the Right Exit, and a fire warden was whistling and directing towards the Left Exit. The participants were required to choose an exit (left or right) by simply clicking a button on the controller.
4. After choosing an exit, the current scenario was completed, and participants respawned in the train to start the next scenario (the beginning of Step 3).
5. This process was repeated eight times for each participant, with a unique scenario presented in each iteration (Table 2). The sequence of the eight scenarios changed randomly for each participant to avoid the order of the scenario impacting the participants' decisions.
6. After the VR experience, participants were asked to complete a questionnaire on a tablet. The questionnaire collected data regarding the participants' demographics, prior experience with VR, and knowledge of fire emergencies. In addition, the questionnaire gathered feedback on the realism of the VR experiment, ease of use, emotional state, urgency perception, and perceived behavioural validity. Most of the data was collected using seven-point Likert scale questions (from −3 = "strongly disagree" to +3 = "strongly agree"), with an additional "I do not know" option. The items used for the questionnaire were adapted from those used by Lovreglio et al. [62]. Further, at the end of the experiment, participants received a 10 NZD voucher to compensate them for their time.

During the experiment, the participants were not informed that the real purpose of the experiment was to observe the influence of social factor and role-rule factor on their exit choice during an evacuation, as they were told to choose the exit that they preferred.

3.3 Participants

A total of 131 individuals participated in the study, with the majority being either University employees or students. The participants were recruited via social media platforms and flyers distributed on campus. The sample consisted of ages 16 to 71 years, with 75 identifying as female and 56 as male (see Table 3). The average age was 31.7 years, with a standard deviation of 10.7 years. The 25th percentile age was 22 years, and the 75th percentile was 40 years.

The sample used in this work allows for the collection of 1048 observations (131x8). This number of observations is well above the minimum required when using the Hsieh method for power analysis. In fact, when assuming an alpha of 0.05, a power of 0.8, a sample proportion and ρ^2 of 0.5, the required number of observations to detect a small effect

Table 3 Estimated parameters for Multinomial Logit Model

McFadden's adj R^2=0.282
Log Likelihood=−485.12

Variable	Estimate	Std error	z-value	p-value
$const_R$	0.263	0.115	2.275	0.023
β_{NPC}	0.035	0.010	3.555	0.000
β_I	2.739	0.225	12.172	0.001
β_{FF}	0.559	0.329	1.698	0.090

size (OF= 1.2) is 306 [63, 64]. We chose to exceed this minimum sample size to ensure greater statistical reliability and robustness in our findings. By increasing the sample size, we can better capture potential variability within the data and reduce the margin of error, thus enhancing the validity of the conclusions drawn from our analysis.

3.4 Discrete Choice Modelling

The data gathered from the experiments were assessed using random utility models. Random utility models are dependent on the following assumptions [65, 66]:

- A decision-maker q assigns a utility $U_{q,i}$ to each available choice alternative i. The utility is defined by a measurable component $V_{q,i}$ and a random component $\varepsilon_{q,i}$:

$$U_{q,i} = V_{q,i} + \varepsilon_{q,i} \tag{1}$$

  This equation facilitates the explanation of two significant concepts: individuals with identical attributes and confronted with the same set of choices might opt for different alternatives, and some individuals may not consistently choose what seems to be the optimal option.
- The measurable component has a linear specification defined by the following equation:

$$V_{q,i} = \sum_{j} \beta_{i,j} X_{q,i,j} \tag{2}$$

where $X_{q,i,j}$ are the known values of the factors j perceived by the decision-maker q affecting the choice for the alternative i, and $\beta_{i,j}$ are parameters weighting the preferences of the decision-makers related to the factors j. $\beta_{i,j}$ are the parameters to estimate [40].

