POLITECNICO DI BARI

SCUOLA INTERPOLITECNICA DI DOTTORATO

Doctoral Program in
Environmental and Territorial Safety and Control

Final Dissertation

Modelling Decision-Making in Fire Evacuation based on Random Utility Theory

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4th April 2016

ABSTRACT

Recent fire accidents and terrorist events have highlighted that further work can be done to improve the safety of buildings during fire evacuations. To date, several evacuation models and tools have been developed to predict the safety of a building by comparing the time necessary to evacuate it and the time at which the conditions of the given environment become unacceptable. However, despite the increasing availability of new models and tools, many 'crude' assumptions are still made to represent human behaviour in fire. Another limitation acknowledged by several authors regards the modelling of evacuees' decision-making. In fact, many crucial decisions affecting the evacuation time – such as the decision to start investigating and evacuating, the route choice, etc. – are often inputs rather than outputs of evacuation models.

This work is an attempt to fill the gaps in the existing evacuation models by investigating the use of Random Utility Theory to develop new evacuees' decision-making models. Random Utility Theory has been developed over the last century to model discrete choices combining a utility based structure and the paradigm of rational decision-makers. This theory has been used in many different fields– economics, transportation, marketing, etc. – to investigate and predict several discrete choices. This work aims at investigating if this theory can be used to model human behaviour in fire, comparing the assumptions underpinning the theory and the existing knowledge on evacuees' decision-making. Then, a general data-based methodology is introduced in this work to use Random Utility Theory to estimate new evacuees' decision-making models. This methodology combines existing understanding on how evacuees make decisions and existing or new behavioural data. This work analyses all the different combinations of techniques and research methods (i.e. research strategies) that can be used to collect behavioural data aimed at calibrating evacuees' decision-making. This analysis identifies the pros and cons of each type of behavioural data in terms of several criteria, such as internal, external and ecological validity, experimental control, ethical issues, etc.

The general methodology introduces in this work is finally used to investigate three evacuees' decisions: (1) the decision to start investigating and evacuating; (2) exit choice; (3) local movement choices.

The first decision is investigated using observations (Revealed Preferences) of evacuees participating in unannounced evacuation drills in a cinema theatre. This dataset includes five unannounced evacuation trials carried out in a cinema theatre in Sweden involving 571 participants.

The second decision is studied using an online questionnaire and hypothetical scenario experiments (Stated Preferences). This dataset includes Stated Preferences from 1,503 respondents from all over the world for 12 hypothetical evacuation scenarios illustrating a metro station with two available exits. The survey administered the hypothetical evacuation scenarios using pre-recorded videos and was distributed using the Internet (i.e. non-immersive Virtual Reality).

The third decision is investigated using observations (Revealed Preferences) of participants in an immersive Virtual Reality experiment. The dataset includes the trajectories of 96 participants, who were asked to evacuate from a road tunnel interacting with the physical virtual environment using a joypad.

The methodology introduced in this work represents a useful tool to identify all the factors affecting evacuees' decision-making and the impact of each factor on the choices. The application of this methodology for the three selected choices has made it possible to identify the pros and cons of the adopted research strategies. Moreover, this work highlights the need for more advanced research strategies to develop future decision-making models.

Keywords: evacuation modelling; decision-making modelling; random utility theory; human behaviour in fire; virtual reality

SOMMARIO

I recenti incendi ed attacchi terroristici hanno evidenziato come sia necessario effettuare nuovi studi per migliorare la sicurezza di edifici durante la loro evacuazione. Ad oggi, diversi strumenti come modelli di esodo sono stati sviluppati per predire la sicurezza di un edificio durante le fasi di evacuazione dovuta ad incendi, Tale analisi è fatto comparando il tempo necessario per evacuare l'edificio ed il tempo in cui le condizioni dell'ambiente diventano letali per gli occupanti. Tuttavia, nonostante l'incremento di nuovi modelli di esodo, la rappresentazione del comportamento umano in presenza di incendio è ancora basato su assunzioni semplicistiche. Diversi autori hanno anche evidenziato che un ulteriore limitazione dei modelli esistenti è la rappresentazione del processo decisionale delle persone mentre evacuano da un edificio. Infatti, molte decisioni prese dalle persone per evacuare da un edificio – si pensi alla decisione di iniziare ad investigare cosa sta accadendo e di evacuare, la scelta della via di fuga, etc. – sono spesso un input più che un output del modelli di esodo.

Il seguente lavoro di tesi è un tentativo di colmare questa lacuna dei modelli di esodo attraverso l'uso della Teoria dell'Utilità Aleatoria sviluppando nuovi modelli del processo decisionale. La Teoria dell'Utilità Aleatoria è stata sviluppata nel corso dello scorso secolo al fine di modellare le scelte discrete combinando una struttura matematica basata sull'utilità ed il paradigma di decisori razionali. Questa teoria è stata applicata in differenti campi di ricerca – economia, trasporti, marketing, etc. – al fine di predire diverse scelte discrete. Questo lavoro è finalizzato ad investigare se questa teoria può essere utilizzata per rappresentare il comportamento umano in presenza di incendi. Questa indagine è fatta comparando le assunzioni alla base della teoria e le conoscenze attuali sul processo decisionale delle persone evacuate. Questo lavoro introduce anche una metodologi generale al fine di utilizzare la Teoria dell'Utilità Aleatoria per la stima di nuovi modelli del processo decisionale utilizzando dati comportamentali. Questa metodologia combina le conoscenze esistenti su come le persone prendono le loro decisioni per evacuare un edificio e dati comportamentali di casi studio nuovi o esistenti. Questo lavoro analizza tutte le possibili combinazioni di tecniche e metodi di ricerca (ovvero strategie di ricerca)

che possono essere utilizzate per raccogliere dati comportamentali finalizzati a calibrare i nuovi modelli del processo decisionale. Questa analisi consente di identificare i pro e contro dei diversi tipi di dati utilizzando diversi criteri, come la validità interna, esterna ed ecologica, il controllo sperimentale, le questioni etiche, etc.

La metodologia generale introdotta in questo lavoro è in fine utilizzata per studiare tre decisioni: (1) la decisione di iniziare ad investigare ed evacuare; (2) la scelta dell'uscita e (3) le scelte di navigazione locale.

La prima decisione è studiata utilizzando osservazioni (Preferenze Rivelate) di partecipanti ad una serie di prove di evacuazione antincendio da un cinema/teatro. Questi dati includono cinque prove di evacuazione eseguite in un cinema/teatro svedese coinvolgendo 571 partecipanti.

La seconda decisione è studiata usando un questionario online che include scenari ipotetici (Preferenze Dichiarate). Questi dati includono Preferenze Dichiarate di 1,503 partecipanti al questionario provenienti da tutto il mondo. Gli scenari ipotetici utilizzati in questa indagine rappresentano una stazione di metro con due uscite. Questi scenari sono stati mostrati attraverso video preregistrati che mostrano un ambiente virtuale.

La terza decisione è investigate utilizzando osservazioni (Preferenze Rivelate) di partecipanti ad un esperimento in Realtà Virtuale. I dati includono le traiettorie di 96 partecipanti, i quali avevano il compito di evacuare da un tunnel stradale interagendo con l'ambiente virtuale utilizzando un joypad.

La metodologia introdotta in questo lavoro di tesi rappresenta uno strumento utile per identificare sia tutti i fattori che influenzano le decisioni prese dalle persone che evacuano un edificio sia per quantificare l'impatto di ogni singolo fattore sulla scelta. L'applicazione di questa metodologia per le tre scelte selezionate consente di identificare i pro e contro delle strategia di ricerca adoperate. Inoltre, questo lavoro evidenzia il bisogno di strategie di ricerca più avanzate al fine di sviluppare e calibrare i modelli del processo decisionale del futuro.

ACKNOWLEDGEMENTS

To be added before the final submission

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ABBREVIATIONS

ASET: Available Safe Egress Time
FED: Fractional Effective Doses
RP: Revealed Preference
RSET: Required Safe Egress Time
SP: Stated Preference
VR: Virtual Reality

1. INTRODUCTION

Recent fire accidents (e.g. Mont Blanc tunnel 1999, Frèjus tunnel 2005) and terrorist attacks (e.g. New York 2001, Madrid 2004, London 2005 and Paris 2015) have shown that existing transportation systems and buildings may fail to provide adequate safety conditions during evacuations. Many tragic events have highlighted that evacuees may not behave according to the designers' and planners' expectations during fire emergencies (Proulx 2002).

Despite all the technological progress in the last decades to reduce the number of deaths or injuries, several events have shown that it is not always possible to fully predict and prevent human behaviour during fire emergencies. For instance, a study on the World Trade Centre evacuation carried out after the terrorist attacks of 2001 highlighted that many evacuees interviewed after the disaster stated that they took more than 17 minutes to start evacuating (Galea et al. 2007). Another example of behaviour which led to dramatic consequences was observed is in the Mont Blanc tunnel in 1999. In this accident, twenty-seven of the thirty-nine victims took the decision to remain in their own vehicles whereas two sought refuge in other vehicles, perishing from suffocation (Carvel & Beard 2005). Similar behaviour was observed in 2010 during an evacuation due to a false alarm, which occurred in a German road tunnel full of commuters because of a traffic jam. Only a few commuters followed the instruction to evacuate given to them (Kinateder 2012). Therefore, it is evident that an increase in the safety level and resilience of new and existing transportation systems and buildings in case of emergency requires deep insight into how evacuees behave and the factors affecting their behaviour during such emergencies.

Human behaviour during fire emergencies has been investigated for over a century. One of the earliest documented investigations on human behaviour focusing on velocity of pedestrian movement was carried out in US in 1909 (National Bureau of Standards 1935). Different institutions (e.g. National Fire Protection Association, London Transit Board) conducted similar investigations over the first half of the last century (Bryan

1999).The research in this field was continued by Bryan (1957) in the late 1950s and by Wood (1972) in the early 1970s and then eventually elaborated in the 1980s by Canter et al. (1980) with a book entitled "*Fire and Human Behaviour*" summarising the state-of-the-art coming from the first International seminar on human behaviour in fire (Kuligowski & Mileti 2009). Nowadays, the interest in this field is still growing in the scientific community, which has started an ad hoc series of symposiums on "*Human Behaviour in Fire*" (Proulx 2002). This raises a few questions: Why is it necessary to investigate human behaviour during emergencies? How can these studies on human behaviour help improve the safety and resilience of new and existing transportation systems and buildings?

Studies on human behaviour can improve the safety and resilience of new and existing transportation systems and buildings in different and interrelated ways. These studies can support (a) the assessment of the risk, (b) the training and preparation for future fire events and (c) fire safety design (Canter 1980a). Understanding how people behave in the case of fire evacuation is essential to bring the design of buildings and infrastructures into line with evacuee needs during an incident (Kobes et al. 2010). Therefore, these studies are fundamental to develop new codes and regulations aimed at addressing this design issue.

Nowadays, the building codes as well as infrastructure codes can be classified into prescriptive-based and performance-based. The former type of code consists of providing requirements which prescribe the solutions without explicitly stating the intent of the requirement, whereas the latter type introduces desired objectives giving the designer the freedom to choose among the design solutions meeting the objectives (Hadjisophocleous et al. 1998). In detail, the performance-based approach requires a comparison between the ASET (Available Safe Egress Time) and the RSET (Required Safe Egress Time). ASET is a time-threshold indicating the tenability limits after which the conditions of the given environment become unacceptable while RSET is the time needed by evacuees to escape safely (Proulx 2002; Nelson & Mowrer 2002). Different tenability criteria can be used to calculate ASET (NFPA 2002). One of the most used criteria is the intoxication rate which can be assessed using Fractional Effective Doses (FED), defined by Purser (2002). The current state of-the-art also presents many methods and models aimed at simulating the evacuation process, which can be used to asses RSET (Nelson & Mowrer 2002; Gwynne et al. 1999; Kuligowski et al. 2010).

The impact of studies on human behaviour on the final design of buildings and transportation systems depends on the type of code adopted. Appleton (1980) represents the process through which data on human behaviour can eventually affect the prescriptive regulations as indicated in Figure 1. The diagram indicates that knowledge on how people cope with an emergency can be abstracted as a set of simple assumptions, which are then formulated into the regulations.

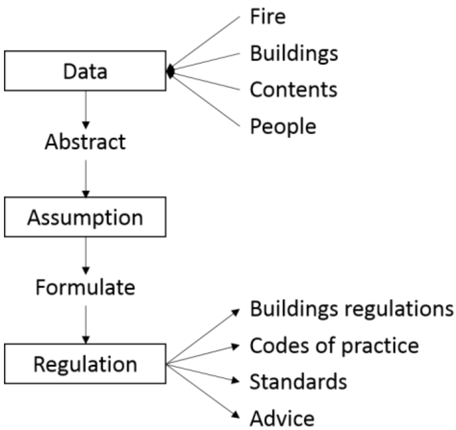


Fig 1.1 – Process of regulation writing (Appleton 1980)

Appleton (1980) points out that this approach seems to work reasonably well in traditional buildings (i.e. buildings having a regular layout) but it is questionable in the presence of non-conventional buildings which are likely to be larger and more-complex. Other criticisms on the prescriptive code have been raised by many other authors more recently. For instance, Hadjisophocleous et al.(1998) and Tavares (2009) provide an insight into the advantages associated with the shift from prescriptive-based code to performance-based code in different countries. Kobes et al. (2010) point out that previous fire accidents highlighted that the existing prescriptive code had not adequately supported the evacuation of people from buildings and transportation systems, whereas Tavares (2008) and Gwynne et al. (2015) argue that the performance-based code has become more popular since it is easier to apply when assessing the safety of new, unorthodox and complex buildings.

In the performance-based context, studies on human behaviour have a greater and more direct impact on the final design of buildings and infrastructures. In fact, the performance approach relies mainly on knowledge on how people behave during evacuations to define evacuees' untenable conditions (ASET) and to develop evacuation models, which can estimate RSET. These models represent useful tools to perform risk analysis and eventually improve the safety and resilience of new and existing transportation systems and buildings. The flexibility of these models allows the simulation of a large number of scenarios in a relatively short time. Several input parameters of these models can be easily modified in order to represent completely different evacuation scenarios (Ronchi 2012). The next section provides a summary of the existing state-of-the-art of evacuation modelling.

1.1 Evacuation Modelling

In the last decades, several models have been introduced into the literature to describe and predict human behaviour during emergency evacuations. These models could have a different nature since their aim could be to provide either a *quantitative* estimation to assess the safety of building and transportation systems (i.e. engineering models) or a *qualitative* description of the process characterizing human behaviour during emergencies (i.e. conceptual models). The next section provides an insight into the quantitative models simulating evacuation.

