POLITECNICO DI TORINO

Corso di Laurea Magistrale in Ingegneria Edile

A.A. 2022/2023

Sessione di Laurea Dicembre 2023

Virtual Reality and Human Behaviour in Fire: An Exit Choice Experiment to Measure Social Influence and Role-Rule Influence

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Abstract

In the event of a fire emergency in a built environment, human behaviour plays an important role, since building occupants need to make several evacuation decisions. Exit and route choices are one of them. It is fundamental to investigate which factors influence this choice. Understanding how humans weigh different factors when they make a choice is crucial to design a safe built environment for evacuations.

The main objective of this work is to study the exit choice of occupants during fires and develop an exit choice model which could be implemented in future evacuation software tools. In particular, this research focuses on the influence of two different factors: the social influence and the role-rule factor. To achieve this goal, this work uses a new immersive virtual reality experiment to investigate exit choice during a fire evacuation in a metro station. This experiment involves 131 random participants who were asked to choose between two possible exits in different evacuation scenarios. These scenarios differ in the presence or not of an instructor guiding participants, the authority of the instructor and the presence or not of other evacuees who use a specific exit. Using the collected data, a discrete choice model was estimated to investigate if and how these factors affected the participants' decisions. The results of the models show that all the factors considered influence the participants' choices. In addition, the results show that the higher the authority level of the instructor the more participants follow the instructions. Finally, other models were developed to analyse the impact of demographic factors (i.e., age, nationality, handedness and BMI) on the choice of participants. In this case, the results do not show evidence that demographic factors have an impact on the exit choice. This work provides several novelties in terms of findings, and it has implications for both fire safety designs and future VR evacuation experiment designs. This study is the first one that investigates a unique combination of the variables mentioned above and their interactions.

Keywords: Exit Choice, Fire Safety Engineering, Human Behaviour in Fire, Evacuation, Discrete Choice Model, Virtual Reality.

1 Introduction

Fire safety is a fundamental aspect to consider when designing buildings and infrastructures as well as any built environment which is exposed to fire risk (e.g., factories, oil plants). Fire safety aims to enhance human life safety and protect properties, heritage, and the environment [1]. This goal is achieved by studying, promoting, acting, and testing standards, measures, and precautions that try to avoid the occurrence of a fire and, if happens, to limit its consequences [2].

In the field of fire safety, there are two main approaches: the prescriptive-based approach and the performance-based approach. The first one consists of applying some technical regulations that allow for obtaining a suitable level of fire safety. In this case, the risk assessment is performed by the legislator. The second approach provides the definition of some performances that must be obtained, and it is necessary to demonstrate the achievement of these objectives [3]. In this case, the risk assessment is performed by the designer by using back-of-the-envelope (manual) calculations or computer-based simulations of the fire and smoke spread and the evacuation process [4].

The most widely used model for manual calculations is the hydraulic model which simplifies the behaviour of evacuees by using a set of macroscopic equations [5]. Regarding computer-based models, the number of these models for fire safety engineering applications and their sophistication is continuously increasing. Therefore, it is important to gain a better understanding of the experiences of current users for the development of future generations of computer pedestrian evacuation models. Some studies [6], [7] highlight the need for other investments in research and data collection to verify, validate and develop new models. The proliferation of these tools has played a key role in making performance-based designs feasible worldwide.

In the last decades, many countries worldwide have integrated the performance-based approach to their building codes which used to be prescriptive-based [8]. This change was prompted by several factors, including the negative aspects of the prescriptive codes, economic and social considerations, progress in fire science and engineering, and the harmonization of regulation systems worldwide. The performance-based approach has improved the regulatory framework by clearly establishing code objectives and safety criteria while leaving it up to the designer to determine how to achieve these objectives [9]. In fact, the introduction of this approach makes the codes more flexible, functional, less complex, and easier to apply while allowing for innovation. This code change has been also affecting the Italian legislation.

The regulatory landscape in Italy had several changes in recent years. The first step towards the performance-based approach was made in 2009 by guidelines for road tunnel safety design [10]. This document provides general information on people's performance during evacuations and methods to simulate them. However, this information is often based solely on historical accident databases therefore it presents a lack of behavioural data for the calibration of evacuation models [11].

The main change in the Italian legislation happened in 2015, when a new code was introduced by D.M. 03/08/2015 entitled “Codice di Prevenzione Incendi”. The purpose of this code is to simplify the present standards to obtain a new methodological approach aligned with technological progress and international standards. The approach proposed in this code is defined as semi-prescriptive because it gives technical regulations suggested by the legislator and it also allows the adoption of alternative solutions that can be verified using the fire safety engineering method [3].

While the performance-based approach is becoming more popular worldwide, there is a constant need for better tools to support Fire Safety Engineering, especially in the evacuation domain. In the following sections, the importance of Fire Safety Engineering is explained (Section 1.1) and the fundamental aspects of evacuation and how it’s strictly influenced by human behaviour are described (Section 1.2). Finally, the objectives of this thesis are illustrated in Section 1.3.

1.1 Fire Safety Engineering

The term Fire Safety Engineering refers to the application of engineering principles, rules, and expert judgments based on the scientific evaluation of the combustion phenomenon, the effects of the fire, and human behaviour, with the aim of saving human lives, and protecting properties and the environment [3]. Fire Safety Engineering is significant because, in some complex structures that pose a high risk of property or life damage (e.g., large volume spaces, telecommunication, or power-generating facilities), solely prescriptive measures may not suffice in meeting their needs [2].

The chapter “Performance-Based Design” of the SFPE [12] defines performance-based design as “an engineering approach to fire protection design based on:

- Agreed upon fire safety goals and objectives;
- Deterministic and/or probabilistic analysis of fire scenarios;
- Quantitative assessment of design alternatives against the fire safety goals using engineering tools, methodologies, and performance criteria.”

The application of Fire Safety Engineering allows the definition of suitable design solutions by performing quantitative analysis. The designer defines the aims of the project and transforms them into quantitative performance thresholds; afterwards, the designer establishes several design fire scenarios. Fire scenarios are the most severe incidents that may reasonably occur in the activity [3]. Manual or computer-based modelling tools allow designers to describe and calculate the effects of the fire scenarios related to the design solution assumed. If the design solution allows maintaining a suitable margin of safety with respect to previously established performance thresholds, this solution is acceptable.

To evaluate the safety of a given design solution, the performance-based approach involves comparing the Available Safe Egress Time (ASET) with the Required Safe Egress Time (RSET) [13]. ASET is the time that can pass before the environment becomes too dangerous to escape from, while RSET is the time required for all evacuees to exit safely. Designers evaluate ASET by considering several tenability criteria, such as smoke layer heights, intoxication of evacuees, etc. The main criterion is Fractional Effective Doses (i.e., the doses of toxic products inhaled by occupants during the passage of time) [11]. Regarding the evaluation of RSET, many methods and models exist in the current state of the art that simulate the evacuation process.

Existing theories and data are used to develop evacuation models that estimate the time necessary to evacuate a building or transportation system (RSET). These models are valuable tools for analysing potential risks and improving safety measures. In addition, they're flexible enough to simulate numerous scenarios in a relatively short time [14]. By adjusting the input parameters, the models can easily represent different evacuation scenarios. However, it is fundamental that the designers select the most appropriate modelling approach for the analysis and input parameters [15]. As such, the analysis of the evacuation process with the performance-based approach relies heavily on the existing scientific knowledge of human behaviour in fire.

1.2 Evacuation and Human Behaviour

The design of evacuation can be a very complex task and it represents a crucial aspect of Fire Safety Engineering, because, according to statistical data, many of the fatalities and damages caused by fires can be traced more to human error than to engineering failure [16]. Over the past few decades, studies on pedestrian evacuation dynamics increased and became a key research topic [17], [18], [19], [20]. It is fundamental to understand the evacuation dynamics as this knowledge is essential to reduce deaths and property losses in case of unexpected accidents or disasters. Considerable research has been made and different evacuation models have been developed by scholars in this area [21], [22].

The critical factors that define the fire response performance and therefore the evacuation of the building occupants can be divided into three categories: human features, building features and fire features (see Figure 1) [23]. The nature of the fire has a great influence on the level of fire response performance. The characteristics of a building have a direct consequence on its fire response performance, as it is a physically enclosed environment where people carry out different activities. Additionally, human nature also plays a significant role in determining the level of fire response performance. In order to examine this, it is important to study behaviour at both individual and group levels. This includes examining character traits, knowledge, experience, powers of observation and judgment, mobility, and social interactions between people present, level of engagement, roles or responsibilities in the building, and situational characteristics such as awareness, physical position, and familiarity.

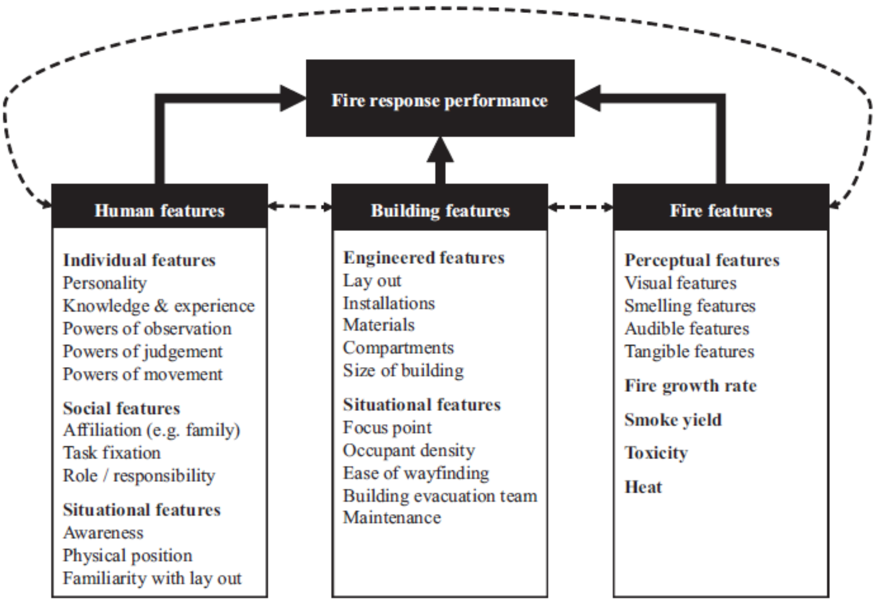

Figure 1. Fire response model [23]

As stated in Section 1.1, the performance-based approach to fire safety is based on the comparison between ASET and RSET. In this work, it will be analysed the computation of RSET. This time is often categorised into four main times: the detection time, the warning time, the pre-evacuation time, and the movement time. The detection time estimates the time when ignition begins until the moment when the fire is detected. The warning time estimates the time when the fire is detected until the moment when occupants are informed of the danger. The pre-evacuation time corresponds to the time when occupants are informed until an individual or group begins purposive evacuation movement to a place of safety. The pre-evacuation time is in turn divided into two: the recognition time and the response time. The movement period is the time in which the movement toward a safe place occurs [24]. Figure 2 shows the engineering timeline explained above.

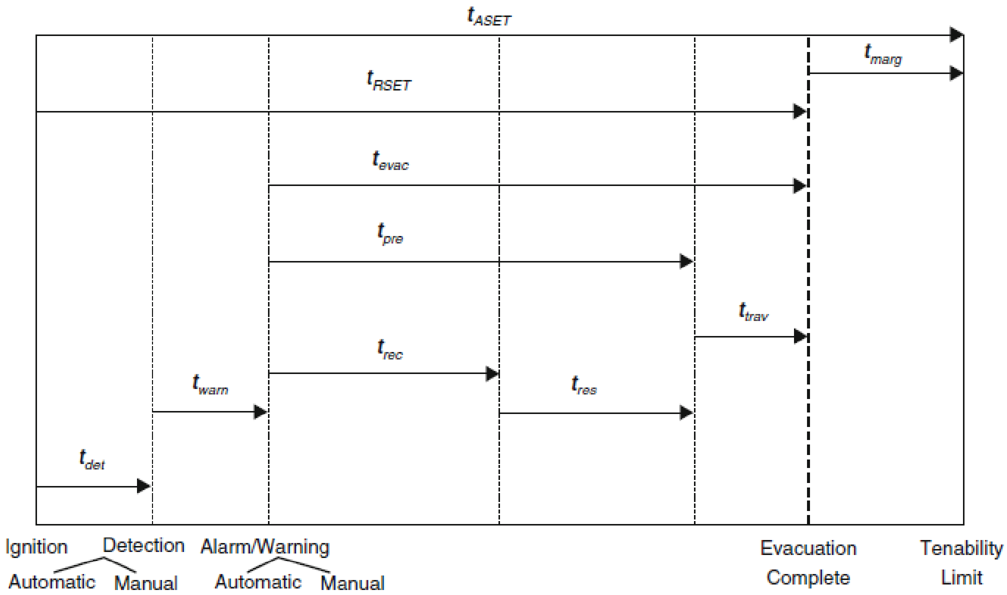

Figure 2. Engineering timeline [24]

Quantifying evacuation time is a key task for fire safety engineers. Evacuation time is strongly affected by differences in pre-evacuation and speeds which can depend on different physiques, ages, genders, psychology, etc. [25]. Further, other key factors are route/exit choices and complex interactions between people and the environment (comprehensiveness of guidance signs, familiarity with the environment, suitability of emergency lighting, etc.) [26], [27]. These aspects cause various *ripple effects*, making orderly evacuation difficult to reach [28].

In particular, it is important for fire safety engineers to identify and use appropriate pre-evacuation data distributions as they can significantly affect the results of evacuation simulations. However, pre-evacuation data is often limited, incomplete and presented in a format that can be challenging to use in these simulations. For instance, Lovreglio et al. [29] provide a pre-evacuation database useful to estimate pre-evacuation distributions.

Therefore, the study of human behaviour in fire emergencies must be the core of all life safety projects. It is necessary to examine how people respond to emergencies, including their awareness, attitudes, behaviours, motivations, beliefs, coping strategies, and decisions. This field is highly multidisciplinary and involves professionals from various fields in addition to engineering, such as architecture, law, sociology, computer science, psychology, mathematics, human factors, ergonomics, and communications [30].

One of the first conceptual models[1] describing human behaviour in a fire is the one proposed by Fridolf et al. [31] (see Figure 3). It uses the following sequence categories: interpret, prepare, and act. Each category constitutes a sequence of consecutive actions that people perform. By adopting this model, human behaviour in a fire can be explained without the use of the term "panic", which represents a questioned topic within the research community. In fact, some studies [32], [33] demonstrate that descriptions of "panic" relate more to scare or increased anxiety than any kind of behaviour leading to the death or injury of a person. People under stress behave relatively rationally, controlled, and appropriately [34]. The studies show that some suboptimal behaviours (e.g., an evacuee not selecting the closest and safest exit) are mostly due to a lack of information.