The Multinomial Logit Model is the simplest and most popular practical discrete choice model. It can be generated assuming that the random components are distributed as Extreme value Type I with variance $\frac{\pi^2}{6}$ and these distributions are independent and homoscedastic [66]. By assuming this, the probability that the decision-maker q selects alternative i can be formulated by the following equation (i.e., multinomial logit formulation):

$$P_{q,i} = \frac{\exp\left(V_{q,i}\right)}{\sum_{k} \exp\left(V_{q,k}\right)} \tag{3}$$

This equation can be employed to build a likelihood function, which is then utilised to estimate the $\beta_{i,j}$ parameters by identifying the parameter combination that maximises the likelihood function under the assumption of a constant parameter (or random parameters in the case of a mixed logit model). Under the assumption of random parameters, Equation 3 can be rewritten as:

$$P_{q,i} = \int \frac{\exp\left(V_{q,i}\right)}{\sum_{k} \exp\left(V_{q,k}\right)} f\left(\beta_{i,j}, \alpha_{ijz}\right) d\beta_{i,j} \tag{4}$$

where the f function is the probability density function of the $\beta_{i,j}$ parameters and α_{ijz} are parameters defining the f function. Equation 4 does not generally have a closed solution. However, the probabilities can still be estimated using Monte Carlo techniques [66]. This more advanced solution represents a useful modelling tool to assess if there is heterogeneity in the perception of the factors under investigation. In this work, the multinomial logit models have been estimated using the "mlogit" package available in R Studio [67].

In addition, to observe the predictability of the model, the concept of a confusion matrix has been used. A confusion matrix of size n x n associated with a classifier shows the predicted and actual classification, where n is the number of different classes. In this study, we use a 2x2 confusion matrix, where:

- a is the number of correct negative predictions,
- b is the number of incorrect positive predictions,
- c is the number of incorrect negative predictions,
- d is the number of correct positive predictions.

Based on the definition of [67], the prediction accuracy and classification error can be obtained from this matrix as follows:

$$\mathrm{Accuracy} = \frac{\mathrm{a} + \mathrm{d}}{\mathrm{a} + \mathrm{b} + \mathrm{c} + \mathrm{d}} \tag{5}$$

$$\mathrm{Error} = \frac{\mathrm{b} + \mathrm{c}}{\mathrm{a} + \mathrm{b} + \mathrm{c} + \mathrm{d}} \tag{6}$$

The choices predicted by the model can be calculated using Eq. 2 to measure the utility by knowing the model's parameters. Subsequently, by using Eq. 3, it is possible to estimate the probability of choosing an exit. It is then assumed that the predicted choice has the highest probability. In this work, the scenarios where the probabilities are 50% and 50% were not considered because all variables were equal to zero.

Another important matrix was used to compare different models and understand the one that better fits the data: likelihood and McFadden's adjusted R2. The likelihood gives an idea of how well a model fits the data. In contrast, McFadden's adjusted R2 calculates the log-likelihood ratio for the specific and intercept-only models and subtracts this ratio from 1. The formula that allows us to determine McFadden's adjusted R2 is shown in Eq. 7 [68].

$$\mathrm{R}^2 = 1 - \frac{\ln\hat{\mathrm{L}}(\mathrm{V_i}) - \mathrm{K}}{\ln\hat{\mathrm{L}}(\mathrm{V_0})} \tag{7}$$

where $\ln\hat{\mathrm{L}}(\mathrm{V_i})$ is the log-likelihood of the specific model, $\ln\hat{\mathrm{L}}(\mathrm{V_0})$ is the log-likelihood of the intercept-only model, and K is the number of parameters in the proposed model, which penalises the matrix for introducing several parameters in the model.

Finally, boxplots were used to analyse participants' responses to the post-experiment survey on different aspects of the VR experience (see Section 3.2), assessing the mean response and the spread of answers.

4 Results

This section provides the results of the exit choice model proposed in Section 4.1. Then, a sensitivity analysis is provided in Section 4.2. Section 4.3 concludes by presenting respondents' feedback about the VR experience.