1.1.1 Engineering Evacuation Models

One the most important pieces of information that is necessary for engineers to evaluate the safety of buildings and transportation systems is the total time taken by evacuees to reach a safe place, i.e. RSET (Proulx 2002). One of the simplest and most used engineering approaches used for this purpose is the time-line model, which defines RSET as the sum of several sequential sub-times (Purser & Bensilum 2001; Proulx 2002; Nelson & Mowrer 2002). This model is undoubtedly a simplification of the real evacuation process, but it gives a quantitative analysis in a relatively short time and it has been included in various legislation, e.g. ISO 16730-5 (2013), BSI PD 7974-6 (2004), etc.

Following the time-line paradigm, RSET can be divided using different approaches. In this thesis, the sub-times taken into account are the ones proposed by Proulx (2002):

$$RSET = \Delta T_{det} + \Delta T_{al} + \Delta T_{evac} \qquad \text{Eq. 1.1}$$

where ΔT_{det} is detection time, which is the time from the beginning of an emergency to the time at which the emergency is detected whereas ΔT_{al} is the time required to activate the alarm once the emergency has been detected. In some cases these two events could be almost simultaneous (i.e. fire detected by an electronic device), but in other cases there could be a delay, for instance, if the alarm system is activated manually by an evacuee at a pull-station (Proulx 2002). There are many other cases in which an alarm cannot be activated or does not work and evacuees will eventually perceive other cues different from an alarm (e.g. presence of smoke, other evacuees' behaviour, etc.) that will make them aware of the emergency. In these latter cases, both ΔT_{det} and ΔT_{al} are equal to zero. Finally, ΔT_{evac} is the total evacuation time which can be divided into two major components: the pre-evacuation time, ΔT_{pre} and the movement time, ΔT_{mov} (Purser 2003). The former is the delay time to start evacuation movement and it starts when evacuees are exposed to the first cues, e.g. alarm, smoke, etc., and ends when they begin to evacuate moving towards a safe place. The latter is the time spent by the evacuees to reach a safe place once they start their purposeful movement towards it. Different classifications have been developed to categorize the times making up the pre-evacuation time. The most common sub-division includes recognition, ΔT_{rec}, and response time, ΔT_{res} (Purser & Bensilum 2001; Nelson & Mowrer 2002):

$$\Delta T_{evac} = \Delta T_{rec} + \Delta T_{res} + \Delta T_{mov} \qquad \text{Eq. 1.2}$$

The recognition time is the time required for an evacuee to take the decision to evacuate once he has perceived the first cue. The response time is the interval between the time at which the evacuation decision is taken and the time at which an evacuee starts moving towards a safe place.

RSET is always compared to the time when untenable conditions occur during an evacuation (i.e. ASET). For instance, in case of fire emergencies the untenable conditions may depend on the intoxication rate due to smoke inhalation, i.e. FED (Purser 2002) or the collapse of the structure (NFPA 2002). Figure 1.2 illustrates the different components which have been introduced in Equations 1.1 and 1.2.

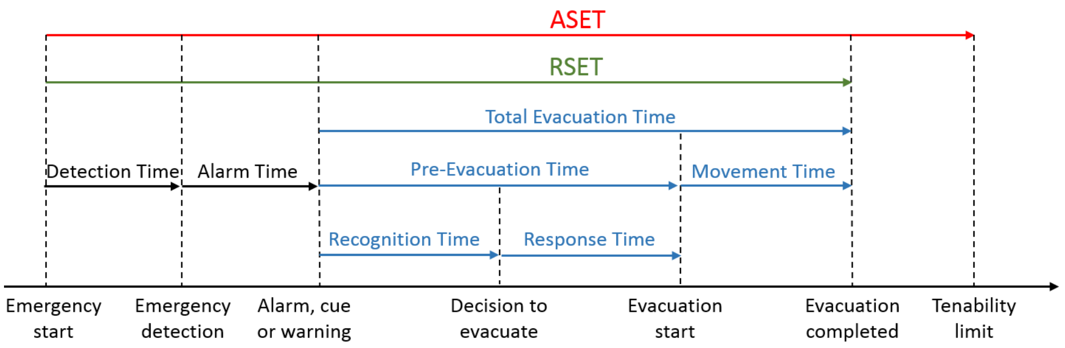


Fig.1.2 – Time-line model representation

To date, RSET can be calculated by using both engineering equations and more sophisticated computational tools implementing different types of evacuation models (Proulx 2002). Several review papers have been published comparing the features of the existing building evacuation models (Kuligowski et al. 2010; Gwynne et al. 1999), investigating the methodological approaches used in these models (Zheng et al. 2009) and analysing their applications in the context of high-rise building evacuations (Ronchi & Nilsson 2013a). However, one key issue about these reviews is the rapid advances in the evacuation model capabilities and development, which makes it difficult to provide up-to-date information on the existing state-of-the-art (Ronchi 2012). To address this issue, an on-line platform (www.evacmod.net) aimed at providing updated information about existing models has been developed (Evacuation Modelling Portal 2015; Ronchi & Kinsey 2011).

These reviews highlight that three different approaches can be used to simulate evacuations: namely micro-simulation, macro-simulation and meso-simulation. Micro-simulation tracks the detailed movement and interaction of individual entities, i.e. agents. On the other hand, macro-simulation tools represent the aggregate behaviour of pedestrians based on equations derived from analogies with hydraulic flows, using Navier-Stokes-type systems (Hoogendoorn 2001). Finally, the meso-simulation approach represents a compromise between micro and macro-simulators. The choice of the approach could depend on the scale of the problem, the focus of the investigation, the available computational power, and many other factors (Kuligowski et al. 2010).

Among the available approaches, in recent decades the microscopic models have become the most popular to simulate the evacuations from buildings and transportation systems (Gwynne et al. 2015). One of the main reasons is that advances in computer science have gradually reduced the problems associated with computational costs (Mollick 2006). However, many other reasons supporting the use of microscopic pedestrian models are discussed by Hoogendoorn (2001).

Among the existing microscopic evacuation models, it is possible to distinguish two broad classes, namely deterministic models and stochastic models (Lovreglio, Ronchi, et al. 2014). The deterministic approach is easier to use but it has the limitation of only representing average behaviours (Gwynne et al. 1999). Thus, a deterministic model or sub-model may not be able to represent the unexplained variance in human behaviour in an exhaustive way. The stochastic approach is a strategy to simulate behavioural uncertainty (see Section 2.1.2) because it allows the modelling of different behaviours starting from the same conditions (Ronchi et al. 2013; Lovreglio, Ronchi, et al. 2014).

Despite the proliferation of many new microscopic evacuation models, several authors have raised criticisms on the state-of-the-art of the existing evacuation models (Groner 2004; Kuligowski 2013; Gwynne et al. 2015). The main obstacle for reliable predictions of the total evacuation time is not the simulation of evacuee's movement, but the current ability to predict evacuees' decision-making about when, where and how they move to reach a safe place during an emergency (Groner 2004). In fact, the literature still argues that evacuation modellers have made many more oversimplifications in some modelling areas, e.g. modelling of the decision-making process, rather than in others, e.g. modelling of physical movement (Kuligowski 2013; Gwynne et al. 2015). Existing models have several gaps in terms of simulation of the decision-making process that determines evacuees' actions (Groner 2004). Many existing evacuation models make crude assumptions that do not allow many of the expected evacuation behaviours to be represented (Gwynne et al. 2015). Many other models leave the users the possibility of choosing input settings defining critical aspects of the evacuation process (e.g. pre-evacuation time, exits selected by agents, etc.) to compensate for model omissions (Gwynne et al. 2015). Therefore, several evacuees' choices are defined by the users before the simulation rather than predicted by the model. This approach could lead to either too optimistic or too conservative estimation of the RSET. Therefore, buildings and transportation systems could have procedures and solutions which result in an unsafe design on the one hand or an unnecessary and costly one on the other (Kuligowski 2013). These modelling issues are further amplified by the lack of behavioural data for the input setting, such as the pre-evacuation time (Proulx 2002). Moreover, the absence of well-defined instructions in codes and regulations, especially in countries where the performance-based code is relatively new, may aggravate the modelling tasks (Ronchi 2012).

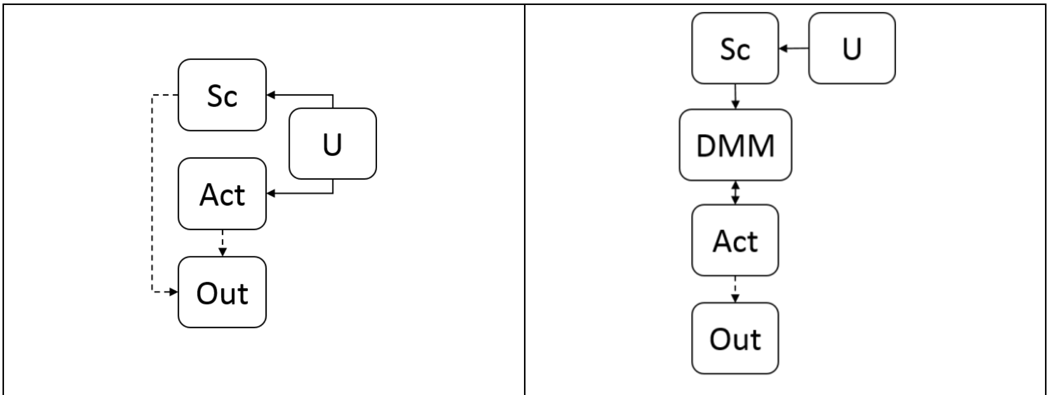
Several researchers have highlighted that the main reason of the use of crude assumptions to characterize the evacuees' decision-making process instead of using proper decision-making models is the absence of robust, comprehensive and validated conceptual model (Kuligowski 2013; Gwynne et al. 2015; Gwynne & Kuligowski 2015). Another problem concerning the limitations of existing models is the lack of calibrating procedures and data to improve their predictability. The following sections aim to summarise the current state-of-the-art of conceptual models of evacuee's behaviour and model calibration.

1.1.2 Conceptual Evacuation Models

A conceptual model is a model which provides a formal description of the physical and social aspects of the real world for purposes of representing the key parts of a system (under investigation) and the interaction between these parts (Mylopoulos 1992). In the field of human behaviour in fire, Gwynne and Kuligowski (2015) have extended this definition stating:

"*A conceptual behavioural model is a composite of existing theories and data that has been drawn together to represent some portion of evacuee behaviour*." (Gwynne & Kuligowski 2015, p. 23)

Many such models have been developed to understand the key features affecting human behaviour during emergencies. These models are supposed to be the theoretical and empirical basis for the development of new decision-making models, which could lead to engineering models producing more reliable predictions. Figure 1.3 illustrates the impact that a decision-making model has on the structure of microscopic evacuation models according to Gwynne et al. (2015) and how conceptual models may affect the prediction of engineering models.



(a) Non-implemented decision-making model. User drives performance	(b) Implemented decision-making model. User sets scenarios

Fig. 1.3 – Model representation. Sc: Scenario, Act: evacuee actions, Out: outcome, U: user, DMM: decision-making model (Gwynne et al. 2015)

In the approach described in Figure 1.3 (a) there is no decision-making model and hence the conceptual model defining the evacuees' behaviour relies entirely on user inputs. Therefore, no behaviour is simulated since the behavioural responses are pre-set by the user:

"*Behavioural actions are an input rather than an action*" (Gwynne et al. 2015, p. 7)

In contrast, the approach depicted in Figure 1.3 (b) includes a decision-making model generating the evacuees' actions depending both on external factors characterizing the simulated environment and on internal factors defining the simulated evacuees (i.e. agents). In fact, the implemented decision-making model internalizes the external factors that influence the decision-making process and it combines these pieces of information with existing internal information to select the most appropriate response. In this second case, the user is only supposed to choose the evacuation scenario and the real-world factors from the building conditions/situations that may influence human performance and behaviour (Gwynne et al. 2012; Nilsson & Fahy 2016). Therefore, the conceptual model defining the evacuees' decision-making is not an input provided by the user, but it represents the basis on which the decision-making model is developed.

Bryan (2002), Kuligowski (2011) and Gwynne et al. (2015) have identified several existing conceptual models related to the field of evacuation behaviour in fire. One of the first conceptual models is the one proposed by Withey (1962) which describes the cognitive process involved in identifying and evaluating an emergency defining seven psychological and physical processes used by evacuees, namely, recognition, validation, definition, evaluation, commitment and reassessment. In contrast, Breaux et al. (1976) identify only three processes: recognition/interpretation, behaviour (i.e. action/ no action) and the outcome of the action (i.e. evaluation long-term effects), even though there are several similarities with Withey's model (Bryan 2002). A further conceptual model developed to represent the key sequences of action evacuees commonly undertake is the one proposed by Canter et al. (1980). This model highlights how the information is processed in order to define the response to a fire emergency by interpreting the available information, preparing to act and eventually acting choosing between four alternatives:

evacuate, fight, warn and wait. A further more recent model is the one proposed by Kuligowski (2011) aimed at explaining the evacuees' response during the 9/11 evacuation.

Gwynne et al. (2015) and Kuligowski (2013) have raised several criticisms against the existing conceptual models. Some of these models (such as the model by Canter et al. (1980)) provide limited details regarding the applications of the decision-making process in specific circumstances, others (such as the model by Kuligowski (2011)) only refer to a specific situation. Furthermore, other existing models, such as the stress model by Proulx (1993), need to be coupled with other theories since they describe partial attributes that affect the decision-making process rather than focusing on the overall process (Gwynne et al. 2015).

A more recent attempt to define a robust and comprehensive conceptual model is the Protective Action Decision Model (PADM) developed by Kuligowski (2013). This model is based on over 50 years of empirical studies of hazards and disasters and provides a framework describing the decision-making steps that affect the protective actions taken in response to an emergency. Kuligowski (2013) identifies the following steps: perception of the information, attention to the information, comprehension of the information, evaluation of the nature of the threat, risk estimation, identification of protective actions, selection of a protective action and execution of the selected protective action. The processing of the available information is carried out by answering the following questions:

1) Is there a real threat that I need to pay attention to?
2) Do I need to take protective action?
3) What can be done to achieve protection?
4) What is the best method of protection?
5) Does protective action need to be taken now?

In answering these questions, evacuees proceed through the perceptual-behavioural steps, in which the outcome of the process is the performance of a behavioural action in response to the emergency. In many cases, evacuees cannot answer these questions because of a lack of available information. Therefore, they need to engage in information seeking tasks by answering several other questions as illustrated in Figure 1.4.