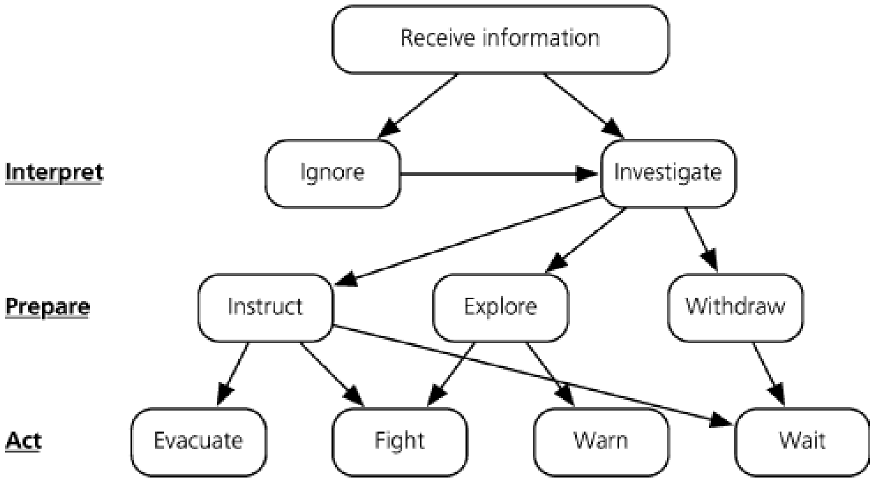

Figure 3. A general model for explaining the behaviour sequences in fire [31]

Another important conceptual model of human behaviour in fire is the Protective Action Decision Model (PADM). This model was originally proposed by Lindell and Perry [35] for large-scale disasters and it has been adopted by several authors to explain building evacuation too [36], [37]. PADM includes the factors that influence individuals' adoption of protective actions. Studies on individual response to disasters provide results that can be observed on the summary proposed in Figure 4. This chart provides a graphic representation of the model.

[1] Conceptual models: to an observer B, an object A* is a conceptual model of an object A to the extent that B can use A* to answer questions that interest him about A, and if the model does not have any physical reality [100].

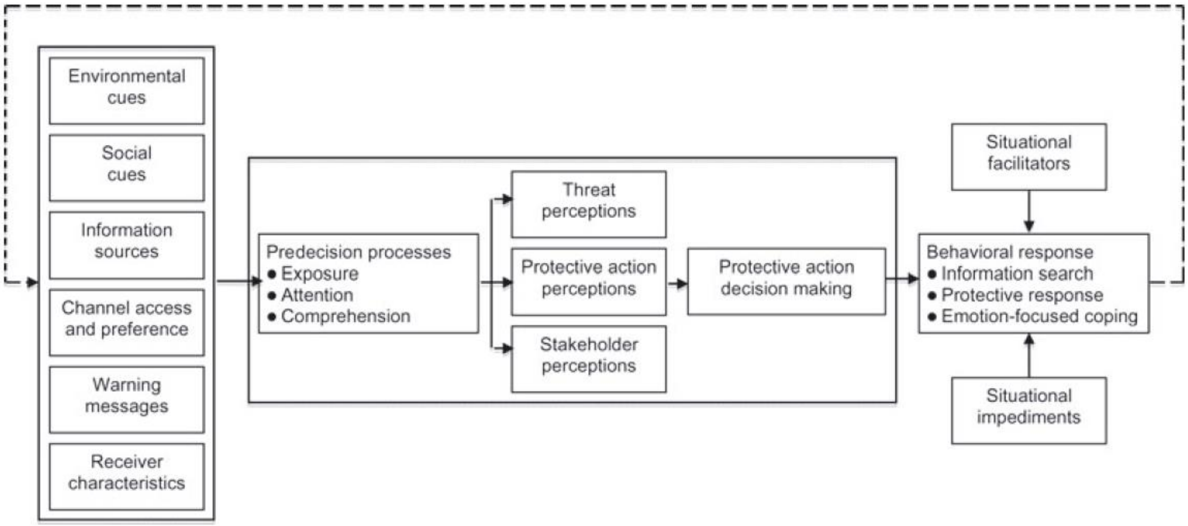

Figure 4. Information flow in the PADM [35]

Environmental cues, social cues, and warnings are the first steps of the decision-making process. Changes in receivers' beliefs and behaviours are considered the relevant effects, by knowing that receivers' characteristics are physical (i.e., strength), psychomotor (i.e., vision and hearing), and cognitive (i.e., mental models/schemas, native language), abilities and economic and social resources. PADM allows to understand how people usually make decisions to protect against ambient risks. These stages are sequential, as the stages within the information-seeking process. However, not in all cases people follow steps in the model in the exact sequence shown in Figure 4.

Pedestrian evacuation dynamics has been thoroughly studied but significant work is needed to develop engineering models which are extensive, vigorous, and validated theory on human behaviour during evacuation from building fires. Currently, without comprehensive conceptual and data-driven models, evacuation software tools are limited in how the evacuation process is simulated. Evacuation software often requires extensive input data on evacuee behaviour to compensate for model omissions [7]. The absence of a comprehensive conceptual model of evacuee behaviour and data-driven models has important consequences for users, developers of evacuation models, and evaluators of evacuation analysis. As shown in Figure 5 (approach 1), the model requires the user to recognize the scenario that the evacuees are encountering. However, numerous existing models necessitate the user to predict how people will react to specific scenario conditions. In some cases, the user may need to provide additional data to make up for the lack of a conceptual model, in addition to the data used to set up the model for the scenario under investigation.

Evacuation modelling, currently, can become problematic in the following cases:

- if the user assumes that dictated agent behaviours are actually a model prediction;

- if the behavioural response is significantly reduced with the aim to match the user assumptions during model configuration;
- if the user is not qualified [7].

Current evacuation models rely on user input to predict fire evacuation scenarios, which can lead to inaccuracies. Hence, the next generation of models should be designed to predict individual and group behaviour in a building fire using situational conditions, rather than depending on ad-hoc user input. This approach would ensure consistency and accuracy in the predicted behaviours and take the burden away from designers to prescribe actions. [36]. One of the behaviours that should be estimated by future models, and not set by users as input, is the exit/route choice, studied in this work. A possible modelling roadmap is proposed by Gwynne et al. [7]. They propose a schematic representation (Figure 5) of three different approaches characterized by different relationships between the user and the model: the first one represents the current situation and the other two represent the aspirations for the next generation.

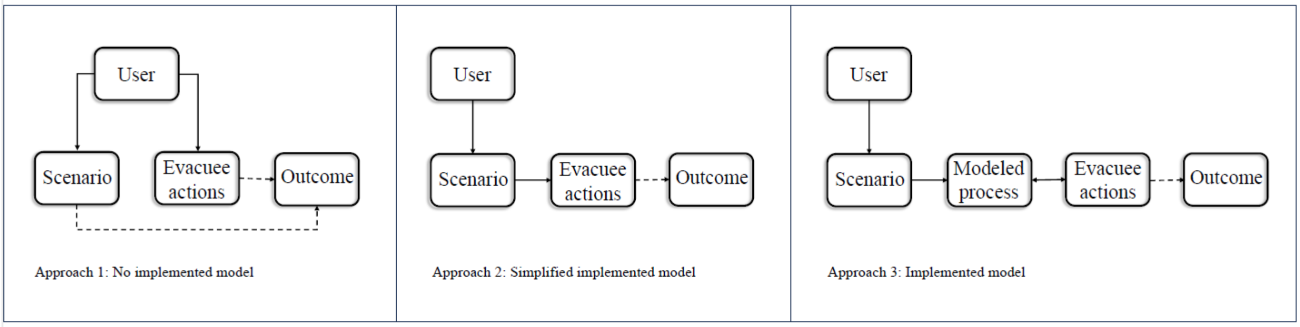

Figure 5. Model representation [7]

In this work, the exit-route choice will be analysed; it is an important aspect that regards human behaviour, and consequently influences evacuation in case of fire. In particular, we will see how the social influence and role-rule model (explained in detail in Sections 2.2 and 2.3) can influence this choice.

1.3 Motivation and Objectives

The aim of the work is to move towards the development of the next generation of data-driven models and the following implementation within existing or new evacuation software tools. This approach would allow model users to depict essential evacuee actions within the modelling framework without directly imposing them on the current scenario. The evacuee behaviour analysed in this study is the exit choice.

The main objective of this work is to study the exit choice of occupants during fires and develop an exit choice model which could be implemented in future evacuation software tools. In particular, this research focuses on the influence of two different factors on this choice: social influence and role-rule factor.

To achieve this goal, this work uses a new immersive virtual reality experiment on exit choice during a fire evacuation in a metro station. This experiment was developed at the Lab of Digital Built Environment of Massey University. This virtual reality application was used in this research to collect new data and estimate a new exit choice model. This experiment involved 131 random participants who were asked to choose between two possible exits in 12 different scenarios, but each participant was asked to make only 8 choices in total. These 12 scenarios differ in the presence or not of an instructor guiding participant, the authority of the instructor (underground staff member or firefighter) and the presence or not of other evacuees who use a specific exit.

Using the collected data, a discrete choice model was estimated to investigate if and how these factors affected the decisions of the participants. In addition, other models were developed to analyse the impact of demographic factors on the choice of participants. Finally, the model is tested in this work by performing sensitivity analysis.

2 Background

This section offers insights into the factors affecting exit choice, including social and physical factors (Sections 2.2 – 2.4). Additionally, it provides a summary of relevant studies using VR technologies to investigate exit choice (Section 2.5).

2.1 Exit/Route Choice

In the event of a fire emergency, it is important that people use the closest and safest emergency exits to reach a safe place as fast as possible. The exit and route choices can significantly affect evacuation performance [38], [31]. Numerous studies [39], [40], [41], [42] have investigated exit choice during fires, and researchers from all around the world are working on various aspects of this topic. These researchers have identified several elements that can affect evacuee exit choices, such as social influence, evacuation systems' affordances, familiarity, the geometry of the building, and injurious conditions within the environment itself (i.e., smoke) [30].

During a fire emergency, people may not always make optimal decisions due to limited perception and difficulty combining information. Instead, they rely on preferences [7]. Gao et al. [40] have identified three major effects on decision-making: the compromise effect, the similarity effect, and the attraction effect. The first effect describes how an option is perceived as more attractive when it is seen as a middle ground between other options rather than as an extreme option [43]. The similarity effect occurs when the presence of a similar option leads to a decrease in choice for similar options and an increase in choice for dissimilar options [44]. The attraction effect happens when adding a similar (but inferior compared to another one) option to the choice set enhances the likelihood of selecting the superior option [45].

The factors that influence the exit decision, according to the studies made by Duives et al. [42] and Kinateder et al. [39], are the following: the distance to the exit, the angle that the exit route makes with respect to the current direction of movement, familiarity exits, and the exit choice of the other evacuees. Other studies [46], [47] demonstrate that people have a tendency to evacuate via familiar routes and exits; it is called affiliative behaviour, and it occurs when people move towards "familiar persons and places", that usually correspond to the main entrances. In some cases, people prefer not to adopt a new route or an exit previously unknown, even if they are available and/or closer.

Experiments performed by Augustijin-Beckers et al. [48] demonstrate that not everyone follows the nearest exit when leaving a building. While about half of the people (48,5%) do choose the nearest exit if known, 20,7% of people return to the main entrance and 20,8% follow other evacuees. The assumption made by most models that evacuees go to the nearest exit is not always true. Instead, according to the study performed by Duives and Mahmassani [42], people usually consider four criteria: distance to all exits, number of evacuees that use an exit, choices made by other individuals, and the throughput of a specific exit.

Therefore, the evacuee's choice of exit can be influenced by other occupants, and this influence can be different based on the number of people present in the scenario [49]. A study performed by Haghani et al. [50] demonstrates that, in very large crowds (more than 75 people), participants don't follow "the crowd". However, studies involving a smaller number of participants provide other information: Lin et al [51] found that participants tend to follow the majority of evacuees who choose an exit when participants are around 50. This finding is true across multiple cultures.

Sime [52] studied a post-fire investigation and concluded that "the three main factors that influence the direction of movement and choice of exit in an evacuation are:

- A person's role (i.e., staff member or visitor) and their familiarity with escape routes;
- A person's ties to individuals in other parts of the building (i.e., family members and friends);
- The proximity of emergency exit doors."

In the following sections (Sections 2.2 and 2.3), two important factors that influence the exit choice will be analysed: social influence and role-rule factor.

2.2 Social Influence

Social Influence is the subject that studies how individuals' beliefs, thoughts, emotions, opinions, or behaviours are affected by others in the social network. Several disciplines are often influenced by social factors, including emergency decisions. The decision-making process of an individual depends on their personal constraints which are significantly influenced by their social network [53]. Deutsch et al. [54] define two distinct forms of Social Influence: *normative SI* and *informational SI.* The first one is defined as "the pressure social norms and expectations exert on behaviour"; the second one describes that "the behaviour of others is a source of information about how to react in an ambiguous or insecure situation."

The impact of Social Influence on human behaviour has been extensively documented in academic literature. Research conducted by Asch [55] illustrates that hearing the options of others can sway an individual's decision and even lead to make mistakes. Another important work was performed by Latané and Darley [56] and it represents the beginning of the development of research that examines helping behaviour in dangerous situations. In these investigations, the bystander effect was explained and demonstrated: the diffusion of responsibility tends to make people less inclined to offer assistance when others are present. Some years later, Latané [57] introduced the Social Impact theory, which suggests three fundamental principles for explaining SI:

- SI is a product of societal pressures;
- SI is directly related to the number of sources of influence;
- The more exposure people have to SI, the less impact each individual experiences as a target of that influence.

During emergency situations, 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 some unclear situations, what may be emergencies, a useful source of information can be the behaviour of other occupants [58]. Therefore, the presence of others in emergency situations influences an individual's behaviour. The time of emergency situations in which the social influence assumes particular importance is the initial phase because in this phase the individual tries to find all the possible and necessary information. Nilsson and Johansson [59] demonstrate that, when information is partial (i.e., ambiguous fire cues), social influence is more significant and increases with decreasing distance between people. Therefore, closer people have more impact on individuals than people who are further away.

For the purpose of this work, it is necessary to examine Social Influence in the virtual world and to understand if the same mechanisms and phenomena occur. Many traditional findings from Social Influence research have been duplicated effectively in Virtual Reality (VR), as demonstrated in certain studies [60], [61], [62]. These studies indicate that VR can be a successful platform for studying Social Influence [63]. However, a significant drawback in VR studies related to SI is that virtual agents might be perceived differently from real people, as participants may not recognize animated agents as humans [64].

2.3 Role-Rule Model

The role-rule model represents the relationship between roles, rules and behaviour, and it is a crucial aspect of human behaviour in fire emergencies.

To analyse this important factor, Fridolf et al. [31] study a good example that allows to understand the behaviour of people during an emergency at an underground station: the King's Cross fire. This case demonstrates the relationship between roles, rules and behaviour. Fridolf et al. [31] observed that the recognition, interpretation, and response to the first fire cues ware correlated with the role of an individual, by analysing the different behaviours of people with different roles (police, underground staff, and tunnel users). The role-rule model allows to understand that one's prior knowledge and experience before a fire can impact their behaviour during the fire. This was evident during the King's Cross fire, where staff members and police took on the role of authority and gave instructions to passengers, while the passengers reacted differently. This highlights the significance of preparedness and training in handling emergency situations.

The King's Cross fire is a clear example that shows the significance of the role-rule model. The behaviour sequence that a person adopts during a fire (i.e., interprets, prepares, and acts), according to the models, depends on the daily role a person takes on and the associated rules.

This study [31] also observed that there was a difference in terms of response between instructions provided by the police present at the station and instructions from staff members: the police received a better response from the passengers. It could be explained by recognizing that people see the police as having more authority than underground staff in a non-fire situation. Some research [65], [66] on policing and public order shows that people's response is not just influenced by how clear and useful the guidance is, but also by their perception of the organizations delivering that guidance. Templeton et al. [67] observed that trust in fire safety guidance is an essential factor and it should be incorporated into evacuation models.