4.1 Exit Choice Models

In this work, a multinomial logit model formulation is proposed. The model presented is linear, so it is possible to estimate $\beta_{i,j}$ weighting the impact of NPC, I and FF (see Table 1 for definitions) using Equation 8:

$$\begin{aligned} & V_i = const_R + \beta_{NPC} \cdot NPC_i + \beta_I \cdot I_i + \beta_{FF} \cdot FF_i \\ & i = L, R \end{aligned} \tag{8}$$

The intercept ($const_R$) was assigned only to the Right Exit. The estimated parameters for the model presented are displayed in Table 3. The model shows that all the parameters are statistically different from zero, with the p-values below the significance level of 0.05, except for β_{FF} which is partially significant (p-value < 0.1). In other words, the model shows that all the variables under examination impacted the decision-making process. In particular, according to the parameters, it is observed that variable I is around 78 times larger than the variable NPC. This result means that to compensate for the presence of a metro staff member who indicates an exit, it is necessary to have approximately 78 virtual evacuees using the other exit. This effect is even greater when a firefighter is present, and 94 virtual evacuees need to use the other exit to compensate for this.

In addition, a confusion matrix was used to observe the model's reliability. In this case, it was necessary to calculate how many choices made by participants matched the predicted ones. The choices were found to match in 806 of the 1048 scenarios or 77% of the time. It is also possible to observe that 61% of these matched choices were for the Left Exit (i.e., the exit indicated by the fire warden).

In this work, we also estimate a mixed logit model, assuming that both the β_{NPC} and β_I parameters in Equation 8 have a normal random distribution. This model was estimated using the panel data estimation setting, which takes into account that the choices made by the same participant are not independent and assumes that the random parameters of a participant are the same for all of their choices [69, 70]. The estimated parameters for the model presented are displayed in Table 5. The McFadden's adjusted R2 indicates that the random structure of the model improved the fit. This is also demonstrated by the Likelihood Ratio Test, which shows that the mixed logit provides a better fit with a p-value smaller than 0.001. On the other hand, while focusing on the predicted choice made by the model, the Mixed Logit Model is equivalent to the Multinomial Logit Model. Although changing the values of the estimate choice probabilities, the random structure provides new probabilities that are not too dissimilar from the Multinomial Logit Model. As such, the classifications with the confusion matrix can be considered the same.

A key feature of the Mixed Logit Model is that it is possible to analyse the heterogeneity of how the sample perceived the virtual evacuees (NPC) and the fire warden (I). The results in Table 4 show that there is a significant heterogeneity for both factors. In fact, both SD_ β_{NPC} and SD_ β_I are statistically significant. It is possible to assess this heterogeneity by drawing the normal distribution for the parameters associated with NPC and I (see Figure 5). The figure shows that all the likely values for the parameter associated with I are positive. This means that the presence of a fire warden always positively affects the selection of an exit. Conversely, the distribution for the NPC parameter has both positive and negative values. Although the vast majority of people followed other evacuees, there were instances in which participants decided to select the less crowded exit.

Based on Table 2 and Table 5, it can be observed that when a fire warden directs participants to the left (Scenarios 5–12), the likelihood of participants exiting left increases

Table 4 Estimated parameters for Mixed Logit Model

McFadden's adj R^2=0.290
Log Likelihood=−477.54

Variable	Estimate	Std error	z-value	p-value
$const_R$	0.284	0.119	2.394	0.017
β_{NPC}	0.039	0.011	3.505	0.000
β_I	3.276	0.340	9.631	0.000
β_{FF}	0.647	0.361	1.794	0.073
SD_ β_{NPC}	0.053	0.015	−3.663	0.000
SD_ β_I	1.027	0.319	−3.217	0.001