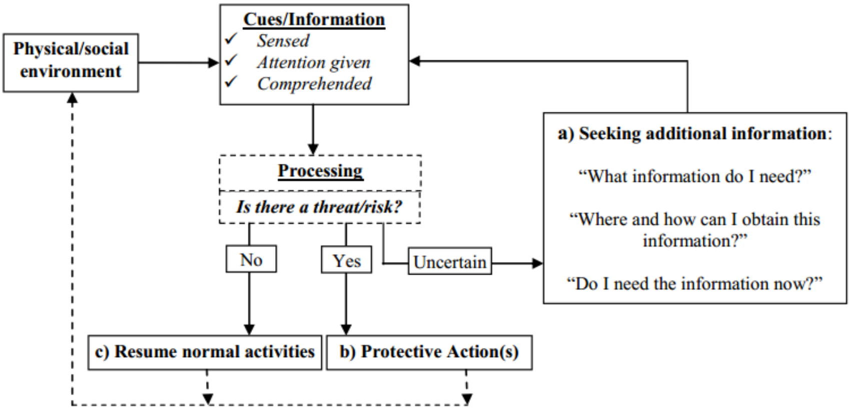


Fig. 1.4 – The protective action decision model by Kuligowski (2013). Picture source: (Kuligowski 2015)

Even though the PADM provides a framework from which a conceptual model can be developed, it does not address the specifics related to building fires, such as the factors that would influence the different stages of the decision-making process, the types of behaviour that could occur at various stages and the nuances unique to building fires (Gwynne & Kuligowski 2015). To overcome this limitation, Gwynne et al. (2015) have expanded this theoretical framework introducing fire-related behavioural statements. The authors identify a list of twenty-four behavioural statements to use to represent the consequential phases defining the decision-making process, namely cue processing, situation and risk assessment, response selection and action (Figure 1.5). Gwynne and Kuligowski (2015) have successively expanded these statements including three other behavioural statements.

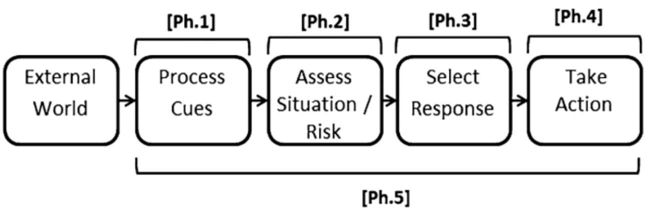


Fig. 1.5 – Grouping of behavioural statements according to Gwynne et al. (2015). Picture source: (Gwynne et al. 2015)

On one hand, these behavioural statements represent guidelines to make engineering models more representative of the current understanding about evacuees' decision-making. On the other hand, the use of behavioural statements in the future generation of evacuees' decision-making is a necessary condition for the achievement of more predictive models, but it is not sufficient. In fact, combining these statements with other assumptions, which are necessary to develop engineering models, could generate results that still contain significant gaps in the simulated evacuee response (Gwynne et al. 2015).

Gwynne et al. (2015) have also introduced the structure of a simplified behavioural model suitable for implementation within a microscopic egress model (i.e. agent-based). This model structure extends the original form by Gwynne (2013), which was aimed at reflecting the theoretical developments made by Kuligowski (2011) regarding the 9/11 WTC evacuation. Figure 1.6 illustrates a simple example of this model. It is assumed that an evacuee perceives both physical (C_p) and social cues (C_s) from the external world (ExtW). These cues are internalized and processed in the first block (Cue Processing). These pieces of information are then used in the second block to assess the emergency and eventually generate a response. Gwynne et al. (2015) identify several sub components aimed at processing the information, assessing the situation and selecting the response action. However, the authors acknowledge that even though the proposed structure outlines the types of component that are necessary in an evacuation decision-making model, this structure needs to be specified in much greater detail for future implementation.

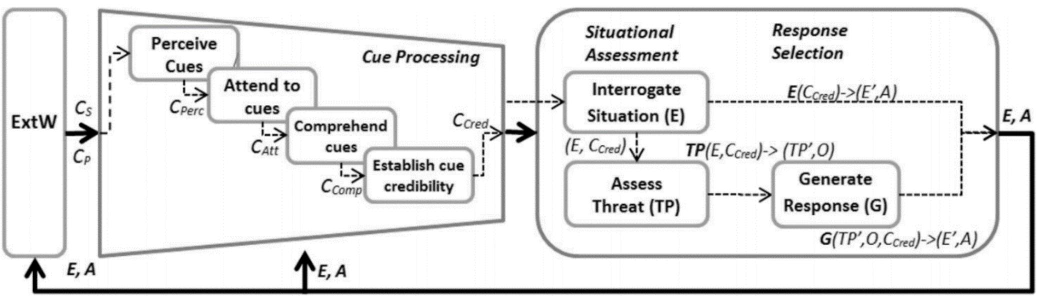


Fig. 1.6 – Structure of the behavioural model by Gwynne et al. (2015). Picture source: (Gwynne et al. 2015)

Despite the acknowledged need for a comprehensive conceptual decision-making model, both the behavioural statements described by Gwynne et al. (2015) and the decision-making framework outlined by Kuligowski (2013) can be used as a starting point to develop new computational evacuation decision-making models. If fact, these findings provide a theoretical basis for both selecting a consistent mathematical framework to simulate evacuees' decision-making and specifying decision-making models.

Despite the differences between the conceptual models available in the literature, there are invariant features in the representation of the decision making process, which can be identified. In fact, the decision-making process affecting evacuees' behaviour can be conceptually summarized with three sub-sequential stages: information perception and processing, situation assessment, action selection. This model assumes that the decision-making process starts with the perception and processing of the information from the evacuation social/physical environment. This first step makes a decision-maker internalize the factors that could affect his choice. The processed information is then used to assess the evacuation context of choice (i.e. definition of the possible responses, the pros and cons of choosing an action, etc.). Subsequently, once the situation has been assessed, the decision-maker can select a course of action. The result of this decision-making process can be visualized through the action made by the evacuees who could affect the external world and the evacuees' capacity to perceive/process external cues and to assess the evacuation scenario as indicated in Figure 1.7.

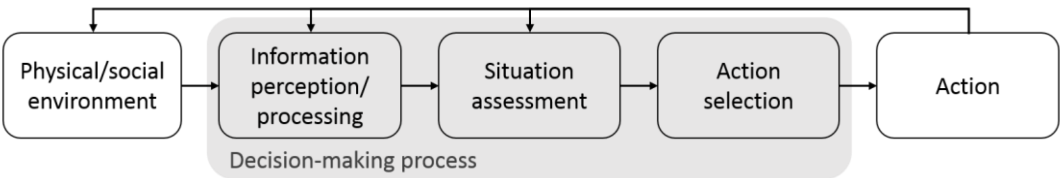


Fig. 1.7 – Conceptual structure of the decision-making process coming from a review of the existing conceptual model.

1.1.3 Model Calibration

Once an evacuation decision model has been theoretically identified (i.e. identification of the type of choice and the factors affecting the choices) using behavioural assumptions and mathematically specified (i.e. identification of the equations linking factors to the final choice), one of the main problems is the calibration of the model parameters in order to reproduce not only the qualitative features but also reliable quantitative outcomes (Helbing et al. 2003). Calibrating a model consists of choosing the set of parameters optimising one or more goodness-of-fit measures, which are a function of both these parameters and the observed data (Ortuzar & Willumsen 2011). In other words, model calibration represents the link between a model and behavioural data.

Two approaches have been developed to perform the calibration of evacuation models: top-down and bottom-up (Boltes et al. 2014). The first approach consists of selecting the set of parameters in order to reproduce observed macroscopic performances. This approach is also known in the literature as the macroscopic approach and it is based on the use of fundamental diagrams and evacuation time estimations (Schadschneider et al. 2001; Guo & Huang 2011). This approach has been mainly used whenever the microscopic behaviours are unknowns (Boltes et al. 2014). In contrast, the bottom-up approach, also known as the microscopic approach, consists of estimating the model parameters looking directly at the microscopic performances of the dynamic system. These estimations can be made using different techniques, such as least-squares estimation, maximum likelihood estimation and Bayesian estimation (Greene 2011). This approach allows the observed macroscopic performance to be used to validate the calibrated models. Therefore, the microscopic approach allows both local and global dynamics to be verified (Boltes et al. 2014).

Despite the possibility of using several calibrating approaches, the calibration of evacuation decision-making models required several other issues to be solved. The main issue identified by several authors is related to lack of data necessary to calibrate and validate evacuation decision models (Galea 1998; Gwynne et al. 1999; Lovreglio, Ronchi, et al. 2014). However, even when these data are available, they need to be processed to develop datasets suitable for the calibration of evacuation decision-making models. Therefore, there is also the need to develop ad hoc datasets using existing or new behavioural data.

1.2 Research Motivations and Objectives

The previous section outlined a number of critical aspects of existing evacuation models. One of the main issues raised in the previous sections is that a lot of effort has been made to investigate and model evacuees' movement but relatively few studies focus on evacuees' decision-making processes. Therefore, there is a need for decision-making models to develop an evacuation model in line with the structure in Figure 1.2-b. The fulfilment of this need represents the first motivation for this thesis. Another issue identified in the previous section is the lack of calibrating procedures to calibrate the new and existing decision-making models using behavioural data. The need for calibrating procedures linking decision-making models and behavioural data represents the second motivation for this thesis.

The main objective of this work is to fill these gaps by investigating the possibility of using Random Utility Theory to develop/calibrate new decision-making models. Random Utility Theory assumes that the decision-maker chooses the alternative yielding the maximum utility and that this utility is not completely known to the modeller, so it has to be considered partially stochastic (Ortuzar & Willumsen 2011; Cascetta 2009). To date, many different more complex models/formulations have been introduced into the literature to address the limitations of the first formulations of random utility models and applications of Random Utility Theory have been proven successful in many different areas, including transportation, energy, marketing etc. (Hensher et al. 2005; Train 2009; Cascetta 2009). Few applications of Random Utility Theory to model human behaviour in fire emergencies have been described in the literature before the beginning of this thesis (Duives & Mahmassani 2012; Lovreglio, Borri, et al. 2014). However, none of these works investigates whether or not the assumptions of Random Utility Theory are in line with the existing knowledge on evacuees' decision-making process and the potential offered by

Random Utility Theory can be applied to develop new decision-making models. This represents the third motivation for this thesis.

Beyond the broad objective identified in the beginning of this section, several other specific objectives need to be defined and discussed in detail. This research has three key sub-objectives:

1) Investigate the advantages and disadvantages of using Random Utility Theory to develop new evacuation decision-making models simulating evacuees' choices.

Before applying Random Utility Theory, it is necessary to identify the general assumptions underpinning the theory and verify whether these assumptions are in line with the existing understanding of evacuees' decision-making process. This can be achieved by investigating both the general behavioural assumptions coming from the existing literature on decision-making and human behaviour during emergencies and by identifying the features of the decisions that evacuees need to take during their evacuation. If/how new decision-making models based on Random Utility Theory could improve the existing models represents a key question for this thesis.

2) The second objective of this work is to reduce the existing gaps between real evacuation and simulated evacuations. This goal can be fulfilled both by developing a modelling approach simulating the real decision-making process during evacuation and by calibrating the proposed model with existing or new datasets. The calibration issues are addressed in this work by proposing formulations aimed at estimating the parameters of the proposed model specification based on Random Utility Theory. These formulations allow the impact that a factor has on the choice to be quantified and then statistically testing whether a factor has affected evacuee's decisions in a controlled environment. Therefore, it is possible to compare the influence of different factors on the decision-making.

3) The last and ultimate objective of this work is to identify the available data collection techniques and research methods, which can be used to collect behavioural data for

calibrating decision-making models based on Random Utility Theory. The Pros and Cons of the different research strategies (i.e. combinations of data collection techniques and research methods) as well as the impact of these strategies on the final model need to be discussed. The aim of this thesis is to show how different strategies can be used to pursue several research goals. To address these issues, different behavioural data sets have been used to develop evacuation decision-making models based on Random Utility Theory. The datasets introduced by this work are created using different sources of data, namely unannounced evacuation drills and Virtual Reality (VR) experiments carried out by the Division of Fire Safety Engineering of Lund University (Sweden) and a new online stated preference survey carried out on an international scale with the cooperation of the Transport Research Institute of Edinburgh Napier University (UK) and the Department of Transportation and Projects and Processes Technology of the University of Cantabria (Spain).

1.3 Outline of the Thesis

The present thesis consists of six chapters and one appendix.

In Chapter 1 (Introduction), the research problem is described, highlighting the need for decision-making models to model human behaviour in fire and the existing modelling issues and limitations. This analysis is aimed at identifying the motivations and related research objectives of this thesis. The chapter ends by introducing this outline of the thesis.

Chapter 2 (Method) starts by describing the assumptions underpinning Random Utility Theory and verifying whether these assumptions are in line with the existing literature on evacuees' decision-making processes. Then, a modelling procedure and the model formulations used to develop new decision-making models are introduced and discussed. Chapter 2 continues by identifying and describing the data-collection strategies available to collect behavioural data aimed at calibrating new decision-making models based on Random Utility Theory. Then, the selected choices and strategies investigated in this thesis are introduced. The chapter ends by describing the methodological limitations of this thesis.

Chapter 3 (Case Study 1: Decision of Start Investigating and Evacuating) investigates the possibility of modelling the decision to start investigating and evacuating. A pre-evacuation decision-making model is presented based on Random Utility Theory and the behavioural states introduced by Reneke (2013). The pre-evacuation model is calibrated using data from unannounced evacuation drills in a cinema theatre to identify the social/physical factors affecting evacuees' pre-evacuation behaviour.

Chapter 4 (Case Study 2: Exit Choice) introduces a decision-making model based on Random Utility Theory to investigate the impact of different social/physical factors affecting exit choice at the same time. This is carried out using an online Stated Preferences survey.

Chapter 5 (Case Study 3: Local Movement Choices) introduces a procedure to calibrate the existing discrete choice models based on Random Utility Theory formulation (i.e. floor field pedestrian cellular automaton models) using pedestrian trajectories. This procedure is tested using trajectories collected during a VR experiment.

Chapter 6 (Conclusions) provides the conclusions of this thesis highlighting the possible impact of this research in real world applications and possible directions for future studies.

2. METHODS

The main objective of this thesis is to investigate if Random Utility Theory can be used to develop new evacuation decision-making models and the possibility of using modelling techniques based on Random Utility Theory to calibrate these new models.