Another study performed by Proulx [68] introduced a stress model and ways to reduce it. It was found that providing precise information is an effective way to reduce stress and induce a reaction in the event of a fire. Precise information can help people interpret the situation accurately, which in turn enhances decision-making and problem-solving abilities, ultimately leading to a decrease in stress. To ensure an efficient evacuation during an emergency, it is crucial to communicate precise information about the situation, its location, and what is expected from the public. To achieve this objective, the definition of rules and roles of people are fundamental. The method of transmitting this information, the exact content of the message, and the most effective procedure for coordinating the actions of all players during an emergency evacuation are important questions that still need to be explored.

2.4 Demographics Data

In addition to these external environmental factors, it is also important to focus on the individual-specific impact of demographic variables on exit choices. There is not general agreement on if/how demographic variables can affect these choices. In fact, several studies [42], [69] do not show any evidence that individual attributes (e.g., age, gender, BMI, nationality, left-handed or right-handed, etc.) are significant. On the other hand, other studies, presented in the following paragraphs, found statistical influences of some demographic variables on the exit choices.

Xu et al. [70] studied exit choice during an airplane’s emergency evacuation and their results show that individuals with a bigger BMI index are more likely to use back exits. These results suggest that a person’s body type might slightly influence their decision-making. Instead, Song and Lovreglio [71] analyse the impact of demographic variables (i.e., nationality, age, gender, education, BMI, disability, training and previous experience with evacuation) on exit choices and demonstrate that they all have a significant impact on exit choices. However, these results could be due to the big data nature of their sample.

Another two relevant studies are the one published by Veeraswamy et al. [72] and Troncoso [73]. The former work [72] studied wayfinding behaviour within buildings through an international questionnaire. They demonstrate that handedness, which is a genetic factor, and the side of the road people are used to driving on, which represents a cultural factor, significantly affect their choice of routes. The handedness is the main influencing factor, and the driving side is influenced by handedness. Thus, to predict the wayfinding behaviour, it is important to consider the handedness of an individual and the country of origin. On the other hand, Troncoso [73] found that, when considering Chinese and European individuals in Sweden, cultural backgrounds do not seem to influence people’s choices during a simulated evacuation. Despite this, traditions and culture may still have an impact on how people think and behave.

2.5 Virtual Reality Experiments

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, Virtual and Augmented Reality (VR and AR) have gained popularity in the safety research community [74]. Different combinations of hardware and software allow access to these technologies to the public. Therefore, it is essential to review the existing literature to analyse the strengths and weaknesses of these nascent technologies [75].

The primary goal of both VR and AR is to offer users virtual content. However, these technologies differ in how they integrate virtual content with the real world [75]. Figure 6 illustrates the conceptual framework proposed by Milgram & Kishino [76], emphasizing the distinctions between VR and AR. They provided a virtuality continuum, with VR at one extreme, offering a completely synthetic experience comprising solely virtual content. The scheme also identifies various mixed reality technologies that blend real and virtual content. In addition, AR and VR can be categorized based on the hardware solutions they employ: VR technologies are divided into immersive and non-immersive solutions. Non-immersive VR relies on displaying virtual content through a screen, while immersive VR uses technologies like Head-Mounted Displays or Cave Automatic Virtual Environments to create more immersive experiences [75]. In this work, only the VR will be discussed.

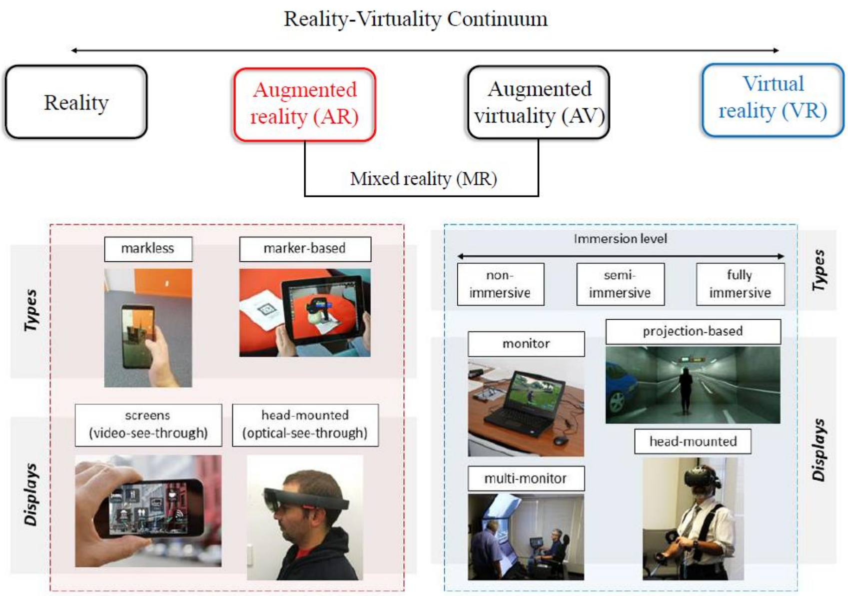

Figure 6. VR and AR position in the reality-virtuality continuum [76] *and their hardware solutions* [77]

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) [78]. Therefore, VR in not limited to computer-generated environments or any specific technology. VR is a research tool that balances between ecological validity and the ability to control experiments. If this balance is reached, this tool can serve as an effective, versatile, and affordable training platform for scenarios related to safety. There exist several studies that explore the use of VR to understand human behaviour and train individuals for emergency scenarios [79], [80], [81], [82].

The review by Lovreglio et al. [75] highlights the wide range of hardware options available for researchers to study human behaviour during disasters. The choice of the most suitable hardware configuration is influenced by the research budget and objectives. The review also emphasizes the extensive utilization of VR solutions in studying human behaviour during disasters, with a particular focus on building fires. However, studies are concerned about the ecological validity of the data collected using VR (i.e. whether behave similarly in real disasters and VR) [83]. While some studies [64], [84], [85] have attempted to explain this crucial issue, more studies comparing real and virtual scenarios are necessary to quantitatively evaluate the ecological validity of VR investigations.

It can be assumed that ecological validity exists if participants show similar reactions in terms of their behaviour, emotions, cognition, and psychophysiology in both the virtual and real-world scenarios [86]. Nonetheless, the level of emotional reaction that is elicited in a virtual laboratory setting may not be equivalent to that experienced in a real-life fire emergency [83]. It is not necessary for the participants to believe that the simulated fire scenario is authentic to establish ecological validity. Even if the participants are aware that what they are seeing is a simulation, perceptual input like visual simulation can still provoke emotional reactions [87].

Kinateder et al. [83] 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. On the other hand, the major drawback is the reduced ecological validity when compared to field and case studies. Additionally, there is a lack of validation studies specifically for human behaviour in fire.

Finally, Virtual Reality can be employed to create challenging laboratory experiments that concern human behaviour in fire. It allows to study how people respond to fire-related stimuli such as flames or smoke, and it facilitates the meticulous collection of behavioural and psychophysiological data within controlled simulated situations [83]. VR is a promising tool for comprehending human behaviour in fire and enhancing fire safety measures.

2.6 Summary

In the previous sections, some studies regarding factors affecting exit choice have been analysed. A considerable number of studies analysed the impact of these factors independently influencing exit or route selection, but only a limited amount of research has considered multiple factors simultaneously (e.g., [88], [49]). However, no study was identified that analysed the combined effect of social influence and role-rule factor on exit choices.

In the following chapter, the methods involved in the work will be described.

3 Methods and Materials

This section regards methods and materials used to perform the experiment. Section 3.1 provides a detailed description of the Virtual Reality 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 Set-up

Throughout the VR experiment, the participants are situated within a virtual metro station where they are asked to choose an exit to evacuate the metro during a fire emergency. The participant can choose between two different exits (i.e., Left Exit and Right Exit) as illustrated in Figure 7. The virtual metro has an exit sign indicating that there are two available paths for evacuation (see Figure 9).

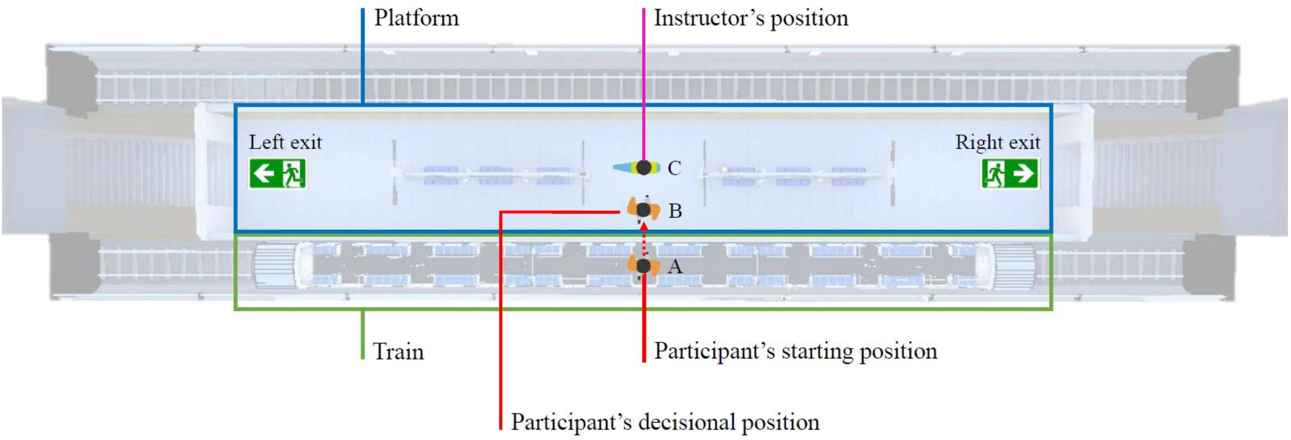

Figure 7. Geometry of the virtual environment and position of people involved

Figure 7 shows the geometry of the metro station, which does not represent any real or existing infrastructure. The model of the metro station was purchased from Sketchfab [89]. Figure 7 also highlights the positions of participant (starting position "A" and decisional position "B") and instructor (position "C"). The participants are initially placed into the train (position "A") with other virtual evacuees (when they are present). After receiving an alarm signal, and all the other evacuees are out of the train (when they are present), the participants move automatically to the second position highlighted in the picture (position "B"), which represents the place where they have to make the exit choice (note: the participant movement is controlled by a computer code and it does not require any physical movement of the participant). The exits from the platform are two stair ramps, and they are indicated in Figure 7 by the exit sign.

The experiment includes 12 different scenarios in which the environmental conditions change but the geometry is kept constant. The scenarios differed by the presence and the number of virtual evacuees (see Figure 8), by the presence of an instructor who directs participants toward one of the exits and by the authority of this instructor (see Figure 9). Therefore, it is possible to define the following variables:

- NPC: the number of virtual evacuees using the exit;
- I: the presence of an instructor who indicates the way out;
- FF: the authority of the instructor (i.e., metro staff or firefighter).

These variables have been introduced to study the influence of two different factors on the exit choice: social factor (see Section 2.2) and role-rule factor (see Section 2.3). In addition, the presence of a different instructor with more authority allows to understand if people trust different instructors in different ways, and consequently the behaviour changes.

To investigate the influence of all variables, conflicting information was provided to the participants in the experiment: the instructor (when he is present) always indicates the left exit while the virtual evacuees (when they are present) always go to the right exit (Figure 10).

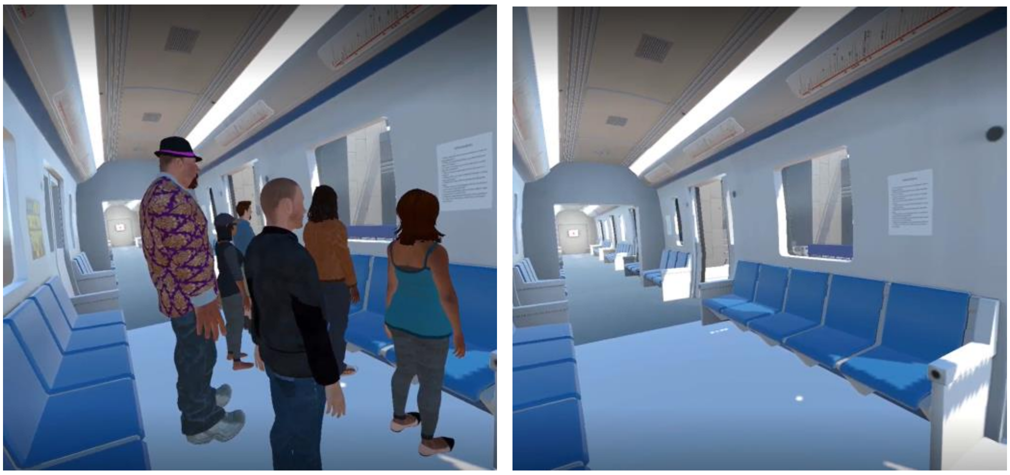

Figure 8. Screenshots of the virtual experience showing the presence or not of people in the metro station

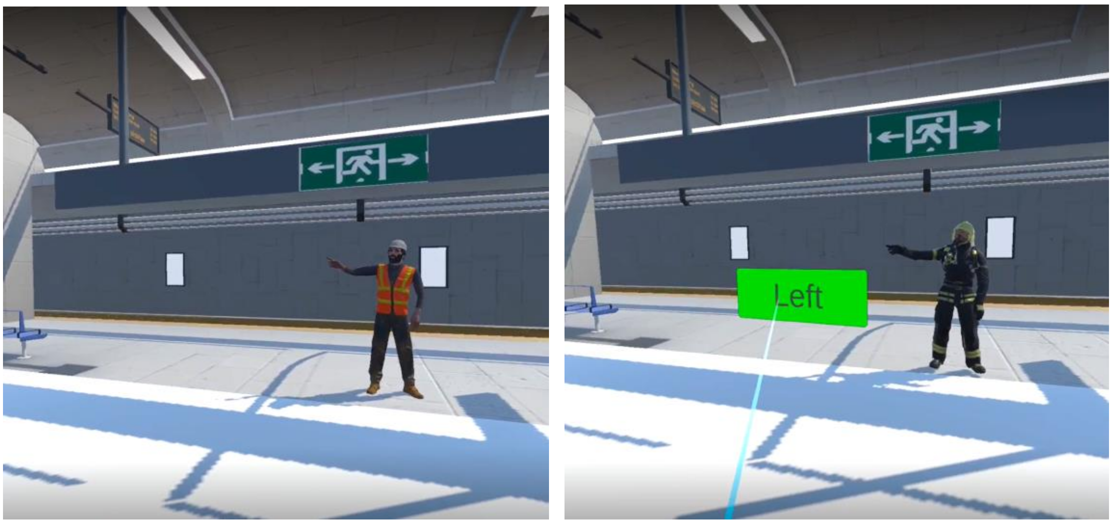

Figure 9. Screenshots of the virtual experience showing the presence of two different instructors

Figure 10. Screenshots of the virtual experience showing conflicting information provided to the participant

All variables have a number of dimensions that can be different within the experiment. The number of virtual evacuees leaving the metro station (NPC) can be equal to 0, 1, 10 or 20. The variable related to the instructor (I) is Boolean and, therefore, it can be equal to 0 (the instructor is not present) or 1 (the instructor is present). If the I variable is equal to 1, it is possible to introduce another Boolean variable (FF) that can be equal to 1 if the instructor is a firefighter or equal to 0 if the instructor looks like a metro staff member. The recap of the levels and values for each variable is provided in Table 1.