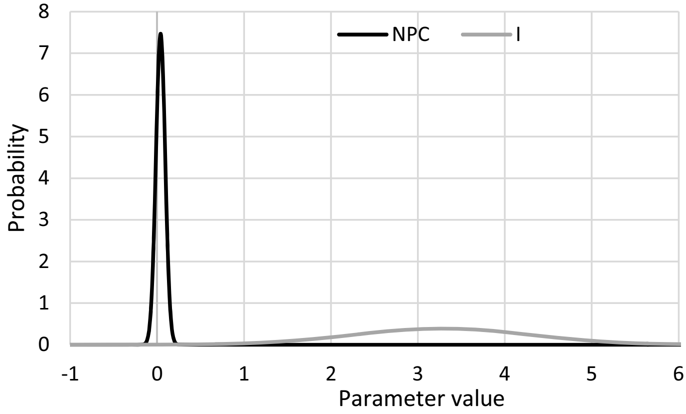

Fig. 5 Random distributions for the parameters associated with NPC and I

Table 5 Frequency of exit choices for each scenario

Scenario	Left		Right	
	#	%	#	%
Scenario 1	64	48.85	67	51.15
Scenario 2	46	35.38	84	64.62
Scenario 3	47	35.88	84	64.12
Scenario 4	37	28.46	93	71.54
Scenario 5	62	93.94	4	6.06
Scenario 6	61	93.85	4	6.15
Scenario 7	57	86.36	9	13.64
Scenario 8	56	84.85	10	15.16
Scenario 9	61	93.85	4	6.15
Scenario 10	64	98.46	1	1.54
Scenario 11	59	90.77	6	9.23
Scenario 12	60	92.31	5	7.69

by 50–60% (reaching around 90%) compared to scenarios where no fire warden is present (Scenarios 1–4). Additionally, when the fire warden is a firefighter, the probability of participants choosing the Left Exit further increases. It is also evident that as the number of virtual evacuees using the Right Exit increases (such as from Scenario 1 to Scenario 4, from Scenario 5 to Scenario 8 or from Scenario 9 to Scenario 12), the probability of people choosing the Right Exit also increases. The data in Table 5 shows that there was no left or right bias for Scenario 1 (no fire warden or virtual evacuees).

We finally assessed if the participants had any learning effect since they repeated their choice eight times. This was testing as done in [40] to assess if the first choice made by each participant was significantly different from the remaining seven choices. The results did not indicate any change suggesting that the participants were consistent in making their choices.

4.2 Sensitivity Analysis

Sensitivity analyses demonstrate how the variables considered in the multinomial logit model proposed in Section 4.1 can influence the probability of selecting an exit. The multinomial logit in Table 3 is tested as Monte Carlo simulations are not required to estimate probabilities given its closed formulation. In this section, three different analyses are conducted to identify the influence of all variables included in the model. The first analysis investigates the probability that participants will choose the Right Exit by varying the number of virtual evacuees that use each exit (the value of NPC varies from 0 to 30) where the fire warden is not present (I = 0). The representation of this analysis is obtained by using 3D surface plots. The results of Scenario 1 are shown in Figure 6a.

In line with the sign of β_{NPC}, it can be observed that increasing the number of virtual evacuees moving towards the Right Exit (i.e. increasing NPC) increases the probability of this exit being selected by participants. In addition, increasing NPC for the left exit leads to a decreased probability of the Right Exit being selected.

The second scenario is the same as the first but also includes a metro staff member in a hi-vis vest and hard hat directing people towards the Left Exit (I = 1). Similarly, the third analysis follows suit, but the fire warden is a firefighter (FF = 1). The results of Scenarios 2 and 3 are shown in Figure 6b and Figure 6c, respectively.