Section 2.1 investigates whether Random Utility Theory can be a valuable theoretical framework to develop evacuation decision-making models. This is achieved by describing the general assumptions of this theory and identifying the key aspects affecting evacuees' decision-making. Section 2.2 defines the steps required to develop an evacuation decision-making model based on Random Utility Theory whereas Section 2.3 introduces the mathematical formulation of the random utility models and the equations that can be used to calibrate these models. The possible data-collection approaches, which can used to collect behavioural data to calibrate decision-making models, are discussed in Section 2.4 and the selected strategies used in this research are described in Section 2.5. This chapter ends with the identification of the limitations affecting Random Utility Theory, the selected modelling formulation and behavioural data used in this thesis.

2.1 Random Utility Theory and Evacuation Decision-Making

This section aims at assessing if Random Utility Theory can be used to develop new evacuation decision-making models. To address this goal, it is necessary to focus on the main assumptions underpinning this theory.

2.1.1 Random Utility Theory

The first work based on this theory was conducted in the first half of the last century. Thurstone (1927) introduced the mathematical formulation for the binomial probit model with his pioneering work entitled 'A Law of Comparative Judgment'. Despite this work, the main development and spreading of Random Utility Theory started in the 1960s thanks to both the increasing availability of survey data on individual behaviour and the advent of digital computers (McFadden 2001). In these years, Marschak (1960) introduced Thurstone's work into economics investigating the theoretical implications for choice probabilities of maximization of utilities that contained random elements whereas McFadden (1968) developed the formulation for the multinomial logit model, winning the Nobel prize in Economics in 2000.

Random Utility Theory is the most common theoretical framework/paradigm, which has been used over the last 50 years to develop *discrete choice* models. This theory has been discussed in detail in the field of transportation and it is based on the following general assumptions (Cascetta 2009; Ortuzar & Willumsen 2011):

1. Decision-makers belonging to a given population P, act rationally selecting the option which maximizes their personal utility (i.e. *Homo economicus*). This utility is affected by physical, social and economic constraints.

2. Every decision-maker has a set of available alternatives $\boldsymbol{A} = \{A_1, \dots, A_n\}$.

3. It is possible to define a vector $\boldsymbol{X} = \{\boldsymbol{X^I}, \boldsymbol{X^E}\}$ including measured internal and external factors. The internal factors ($\boldsymbol{X^I}$) include decision-makers' personal characteristics and demographics whereas the external factors ($\boldsymbol{X^E}$) include all the characteristics/attributes of the available alternatives (i.e. social/physical factors affecting the choice of these alternatives). Therefore, each *q* decision-maker having a particular set of personal attributes $\boldsymbol{x^I} \in \boldsymbol{X^I}$ faces his predetermined choice set $\boldsymbol{A}(q) \in \boldsymbol{A}$ which is defined by a set of choice attributes $\boldsymbol{x^E} \in \boldsymbol{X^E}$.

4. Each *q* decision-maker associates to each $A_j \in \boldsymbol{A}(q)$ a utility U_{jq}. Since it is not possible to have complete information regarding all the elements considered by the *q* decision-maker, it is possible to assume that U_{jq} is the sum of two components:

$$U_{jq} = V_{jq}(\boldsymbol{\beta}|\boldsymbol{x}) + \varepsilon_{jq} \qquad \text{Eq. 2.1}$$

where V_{jq} is a measurable and systematic part which is a function of the measurable attributes $\boldsymbol{x} = \{\boldsymbol{x^I}, \boldsymbol{x^E}\}$. V_{jq} includes $\boldsymbol{\beta}$ parameters which can be assumed to be constant for the decision-makers belonging to a given population P (fixed-coefficient models) or to vary among the population P (random parameter models) as discussed in Section 2.3 (McFadden & Train 2000).

ε_{jq} is a random part which includes several factors (Cascetta 2009):

a) Variability among decision-makers and variations in tastes and preferences between different decision-makers and for a single decision-maker over time (i.e. a decision-maker facing the same situation at different times can take different choices).

b) Decision-maker's error in the evaluation of the attributes which affect his choice.

c) Modeller's error in measuring the attributes that are included in the systematic part.

d) Attributes that affect the choice but may not be included in the systematic part since they could be difficult or impossible to quantify.

e) Some attributes included in the model could be an imperfect representation of the actual attributes affecting the choice.

It is possible to assume that ε_{jq} are random variables with mean 0 and a certain probability distribution depending on the type of the model, as discussed in Section 2.3.

5. The q decision-maker selects the maximum-utility available alternative from his choice-set $\boldsymbol{A}(q)$ if and only if:

$$U_{jq} \geq U_{iq}, \forall\, A_i \in \boldsymbol{A}(q)$$
$$\Leftrightarrow$$
$$V_{jq} - V_{iq} \geq \varepsilon_{iq} - \varepsilon_{jq}, \forall\, A_i \in \boldsymbol{A}(q) \qquad \text{Eq. 2.2}$$

Equation 2.2 shows that it is not possible to determine with certitude the decision made by the *q* decision-maker, since $(\varepsilon_{iq} - \varepsilon_{jq})$ is not known. However, assuming that the random parts ε_{jq} have their own random distributions, it is possible to estimate the probability of the *q* decision-maker choosing the alternative A_j. Different random utility models can be estimated according to the assumptions made on the random distribution of the random parts, as discussed in Section 2.3.

The next sub-sections aim at identifying and describing the key aspects related to evacuees' decision-making, which are useful to investigate whether Random Utility Theory could be a valid theory to be used to address the need for new evacuation decision-making models.

2.1.2 Decision-Making during Evacuation

Evacuation behaviour has been investigated since the beginning of the last century by many researchers and institutions (Bryan 1999). These studies have highlighted the complexity of this behaviour and that many factors can affect the decision-making process behind this behaviour (Bryan 2002; Proulx 2002; Kobes et al. 2010).

Evacuees facing an emergency need to take several decisions to evacuate a building and/or transportation system (Lovreglio 2014). Regardless of the type of structure, the interpretation of the situation to become aware of the danger represents the first decision-making task affecting evacuees' behaviour (Kobes et al. 2010; Kuligowski 2013). This task occurs during the recognition time and it can be achieved by choosing to engage in a series of activities aimed at acquiring more sources of information whenever the information about what is going on is not readily available. Therefore, evacuees could engage in the *milling process* (i.e. they start talking and milling around with others in an effort to get a better understanding of the situation at hand) selecting several actions (Proulx 2002; Proulx & Fahy 2008). In other words, evacuees need to choose between different possible actions that can help them to get a clear understanding of the emergency in order to assess the situation and make a decision on the best evacuation response. This process is important since the following decisions, namely the decision to start evacuating (defining the passage from recognition to response time) depends upon all the cues that the evacuees have perceived and internalized (Canter et al. 1980; Bryan 2002). Many studies have shown that evacuees have trouble estimating the real danger of an emergency situation and this could delay the decision to evacuate (Kobes et al. 2010). For instance, evacuees' belief about the speed at which fire and smoke spread are often incorrect (Purser & Bensilum 2001; Proulx 2001).

Once the decision to evacuate has been taken, the response phase starts and evacuees have to deal with several other decision-making tasks aimed at defining the strategy to reach a safe place. Before starting the movement toward a safe place, evacuees could decide to engage in different pre-evacuation activities. In fact, several papers and reports document that evacuees, before starting evacuating, could take several actions including: taking care of work-related duties, gathering personal items, looking for people with whom they have social bonds, changing clothes or shoes, etc. (McConnell et al. 2010; Sherman et al. 2011). At this stage, the wayfinding (i.e. route choice) is one of the fundamental tasks which determines the success of an evacuation (Nilsson 2009; Fridolf, Ronchi, et al. 2013; Lovreglio, Borri, et al. 2014).

Finally, once evacuees start their movement toward a safe place (movement time) they need to make short term decisions (i.e. local movement choices) to go through the selected path interacting with other evacuees, physical obstacles including fire and smoke (Kirchner & Schadschneider 2002; Antonini et al. 2006; Fridolf, Ronchi, et al. 2013). All the local movement choices include several navigation decisions such as the choice of a direction and speed selection (Antonini et al. 2006). Moreover, during the movement time, evacuees could still modify their evacuation strategy by selecting new routes to get out of the structure.

Figure 2.1 summarizes the decisions that need to be taken by evacuees dividing them into different steps defined by the time-line model described in Section 1.1.1. Most of the decisions listed in Figure 2.1 are discrete choices (i.e. choices between two or more discrete alternatives). For instance, the decision to start investigating and evacuating are both binary choices since an evacuee can either choose to start these activities or not. Therefore, Random Utility Theory, which is a framework to develop discrete choice models, can be formally used to model this kind of choices by assigning a utility to each alternative as discussed at the beginning of this section.

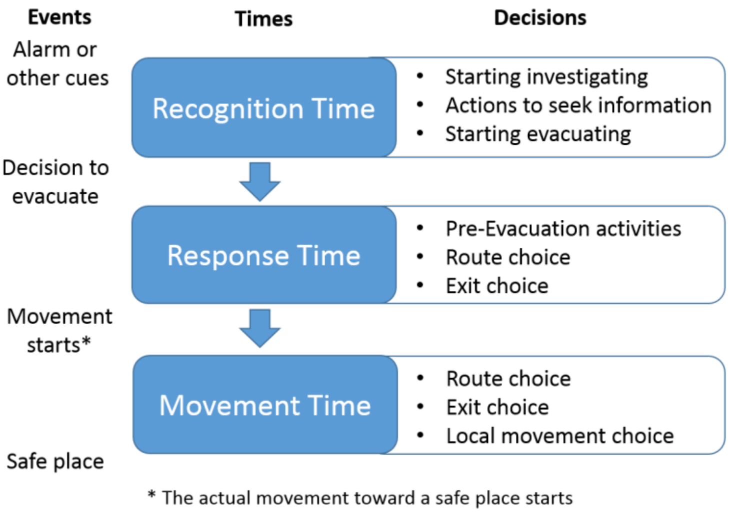


Fig. 2.1 – Decisions to be taken during the recognition, response and movement time

However, some of these choices such as the local movement choices are not discrete but continuous. For instance, an evacuee can choose his/her direction steering over 360 degrees whereas the decision of his speed can vary between different continuous values bounded by the maximum speed. In these cases, the use of Random Utility Theory is not straightforward. This theory can still be applied by discretizing the continuous variables and transforming them into equivalent discrete variables. This approach is in line with the general paradigms already used in evacuation modelling adopted by several existing evacuation models to deal with the continuity of time and space (the use of time-steps or space discretization) (Kuligowski et al. 2010). Moreover, several studies have proved that this approximation allows realistic pedestrian and evacuation models (Kirchner & Schadschneider 2002; Antonini et al. 2006). However, a modeller should be aware that such a limitation could be too crude to develop comprehensive evacuation models for specific situations such as crowded scenarios (Lovreglio, Ronchi, et al. 2016). Another approach overcoming this limitation can be the use of a continuous spatial choice model, i.e. an extension of the discrete choice models for decision involving continuous variables (Ben-Akiva & Watanatada 1981).

Some of the aforementioned decisions (such as path choice) could be dynamic over time due to the lack of information to take a single choice (Lovreglio, Borri, et al. 2015). In these cases, the final choice is the result of partial ongoing choices. For instance, the final path of evacuees can be the result of the preliminary choices of hyperpaths (i.e. a set of paths having a partial common itinerary) which they make during their movement toward a safe place. Figure 2.2 shows an evacuee who has to choose between four different paths leading to four different exits. When he/she starts evacuating, he/she could choose between hyperpaths A and B as first choice at time t_1. Then, he/she has to choose the final path only once the paths forming a hyperpath diverge due to a second choice at time t_2 ($t_2 > t_1$). Therefore, the evacuee postpones the decision of the final path until time t_2 since he/she will have more accurate information about the evolution of the scenario at that time.

Random Utility Theory can represent this kind of decision-making structure. In fact, the decision taken by the simulated evacuees (i.e. agents) can be represented at different times by only considering the amount of information available at these different evacuation stages. The information used to take a choice can be modified depending on the position of the agent and how the simulated environment is sensed by it.

Decision making during emergencies is different from everyday decision-making, in which humans are generally supposed to be able to make choices having enough time to collect information and to evaluate every possible outcome (Starcke & Brand 2012). The common idea on these decisions is that (a) they must be made quickly, (b) they might be irrevocable and (c) available information on which to assess the situation and to base a decision could be limited or overwhelming (Proulx 1993). The literature argues that the time pressure (i.e. the limited time available to evacuees), emotional state (i.e. anxiety and fear) and the psychological stress (i.e. unpleasant emotional state due to environmental events or stimuli (Janis & Mann 1977)) can affect the way in which evacuees process the sources of information and take decisions (Proulx 1993; Ozel 2001; Starcke & Brand 2012; Kuligowski 2013). In contrast to everyday decision-making, the rate of information processing could dramatically increase because of both the increase in the amount of data as well as the decrease in the time available to process these data (Ozel 2001). These findings raise several questions: How do evacuees cope with decision-making tasks under stress? Do they panic or behave rationally? The following subsection aims at answering this question by considering the existing literature on the concept of panic during evacuations.

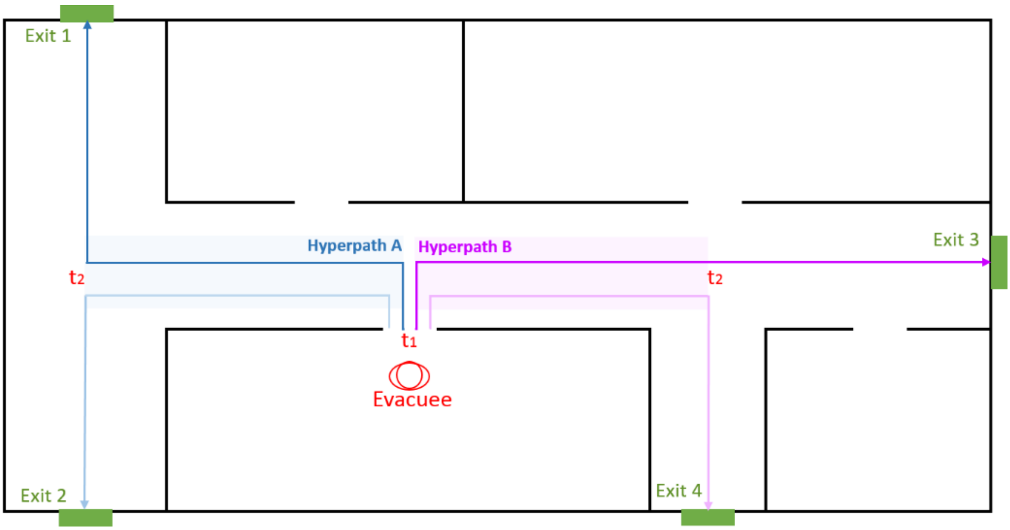


Fig. 2.2 – Example of hyper-paths for a building. Picture source: (Lovreglio, Borri, et al. 2015)

2.1.3 Panic Behaviour vs. Rational Behaviour

The dramatic consequences of catastrophic events are very often attributed to 'panic' by the media. Many definitions for the concept of panic have been suggested in the literature (Fahy et al. 2012) . ‘Panic’ is usually defined as some sort of irrational behaviour known as ‘non-adaptive behaviour’ which consists of a population fleeing without regard for others, inflicting physical injuries on themselves and others (Bryan 2002).