Variable	Right Exit		Left Exit	
	Levels	**Values**	**Levels**	**Values**
NPC – Number of evacuees using the exit	4	0, 1, 10, 20	1	0
I – Presence of instructor	1	0	1	1
FF – Presence of instructor who is a firefighter	1	0	1	1

Table 1. Levels and values of each variable

The experimental scenarios that represent the different immersive VR experiences are shown in Table 2. These scenarios are divided into three different classes depending on the value of I and FF. The class A was experienced by the total amount of participants (131 people), the class B was experienced by 66 participants and the class C by 65 participants. As such, each participant was asked to make only 8 choices in total. This experiment choice was made to reduce experimental fatigue for the participants.

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

Table 2. Experimental scenarios

The VR experience was developed using the integrated platform "Unity", which is a popular gaming engine for developing VR applications. Regarding the virtual environment, the 3D model of the metro station was sourced from Sketchfab and subsequently imported into Unity. To generate NPCs (Non-Player Characters), a low-cost and high-quality human body model generation algorithm was used.

Within the framework of the XR Interaction Toolkit, the comprehensive interaction mechanism (e.g., movement and animation of the NPCs, movement of the player, randomization of the scenes, data storage, and audio management) was programmed in C#. The application has been developed by the research team of the Digital Built Environment Lab at Massey University.

Participants interacted with the virtual environment using the Oculus Meta Quest 2. It provides a headset and two controllers. This headset is characterized by six degrees of freedom, it tracks the movement of both head and body, and then translates them into VR with realistic precision. The specifications of the technology are the following:

- Fast-switch LCD display
- 1832 x 1920 resolution per eye
- 60, 72, 90 Hz refresh rate supported
- Glasses compatible

In addition, the headset is equipped with 3D positional audio technology, enabling users to hear what's all around.

3.2 Experimental Procedure

The experiment was executed between July and September 2023 at Massey University's Albany Campus in Auckland, New Zealand. The experimental procedure involves the following steps:

1. Before participating in the experiment, the participants were initially required to read a participant 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. All the participants completed the experiment (see Section 3.3 for the description of the sample).
2. After a brief introduction to explain how the VR headset works, participants were asked to stand up and wear the VR headset; the participants were allowed to stand anywhere in the room and only use one of the two manual controllers. A representation of the physical space where the experiment took place is shown in Figure 11.
3. After wearing the VR headset, participants are immersed in the metro station and the evacuation starts a few seconds later. At the beginning, the participants are placed into the

train (position "A" in Figure 7) and then they are automatically moved outside the train. In this second position (position "B" in Figure 7), the participant must choose an exit (Left or Right).

4. This procedure is repeated 8 times per participant and in each of them the scenario is different (Table 2). The sequence of the 8 scenarios changes randomly for each participant.
5. After the VR part of the experience, a post-experiment survey was dispensed to gather participants' information using a tablet. The questionnaire collects data regarding participants' demographics and their prior experiences with virtual reality and their knowledge of fire emergencies. In addition, the questionnaire gathered feedback on the realism of the VR experiment, ease of participation, emotional state, social identity, urgency perception, and behaviour validity. Most of the data was collected by using seven-point Likert scale questions (from -3 = "strongly disagree" to +3 = "strongly agree"). Participants also have the possibility to choose "I do not know". The complete questionnaire can be found in Appendix 1.

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.

Figure 11. Physical space used to carry out the VR experiment

3.3 Participants

The majority of participants were enlisted via social media platforms and flyers distributed on the campus, especially in the library building of Massey University, Albany Campus (New Zealand). A total of 131 individuals participated in the study, with the majority being either employees or students affiliated with Massey University. The sample comprised 75 females and 56 males, with ages spanning from 16 to 71 years, as shown in Figure 12. 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. Participants' nationality was heterogeneous, but most people defined themselves as Asian (around 67%); then approximately 17% of participants were from New Zealand and around 16% were from other countries of the world. Another important data collected about the sample is the BMI, calculated by knowing the height and the weight of participants: $BMI = \frac{w}{h^2}$. The distribution of the participants' BMI is shown in Figure 13.

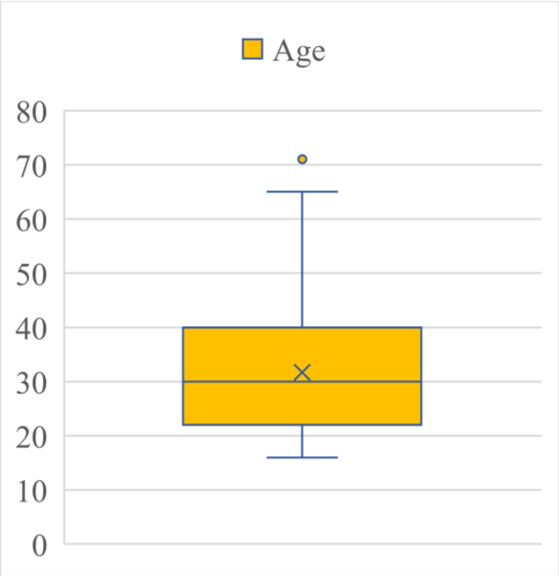

Figure 12. Participants age

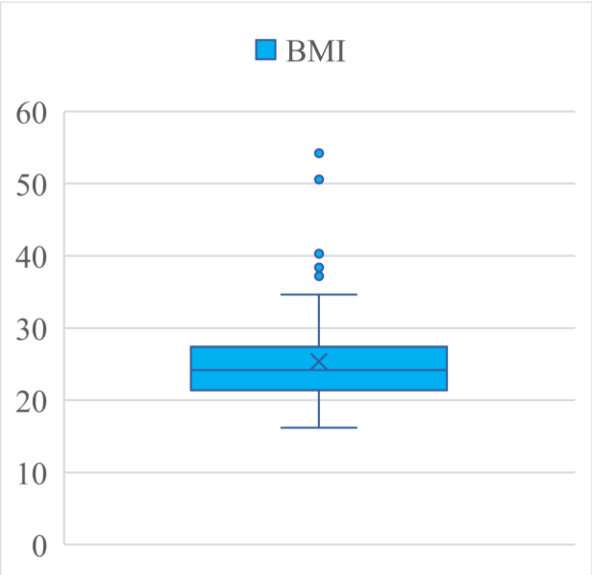

Figure 13. Participants BMI

3.4 Data Analysis

The data gathered from the experiments were assessed using random utility models. In fact, several model specifications of Multinomial Logit Models are estimated in this study. Random utility models are dependent on the following assumptions [90], [91]:

- 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 $\varepsilon_{q,i}$:

$$U_{q,i} = V_{q,i} + \varepsilon_{q,i} \qquad \text{Eq. 1}$$

  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:

$$V_{q,i} = \sum_{j} \beta_{i,j} X_{q,i,j} \qquad \text{Eq. 2}$$

  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 [49].

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 [90]. By assuming it, the probability that the decision-maker q selects alternative i can be formulate by the following equation (i.e., multinomial logit formulation):

$$P_{q,i} = \frac{exp(V_{q,i})}{\sum_k exp(V_{q,k})} \qquad \text{Eq. 3}$$

This equation can be employed to build a likelihood function which is then utilized to estimate the parameters $\beta_{i,j}$, by identifying the parameter combination that maximizes the likelihood function. In this work, the multinomial logit models have been estimated using the "mlogit" package available in R Studio [92].

In addition, to observe the predictability of the model, the concept of 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 [93]. Figure 14 shows a confusion matrix for n=2, 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.

	Predicted Negative	Predicted Positive
Actual Negative	a	b
Actual Positive	c	d

Figure 14. The confusion matrix of the two-class classification problem [93]

The prediction accuracy and classification error can be obtained from this matrix as follows:

$$Accuracy = \frac{a+d}{a+b+c+d} \qquad \text{Eq. 4}$$

$$Error = \frac{b+c}{a+b+c+d} \qquad \text{Eq. 5}$$

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

Another important concept has been used to compare different models and understand the one that fits data in a better way: likelihood and McFadden's R^2. The likelihood gives an idea of how well a model fits to the data, instead, McFadden's R^2 calculates the ratio of the log-likelihood for the specific model and an intercept-only model and subtracts this ratio from 1. The formulation that allows to determine McFadden's R^2 is shown in Eq. 6 [94].

$$R^2 = 1 - \frac{\ln \hat{L}(V_i)}{\ln \hat{L}(V_0)} \qquad \text{Eq. 6}$$

Where $\ln \hat{L}(V_i)$ is the log-likelihood of the specific model and $\ln \hat{L}(V_0)$ is the log-likelihood of the intercept-only model.

In the end, boxplots were used to analyse participants' responses to the post-experiment survey on different aspects of the Virtual Reality 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 models proposed in the Sections 4.1 and 4.2 of this work. In particular, Section 4.1 concerns models about external environmental factors and Section 4.2 relies on models that consider demographic factors. Then, a sensitivity analysis, performed considering one of the models presented, is provided in Section 4.3. The last Section 4.4 presents respondents' feedback about the VR experience.

4.1 Exit Choice Models – External Factors

In this work, two multinomial logit model formulations are proposed. The first model (*Model 1*) is linear, so it was possible to estimate $\beta_{i,j}$ weighting the impact of NPC, I and FF (see Table 1 for definitions) using Equation 7:

Model 1

$$V_i = const_R + \beta_{NPC} \cdot NPC_i + \beta_I \cdot I_i + \beta_{FF} \cdot FF_i$$
$$i = L, R \qquad \text{Eq. 7}$$

The intercept ($const_R$) was assigned only to the Right Exit for all the models. The estimated parameters for *Model 1* 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, with the exception of β_{FF} which is partially significant (p-value < 0.1). In other words, *Model 1* shows that all the variables under examination had an impact on the decision-making process. In particular, according to the parameters, it is possible to observe that variable I is around 11 times bigger than the variable NPC. This result means that to compensate for the presence of an instructor who indicates an exit, it is necessary the presence of around 11 virtual evacuees who use the other exit. On the other hand, in the case of the presence of a firefighter, to compensate it is necessary the presence of around 13 virtual evacuees who use the other exit.

McFadden's $R^2 = 0.286$ Log Likelihood $= -485.12$

Variable	Estimate	Std error	z-value	p-value
$\boldsymbol{const_R}$	0.263	0.115	2.275	0.023
$\boldsymbol{\beta_{NPC}}$	0.244	0.065	3.752	<0.001
$\boldsymbol{\beta_I}$	2.741	0.225	12.184	<0.001
$\boldsymbol{\beta_{FF}}$	0.559	0.329	1.698	0.090

Table 3. Estimated parameters for Model 1

In addition, to observe the reliability of the model, the concept of confusion matrix has been used. In this case, it was necessary to calculate how many choices effectively made by participants matched the predicted ones. The choices matched are 806 and the total amount of scenarios, considering all participants, is equal to 1044. The percentage of choices matched is equal to 77%. It is also possible to affirm that 61% of these matched choices were for the Left Exit (i.e., the exit indicated by the instructor).

The second model (*Model 2*) estimated in this work is not linear and it involves a logarithmic transformation of the NPC variable. Utilizing logarithmic transformations on variables in a regression model is a commonly employed method for determining the presence of a non-linear relationship between the independent and dependent variables [95]. In this case, we tested the non-linearity only for the variable NPC, because the variables I and FF are Boolean. The equation for *Model 2* is the following:

Model 2

$$V_i = const_R + \beta_{NPC} \cdot \ln(NPC)_i + \beta_I \cdot I_i + \beta_{FF} \cdot FF_i$$

$$i = L, R$$

Eq. 8

The estimated parameters for *Model 2* are shown in Table 4.

McFadden's $R^2 = 0.287$ Log Likelihood $= -484.38$

Variable	Estimate	Std error	z-value	p-value
$\boldsymbol{const_R}$	0.162	0.131	1.241	0.215
$\boldsymbol{\beta_{NPC}}$	0.244	0.065	3.752	<0.001
$\boldsymbol{\beta_I}$	2.741	0.225	12.184	<0.001
$\boldsymbol{\beta_{FF}}$	0.559	0.329	1.698	0.090

Table 4. Estimated parameters for Model 2

The model shows that all parameters are statistically different from zero, having their p-values below the level of significance of 0.05, with the exception of β_{FF} which is partially significant (p-value <

0.1). *Model 2,* according to *Model 1*, shows that all the variables under examination had an impact on the decision-making process.

Also for *Model 2*, the confusion matrix has been calculated. The percentage of choices matched is equal to 77%, the same percentage as *Model 1*.

By observing these data it is possible to affirm that *Model 2* fits data in a better way than *Model 1*, because McFadden's R^2 is closer to 1. For this reason, the model considered for the demographic analysis (Section 4.2) and for the sensitivity analysis (Section 4.3) is *Model 2*.

4.2 Exit Choice Models – Demographic Factors

After the observation of two multinomial logit models related to external factors, models concerning demographic factors were analysed. By considering *Model 2* as the basis*,* the following demographic factors have been examined: age, nationality, BMI and handedness. Regarding nationality, it was tested the difference between people from New Zealand and people from other countries in the world.

Model 3 relies on age, and it is described by the following equation:

Model 3

$$V_i = const_R + \beta_{NPC} \cdot \ln(NPC)_i + \beta_{NPC\_Age} \cdot \ln(NPC)_i \cdot Age + \beta_I \cdot I_i + \beta_{I\_Age} \cdot I_i \cdot Age + \beta_{FF} \cdot FF_i \qquad i = L, R \tag{Eq. 9}$$

The estimated parameters for *Model 3* are shown in Table 5. The model shows that the parameters related to the demographic factor (i.e., age) are not statistically different from zero, with the p-values above the significance level of 0.05. Therefore, *Model 3* does not show evidence that the variable under examination have an impact on the decision-making process.

$$\text{McFadden's } R^2 = 0.288 \qquad \text{Log Likelihood} = -484.21$$

Variable	Estimate	Std error	z-value	p-value
$\boldsymbol{const_R}$	0.164	0.131	1.253	0.210
$\boldsymbol{\beta_{NPC}}$	0.264	0.074	3.560	<0.001
$\boldsymbol{\beta_{NPC\_Age}}$	-0.002	0.002	-0.564	0.573
$\boldsymbol{\beta_{I}}$	2.778	0.236	11.792	<0.001
$\boldsymbol{\beta_{I\_Age}}$	<0.001	0.018	0.033	0.974
$\boldsymbol{\beta_{FF}}$	0.473	0.535	0.885	0.974

Table 5. Estimated parameters for Model 3

Model 4 relies on nationality, and it is described by the following equation:

Model 4

$$V_i = const_R + \beta_{NPC} \cdot \ln(NPC)_i + \beta_{NPC\_N} \cdot \ln(NPC)_i \cdot N + \beta_I \cdot I_i + \beta_{I\_N} \cdot I_i \cdot N + \beta_{FF} \cdot FF_i$$

$$i = L, R$$

Eq. 10

The estimated parameters for *Model 4* are shown in Table 6. The model shows that the parameters related to the demographic factor (i.e., New Zealand nationality or not) are not statistically different from zero, with the p-values above the significance level of 0.05. Therefore, *Model 4* does not show evidence that the variable under examination have an impact on the decision-making process.