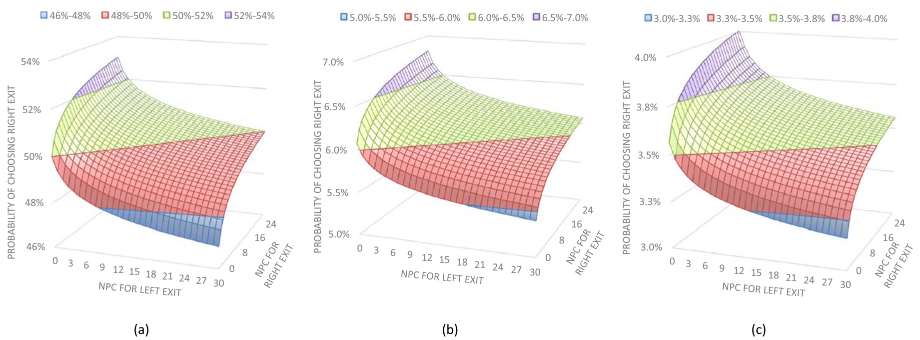

Fig. 6 Sensitivity analysis of (**a**) Scenario 1: No fire warden, **b** Scenario 2: The fire warden is a metro staff member who directs people towards the Left Exit; **c** Scenario 3: The fire warden is a firefighter who directs people towards the Left Exit

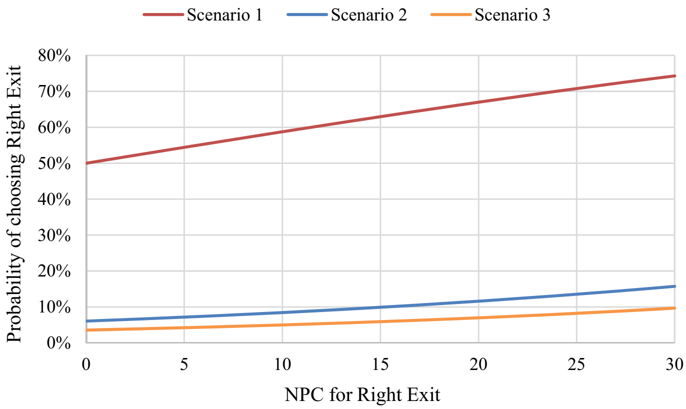

Fig. 7 Sensitivity analysis - Comparison between scenarios

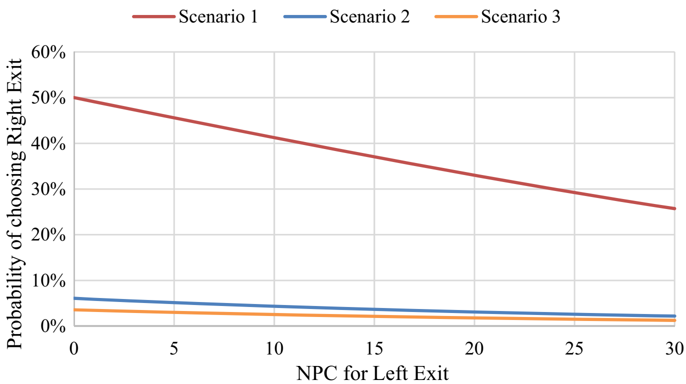

Fig. 8 Sensitivity analysis - Comparison between scenarios

To compare different scenarios, it is possible to create two-dimensional charts showing the probability of exit selection (Figure 7 and Figure 8) by sectioning the graphs shown in Figure 6. Figure 7 shows a section of the 3D graphs when NPC for the left exit equals zero, while Figure 8 shows the same scenario for the Right Exit. Figure 7 shows that the probability of choosing the Right Exit increases from 50% to 74% for Scenario 1. This means that participants are more likely to follow the crowd of virtual evacuees when a fire warden is absent. This increment is lower for scenarios when a fire warden is present. In fact, for Scenario 2 (metro staff member), the probability only increases from 6% to 16%, and for Scenario 3 (firefighter), the probability increases from 4% to 10%. Figure 8 and 9 shows that the probability of choosing the Right Exit decreases as increasing numbers of virtual evacuees move towards the Left Exit (i.e. NPC is increased). For Scenario 1 (no fire warden), the probability decreases from 50% to 26%. For Scenario 2 (metro staff member), the probability decreases from 6% to 2%, and for Scenario 3 (firefighter), the probability decreases from 4% to 1%.