Over the last decades, the concept of panic has been discussed by several authors for a variety of situations and has been adopted in the fire context to explain tragedies and to justify changes in codes and standards (Sime 1980; Keating 1982). However, the common conception of panic was challenged by investigations of specific disasters carried out by several researchers in the 1970s (Canter et al. 1980; Sime 1980; Haber 1980). In fact, these studies started suggesting that the concept of panic is a myth on which to blame the results of tragedies instead of considering the possibility that building designers and managers could be responsible for these tragic results (Keating 1982; Fahy et al. 2012).

Sime (1980) has indicated that the panic behaviour is often attributed to a person by an ‘observer’ whereas the person, who is supposed to be panicking, has a very different perception of his own status. Such a trend has also been observed by Brennan (1999) interviewing survivors of several fires which occurred in Australia. These interviews highlight that a survivor generally attributes panic behaviour to other evacuees, whereas he/she describes his/her behaviour in more rational terms. The same conclusion was reached by Fahy et al. (2012) analysing the interview data from different case studies, e.g. Gothenburg discotheque fire 1998, World Trade Center attack 2001, station night club fire 2003, etc.. After their analysis, the authors argued that many aspects of the evacuees’ behaviour can be rationalized when the event is seen from the subject’s perspective. Moreover, the authors argue that the judgment on the occurrence of panic during an evacuation is strongly affected by the outcome of the events by using this example:

“*For example, when a crisis response, such as re-entering a burning building, results in a fatality, it is labelled as ‘panic’, yet when the identical response results in lives saved, it is labelled as ‘heroic’.*” (Fahy et al. 2012, p. 335)

However, there are also many cases in which survivors used the term ‘panic’ to describe their own behaviour, but the actual actions demonstrated that they did not really panic. A careful analysis has shown that this term is used by them to describe more a state of heightened fear and anxiety than any kind of non-adaptive behaviour leading to the death or injury of a person (Fahy et al. 2012).

In conclusion, it is possible to argue that, according to the existing literature, human behaviour under stress is ‘relatively’ rational, controlled and adaptive (Quarantelli 1977; Canter et al. 1980; Bryan 2002; Kobes et al. 2010). These findings are in line with Simon’s assumption that human beings are ‘information processing entities’ having processing capacities which can be limited by the circumstances created by emergencies, known in the literature as ‘bounded rationality’ (Simon 1960; Ozel 2001). Therefore, even though emergencies can distort and change the mechanisms by which evacuees make decisions, it is still possible to assume that these choices are still rational. In fact, evacuees make their decisions in a way that is procedurally reasonable in light of the available information and means of computation (Simon 1986; Simon 1978; Starcke & Brand 2012).

These findings support the possibility of using Random Utility Theory to develop evacuation decision-making models since one of the main assumptions of this theory is that decision-makers act rationally, selecting the alternative which maximizes their utility. However, even though Random Utility Theory assumes that evacuees maximize their utility, this does not mean that their act only individualistically. In fact, evacuees’ utility functions can include social factors, which could make adaptive/collective behaviours rise. Therefore, group behaviour such herding behaviour could arise using the utility structure provided by Random Utility Theory as has been demonstrated by several studies (Schadschneider 2002; Antonini et al. 2006; Lovreglio, Fonzone, et al. 2014; Lovreglio, Fonzone, et al. 2016).

However, the assumption of decision-makers who decide by maximizing their utility could conflict with the 10th behavioural statement identified by Gwynne et al. (2015) summarizing the findings of Simon (1956):

"People tend to satisfy rather than optimize. People are more likely to choose an option that is perceived as "good enough" rather than the best option." (Gwynne et al. 2015, p. 14)

According to Grether et al. (1986), this trend occurs for contexts of choice in which the information environment becomes very rich or the decision task becomes very complex (i.e. many possible alternatives) relative to the decision-makers' available time or expertise. Under these circumstances, a decision-maker may prefer to satisfy rather than optimize because of high costs of acquiring and processing information defining the choice set. This behavior may have a strong impact on the definition of the choice set of evacuees. Therefore, evacuees could not process all the available alternatives defining the context of choice since they could stop looking for further alternative once they have found one which is good enough. For instance, an evacuee choosing an exit in a room having five exits (i.e. complete choice set) may not consider all the available options but he/she could assign a utility to only three exit and choose the option with the relative maximum utility (i.e. the best option of a subset of the complete choice set) rather than absolute maximum utility (i.e. the best option of the complete choice set). Therefore, the use of Random Utility Theory for evacuation decisions having many possible alternatives and a large amount of information to process is still possible. However, it is necessary to couple a random utility model with a sub model able to simulate the creation of the choice set depending on the complexity of the context of choice and evacuees' skills.

2.1.4 Behavioural Uncertainty

Another concept that needs to be discussed is 'behavioural uncertainty'. This concept was introduced into the literature by Ronchi et al. (2013) and refers to the observed uncertainty associated with the stochastic nature of human behaviour. It is worth highlighting that this concept refers to how an external observer, such as a researcher or a modeller, can perceive the evacuation process and the behavioural aspects affecting this process. In fact, the complexity of this phenomenon does not allow an external observer to have a clear understanding of all the physical and social factors affecting human behaviour during evacuations. Therefore, this concept does not conflict with the evacuees' rational paradigm described in Section 2.1.3, but it indicates that the existing knowledge of human behaviour does not allow researchers to have a clear understanding of all the *if-then* conditions affecting evacuees' decisions as well as the behavioural difference between evacuees.

The concept of behavioural uncertainty is the result of several investigations showing that human behaviour during evacuation can be seen as a stochastic process (Averill 2011). In fact, the evacuation of the same building or transportation system with the same people starting in the same places on consecutive days could lead to very different results (Averill 2011). This is due to both the complexity of the situation and the complexity of evacuees' decision-making processes. Therefore, the divergence of the results could be explained by considering that a change in the state of a complex system, which could be imperceptible to an external observer, can result in large differences in a later state (i.e. butterfly effect) (Helbing & Lämmer 2008). Therefore, two evacuation scenarios apparently similar to external observers may lead to different results.

Lovreglio et al. (2015) have defined two sources of behavioural uncertainties, namely Intrinsic Behavioural Uncertainty, and Perceptions and Preferences Behavioural Uncertainty. Intrinsic Behavioural Uncertainty captures the fact that (a) the choices taken by different decision-makers perceiving a situation in the same way may be different (i.e. evacuees having the same risk perception of evacuation scenarios can act differently depending on their risk aptitude); and (b) the same decision-makers could choose different actions when they face the same situation at different times. Perceptions and Preferences Behavioural Uncertainty is related to different decision-makers' perceptions (i.e. different decision-makers can have different quantitative estimates of the same factor) and preferences (i.e. a certain factor may have different importance to different evacuees) concerning the variables that influence the choice. Therefore, the source of behavioural uncertainty explains why evacuees/pedestrians do not always make the same decisions under the ‘apparently’ same circumstances (Hoogendoorn & Bovy 2004).

Behavioural uncertainty can be simulated in decision-making models developed using Random Utility Theory since these models are stochastic (i.e. they predict the probability that an alternative is selected). As highlighted in Section 2.1.1, one of the goals of the random part of Equation 2.1 is to represent the variability between decision-makers. In fact, this parameter can simulate both variations in tastes and preferences among different decision-makers and for a single decision-maker over time (i.e. a decision-maker facing the same situation at different times can take different choices). Therefore, Random Utility Theory allows the simulation of both Intrinsic Behavioural Uncertainty and Perceptions and Preferences Behavioural Uncertainty. Moreover, Lovreglio et al. (2015) argue that the simulation of variations in tastes and preferences between different people (i.e. Perceptions and Preferences Behavioural Uncertainty) can also be improved using a random parameter approach such as random parameter logit models, also known as Mixed Logit Models (McFadden & Train 2000; Train 2009).

2.1.5 Advantages of Random Utility Theory

This section has described the main assumptions of Random Utility Theory to verify whether this theory can be adopted to develop evacuation decision-making models. The results of this section show that the mathematical framework provided by Random Utility Theory can be used to develop new decision-making models for several reasons:

1. Random Utility Theory provides the mathematical framework for disaggregate behavioural models aimed at predicting the behaviour of single decision-makers. Therefore, it is suitable for a microscopic approach (i.e. agent-based approach) to simulate the evacuation process.

2. The analysis of the decision-making process during evacuation (Section 2.1.2) highlights that many decisions taken during evacuation (with the exception of navigation)

are discrete. Random Utility Theory, providing one of the most used mathematical frameworks to develop discrete choice models, can be used to simulate these discrete evacuation choices. Moreover, the literature has proved that this framework can also be used for modelling continuous choice by transforming them into equivalent discrete choices.

3. The analysis conducted in Section 2.1.3 shows that the actions taken by evacuees derive from a rational decision-making process. Therefore, Random Utility Theory is in line with this observation since it assumes that a decision-maker acts rationally, maximizing their utility. However, in complex situation characterized by the processing of a large amount of information and time pressure, a random utility model may need to be coupled with a sub-model, which extracts a subset of alternatives from the complete set of alternatives as discussed in Section 2.1.3.

4. Random Utility Theory allows the simulation of the uncertainty related to evacuees' behaviour. In fact, the two sources of behavioural uncertainty (i.e. Intrinsic Behavioural Uncertainty and Perceptions and Preferences Behavioural Uncertainty) can be simulated using random terms and random parameters.

The methodological steps used to develop new decision-making models based on Random Utility Theory are described in the next section.

2.2 Modelling Procedure

The development of decision-making models based on Random Utility Theory consists of several steps. The procedure used in this thesis is illustrated in Figure 2.3 and it can be used to develop a decision-making model for any choice affecting evacuees' behaviour described in Section 2.1.2.

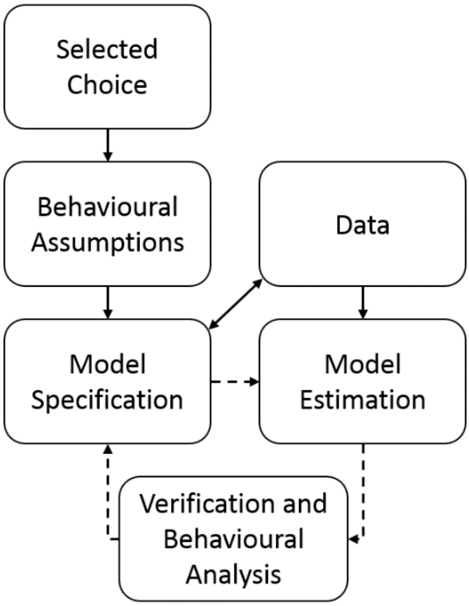


Fig. 2.3 – The steps involved in the identification of a decision-making model for a selected choice.

The procedure starts with the selection of the choices to be simulated by the decision-making model. Once the choices have been selected, the modeller needs to identify the behavioural assumptions affecting the choices. This issue can be addressed by investigating the existing literature on decision-making during evacuations as well as by using existing behavioural statements such as those proposed by Gwynne et al. (2015) and Gwynne and Kuligowski (2015). This step is aimed at identifying the structure of the choice (e.g. number of alternatives: binary, multinomial choice, etc.) and eventually the external and internal factors that may affect the choice. External factors include all the factors deriving from the physical/social evacuation environment whereas the internal ones include the decision-makers' demographics (e.g. age, gender, etc.) and personal characteristics (e.g. previous experiences, sensory and cognitive impairments, etc.).

Once the behavioural assumptions have been selected, it is possible to specify the model for the selected choice. The specification of a model consists of the selection of the mathematical framework (i.e. which random utility model to use) and the definition of the utility functions (i.e. which factors to include in the model) of the possible alternatives. In this work, the mathematical framework selected is the one provided by the Mixed Logit

Models (McFadden & Train 2000; Hensher et al. 2005; Ortuzar & Willumsen 2011). The equations defining these models as well as their advantages are discussed in Section 2.3. Once the mathematical framework has been selected, utility function specifications need to be addressed. On one hand, the utility specification can be limited by data since a factor can be included in the model only if it is included in the dataset. It may be that a single dataset does not include all the factors that can theoretically affect the choices. This issue is evident whenever a dataset is created using observations from real accidents or experiments carried out for other purposes (i.e. purposes different from the developing of a decision-making model). On the other hand, the model specification can affect the data collection procedure. New experiments can be carried out with the main purpose of calibrating a specified decision-making model. In these cases, the experiments are designed to include all the factors considered relevant to develop a specific decision-making model. For instance, experiments can be designed and carried out to investigate the mutual impact of social influence and emergency signage on exit choice.

Model estimation is the following step. The estimation is performed by optimizing an objective function. In this work, the maximization of likelihood functions has been used since this approach fits the stochastic nature of random utility models as it is discussed in Section 2.3. This function can be calculated using different sources of behavioural data collected with different research techniques and methods as discussed in Section 2.4 (Kinateder et al. 2014; Lovreglio 2014).

Once the model has been estimated, it is necessary to verify whether the factors included in the model statistically affect the decision and if the estimated parameters have values coherent with the behavioural assumptions. At this stage, modellers need to identify potential errors in the first model specification due, for instance, to co-variation between two independent variables included in the model or possible interactions between variables. Therefore, the modeller may need to specify several other models to identify the final one, which is eventually consistent and coherent with the behavioural assumptions (i.e. behavioural analysis) and only including the factors that actually affect the choice. This iterative procedure allows (a) the verification whether a factor affects the choice, (b) the calculation of the intensity of this influence and (c) the assessment of the uncertainty of this influence (i.e. constant vs. parameter parameters, see Section 2.3).