McFadden's $R^2 = 0.288$ Log Likelihood $= -484.12$

Variable	Estimate	Std error	z-value	p-value
$\boldsymbol{const_R}$	0.164	0.131	1.245	0.213
$\boldsymbol{\beta_{NPC}}$	0.231	0.068	3.393	<0.001
$\boldsymbol{\beta_{NPC\_N}}$	0.084	0.127	0.665	0.506
$\boldsymbol{\beta_{I}}$	2.740	0.244	11.208	<0.001
$\boldsymbol{\beta_{I\_N}}$	0.045	0.480	0.093	0.926
$\boldsymbol{\beta_{FF}}$	0.551	0.331	1.664	0.096

Table 6. Estimated parameters for Model 4

Model 5 relies on BMI, and it is described by the following equation:

Model 5

$$V_i = const_R + \beta_{NPC} \cdot \ln(NPC)_i + \beta_{NPC\_BMI} \cdot \ln(NPC)_i \cdot BMI + \beta_I \cdot I_i + \beta_{I\_BMI} \cdot I_i \cdot BMI + \beta_{FF} \cdot FF_i$$

$$i = L, R$$

Eq. 11

The estimated parameters for *Model 5* are shown in Table 7. The model shows that the parameters related to the demographic factor (i.e., BMI) are not statistically different from zero, with the p-values above the significance level of 0.05. Therefore, *Model 5* does not show evidence that the variable under examination have an impact on the decision-making process.

$$\text{McFadden's } R^2 = 0.288 \qquad \text{Log Likelihood} = -483.95$$

Variable	Estimate	Std error	z-value	p-value
$\boldsymbol{const_R}$	0.162	0.131	1.235	0.217
$\boldsymbol{\beta_{NPC}}$	0.410	0.196	2.091	0.037
$\boldsymbol{\beta_{NPC\_BMI}}$	-0.007	0.007	-0.901	0.367
$\boldsymbol{\beta_{I}}$	3.216	0.757	4.250	<0.001
$\boldsymbol{\beta_{I\_BMI}}$	-0.019	0.028	-0.661	0.508
$\boldsymbol{\beta_{FF}}$	0.560	0.330	1.696	0.090

Table 7. Estimated parameters for Model 5

Model 6 relies on handedness, and it is described by the following equation:

Model 6

$$V_i = const_R + \beta_{NPC} \cdot \ln(NPC)_i + \beta_{NPC\_H} \cdot \ln(NPC)_i \cdot H + \beta_I \cdot I_i + \beta_{I\_H} \cdot I_i \cdot H + \beta_{FF} \cdot FF_i$$

$$i = L, R$$

Eq. 12

The estimated parameters for *Model 6* are shown in Table 8. The model shows that the parameters related to the demographic factor (i.e., right-handed or left-handed) are not statistically different from zero, with the p-values above the significance level of 0.05. Therefore, *Model 6* does not show evidence that the variable under examination have an impact on the decision-making process.

$$\text{McFadden's } R^2 = 0.289 \qquad \text{Log Likelihood} = -483.64$$

Variable	Estimate	Std error	z-value	p-value
$\boldsymbol{const_R}$	0.162	0.131	1.239	0.215
$\boldsymbol{\beta_{NPC}}$	0.432	0.175	2.462	0.014
$\boldsymbol{\beta_{NPC\_H}}$	-0.204	0.175	-1.164	0.244
$\boldsymbol{\beta_{I}}$	3.041	0.652	4.664	<0.001
$\boldsymbol{\beta_{I\_H}}$	-0.324	0.661	-0.491	0.623
$\boldsymbol{\beta_{FF}}$	0.562	0.330	1.703	0.089

Table 8. Estimated parameters for Model 6

4.3 Sensitivity Analysis

Sensitivity analyses are performed to demonstrate how the variables considered in *Model 2* can influence the likelihood of selecting an exit. This model has been selected because, compared to *Model 1*, the McFadden R^2 is slightly higher. Three different analyses are conducted to visualize the influence of all variables included in *Model 2*. The first analysis investigates the probability of choosing the Right Exit by varying the number of virtual evacuees that use each exit (the value of NPC varies from 0 to 30), in a case where the instructor is not present. The 3D representation of this analysis is obtained by using 3D plots of surfaces. The results of Scenario 1 are shown in Figure 15.

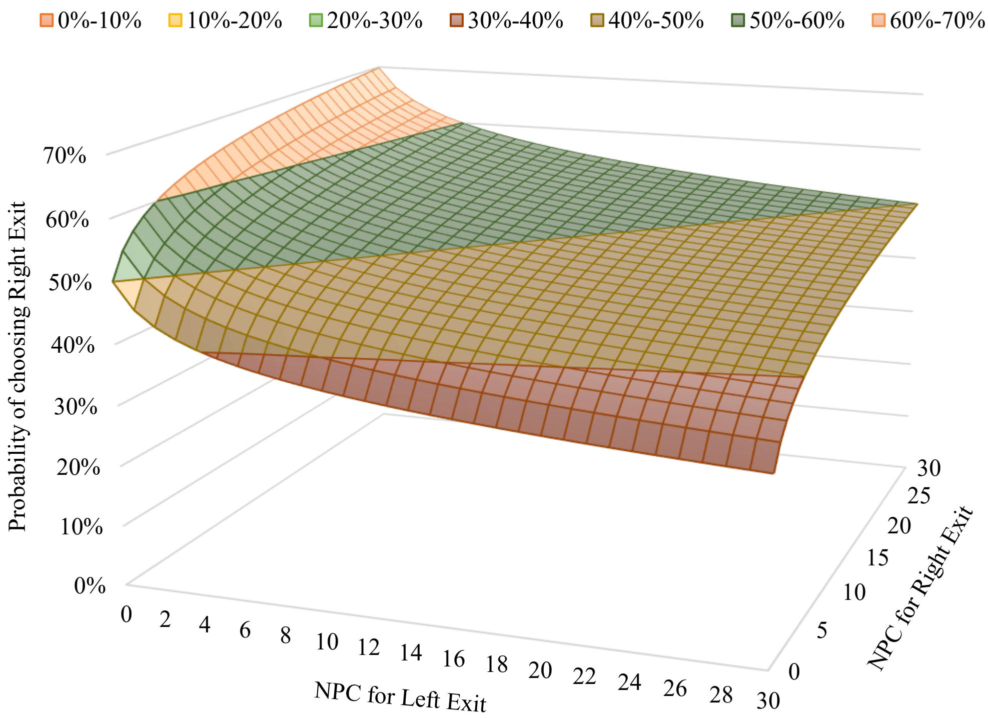

Figure 15. Sensitivity analysis of Scenario 1

In line with the sign of β_{NPC}, it is possible to observe that an increase of the value of NPC for the Right Exit leads to an increase in the probability of this exit being selected. On the other hand, for the Left Exit, the probability of choosing the Right Exit decreases in an increment of NPC. Figure 16 shows the top view of the graph shown in Figure 15.

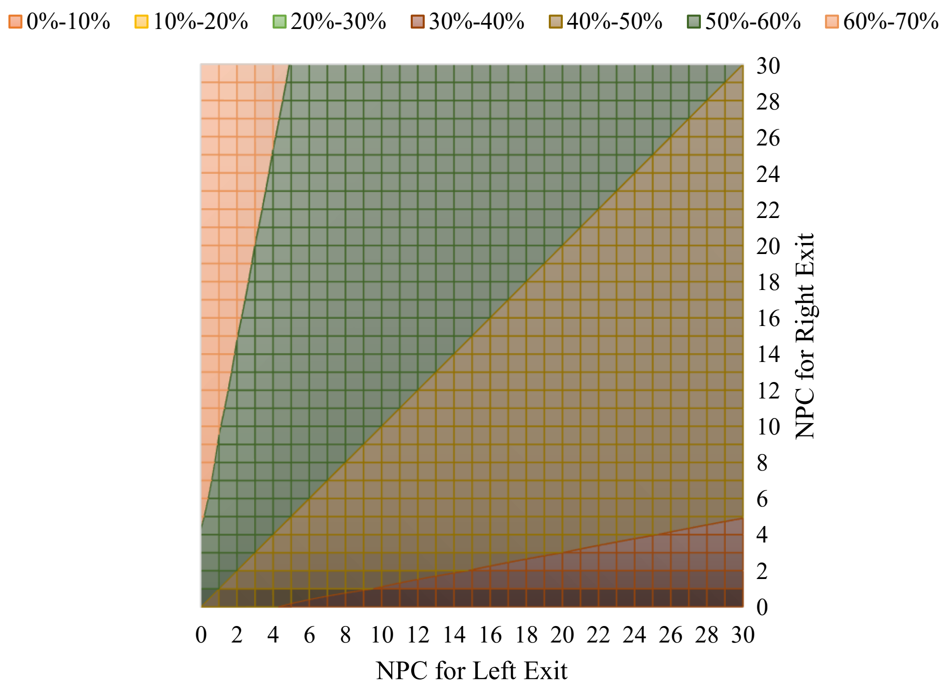

Figure 16. Sensitivity analysis of Scenario 1

The second analysis investigates the probability of choosing the Right Exit by varying the number of virtual evacuees that use each exit (the value of NPC varies from 0 to 30), in a case where the instructor is shown, and he is a staff member. The results of Scenario 2 are shown in Figure 17 and Figure 18.

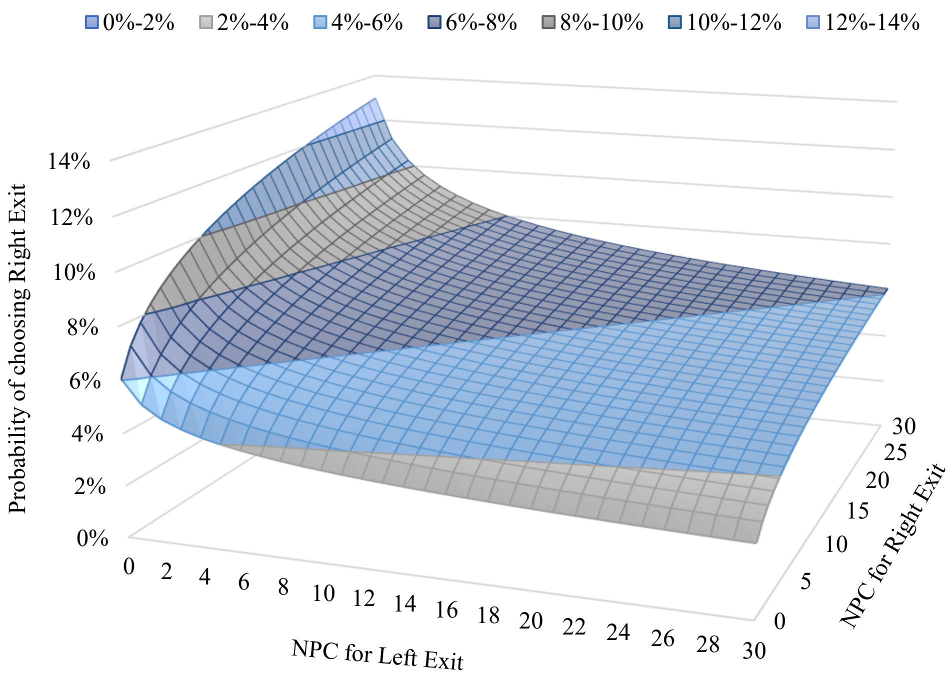

Figure 17. Sensitivity analysis of Scenario 2

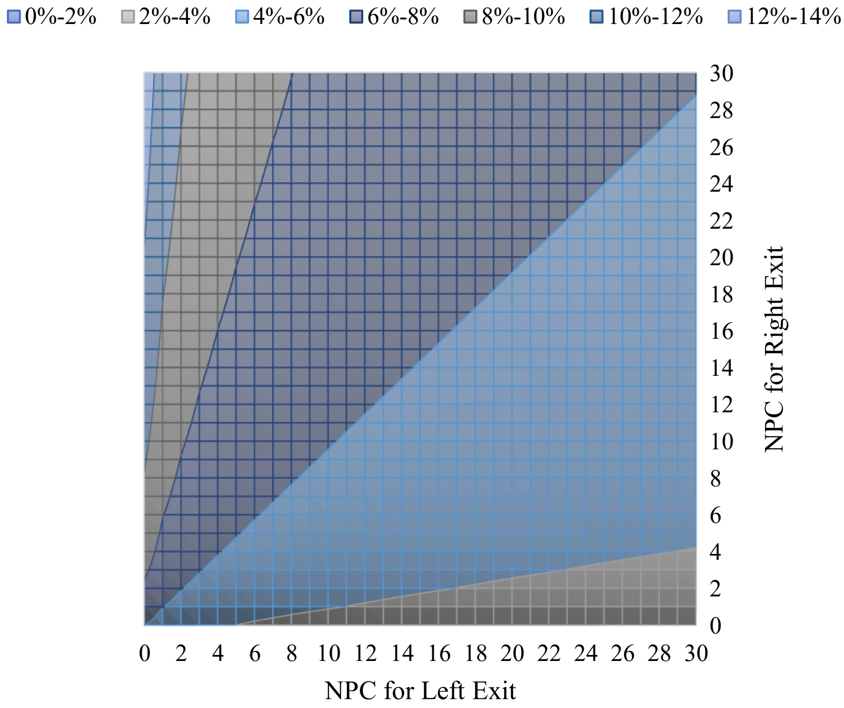

Figure 18. Sensitivity analysis of Scenario 2

The third analysis investigates the probability of choosing the Right Exit by varying the number of virtual evacuees that use each exit (the value of NPC varies from 0 to 30), in a case where the instructor is visualized, and he is a firefighter. The results of Scenario 3 are shown in Figure 19 and Figure 20.