It is important to highlight that the scenarios presented in this section show examples of possible analyses that can be carried out using the model presented in Section 4.1 (see the results in Table 4). This section aims to provide simple examples of the proposed model to illustrate how various factors impact the likelihood of evacuees selecting a particular exit.

4.3 Respondents' Feedback

After the VR experience, a post-experiment survey was used to gather information from participants (see Section 3.2). This survey asked participants to offer feedback on the realism of the experience, their emotional state, their feeling of urgency and times they felt unsafe, their engagement in the VR experience, and the ease with which they could participate in the VR experiment. This feedback is shown in the boxplots in Figure 9, Figure 10 and Figure 11.

The boxplots in Figure 9 show that the participants' levels of negative emotions (fear, tension, and anxiety) during the VR experience were low (note: +3 indicates a high level of negative emotion while −3 indicates a low level). These results can be linked with those displayed in Figure 11, showing that participants did not feel unsafe during the experiment, but they had a relatively high level of perceived urgency and severity. Figure 11 shows that participants scored the realism and interaction of the virtual evacuees lower than the perceived realism of the virtual world and fire warden.

5 Discussion

The goal of this work is to investigate the exit choice of occupants during fires in an underground metro station. In particular, this research focuses on the influence of two different factors on this choice: the social factor (i.e., the number of people using the exits) and the role-rule factor (i.e., the presence of a fire warden directing evacuees). Further, differences between fire wardens were also investigated using two authority figures in the experiment:

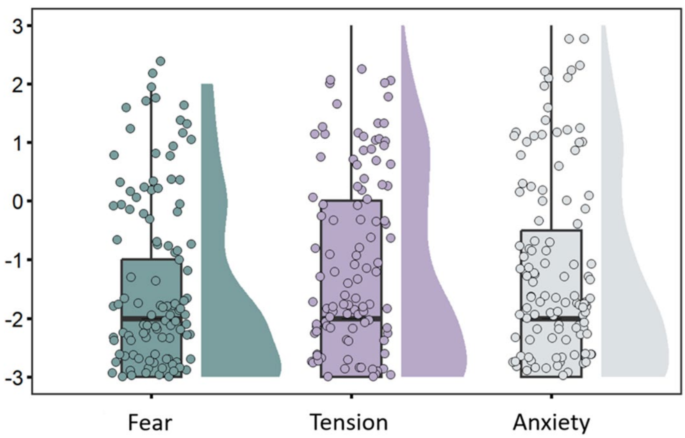

Fig. 9 Participants'scores for emotional state during the VR experience

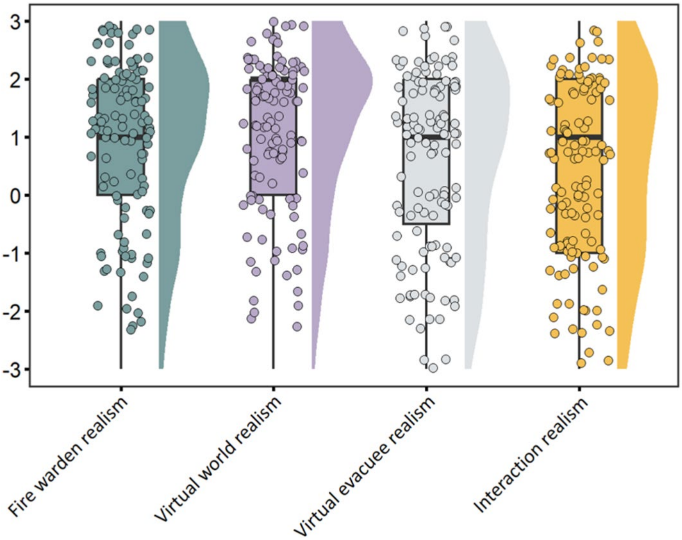

Fig. 10 Participants'scores for the realism of the VR experience

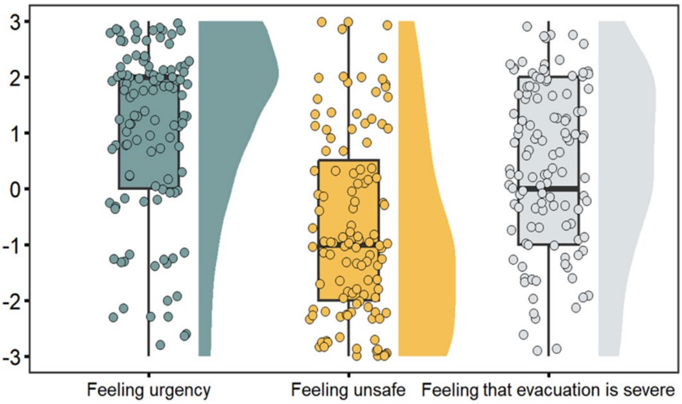

Fig. 11 Participants'scores for urgency, safety and severity

the first half of the participants interacted with a metro staff member, and the second half interacted with a firefighter.

In this work, a discrete choice model is developed to forecast exit choices based on the factors mentioned above. The results of the model show that all experimental factors influence the participants' exit choices. In addition, the results show that participants are more likely to follow instructions from a fire warden with higher authority. The models shown in Table 3 and Table 4 demonstrate that the exit choice decision is the result of a compromise of the factors included in the model. These findings are aligned with previous research in building fire evacuation [31, 33, 35, 40]. However, it is essential to highlight that only a few studies analysed multiple factors [40, 52], and no research was identified that integrated social influence and role-rule factors within a single experiment.

The proposed findings of this study align with the existing literature, indicating signs of convergent validity. Despite the main finding of this study being unique (i.e., the combined effect of the variables listed in the previous sections), some aspects of the results are comparable with prior research, further supporting the convergent validity. In addition, the study measured construct validity by distributing a post-experiment questionnaire to gauge participants'perceived realism levels. The participant's answers scored the VR methodology highly for fidelity, quality of visualisation, and behavioural validity, indicating a high level of ecological validity.

In collecting behavioural data, it is important to consider the advantages and disadvantages of the research methods and techniques used. The research strategy selected should be a combination of appropriate research methods and data collection techniques, taking into account the research objectives and other boundary conditions such as time and cost, ethical considerations, and experimental control [14]. The main aim is to reach the appropriate ecological validity in which participants exhibit similar behavioural, emotional, cognitive, and psychophysiological reactions in both VR and the real world [71]. Ideally, case studies and unannounced evacuation drills are the best way to achieve ecological validity in emergency response research. These methods allow evacuees to experience real-world scenarios, which makes their behaviour less biased than if they know they are part of an experiment. However, case studies have limitations when obtaining real incident data due to privacy and ethical issues. Even when videos of real incidents are available, researchers have no control over the evacuee sample or the variables affecting their choices. As a result, selected choices can only be inferred from the evacuees'behaviour during the emergency, which increases measurement uncertainty [14].

This work provides several novelties in terms of findings. This study is the first to investigate a unique combination of variables (see Table 1) and their combined effect on exit choice. In fact, while several studies have provided insight into the impact of individual variables, this work represents one of the first instances in which the impact of multiple variables was investigated using discrete choice modelling. As such, this work aligns with the methods used in new studies on exit choice during evacuation [32, 40, 72]. This was made possible by asking participants to choose an exit in multiple scenarios. The results show that the variables influence the choice with different weights: the presence of a firefighter indicating the correct choice has a more significant impact on participants than a metro staff member completing the same action. The following paragraphs discuss the conformity of our findings with the existing literature.