2.3 Model Formulation

Starting from the assumptions introduced in Section 2.1.1, different modelling frameworks can be developed depending on (Walker & Ben-Akiva 2002):

1. the assumptions made on the distribution of the random parts ε_{jq} introduced in Equation 2.1 (e.g. normal distribution, Gumbel distribution, etc.);
2. the assumptions made on the estimated parameters (constant over the population vs. randomly distributed);
3. the assumptions made on the $\boldsymbol{X}$ independent variables affecting the U_{jq} since these variable could be observable or latent (i.e. hybrid choice models);
4. the assumptions made on the segmentation of the populations since it is possible to segment the population using both classes defined by observable decision-makers' factors, such as demographics, and latent classes (i.e. latent class models).

The 'classic' random utility models allows the estimation of a single latent factor (i.e. the decision-makers' utilityU_{jq}) by maximizing the likelihood of the preference indicators which could be from Stated Preferences (SPs), Revealed Preferences (RPs) or a combination of both as illustrated in Figure 2.4 (refer to Section 2.4.2 for a discussion of these two different sources of data) (Walker & Ben-Akiva 2002; Train & Wilson 2008). The functional form of the probability of choosing the *j* alternative by *q* decision-maker depends on the hypothesis on the distribution of the random parts ε_{jq}. The widely used multinomial logit models:

$$P_{jq} = \frac{e^{Vjq(\boldsymbol{\beta}|\boldsymbol{x})}}{\sum_k e^{Vkq(\boldsymbol{\beta}|\boldsymbol{x})}} \qquad \text{Eq. 2.3}$$

derives from assuming that the random parts ε_{jq} have a Gumbel distribution with mean 0 and variance $\pi^2/6$ and these are independent and homoscedastic (Ortuzar & Willumsen 2011). The main limitation of this formulation is that it is not flexible enough to deal with the presence of correlated alternatives (e.g. independence of irrelevant alternatives). This formulation satisfies the property of Independence of Irrelevant Alternatives (IIA: P_{iq}/P_{jq} is independent of the remaining probabilities). This property is the direct consequence of the initial assumption that the random parts ε_{jq} are independent and homoscedastic and could make the model fail in the presence of correlated alternatives (see the well-known example of Red Bus/Blue Bus) (Greene 2011; Ortuzar & Willumsen 2011). Moreover, this classic model allows the heterogeneity among decision-makers to be estimated only by using observable personal factors defining them (i.e. gender, age, etc.).

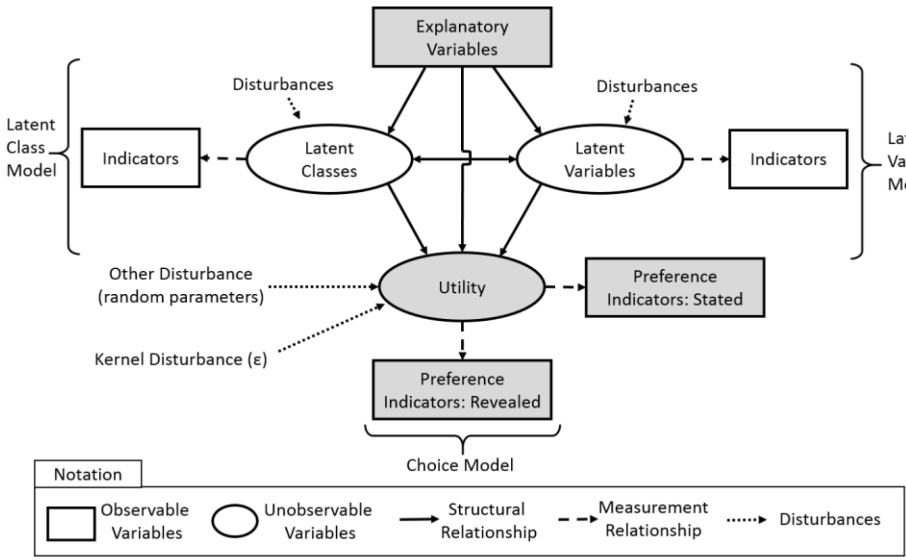


Fig. 2.4 – Generalized random utility model by Walker & Ben-Akiva (2002). The grey boxes in the figure define the classic and mixed random utility model. Picture source: (Lovreglio, Borri, et al. 2015)

To date, several models have been developed to relax this assumption. The Mixed Logit Model is one of the most advanced attempts to solve the issue concerning the correlated alternatives by introducing flexible disturbances (Walker & Ben-Akiva 2002; Train 2009). This is formally addressed by assuming that at least one component of $\boldsymbol{\beta}$ parameters in Equations 2.3 is randomly distributed. This property of Mixed Logit Models allows the simulation of the heterogeneity of the taste of the decision-makers which cannot be described using observable factors (Train 2009).This modelling framework has been proved to be flexible enough to approximate any random utility model (McFadden & Train 2000).

Under the assumption of random $\boldsymbol{\beta}$ parameters, the probability of choosing the *j* alternative by *q* decision-maker introduced in Equation 2.3 can be rewritten as:

$$\widetilde{P_{jq}} = \int \frac{e^{Vjq(\boldsymbol{\beta}|\boldsymbol{x})}}{\sum_k e^{Vkq(\boldsymbol{\beta}|\boldsymbol{x})}} f(\boldsymbol{\beta}|\boldsymbol{\alpha})\, d\boldsymbol{\beta} \qquad \text{Eq. 2.4}$$

where *f* is the probability density function of the $\boldsymbol{\beta}$ parameters, and $\boldsymbol{\alpha}$ is the set of parameters identifying *f* (Train 2009; Greene & Hensher 2010). In general, Mixed Logit Models have no closed solution. However, the probabilities can be estimated by using Monte Carlo techniques. Let $\boldsymbol{\beta_z}$ be vectors of $\boldsymbol{\beta}$ parameters drawn from *f*. An estimation of the probability ($\widetilde{\widetilde{P_{jq}}}$) that the *q* decision-maker selects the *j* alternative can be calculated by randomly drawing R vectors $\boldsymbol{\beta_z}$, calculating the corresponding values of P_{jq}, and then averaging according to the following equation (Train 2009; Greene & Hensher 2010):

$$\widetilde{\widetilde{P_{jq}}} = \frac{1}{R}\sum_{z}^{R} P_{jq}(\boldsymbol{\beta}_z) \qquad \text{Eq. 2.5}$$

$\widetilde{\widetilde{P_{jq}}}$ can be then used to estimate $\boldsymbol{\alpha}$ by maximising the likelihood function. The likelihood for Q decision-makers can be written as:

$$L = \prod_{q=1}^{Q}\sum_{j}^{J_q} y_{jq} \cdot \widetilde{\widetilde{P_{jq}}} \qquad \text{Eq. 2.6}$$

where y_{jq} is equal to 1 if the *q* decision-maker (*q*=1,…,Q) selects the *j* alternative (*j*=1,…,J_q), otherwise it is 0. Numerous techniques are available in the literature to solve the likelihood maximisation problem. Readers can refer to Greene (2011) for a review of these optimisation tools.

Several other solutions have been introduced into the literature to investigate unobserved heterogeneity among decision-makers as illustrated in Figure 2.4. In this thesis, the mathematical framework of the Mixed Logit Models is used for several reasons.

The main motivation is that this modelling approach allows the simulation of both sources of behavioural uncertainty (Intrinsic Behavioural Uncertainty and Perceptions and Preferences Behavioural Uncertainty) introduced in Section 2.1.3. In fact, the 'classic' logit approach considers Intrinsic Behavioural Uncertainty by introducing the random parts ε_{jq} whereas the random parameter assumption of the Mixed Logit Models allows Perceptions and Preferences Behavioural Uncertainty to be taken into account.

On the implementation side, well-established techniques exist to calibrate random parameter logit models as indicated by Equations 2.5 and 2.6. These models can be calibrated using both SPs and RPs as discussed in Section 2.4.2.

Finally, this modelling solution allows the definition of a mathematical formulation for the conceptual model introduced in Figure 1.7. This model identifies three stages for the decision-making process: information perception and processing, situation assessment, action selection. These stages have a specific meaning when Random Utility Theory is used to simulate the choices (see Figure 2.5). The first stage (information perception and processing) consists of the assessment of the external factors ($\boldsymbol{x^E}$) affecting the decision. In other words, before making a choice, a decision-maker needs to quantify the external factors affecting the decision. Once these pieces of information have been processed, the decision-maker needs to assess the global situation. Following Random Utility Theory assumptions, this task is carried out by assigning a utility to each possible discrete alternative. This utility can be a function of both external factors ($\boldsymbol{x^E}$) and internal factors ($\boldsymbol{x^I}$). Eventually, the decision-maker chooses an alternative (i.e. an action) by selecting the one having the maximum utility. Figure 2.5 also illustrates the impact of the two sources of behavioural uncertainty on the decision-making process.

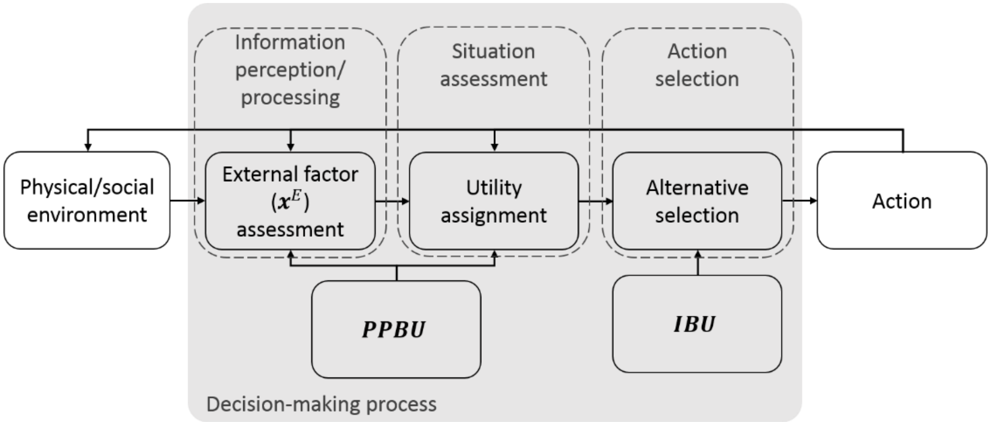


Fig. 2.5 – Decision-making process based on the random parameter logit (IBU: Intrinsic Behavioural Uncertainty; PPBE: Perceptions and Preferences Behavioural Uncertainty)

Perceptions and Preferences Behavioural Uncertainty affects the first two stages of the decision-making process through the random $\boldsymbol{\beta}$ parameters. First, this randomness takes into account that different decision-makers can have different quantitative estimates of the same external factors ($\boldsymbol{x^E}$) and that these estimations can be different from the actual values. For instance, considering an exit choice situation in which the decision is affected by the number of people close to the exits, different decision makers can have a different perception of the number of people close to each exit. In other words, the actual number of people close to the exits is internalized by the decision makers becoming information affecting the choice. In this process, the original number can be subject to change since the every decision maker can have a different perception of this number. Then, the random parameters consider that a certain factor might have different importance to different evacuees to defining the utility for the available alternative. Using the same example of the exit choice, some decision-makers could be positively affected by the number of people close to an exit manifesting herding behaviour (i.e. the decision-maker is attracted by the most crowded exit) whereas others could be negatively affected showing crowd-avoidance behaviour (Lovreglio, Fonzone, et al. 2016). Therefore, the utilities associated to these exits differ between the decision-makers.

Intrinsic Behavioural Uncertainty affects the last stage of the decision-making (i.e. action selection) through the random parts ε_{jq}. From a modeller's point of view, it possible to calculate the probability that an alternative is chosen since it is not possible to know the exact utility associated to each alternative. Therefore, the choice can be selected using a random number generator and the probabilities (P_1, P_2, …,P_n) associated to the n available alternatives (A_1, A_2, …, A_n) as indicated in Figure 2.6. This allows the simulation of both (a) the uncertainty related to choices taken by different decision-makers and (b) the uncertainty of the choices taken by the same decision-makers at different times.

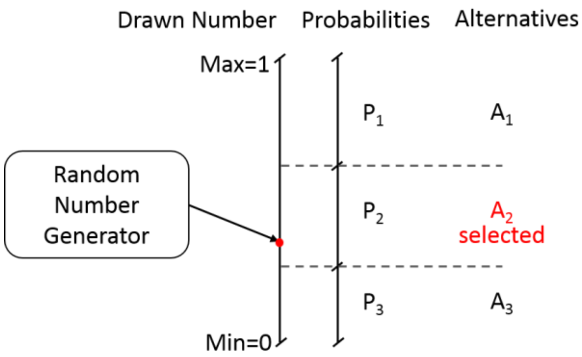


Fig. 2.6 – Alternative selections according Random Utility Theory.

2.4 Data-Collection Approaches

The methodological steps introduced in this work highlights that there is a need for behavioural data (i.e. data about individuals' behaviour and factors affecting them) to develop/calibrate new decision-making models based on Random Utility Theory (see Figure 2.3). These data can be divided into three broad categories:

1. data on the external factors ($\boldsymbol{x^E}$);
2. data on the internal factors ($\boldsymbol{x^I}$);
3. Choices (y_{iq}).

The first type of data includes all of the information concerning the social/physical environment, i.e. external factors ($\boldsymbol{x^E}$). These data should include all the pieces of information regarding the factors that may potentially affect the choice. This is because it is not possible to know *a priori* whether a factor has affected the choice in the investigated situation.

The second type of data includes information regarding the decision-makers' demographics and personal characteristics, i.e. internal factors ($\boldsymbol{x^I}$). These data are often used to segment the sample by investigating systematic differences between evacuees (Lovreglio, Borri, et al. 2015; Lovreglio, Fonzone, et al. 2016).

Both external and internal factors can be seen as independent variables of decision-making models since it is possible to calculate the utility functions associated with the available alternatives through them and in turn, the probabilities that such alternatives can be selected (see Equation 2.3). In contrast, the choices (y_{iq}) are a subset of the behavioural data representing the dependent variable of the decision-making models.

Different techniques can be used to collect behavioural data. These techniques (i.e. questionnaires, interviews and observations) are discussed in Section 2.4.1 whereas the types of choices/preferences that can be collected (i.e. Stated Preferences and Revealed Preferences) are discussed in Section 2.4.2. Finally, the research methods used to investigate human behaviour in fire and the criteria to assess the quality of the behavioural studies and data are introduced in Sections 2.4.3 and 2.4.4 respectively.

2.4.1 Data Collection Techniques

Data collection techniques are the measuring instruments that researchers can use to collect any type of behavioural data. These techniques include questionnaires, interviews and observations. Researchers can choose to use only one of these tools or a combination of them to improve the quality of behavioural research (Nilsson 2009).