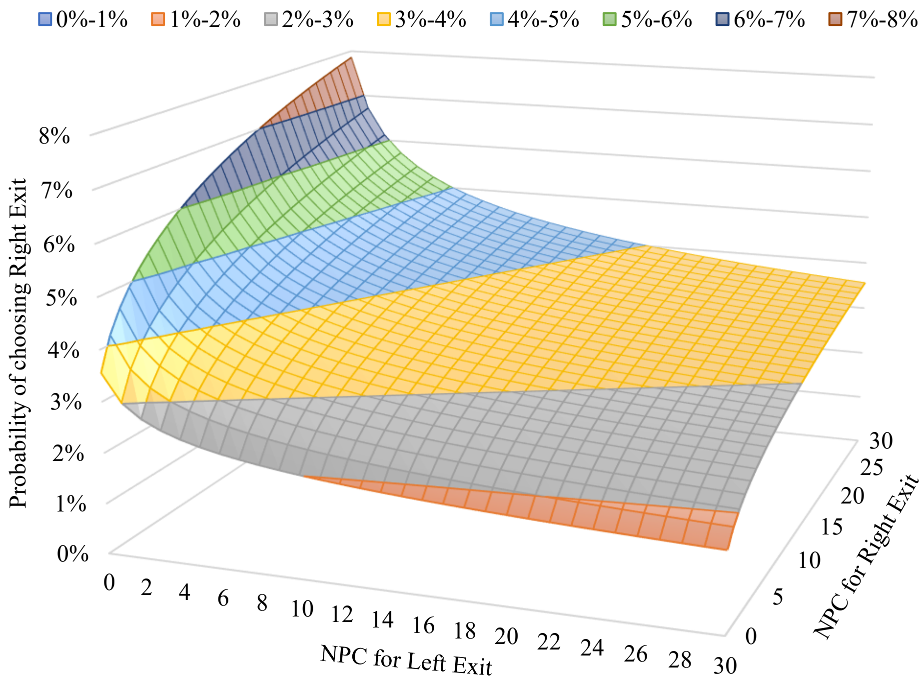

Figure 19. Sensitivity analysis for Scenario 3

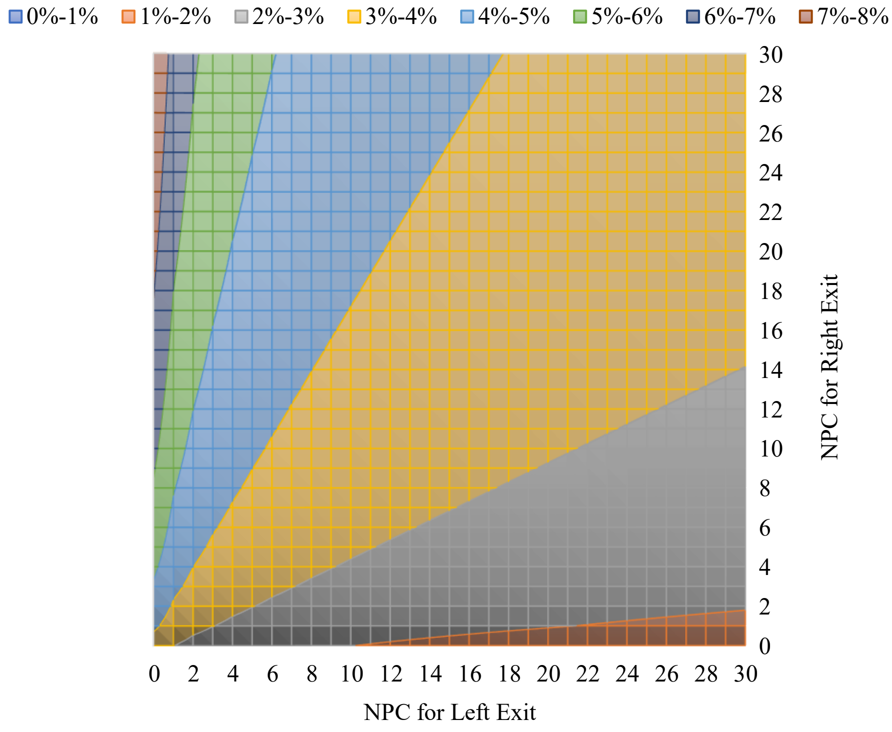

Figure 20. Sensitivity analysis for Scenario 3

To compare different scenarios, it is possible to observe two-dimensional charts (Figure 21 and Figure 22) obtained sectioning the 3D graphs shown in Figure 15, Figure 17 and Figure 19. Figure 21 shows a section of the 3D graphs when NPC for Left Exit is equal to zero, instead Figure 22 shows a section with NPC for Right Exit equal to zero.

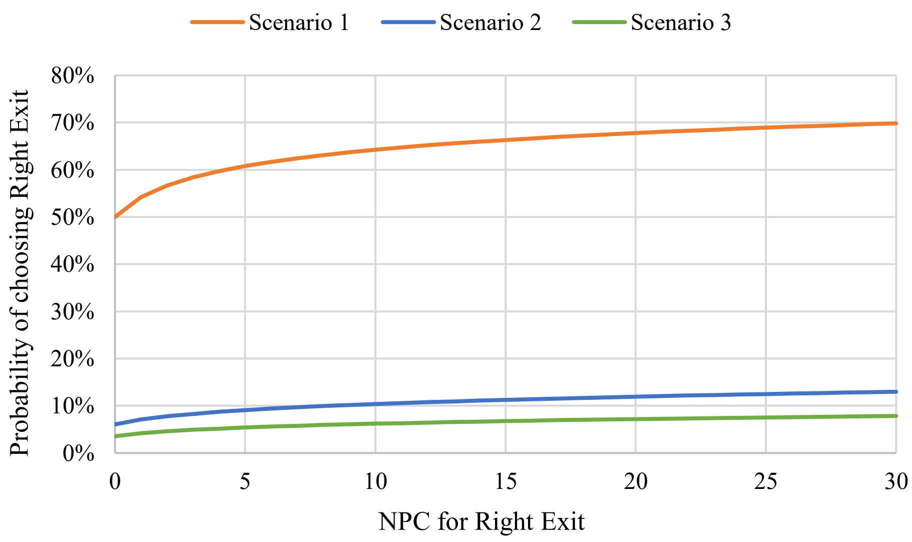

Figure 21. Sensitivity analysis - Comparison between scenarios

For Scenario 1, the probability of choosing the Right Exit increases from 0.5 to 0.7. This increment is lower for the scenarios with the presence of an instructor. In fact, for Scenario 2, the probability increases from 0.06 to 0.13, and for Scenario 3, the probability increases from 0.04 to 0.08.

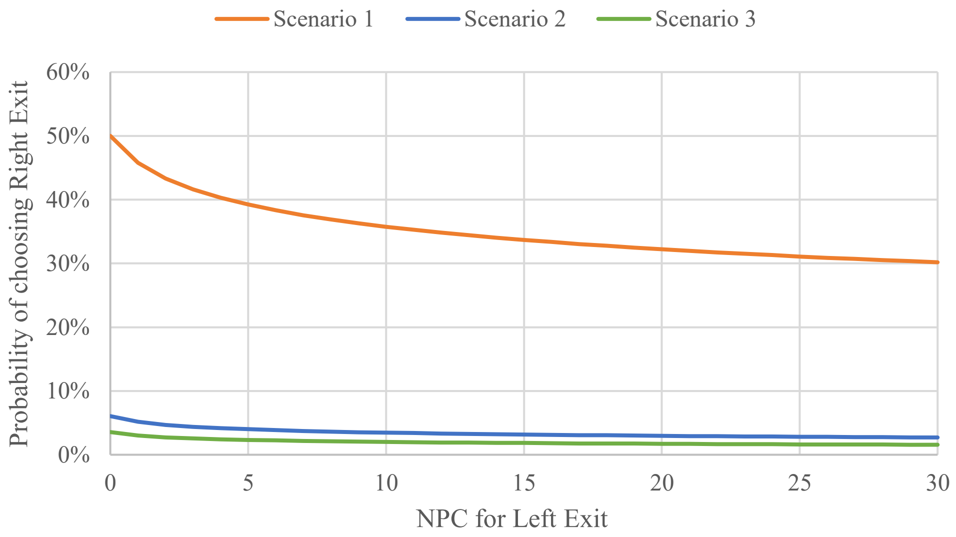

Figure 22. Sensitivity analysis - Comparison between scenarios

Figure 22 shows that, in this case, the probability of choosing the Right Exit decreases in an increment of NPC for the Left Exit. For Scenario 1 the probability decreases from 0.5 to 0.3, for Scenario 2 the probability decreases from 0.06 to 0.03, and for Scenario 5 the probability decreases from 0.04 to 0.02.

It's important to highlight that the analyses presented in this section show examples of possible analyses that can be carried out using *Model 2* (see the results in Table 4). The purpose of this section is to provide simple examples of the proposed model to illustrate how various factors impact the likelihood of evacuees selecting a particular exit.

4.4 Respondents' Feedback

After the Virtual Reality experience, a post-experiment survey was dispensed to participants to collect their information (see Section 3.2). This survey asked participants to offer feedback on the realism of the experiment, on their emotional states, on the feeling of urgency and unsafely, on their engagement in the VR experience, and on the ease with which they were able to take part in the VR experiment. This feedback is shown in the boxplots in Figure 23, Figure 24, Figure 25 and Figure 26.

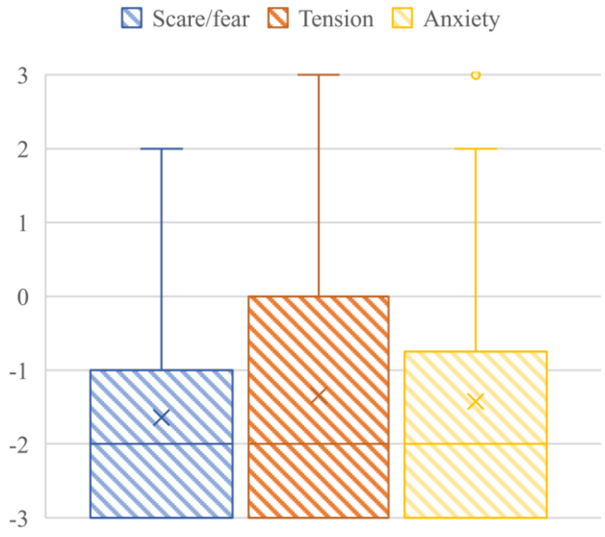

Figure 23. Participants' score on emotional states during the VR experience

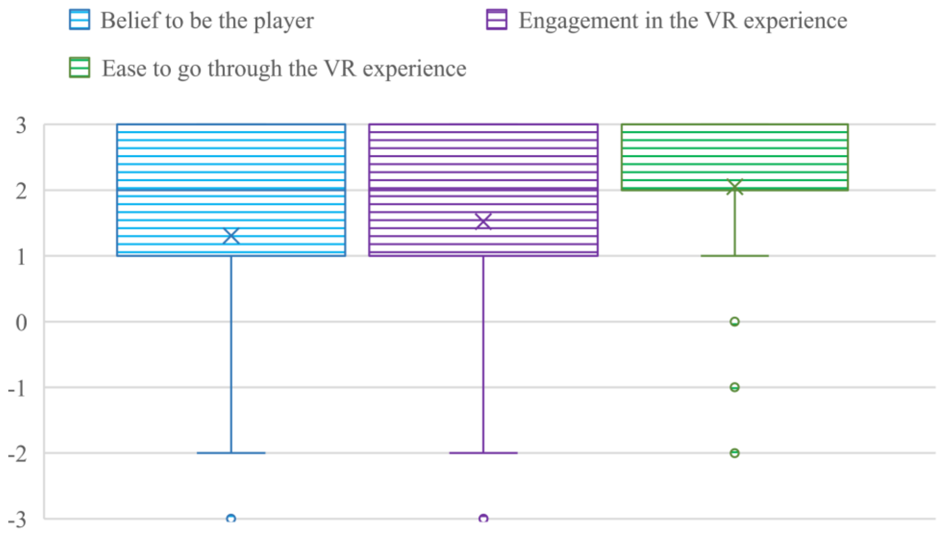

Figure 24. Participants' score on engagement and ease of the VR experience

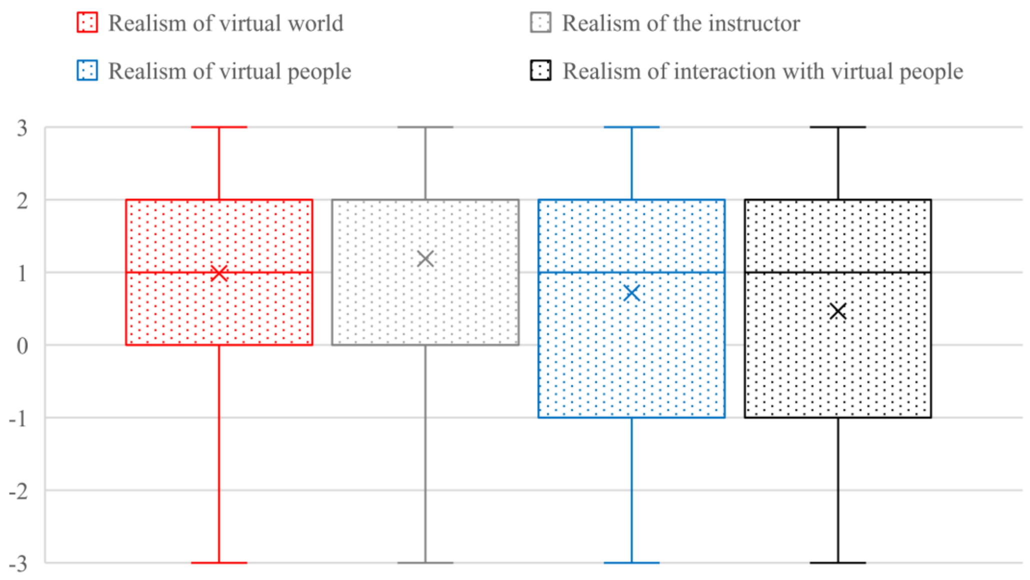

Figure 25. Participants' score on realism of the VR experience

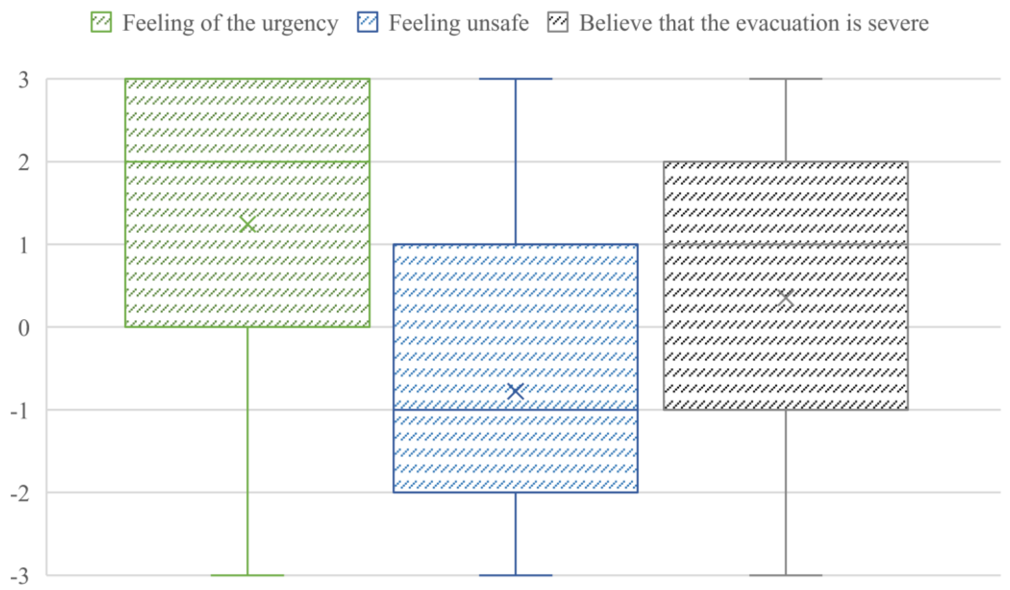

Figure 26. Participants' score about urgency

The box plots in Figure 23 show that the level of stress of participants during the VR experience was not so high. The chart in Figure 26 also demonstrate that participants did not feel unsafe during the experiment. On the other hand, the charts in Figure 24 also show that the scores regarding the engagement of participants in the VR experience and the belief to be a player are high. Regarding the realism of the VR experience (see Figure 25), participants' scores are worse concerning the realism of virtual evacuees and interaction with them. Other results (Figure 26) show that the perception of urgency and severity was quite high.

5 Discussion and Conclusions

The goal of the thesis is to investigate the exit choice of occupants during fires. In particular, this research focuses on the influence of two different factors on this choice: social factor (i.e., the number of people using different exits) and role-rule factor (i.e., the presence of an instructor who direct evacuees). Further, the differences between different instructors were also investigated by using two roles with different authorities in the experiment: the first half of the participants visualized a staff member, and the second part visualized a firefighter.