Studies including multiple factors show similar results in terms of social influence, as people are more likely to follow other people to an exit [40, 59]. This similarity was found in some research performed in experimental buildings or tunnels [42, 73]. Another work that shows similar results is by Nilsson and Johansson [15], who demonstrate that social influence is more significant when information is limited. We illustrate this in our work, as most participants choose the exit used by other virtual evacuees when the fire warden is absent and follow the warden's directions when more information is provided. On the other hand, some contrasts were seen in some studies performed by Haghani et al. [74] and Lovreglio et al. [75], who found that participants mostly preferred less crowded exits. A possible reason for this difference is the distinction between the technologies used to investigate this factor.

Regarding the existing research on the role-rule model, our work supports all of the research analysed in Section 2. All of the studies demonstrate that "the way a person interprets, prepares and acts in the event of a fire is highly dependent on the everyday role that person has adopted and the rules attached to that role" [29]. In particular, this work highlights that people are more likely to trust advice when they have a more favourable perception of the person giving that advice [14, 51]. For example, the model presented in Section 4.1 shows that in the case where the firefighter is present, the probability of choosing the exit indicated is higher.

The findings of this research also underscore the significance of using VR for collecting data on human behaviour during building fires. In our experiment, the alarm signal and the actions of virtual evacuees served as the primary fire cues, enabling researchers to observe participants' exit choices in a controlled and safe environment. It also enables the collection of precise behavioural and physiological data during controlled simulated events. Participants' feedback indicated that the simulation of the virtual world was realistic, but some improvements are necessary for future research, for instance, on the realism of the virtual evacuees. In addition, participants do not feel high levels of anxiety, tension or fear, which makes sense as the VR participants do not see fire or smoke, which is present in many real cases [76].

6 Limitations and Future Research

This work has some limitations. For example, the study's sample is characterised by participants who all live in New Zealand (despite having different nationalities), so it is not possible to consider this sample to be representative of the world's population. Future studies are necessary to understand whether cultural differences can influence the evacuees' behaviour.

Another limitation of this study is that some participants did not perceive the virtual evacuees as being realistic, which may have affected their perception of the virtual evacuees'social interaction and biased the results. However, the self-reported ecological validity suggests that participants behaved in the experiment as they would in a real emergency. To overcome this limitation, future research could use the experimental deception technique proposed by Shipman et al. to enhance the realism of virtual evacuees [28]. With the enhancement of computer graphics and AI applications for VR, this limitation will likely become marginal in future studies.

Additionally, the participant's movement was only virtual and not physical, and the locomotion was controlled using a C# script. This solution was selected to allow the data collection in small rooms where participants were standing still during the experiment. Also, this controlled locomotion solution allowed all participants to have the same experience while reaching position "B" before they made their exit choice. As such, while this approach might have introduced some bias in the participants' decision-making, it is more practical and ensures a consistent experience across all participants.

Finally, the current study employed a mixed between-subjects and within-subjects design, which, although practical and resource-efficient, introduces potential confounding effects associated with repeated measures. A purely between-subjects design can be used in future studies if learning effects impact the decision-making process. Such an approach eliminates repeated-measure biases, ensuring each participant experiences only one experimental condition, thus improving the reliability and validity of the observed effects. Although this design typically requires a larger sample size and more resources, it can offer more precise attribution of observed effects to specific experimental factors.

7 Conclusions

This study examined several social factors influencing evacuees' exit choices during fire emergencies in underground metro stations, focusing on peer social influence, fire wardens' instructions, and the level of authority of the fire wardens. The findings indicate that the influence of both other evacuees and fire wardens affected decision-making. Participants exhibited a strong inclination to follow instructions given by fire wardens, with this effect being more pronounced when the fire wardens appeared more authoritative.

Furthermore, the proposed discrete choice model provides insight into how a combination of these factors influences the probability of evacuees selecting a particular exit. The findings have significant implications for the field of evacuation research. The results highlight the importance of the information provided by fire wardens, as well as their perceived level of authority during an evacuation. Additionally, the findings underscore the necessity of incorporating both social influence theory and role-rule factors when conducting evacuation simulations.

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Data Availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

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