Questionnaires are a set of questions that people can answer by writing (i.e. paper questionnaires) or clicking and typing (i.e. digital questionnaires). The questions included in a questionnaire can be open or closed. The former questions require respondents to write/type their own answers whereas the latter questions provide respondents with response options. Foddy (1993) has identified several pros and cons of both open and closed questions. On one hand, open questions allow respondents to state what they have in mind without being affected by the options suggested by the researchers. Therefore, the answer should ideally reflect what is important and relevant to the respondents. On the other hand, respondents may be inhibited to mention the most relevant aspects affecting their behaviour. In fact, they might not mention what they perceive as obvious. Therefore, open questions need to be coded by researchers to enable quantitative/qualitative analysis. This coding process risks relevant data being lost or misrepresented, creating measurement uncertainty (Ronchi et al. 2013). Such an issue does not affect closed questions since the coding is already determined by the available options, even though the question may miss relevant options (Nilsson 2009). Another disadvantage of closed questions is that the options may inform the respondents about the purpose of the questionnaire and the type of answers that are expected. However, a positive aspect of closed questions is that options work as memory cues making respondents remember answers that could otherwise be forgotten (Foddy 1993).

Interviews present many similar features of questionnaires but they involve oral communication. This feature highlights that this data collection technique depends on the interpersonal skills and training of the interviewers. Therefore, the risk of introducing interviewer bias must be taken into account. There are different types of interviews since they can differ in the number of interviewees involved (i.e. individual vs. group interviews), the structure (i.e. structured, semi-structured and unstructured interviews) and the type of questions (open vs. closed) (Fowler & Mangione 1990). Considering the similarities between interviews and questionnaires, many of the issues already discussed for questionnaires are relevant for interviews (see the discussion about open vs. closed questions). However, one of the advantages of interviewers over questionnaires is that interviewers have the possibility of asking probing questions to clarify or explore a response deeply. These questions should be asked in standardized ways to minimise interviewer bias (Fowler & Mangione 1990; Foddy 1993).

Observations refer to the analysis of the behaviour of people involved in real or experimental tasks. Observations involve some degree of judgement. Therefore, this data collection technique is not free from error since observers may influence the outcomes of the analysis depending on their expectations and abilities (Nilsson 2009). Hence, observations by different researchers can give different results. To cope with this issue, different observation techniques are available to standardize the procedures used in the analysis. The main advantage of observations over interviews and questionnaires is that they allow the investigation of factors which participants in experimental or real situations are not aware or willing to admit. For instance, Latané and Darley (1968) carried out experiments to investigate social interactions during fire emergency and observed that participants were either unaware or unwilling to admit that they were affected by others.

It is possible to summarize by stating that each data collection technique presents advantages and disadvantages. A possible solution to improve the 'quality' of behavioural data can be to combine data collection techniques since they can often complement each other (Yin 2003). For example, interviews can be combined with observations to investigate in depth the behaviour observed during an experiment. This combined approach could also be useful to verify the validity of behavioural data. For instance, when both results from questionnaires and observations support the occurrence of the same particular behaviour, then this behavioural information is more likely to be true than behavioural information obtained with a singular data collection technique.

2.4.2 Stated and Revealed Preferences

The previous section discusses the techniques that can be used to investigate human behaviour. However, the literature on decision-making data collection identifies two specific types of choice data (SPs and RPs) and classifies the existing techniques into two classes depending on the type of choice data collected through these techniques.

SPs techniques refer to a set of techniques aimed at collecting choices stated by decision-makers about their preferences in hypothetical scenarios (Cascetta 2009; Ortuzar & Willumsen 2011). In other words, decision-makers predict what their choices would be if they were living the hypothetical scenarios. Decision-makers can be asked:

a) to choose which option they would adopt in that context (*Stated Choice Studies*);
b) to rate or rank the available options according to their preference (*Conjoint Analysis*);
c) to state their willingness to pay for various policies or product options (*Contingent Valuations*).

In the following part, contingent valuations are not taken into account. Even though these valuations can be useful in marketing and transportation research, these are not found relevant for the purpose of developing new evacuation decision-making models. Stated choice studies are similar to conjoint analyses since in both cases the interviewees are presented with a number of hypothetical alternatives; however, the two methods differ in terms of the response metric. One of the most important criticisms raised against conjoint analyses is that in real life different interviewees would approach rating and ranking tasks in psychologically different manners. Stated choice studies avoid this issue by asking interviewees to select only the best alternative (Ortuzar & Willumsen 2011).Therefore, SP data can be collected using questionnaires and interviews.

RP techniques allow the collection of data about '*actual choices*' made by decision-makers (Ortuzar & Willumsen 2011). Normally, it is possible to obtain data on what decision-makers report they have done in their past to cope with either specific situations they have experienced or pre-assigned tasks. For instance, RPs can include choices that an evacuee made in a real or experimental evacuation. Therefore, both questionnaires and interviews can be used to investigate these preferences. However, these data can also be collected independently by a researcher making observations. Different sources, such as videos, can be used for this purpose. For instance, considering the case of exit choice during an evacuation, the exit selected by an evacuee can be inferred from observing his/her trajectory. In Figure 2.7, an observer can assume that at time t_1 the evacuee selected Exit 1 and he/she changed his/her mind at time t_2 while heading towards the exit. Therefore, RP data can be collected using questionnaires, interviews and observations.

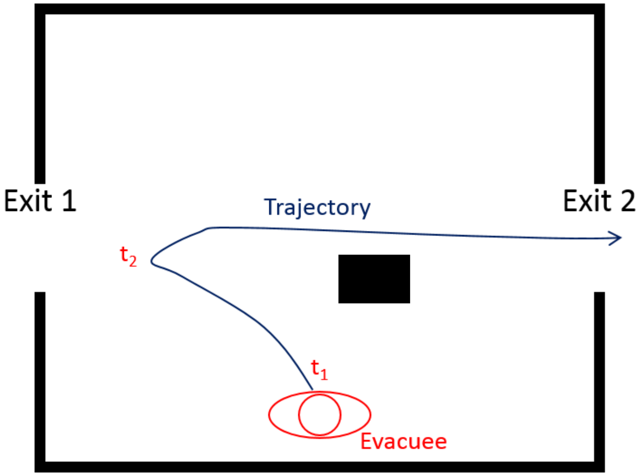


Fig. 2.7 – Revealed exit choice using the evacuees' trajectory

Several authors, such as Cascetta (2009), Ortuzar and Willumsen (2011), have already discussed the pros and cons of using both SP and RP techniques for transportation modelling purposes. They argue that:

1. RPs could not provide sufficient variability to construct good models for several reasons: limited number of observations, limited variability of the factors affecting the choice, etc. Therefore, these data could be poor in terms of statistical efficiency.
2. RPs may be dominated by a few factors, which could make it difficult to detect the potential effect of other secondary factors (e.g. public-transport information services).
3. RP surveys cannot be applied to investigate entirely new policies and engineering solutions, i.e. the investigation of alternatives not available at the time of the survey (e.g. new transport modes or services such as air conditioning).

4. SP surveys can be used to collect more information than RP surveys since each interviewee is usually asked about several choice contexts.

It is worth highlighting that this comparison between SP and RP techniques is made here in the transportation field. In making this comparison, the authors only considered RPs collected in real-life circumstances. In fact, referring to RPs Ortuzar and Willumsen (2011) state that:

"(RPs) limitations would be surmounted if we could undertake real-life controlled experiments within cities or transport systems, but the opportunities for doing this in practice are very limited. Thus, where data from real markets is not available for predicting behaviour or eliciting reliable preference functions, researchers have had to turn to stated preference (SP) methods" (Ortuzar & Willumsen 2011, p. 95)

Therefore, the comparison refers more to the research methods (real life scenarios vs. hypothetical scenarios) associated to SP and RP techniques than the techniques themselves. In contrast, in the field of human behaviour in fire many more research methods can be used to investigate the decision-making, combining them with both SP and RP techniques.

The next section aims at providing a summary of the research methods that can be used to collect data on evacuation behaviour during emergency and whether/how these can be coupled with SP and RP techniques. In the following part of this thesis, SP and RP techniques are considered independently from the research methods with which they are coupled.

2.4.3 Research Methods

Different empirical research methods can be used to collect data on human behaviour during evacuations. These methods include both the investigation of real world emergencies (i.e. case studies) and experiments. Different classifications have been proposed in the literature. The classification provided in this section is inspired mainly by the work of Nilsson (2009), Kinateder et al. (2014) and Nilsson and Kinateder (2015).

Case studies refer to the quantitative/qualitative analysis of real world emergencies. Therefore, human behaviour is investigated in a real-life context, i.e. the context is not artificial or modified by the researchers (Nilsson 2009). Examples of case studies are the official investigations of accidents, which can provide valuable insights into human behaviour in these events. Behavioural data can be collected by interviewing the surviving evacuees, using questionnaires and analysing video-recordings of closed-circuit television. All these techniques allow the choices taken by evacuees (RPs) to be investigated.

Human behaviour experiments refer to a range of different research methods. These are often divided into two broad categories, namely field and laboratory experiments. The former experiments are carried out in real-life settings whereas the latter are in a controlled laboratory environment (Christensen 2007). In both cases, the participants are exposed to a situation that is controlled by the researchers. The degree of control is significantly affected by the exact nature of the experiment. For instance, field experiments can include many factors, which cannot be manipulated or removed by the researchers whereas laboratory conditions could allow them to do so (Nilsson 2009).

Laboratory experiments are carried out in controlled environments that participants do not encounter during every day routines (Christensen 2007). This means that participants have to be recruited for the experiment and, therefore, they are very often aware that they are taking part in a study. In some cases, deceptions can be used by providing participants with misinformation about the real purpose of the study. The environments in which participants are confronted with these scenarios can be physical (i.e. classical laboratory studies) and virtual (i.e. VR experiments). VR experiments can be both immersive and non-immersive. In the former type of experiment, participants are immersed in a computer generated virtual environment. To date, this can be done using different VR technologies, such as head mounted displays or Cave Automatic Virtual Environments. In the latter type of experiments, less immersive techniques, such as desktop computers, are used. One advantage of laboratory experiments over field experiments is the possibility of effectively isolating an aspect of interest, eliminating other confounding variables that could be present in field experiments (i.e. high experimental control).

Field experiments are typically carried out in real world settings, such as real buildings and tunnels, which may be less controlled environments than laboratory settings. However, the threshold between laboratory and field experiments is not always clear (Harrison & List 2004). In fact, according the definition by Christensen (2007), the difference consists of whether the experimental environment is encountered by participants during every day routines or not. Therefore, an evacuation experiment in a real tunnel with participants who have been recruited and informed about the study may be considered as a laboratory experiment even though it is performed in a realistic field enviroment. This is due to the fact that the tunnel may not be part of the participants' everyday routines (Nilsson 2009). Harrison and List (2004) argue that many other aspects need to be considered to provide a more effective definition for field experiments. An effective definition for human behaviour experiments during fire evacuations is the one provided by Nilsson (2009):

"Field experiments are defined as experiments that are performed in a field environment, e.g., a real building or tunnel, that the participants encounter or could encounter during everyday routines. This means that an evacuation experiment that is performed in an office building with participants who are unrepresentative for the setting, e.g., students instead of office workers, is not a field experiment." (Nilsson 2009, p. 18)

Using this definition, it is possible to argue that both evacuation drills can be field experiments or laboratory experiments depending of the familiarity of the population with the environment.

Normally, both laboratory and field experiments investigate the actual behaviour/choices made by participants, collecting data through questionnaires, interviews and observations from video or more sophisticated sensor-based techniques (Ingmarsson et al. 2015). Therefore, these research methods support the collection of RPs.

Hypothetical scenario experiments are an alternative experimental method to collect behavioural data. In these experiments, participants make predictions about their behaviour/choices in emergencies. Therefore, the choices are not revealed but are predicted/stated by the participants (SPs). The hypothetical scenarios can be of different forms, using written descriptions, pictures, or other sensory stimuli in a real or virtual environment. These studies can be performed in very different locations depending on the approach used to present the hypothetical scenarios. In fact, paper and digital surveys can be distributed using mail or the Internet (i.e. online surveys). To increase the realism of the scenarios immersive and non-immersive VR and real settings can also be used.

This section shows that it is possible to collect data to develop new decision-making models using different sources of data. However, modellers should know their pros and cons. The next section introduces the criteria to assess the 'quality' of behavioural data using different research methods.

2.4.4 Validity of Behavioural Data

Several sources of data can be used to develop decision-making models and criteria are necessary to evaluate the quality of behavioural studies and the data collected during such studies. In this section the criteria used by Nilsson (2009), Kinateder et al. (2014) and Nilsson and Kinateder (2015) are introduced and described.

Validity refers to the correctness and accuracy of the findings, i.e. the extent to which a study measures what it is supposed to measure (Nilsson 2009; Nilsson & Kinateder 2015). Different types of validity have been proposed in the literature: internal validity, external validity and ecological validity.

Internal validity refers to the degree to which a method allows causal relationships to be identified among variables (Christensen 2007). In other words, it assesses the extent to which the relationship between dependent and independent variables can be accurately identified. However, even if a relationship is identified in an experimental setting, it does not necessarily mean that this result can be generalized to a real-life setting (see ecological validity for this purpose). Therefore, the assessment of internal validity can rely on the aims and objectives of a particular study. For instance, if an experimental study is intended to assess the effectiveness of different alarm systems, the internal validity of unannounced experiments is greater than that of pre-announced experiments. In fact, the awareness of the participants could affect the relationship between types of alarm (independent variable) and the participants' response time (dependent variable) and therefore awareness can reduce the internal validity.

External validity is the criterion aimed at assessing whether the results of a study can be transferred/generalized to different domain, e.g. people, settings or times, etc. (Christensen 2007). For instance, when developing a decision-making model using data collected in a theatre, the external validity gives a measure of the boundaries in which the model can be used by answering questions such as: Can this model represent the behaviour of a decision-maker in any other theatre having the same target population? Can this model represent the behaviour of a different population in the same theatre?

Both external and internal validity depend mainly on experimental procedure and set-up rather than on the research methods *per se* (Nilsson & Kinateder 2015). Therefore, a comparison between different research methods cannot be made using these two validity criteria. The third type of validity, ecological validity, can pursue this objective. Ecological validity assesses the degree with which a research method can represent the real word scenario under investigation (Brewer et al. 2000). In other words, this criterion is used to evaluate the gap between experimental situations and real situations. Therefore, it involves evaluating whether findings from experiments hold true in real life.

The research methods can be compared/selected considering other criteria, such as time and cost intensity for data collection, experimental control, ethical issues, etc. (Kinateder et al. 2014).