In this work, several models have been developed for the forecasting of exit choice based on the factors previously mentioned. The results of the models show that all the factors considered influence the choice of participants. In addition, the results show that the higher the authority of the instructor the more participants follow the instructions. *Model 2* shown in 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 [30], [42], [39], [49]. However, it is important to highlight that just a few studies analysed multiple factors [49], [88] and no research was identified that integrated social influence and role-rule factor within a single experiment.

Other models were tested to analyse the influence of demographic factors on exit choice. In this case, the results do not show evidence that demographic factors (i.e., age, nationality, handedness and BMI) have impact on the exit choice. The results about demographic factors are aligned with some previous research regarding evacuations [42], [69], but not aligned with others [70], [71], that show opposite results. These differences are probably due to some distinctions in the size of the sample and methods used to collect data, such as questionnaires.

This work provides several novelties in terms of findings. This study is the first one that investigates a unique combination of the variables (see Table 1) and their interactions. It was 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 who indicates the correct choice has greater impact on participants, compared to the presence of an underground staff member doing the same action or the presence of a number of people below 11 who using an exit. In the following paragraphs, the conformity of our findings with the existing literature is discussed.

The studies including multiple factors [49], [88] show similar results in terms of social influence because people were more likely to follow other people to an exit. The same similarity was found in some research performed in experimental buildings or tunnels [58], [96]. Another work that shows similar results is Nilsson and Johansson's research [59] which demonstrates that social influence is more significant when the information is limited. This fact can be demonstrated in this work by observing that, when the instructor is not present, most people choose the exit used by other virtual evacuees, instead when the instructor is present, so more information is provided, people tend to follow his instructions. On the other hand, some contrasts were seen in some studies performed by Haghani et al. [97] and Lovreglio et. al [27], who found that participants mostly preferred less crowded exits. The 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, this work supports all the research analysed in Section 2.3. All 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" [31]. In particular, this work highlights that perceiving the guidance as furnishing adequate practical information was linked with a more favourable perception of the source of the information [14], [65], [66]. In fact, the model presented in Section 4.1 shows that in the case where the firefighter is present, the probability of choosing the exit indicated by the instructor is higher.

The proposed findings of this study align with the existing literature, indicating signs of convergent validity. Despite the main finding of this study (i.e., the combined effect of the variables listed in the previous sections) is unique, there are some aspects of the results that are comparable with previous 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 methodology used in this study (VR) scores high on fidelity and quality of visualization, as well as self-reported behavioural validity, as evidenced by the participants' answers to the post-experiment questions, 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 intensity, ethical considerations, and experimental control [14]. The main objective is to reach the appropriate ecological validity. To assume ecological validity, it is essential that participants exhibit similar behavioural, emotional, cognitive, and psychophysiological reactions in both virtual reality (VR) and the real world [86]. Using case studies and unannounced evacuation drills is 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 knew they were part of an experiment. However, case studies have limitations when it comes to obtaining real accident data due to privacy and ethical issues. Even when videos of real accidents 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].

The findings of this research also underscore the significance of using VR for collecting data on human behaviour during building fires. This work demonstrates that VR can be used to design challenging laboratory experiments on Human Behaviour in Fire because it allows analysing how occupants react to fire cues and it allows collecting precise behavioural and psychophysiological data during controlled simulated events. Participants' feedback indicated that the simulation of the "virtual world" and the fire environment was realistic, but some improvements are necessary for future research. In addition, participants don't feel anxiety, tension or fear and it is consistent with reality because in the VR experience participants do not see fire or smoke [98], as in many real cases, so it is common not to feel that type of emotions. While there were perceptions of urgency and likelihood of similar actions in an actual fire emergency, it's important to note that these perceptions are based solely on participant feedback. We do not have actual data to compare these perceptions to. Nevertheless, this feedback highlights the potential for the continued use of Virtual Reality technology in future studies of human behaviour.

This work has some drawbacks. The sample of this study is characterised by participants who all live in New Zealand (despite having different nationalities), so it is not possible to consider this sample as representative of the world population, because different cultures are not considered. Future studies are necessary to understand if differences in terms of culture can influence the evacuees' behaviour.

Another limitation of this study is that some participants did not perceive the NPCs as realistic enough. This could have affected their perception of the NPCs' 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 can use the experimental deception technique proposed by Shipman et al. to enhance the realism of NPCs [99]. With the enhancement of computer graphics and AI applications for VR this limit is likely to become marginal in future studies.

Finally, considering the methods adopted in this work and the findings, it is possible to expand the research and analyse different topics. For instance, an interesting topic for future studies could be the influence that different types of evacuation signals (i.e., signs, alarm) have on human behaviour and decisions taken during evacuation.

References

[1] V. Kodur, P. Kumar, and M. M. Rafi, “Fire hazard in buildings: review, assessment and strategies for improving fire safety,” *PSU Research Review*, vol. 4, no. 1, pp. 1–23, Apr. 2020, doi: 10.1108/PRR-12-2018-0033.

[2] B. J. Meacham and R. L. P. Custer, “PERFORMANCE-BASED FIRE SAFETY ENGINEERING: AN INTRODUCTION OF BASIC CONCEPTS Society of Fire Protection Engineers Boston, Massachusetts.”

[3] Ministero dell’Interno, “D.M. 03/08/2015 Codice di prevenzione incendi,” 2022.

[4] E. D. Kuligowski, R. D. Peacock, and B. L. Hoskins, “A Review of Building Evacuation Models, 2nd Edition,” 2010.

[5] S. Gwynne and E. Rosenbaum, *Employing the Hydraulic Model in Assessing Emergency Movement in: Hurley M.J., SFPE Handbook of Fire Protection Engineering (fifth edition)*. 2016.

[6] R. Lovreglio, E. Ronchi, and M. J. Kinsey, “An Online Survey of Pedestrian Evacuation Model Usage and Users,” *Fire Technol*, vol. 56, no. 3, pp. 1133–1153, May 2020, doi: 10.1007/s10694-019-00923-8.

[7] S. M. V. Gwynne, L. M. Hulse, and M. J. Kinsey, “Guidance for the Model Developer on Representing Human Behavior in Egress Models,” *Fire Technol*, vol. 52, no. 3, pp. 775–800, May 2016, doi: 10.1007/s10694-015-0501-2.

[8] G. V Hadjisophocleous, N. Benichou, A. S. Tamim, F. Risk, and M. Program, “LITERATURE REVIEW OF PERFORMANCE-BASED FIRE CODES AND DESIGN ENVIRONMENT,” 1998.

[9] B. Meacham, R. Bowen, J. Traw, and A. Moore, “Performance-based building regulation: Current situation and future needs,” *Building Research and Information*, vol. 33, no. 2. pp. 91–106, Mar. 2005. doi: 10.1080/0961321042000322780.

[10] ANAS, “Linee Guida per la progettazione e realizzazione della sicurezza nelle gallerie stradali secondo la normativa vigente,” 2009.

[11] E. Ronchi, “EVACUATION MODELLING IN ROAD TUNNEL FIRES,” 2012. [Online]. Available: www.poliba.it

[12] M. J. Hurley and E. R. Rosenbaum, *Performance-Based Design in: Hurley M.J., SFPE Handbook of Fire Protection Engineering (fifth edition)*. 2016.

[13] V. Babrauskas, J. M. Fleming, and B. Don Russell, “RSET/ASET, a flawed concept for fire safety assessment,” *Fire Mater*, vol. 34, no. 7, pp. 341–355, Nov. 2010, doi: 10.1002/fam.1025.

[14] R. Lovreglio, “Modelling Decision-Making in Fire Evacuation based on Random Utility Theory,” 2016, doi: 10.13140/RG.2.1.1695.5281/1.

[15] S. M. V. Gwynne, E. Kuligowski, M. Spearpoint, and E. Ronchi, “Bounding defaults in egress models,” in *Fire and Materials*, John Wiley and Sons Ltd, Jun. 2015, pp. 335–352. doi: 10.1002/fam.2212.

[16] D. Canter, *Fire and Human Behavior - An introduction, in: Canter, D. (Ed.) Fire and Human Behavior* . 1980.

[17] M. Haghani and M. Sarvi, “Crowd behaviour and motion: Empirical methods,” *Transportation Research Part B: Methodological*, vol. 107. Elsevier Ltd, pp. 253–294, Jan. 01, 2018. doi: 10.1016/j.trb.2017.06.017.

[18] E. Ronchi and D. Nilsson, “Fire evacuation in high-rise buildings: a review of human behaviour and modelling research,” 2013. [Online]. Available: www.serialssolutions.com/en/services/summon]

[19] M. Haghani, “Empirical methods in pedestrian, crowd and evacuation dynamics: Part I. Experimental methods and emerging topics,” *Saf Sci*, vol. 129, Sep. 2020, doi: 10.1016/j.ssci.2020.104743.

[20] M. Haghani, “Empirical methods in pedestrian, crowd and evacuation dynamics: Part II. Field methods and controversial topics,” *Saf Sci*, vol. 129, Sep. 2020, doi: 10.1016/j.ssci.2020.104760.

[21] S. Cao, L. Fu, and W. Song, “Exit selection and pedestrian movement in a room with two exits under fire emergency,” *Appl Math Comput*, vol. 332, pp. 136–147, Sep. 2018, doi: 10.1016/j.amc.2018.03.048.

[22] B. J. Meacham and R. L. P. Custer, “PERFORMANCE-BASED FIRE SAFETY ENGINEERING: AN INTRODUCTION OF BASIC CONCEPTS Society of Fire Protection Engineers Boston, Massachusetts,” 1995.

[23] M. Kobes, I. Helsloot, B. de Vries, and J. G. Post, “Building safety and human behaviour in fire: A literature review,” *Fire Safety Journal*, vol. 45, no. 1. pp. 1–11, Jan. 2010. doi: 10.1016/j.firesaf.2009.08.005.

[24] S. Gwynne and K. Boyce, *Engineering Data in: Hurley M.J., SFPE Handbook of Fire Protection Engineering (fifth edition)*. 2016.

[25] E. Bosina and U. Weidmann, “Estimating pedestrian speed using aggregated literature data,” *Physica A: Statistical Mechanics and its Applications*, vol. 468, pp. 1–29, Feb. 2017, doi: 10.1016/j.physa.2016.09.044.

[26] R. Lovreglio, E. Ronchi, and D. Nilsson, “Calibrating floor field cellular automaton models for pedestrian dynamics by using likelihood function optimization,” *Physica A: Statistical Mechanics and its Applications*, vol. 438, pp. 308–320, Jul. 2015, doi: 10.1016/j.physa.2015.06.040.

[27] R. Lovreglio, A. Fonzone, and L. dell'Olio, "A mixed logit model for predicting exit choice during building evacuations," *Transp Res Part A Policy Pract*, vol. 92, pp. 59–75, Oct. 2016, doi: 10.1016/j.tra.2016.06.018.

[28] K. Wang, W. Yuan, W. Liang, and Y. Yao, "An optimal guidance strategy for fire evacuations," 2023.

[29] R. Lovreglio, E. Kuligowski, S. Gwynne, and K. Boyce, "A pre-evacuation database for use in egress simulations," 2019.

[30] E. D. Kuligowski, *Human Behavior in Fire in: Hurley M.J., SFPE Handbook of Fire Protection Engineering (fifth edition)*. 2016.

[31] K. Fridolf, D. Nilsson, and H. Frantzich, "Fire Evacuation in Underground Transportation Systems: A Review of Accidents and Empirical Research," *Fire Technology*, vol. 49, no. 2. Kluwer Academic Publishers, pp. 451–475, Apr. 01, 2013. doi: 10.1007/s10694-011-0217-x.

[32] R. Fahy, G. Proulx, and L. Aiman, "Panic or not in fire," 2012.

[33] M. Haghani, E. Cristiani, N. W. F. Bode, M. Boltes, and A. Corbetta, "Panic, Irrationality, and Herding: Three Ambiguous Terms in Crowd Dynamics Research," *Journal of Advanced Transportation*, vol. 2019. Hindawi Limited, 2019. doi: 10.1155/2019/9267643.

[34] J. Lin, N. Li, L.-L. Rao, and R. Lovreglio, "Individual wayfinding decisions under stress in indoor emergency situations," 2023.

[35] M. K. Lindell and R. W. Perry, "The Protective Action Decision Model: Theoretical Modifications and Additional Evidence," *Risk Analysis*, vol. 32, no. 4, pp. 616–632, Apr. 2012, doi: 10.1111/j.1539-6924.2011.01647.x.

[36] E. Kuligowski, "Predicting Human Behavior During Fires," *Fire Technol*, vol. 49, no. 1, pp. 101–120, Jan. 2013, doi: 10.1007/s10694-011-0245-6.

[37] R. Lovreglio, E. Ronchi, and D. Nilsson, "An Evacuation Decision Model based on perceived risk, social influence and behavioural uncertainty," *Simul Model Pract Theory*, vol. 66, pp. 226–242, Aug. 2016, doi: 10.1016/j.simpat.2016.03.006.

[38] A. Edrisi, B. Lahoorpoor, and R. Lovreglio, "Simulating metro station evacuation using three agent-based exit choice models," *Case Stud Transp Policy*, vol. 9, no. 3, pp. 1261–1272, Sep. 2021, doi: 10.1016/j.cstp.2021.06.011.

[39] M. Kinateder, B. Comunale, and W. H. Warren, "Exit choice in an emergency evacuation scenario," 2018.

[40] D. Gao, E. Lee, and Y. Y. Lee, "The influence of context effects on exit choice behavior," 2023.

[41] D. Nilsson, H. Frantzich, and W. Saunders, "Influencing Exit Choice in the Event of a Fire Evacuation," *Fire Safety Science*, vol. 9, pp. 341–352, 2008, doi: 10.3801/iafss.fss.9-341.

[42] D. Duives and H. Mahmassani, "Exit choice decisions during pedestrian evacuations of buildings," *Transp Res Rec*, no. 2316, pp. 84–94, 2012, doi: 10.3141/2316-10.

[43] J. S. Trueblood, S. D. Brown, and A. Heathcote, "The Multi-attribute Linear Ballistic Accumulator Model of Decision-making," 2013.

[44] M. S. Spektor, S. Gluth, L. Fontanesi, and J. Rieskamp, "How similarity between choice options affects decisions from experience: The accentuation-of-differences model," *Psychol Rev*, vol. 126, no. 1, pp. 52–88, Jan. 2019, doi: 10.1037/rev0000122.

[45] J. S. Trueblood, S. D. Brown, A. Heathcote, and J. R. Busemeyer, "Not Just for Consumers: Context Effects Are Fundamental to Decision Making," *Psychol Sci*, vol. 24, no. 6, pp. 901–908, 2013, doi: 10.1177/0956797612464241.

[46] J. D. Sime, "AFFILIATIVE BEHAVIOUR DURING ESCAPE TO BUILDING EXITS," 1983.

[47] G. Proulx, "Occupant behaviour and evacuation Proulx, G. NRCC-44983 Occupant Behaviour and Evacuation," 2001. [Online]. Available: www.nrc.ca/irc/ircpubs

[48] E.-W. Augustijn-Beckers, J. Flacke, and B. Retsios, "Investigating the effect of different pre-evacuation behavior and exit choice strategies using agent-based modeling," in *Procedia Engineering*, Elsevier Ltd, 2010, pp. 23–35. doi: 10.1016/j.proeng.2010.07.005.

[49] R. Lovreglio, E. Dillies, E. Kuligowski, A. Rahouti, and M. Haghani, "Exit choice in built environment evacuation," 2022.

[50] M. Haghani and M. Sarvi, "'Herding' in direction choice-making during collective escape of crowds: How likely is it and what moderates it?," *Saf Sci*, vol. 115, pp. 362–375, Jun. 2019, doi: 10.1016/j.ssci.2019.02.034.

[51] J. Lin, R. Zhu, N. Li, and B. Becerik-Gerber, "Do people follow the crowd in building emergency evacuation? A cross-cultural immersive virtual reality-based study," 2020.

[52] J. Sime, "Movement toward the familiar," 1985.

[53] A. M. Sadri, S. V. Ukkusuri, and M. A. Ahmed, "Review of social influence in crisis communications and evacuation decision-making," *Transportation Research Interdisciplinary Perspectives*, vol. 9. Elsevier Ltd, Mar. 01, 2021. doi: 10.1016/j.trip.2021.100325.

[54] M. Deutsch and H. B. Gerard, "A STUDY OF NORMATIVE AND INFORMATIONAL SOCIAL INFLUENCES UPON INDIVIDUAL JUDGMENT," 1980.

[55] S. E. Asch, "Opinions and Social Pressure," vol. 193, no. 5, pp. 31–35, 1955, doi: 10.2307/24943779.

[56] J. Darley and B. Latané, "Group inhibition of bystander intervention in emergencies," 1968.

[57] B. Latane, "The Psychology of Social Impact," 1981.

[58] M. Kinateder *et al.*, “Social influence on route choice in a virtual reality tunnel fire,” *Transp Res Part F Traffic Psychol Behav*, vol. 26, no. PART A, pp. 116–125, 2014, doi: 10.1016/j.trf.2014.06.003.

[59] D. Nilsson and A. Johansson, “Social influence during the initial phase of fire evacuation,” 2009.

[60] L. Bautista, F. Maradei, and G. Pedraza, “Strategies to reduce visual attention changes while learning and training in extended reality environments,” *International Journal on Interactive Design and Manufacturing*, vol. 17, no. 1, pp. 17–43, Feb. 2023, doi: 10.1007/s12008-022-01092-9.

[61] P. W. Eastwick and W. L. Gardner, “Is it a game? Evidence for social influence in the virtual world,” *Soc Influ*, vol. 4, no. 1, pp. 18–32, 2009, doi: 10.1080/15534510802254087.

[62] J. Drury *et al.*, “Cooperation versus competition in a mass emergency evacuation: A new laboratory simulation and a new theoretical model,” *Behav Res Methods*, vol. 41, no. 3, pp. 957–970, 2009, doi: 10.3758/BRM.41.3.957.

[63] M. Kinateder, “Social Influence in Emergency Situations-Studies in Virtual Reality,” 2012.

[64] M. Kinateder and W. H. Warren, “Social influence on evacuation behavior in real and virtual environments,” *Frontiers Robotics AI*, vol. 3, no. JUL, Jul. 2016, doi: 10.3389/frobt.2016.00043.

[65] C. Stott, J. Hoggett, and G. Pearson, “Keeping the peace: Social identity, procedural justice and the policing of football crowds,” *British Journal of Criminology*, vol. 52, no. 2, pp. 381–399, Mar. 2012, doi: 10.1093/bjc/azr076.

[66] S. Reicher, R. Spears, and A. Haslam, *The social identity approach in social psychology in: Wetherall M., Mohanty C.T., The SAGE Handbook of Identities* . 2010.

[67] A. Templeton, C. Nash, M. Spearpoint, S. Gwynne, X. Hui, and M. Arnott, “Who and what is trusted in fire incidents,” 2023.

[68] G. Proulx, “A stress model for people facing a fire,” 1993.

[69] Y. Feng, D. C. Duives, and S. P. Hoogendoorn, “Using virtual reality to study pedestrian exit choice behaviour during evacuations,” *Saf Sci*, vol. 137, May 2021, doi: 10.1016/j.ssci.2021.105158.

[70] C. Xu, Y. Luo, K. Fuellhart, Q. Shao, and F. Witlox, “Modeling exit choice behavior in airplane emergency evacuations,” *J Air Transp Manag*, vol. 112, Sep. 2023, doi: 10.1016/j.jairtraman.2023.102450.

[71] X. Ben Song and R. Lovreglio, “Investigating personalized exit choice behaviour in fire accidents,” 2021.

[72] A. Veeraswamy, E. R. Galea, and P. J. Lawrence, "Wayfinding behavior within buildings - An international survey," in *Fire Safety Science*, 2011, pp. 735–748. doi: 10.3801/IAFSS.FSS.10-735.

[73] J. Troncoso, "Response to Emergency Wayfinding Systems by People from Different Cultures," 2014.

[74] R. Lovreglio and M. Kinateder, "Augmented reality for pedestrian evacuation research: Promises and limitations," *Saf Sci*, vol. 128, Aug. 2020, doi: 10.1016/j.ssci.2020.104750.

[75] R. Lovreglio, "VIRTUAL AND AUGMENTED REALITY FOR HUMAN BEHAVIOUR IN DISASTERS: A REVIEW," 2020. [Online]. Available: https://www.veative.com/blog/gyroscope-important-

[76] P. Milgram and F. Kishino, "A Taxonomy of Mixed Reality Visual Displays Unconscious Computing View project Augmented Reality through Graphic Overlays on Stereoscopic video View project A TAXONOMY OF MIXED REALITY VISUAL DISPLAYS," 1994. [Online]. Available: http://vered.rose.utoronto.ca/people/paul_dir/IEICE94/ieice.html

[77] R. Lovreglio, D. Paes, Z. Feng, and X. Zhao, "Digital Technologies for Fire Evacuations," in *Intelligent Building Fire Safety and Smart Firefighting* , In Press., 2023.

[78] J. Steuer, "Defining Virtual Reality: Dimensions Determining Telepresence," *Journal of Communication*, vol. 42, no. 4, pp. 73–93, 1992, doi: 10.1111/j.1460-2466.1992.tb00812.x.

[79] H. Li, J. Zhang, L. Xia, W. Song, and N. W. F. Bode, "Comparing the route-choice behavior of pedestrians around obstacles in a virtual experiment and a field study," *Transp Res Part C Emerg Technol*, vol. 107, pp. 120–136, Oct. 2019, doi: 10.1016/j.trc.2019.08.012.

[80] R. Lovreglio, X. Duan, A. Rahouti, R. Phipps, and D. Nilsson, "Comparing the effectiveness of fire extinguisher virtual reality and video training," *Virtual Real*, vol. 25, no. 1, pp. 133–145, Mar. 2021, doi: 10.1007/s10055-020-00447-5.

[81] Y. ; Feng, D. ; Duives, W. ; Daamen, and S. Hoogendoorn, "Pedestrian exit choice behavior during an evacuation-a comparison study between field and VR experiment Title: Pedestrian exit choice behavior during an evacuation-a comparison study between field and Yan Feng (Corresponding author) Winnie Daamen," APA, 2019.

[82] Z. Feng, V. A. González, R. Amor, R. Lovreglio, and G. Cabrera-Guerrero, "Immersive virtual reality serious games for evacuation training and research: A systematic literature review," *Comput Educ*, vol. 127, pp. 252–266, Dec. 2018, doi: 10.1016/j.compedu.2018.09.002.

[83] M. Kinateder *et al.*, "Virtual reality for fire evacuation research," in *2014 Federated Conference on Computer Science and Information Systems, FedCSIS 2014*, Institute of Electrical and Electronics Engineers Inc., Oct. 2014, pp. 313–321. doi: 10.15439/2014F94.

[84] Z. Feng *et al.*, “How people make decisions during earthquakes and post-earthquake evacuation: Using Verbal Protocol Analysis in Immersive Virtual Reality,” *Saf Sci*, vol. 129, Sep. 2020, doi: 10.1016/j.ssci.2020.104837.

[85] S. Arias, R. Fahy, E. Ronchi, D. Nilsson, H. Frantzich, and J. Wahlqvist, “Forensic virtual reality: Investigating individual behavior in the MGM Grand fire,” *Fire Saf J*, vol. 109, Oct. 2019, doi: 10.1016/j.firesaf.2019.102861.

[86] C. A. Anderson and B. J. Bushman, “External validity of ‘trivial’ experiments: The case of laboratory aggression,” *Review of General Psychology*, vol. 1, no. 1, pp. 19–41, 1997, doi: 10.1037/1089-2680.1.1.19.

[87] J. Wang, Q. Wu, T. Xie, H. Dou, and Y. Lei, “Influence of Perceptual and Conceptual Information on Fear Generalization: A Behavioral and Event-Related Potential Study,” 2021, doi: 10.3758/s13415-021-00912-x/Published.

[88] M. Kinateder and W. H. Warren, “Exit choice during evacuation is influenced by both the size and proportion of the egressing crowd,” *Physica A: Statistical Mechanics and its Applications*, vol. 569, May 2021, doi: 10.1016/j.physa.2021.125746.

[89] Zeps Janis, “Sketchfab Subway Station 3D Model.” Accessed: Sep. 18, 2023. [Online]. Available: https://sketchfab.com/3d-models/subway-station-bb68e4b3ac6646d2a59bffa7fa7818aa

[90] O. Willumsen, J. De Dios Ortúzar, and L. G. Willumsen, “MODELLING TRANSPORT,” 2011.

[91] D. A. Hensher, J. M. Rose, and W. H. Greene, *Applied choice analysis : a primer*. Cambridge University Press, 2005.

[92] Y. Croissant, “Package ‘mlogit: Multinomial Logit Models.’” 2020. Accessed: Sep. 18, 2023. [Online]. Available: https://cran.r-project.org/web/packages/mlogit/index.html

[93] S. Visa, A. Inoue, and A. Ralescu, “Proceedings of the Twentysecond Midwest Artificial Intelligence and Cognitive Science Conference,” 2011.

[94] J. S. Long and J. Freese, “Scalar Measures of Fit for Regression Models,” 2000.

[95] K. Benoit, “Linear Regression Models with Logarithmic Transformations,” 2011.

[96] Y. Zhu, T. Chen, N. Ding, M. Chraibi, and W. C. Fan, “Follow the evacuation signs or surrounding people during building evacuation, an experimental study,” *Physica A: Statistical Mechanics and its Applications*, vol. 560, Dec. 2020, doi: 10.1016/j.physa.2020.125156.

[97] M. Haghani, M. Sarvi, O. Ejtemai, M. Burd, and A. Sobhani, “Modeling pedestrian crowd exit choice through combining sources of stated preference data,” *Transp Res Rec*, vol. 2490, pp. 84–93, 2015, doi: 10.3141/2490-10.

[98] R. Lovreglio *et al.*, “Prototyping virtual reality serious games for building earthquake preparedness: The Auckland City Hospital case study,” *Advanced Engineering Informatics*, vol. 38, pp. 670–682, Oct. 2018, doi: 10.1016/j.aei.2018.08.018.

[99] A. Shipman, A. Majumdar, and R. Lovreglio, “A quantitative comparison of emotional and movement responses to emergency scenarios between VR and physical experiments,” 2022.

[100] K. Velten, “Mathematical Modeling and Simulation Introduction for Scientists and Engineers,” 2009.

Appendix

1. Questionnaire

Q1. For the 1st VR scenario, why have you chosen your exit?

____

Q2. For the other VR scenarios, why have you chosen your exit?

____

Q3. Please rate your level of agreement with these statements.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree	I do not know
I believed I really was the player in the VR scenario	○	○	○	○	○	○	○	○
After finishing the game, it takes a long time for me to return to the real world psychologically and emotionally	○	○	○	○	○	○	○	○
This VR experience makes me feel scared/fearful	○	○	○	○	○	○	○	○
Overall, this VR experience makes me feel tense/nervous	○	○	○	○	○	○	○	○
Overall, this VR experience makes me feel anxious	○	○	○	○	○	○	○	○
The VR experience was engaging	○	○	○	○	○	○	○	○
I found going through this VR experience easy	○	○	○	○	○	○	○	○
The virtual world was accurate /realistic	○	○	○	○	○	○	○	○

The virtual metro officer was accurate/ /realistic	○	○	○	○	○	○	○	○
The virtual people were accurate /realistic	○	○	○	○	○	○	○	○
The interaction with other virtual people was accurate /realistic	○	○	○	○	○	○	○	○
I would act the same way in real life during the evacuation emergency	○	○	○	○	○	○	○	○
I felt part of a group during the simulation	○	○	○	○	○	○	○	○
I felt it was important to get out as quickly as possible regardless of other people	○	○	○	○	○	○	○	○
I felt the urgency to act/do something during the evacuation emergency	○	○	○	○	○	○	○	○
I felt unsafe while I was in the virtual metro station	○	○	○	○	○	○	○	○
I believed that the evacuation emergency was severe	○	○	○	○	○	○	○	○

Q4. Please rate your level of agreement with these statements.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree	I do not know
I identified with the other people affected in the virtual scenario	○	○	○	○	○	○	○	○
I felt unity with other people in the virtual scenario	○	○	○	○	○	○	○	○
I felt that other virtual people affected by the evacuation were like me	○	○	○	○	○	○	○	○
We were all in danger in virtual scenario	○	○	○	○	○	○	○	○
We all shared the same fate in the virtual experience	○	○	○	○	○	○	○	○
It was all of us against the emergency	○	○	○	○	○	○	○	○

Q5. Gender

- ○ Male
- ○ Female
- ○ Non-binary / third gender
- ○ Prefer not to say

Q6. Age

	0 10 20 30 40 50 60 70 80 90 100
Select your age	

Q7. Nationality

____

Q8. Are you right-handed or left-handed?

○ Right-handed

○ Left-handed

○ None

Q9. Please select your weight and height.

	0 23 46 69 92 115 138 161 184 207 230
Height (cm)	
Weight (kg) :	

Q10. How frequently have you practised in a fire drill?

○ Never

○ Less than once a year

○ Once a year

○ Twice a year

○ More than twice a year

○ Unsure

Q11. How often do you play video games?

○ Everyday

○ Several days a week

○ At least once a month

○ Less than once a year

○ Never

Q12. Have you ever used Virtual Reality?

- ○ Yes
- ○ No

Q14. Please state your level of agreement with these statements.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree	I do not know
I am confident that I am able to effectively deal with an evacuation emergency	○	○	○	○	○	○	○	○
Thanks to my resources, I know how to handle an evacuation emergency	○	○	○	○	○	○	○	○
I would be able to deal with an evacuation emergency even if the building is severely damaged	○	○	○	○	○	○	○	○
I would be able to deal with an evacuation emergency even if I find flame and smoke along the way	○	○	○	○	○	○	○	○
I would be able to deal with an evacuation emergency even if I find objects that may harm me along the way	○	○	○	○	○	○	○	○

The consequences of an evacuation emergency on my safety would be severe	○	○	○	○	○	○	○	○
The consequences of an evacuation emergency would be harmful to me	○	○	○	○	○	○	○	○
I would be vulnerable during an evacuation emergency	○	○	○	○	○	○	○	○