Experimental control refers to the degree to which researchers can control both the experimental procedure and the variables affecting the phenomenon under investigation. In fact, there could be many variables that can potentially affect a specific choice or behaviour and are not of primary interest, e.g. confounding variables (Kinateder et al. 2014). Experimental control could have a strong impact on the internal validity of experiments since high experimental control could allow researchers to directly manipulate the independent variable under investigation.

Finally, experiments with humans introduce several ethical issues. In fact, it is necessary to consider adequately the risks of injury and possible violations of participants' integrity and rights (Nilsson 2009). Even though studies on human behaviour in fire are ruled by ethical standards (e.g. Nuremberg Code, Helsinki Declaration , etc.), there is still an open discussion on ethics in human behaviour in fire research (Boyce & Nilsson 2015). Readers can refer to Nilsson (2009) and Boyce and Nilsson (2015) for a deeper insight into the possible ethical issues related to research on human behaviour in fire.

2.5 Selection of Research Strategy

The techniques and research methods for behavioural data collection have advantages and disadvantages that need to be taken into account when they are used to pursue a research objective. The selection of a research strategy (a combination of research methods and data collection techniques) depends on both research objectives and further 'boundary conditions' (i.e. time and cost intensity, experimental control, ethical issues, etc.).

The first step towards the development of a research strategy is to assess which techniques and methods are suitable for the research objectives. The pros and cons of different strategies need to be taken into account by researchers before selecting the final strategy.

2.5.1 Research Strategy Comparison

Case studies and unannounced evacuation drills represent the best solution in terms of ecological validity. In fact, these methods allow evacuees to interact with real word scenarios. Therefore, their behaviour is not biased by the awareness that they are participating in experiments. Despite the highest level of ecological validity, case studies have the limitation that data from real accidents are often difficult to obtain because of privacy/ethical issues. Moreover, even when real data (in the form of videos) are available, there are two further severe limitations. Firstly, researchers have no control over the evacuee sample and the variables affecting the choices. Secondly, selected choices cannot be directly analysed but only inferred from the evacuees' behaviour in the emergency (observations), thus increasing the measurement uncertainty. For instance, considering the example in Figure 2.7, the decision maker could have already chosen Exit 2 at time t_1 following that trajectory for any other reason whereas an external observer could interpret that he chose Exit 1 at time t_1 and then Exit 2 at time t_2. Questionnaires and interviews with people experiencing the evacuation may help overcome the latter limitation, but interviews can hardly be related to the data extracted from the videos (Lovreglio, Borri, et al. 2015). Finally, case studies are not appropriate to investigate the impact of emergency procedures and systems which are not yet implemented in the real world (Nilsson 2009).

Evacuation drills could overcome the limitations of case studies since they allow researchers to have experimental control. In these types of experiment, researchers could have the possibility of modifying and control both evacuation procedures and systems. However, there are also limitations affecting this research method. The main limitation is related to the high costs of performing such field experiments (Kinateder et al. 2014; Gwynne 2015). Moreover, high frequencies of evacuation drills in buildings can encourage a false sense of safety among evacuees during real accidents since they could think they were once again experiencing a false emergency (Gwynne 2015). A final limitation is the limited experimental control during such experiments (Kinateder et al. 2014). For instance, it is not possible to have complete control over smoke and the social factors that could affect choices. One solution, which has been used to cope with the latter issues, is the use of actors like in the experiments conducted by Latane & Darley (1968). The impossibility of having limited control of the experiment can have a negative impact on the reliability (i.e. degree of repeatability of study in order to get similar results) of the dataset developed using these experiments as discussed by Nilsson and Kinateder (2015). For instance, the impossibility of having full control of smoke makes it almost impossible to repeat an experiment with the same visibility condition as a previous one.

VR experiments represent one of the best compromises between experimental control and ecological validity (Kinateder et al. 2014; Nilsson & Kinateder 2015). In these experiments the experimental control is very high since the virtual physical social environment is completely controlled by researchers. The assessment of ecological validity in these experiments is still an open issue in the literature (Nilsson & Kinateder 2015). Even though several experiments have shown similar behavioural patterns between participants in real and virtual environments, the assessment of validation VR experiments is still under investigation. The future challenges for this research method which may improve ecological validity are mainly sensorial, e.g. the integrations of olfactory stimuli and the perception of touch, the substitution of the game controller (i.e. joypad) with more advanced moving controller systems (i.e. wireless HMD), etc. (Nilsson & Kinateder 2015). A final limitation of immersive VR is that, as in any other laboratory experiment, the participants are often college or university students, since they are easy for researchers to recruit, limiting the experimental cost and time. Using non-immersive VR technology (i.e. desktop computers) could simplify the recruitment problems and reduce the cost since the experimental task can be distributed using the Internet (Lovreglio, Borri, et al. 2014).

Hypothetical scenario experiments (or SP experiments) are the type of experiments that allow direct control of all the factors deemed relevant and data collection is relatively quick and cheap (costs can increase though when face-to-face interviews are used to administer the survey). The ecological validity of these experiments depends mainly on the approach used to present the hypothetical scenarios. Written descriptions, or pictures have a lower ecological validity whereas videos allow higher ecological validity, especially when administered using immersive VR technology. SP experiments allow researchers to have experimental control of the factors that can affect choices, which is higher than that of RP experiments. Therefore, this allows sufficient variability of the independent variables to construct and calibrate good choice models (Ortuzar & Willumsen 2011). This feature can be fundamental whenever researchers need to investigate the impact of a great number of factors on the choices. For this purpose, different survey design strategies (i.e. orthogonal design, efficient design, etc.) have been proposed in the literature (Rose et al. 2008).

2.5.2 Selected Choices and Strategies

All the research methods presented in Section 2.4.3 are potentially suitable to collect data aimed at developing new decision-making models based on Random Utility Theory, however, several other objectives may lead researchers to prefer one method/technique over others.

In this thesis, different strategies are tested in the three case studies introduced in Chapters 3, 4 and 5. This is done to investigate the pros and cons of different strategies and the impact of these strategies on model calibration/development and, validity in line with the third objective of this thesis.

Among all the decisions described in Section 2.1.2, this thesis aims at developing a decision-making model for the following choices:

a) Decision to start investigating and evacuating (Case Study 1);
b) Exit choice (Case Study 2);
c) Local movement choices (Case Study 3).

These decisions are critical during the different stages of the evacuations described in Section 1.1.1. In fact, the decision to start investigating and evacuating are the main decision affecting evacuees' behaviour during the recognition time since all the activities carried out depend on their behavioural state (i.e. normal, investigating and evacuating). Evacuation decision is also important since it draws a line between recognition and response activity. Among all the response activities, one of the most important decisions is the definition of the route strategy. The choice of a route may involve global and local decisions between alternative exits from an enclosed environment. Finally, when a route/exit has been selected and evacuees start moving toward a safe place (i.e. movement stage), evacuees need to move towards their objectives, interacting with the social and physical environment surrounding them and making local movement choices.

In this thesis, three different strategies are selected for the three case studies under investigation, providing deeper insight into the more specific potentialities and limitations of different strategies to calibrate decision-making models based on Random Utility Theory.

Case Study 1 investigates the possibility of using Random Utility Theory to model the decision to start investigating and evacuating using observations (RPs) of evacuees participating in announced evacuation drills in a cinema theatre. This dataset includes five unannounced evacuation trials and was carried out in a cinema theatre in Sweden involving a total of 571 participants (Bayer & Rejnö 1999). The selected trials are those which were analysed by Nilsson and Johansson (2009) using a defined video analysis procedure.

Case Study 2 investigates the impact of many social/physical factors on an exit choice model based on Random Utility Theory and the behavioural uncertainty affecting this choice. This goal is pursued using questionnaires and hypothetical scenario experiments (SPs survey). The SP survey has been developed with the collaboration of the Transport Research Institute of Edinburgh Napier University (UK) and the Department of Transportation and Projects and Processes Technology of University of Cantabria (Spain). This dataset includes SPs from 1,503 respondents from all over the world for 12 hypothetical evacuation scenarios illustrating a metro station having two available exits. The survey administered the hypothetical evacuation using pre-recorded videos and was distributed using the Internet (i.e. non-immersive VR).

Case Study 3 investigates the use of the formulations provided by Random Utility Theory to study the evacuees' local movement choices. Local movement decision-making is the most investigated subject in the field of human behaviour in fire (Kuligowski 2013; Gwynne et al. 2015). However, despite the great interest in the potentialities of the use of a discrete choice model based on logistic assumptions (i.e. the selection is based on the logistic formulation), no calibration procedure has been introduced to estimate the parameters of these models. This case study aims at filling this gap by introducing a procedure based on the likelihood function optimization built using real evacuees' decisions. This goal is pursued using observations (RPs) of participants in an immersive VR experiment. The dataset includes the trajectories of 96 participants, who were asked to evacuate from a road tunnel interacting with the physical virtual environment using a joypad.

Table 3.1 shows a summary description of the three case studies. An assessment of the ecological validity and the experimental control is also provided for each case study. The scale used in this work is not absolute but relative to the three case studies to rank them. Considering the ecological validity, it is possible to argue that the first case study (unannounced evacuation drill) has the highest ecological validity followed by the third case study (Immersive VR experiment) and the second one (Online survey). Focusing on the experimental control, it is possible to see that the third case study has the highest experimental control since the experiment is carried out with VR technology in a laboratory. Therefore, the researchers had the possibility of having high control of the VR scenario (i.e. how the scenario evolves over time) and the experimental procedure. Even though VR is used in case study 2, the experimental control of this case study is lower than that in the third case study because researchers could only control the VR scenario but the experimental procedure was controllable since the survey was distributed using the Internet. The first case study has the lowest experimental control since the researcher could only control the physical factors (alarm types) but they could not control the social factors.

Tab. 3.1 – Summary of the three case studies

Case Study	Choice	Research Method	Data Collection Technique	Evacuation Scenario	Sample Size	Ecological Validity	Exp. Control
1	Start investigating and evacuating	Unannounced evacuation drills	Observations	Cinema theatre	571	High	Low
2	Exit	Online survey	Questionnaire	Metro Station	1503	Low	Medium
3	Local movement	Immersive VR experiment	Observations	Road Tunnel	96	Medium	High

The results of these three case studies are available as journal papers:

Case Study 1:
Lovreglio, R., Ronchi, E. & Nilsson, D., 2015. A model of the decision-making process during pre-evacuation. *Fire Safety Journal*, Vol. 78, pp. 168–179.doi: 10.1016/j.firesaf.2015.07.001

Case Study 2:
Lovreglio, R., Fonzone, A. & dell'Olio, L., 2015. A Mixed Logit Model for Predicting Exit Choice during Building Evacuations. *Under review for Transportation Research Part A: Policy and Practice*.

Case Study 3:
Lovreglio, R., Ronchi, E. & Nilsson, D., 2015. 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.doi: 10.1016/j.physa.2015.06.040

2.6 Limitations

Like all research studies, this thesis presents limitations. The identification of these limitations is fundamental to have a correct interpretation of the results obtained with the methodology introduced in this chapter. The limitations of this research are related to the decision-making theory (i.e. Random Utility Theory), modelling framework (i.e. Mixed Logit Models) and the source of data used to develop new evacuation decision-making models.

2.6.1 Limitations of Random Utility Theory

Random Utility Theory is the most common theoretical framework/paradigm to model discrete choices (Ortuzar & Willumsen 2011). Its validity and limitations have been investigated in many different fields such as energy, transportation, environmental studies, health, marketing, etc. (Train 2009). As discussed in Section 2.1.1 the main assumption underpinning this theory is that decision-makers maximise their net personal utility according the paradigm of '*Homo Economicus*'. However, the paradigm of '*Homo Psychologicus*' has emerged from behavioural and cognitive science since the second part of the last century. Many behavioural studies have demonstrated that humans do not always make strategic decisions that are well calculated, violating the basic axioms of the foundations of utility maximization (Walker 2001; Starcke & Brand 2012). These '*cognitive anomalies*' are due to the fact that decision-makers have trouble handling information and forming perceptions consistently (Ben-Akiva et al. 1999). Many studies have shown that decision-makers may use a variety of ''quick and dirty'' heuristics, which could be simple rules of thumb or ''cognitive shortcuts'' through which they judge and take decisions (Tversky & Kahneman 1974; Kahneman & Tversky 1979; Klein 1999; Kuligowski 2013). Prospect Theory is an attempt developed to take into account some of the decision-making features for decisions taken under conditions of risk and uncertainty[1](Kahneman

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[1]*"Each decision can be placed on a continuum from 'complete ignorance' (not even the possible outcomes are known) through 'uncertainty' or 'ambiguity' (the outcomes are known but their probabilities are not*

& Tversky 1979; Tversky & Kahneman 1992). To date, these two paradigms, Homo Economicus and Homo Psychologicus, have converged into in an integrated approach called Dual Process Theory (Epstein et al. 1996; Starcke & Brand 2012). This theory assumes that humans make both strategic and intuitive decisions, identifying two systems: the rational–analytical system and the intuitive–experiential system. The former (linked to slow and serial but controlled, flexible, neutral, rule-governed and effortful information processing) is involved in rational decisions. The latter allows a fast, parallel, associative, and emotional type of processing supporting intuitive decisions. The interaction between these two systems and the final decision depend on the degree of uncertainty of the context of choice. For instance, in situations that present a low degree of uncertainty both decision systems may act together, whereas the intuitive–experiential system may play a more prominent role compared to the rational–analytical system for choices affected by a high degree of uncertainty (Starcke & Brand 2012). Moreover, the decision making process can change depending on the type of decision-making tasks. According to the literature, decision-making tasks are distinguished by their complexity and familiarity and can be placed on a continuum from 'automatic' (unconscious) tasks to 'planned' (conscious) tasks (Ben-Akiva et al. 1999). An example of an automatic decision is the evacuees' selection of speed and directions whereas possible planned decisions can be the decision to start evacuating or route choices. Psychologists emphasize that emotions may have an impact on both unconscious and conscious decisions (Ben-Akiva et al. 1999). Therefore, the assumptions underpinning Random Utility Theory need to be expanded in future works to include the paradigm of 'Homo Psychologicus' creating a new theory closer to the real decision-making behaviour.

In conclusion, it is possible to argue that there is large gap between behavioural theory and discrete choice models, such as those deriving from Random Utility Theory (see Figure 2.8). According to Walker (2001), this gap is due to the '*driving forces behind the two disciplines'*. In fact, discrete choice modellers are focused on mapping inputs to the decision whereas behavioural researchers try to understand the nature of the decision-making process.

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known) to 'risk' (the outcome probabilities are specified) and, finally, to 'certainty' (only a single outcome is known to result)." (Starcke & Brand 2012, p. 1230)

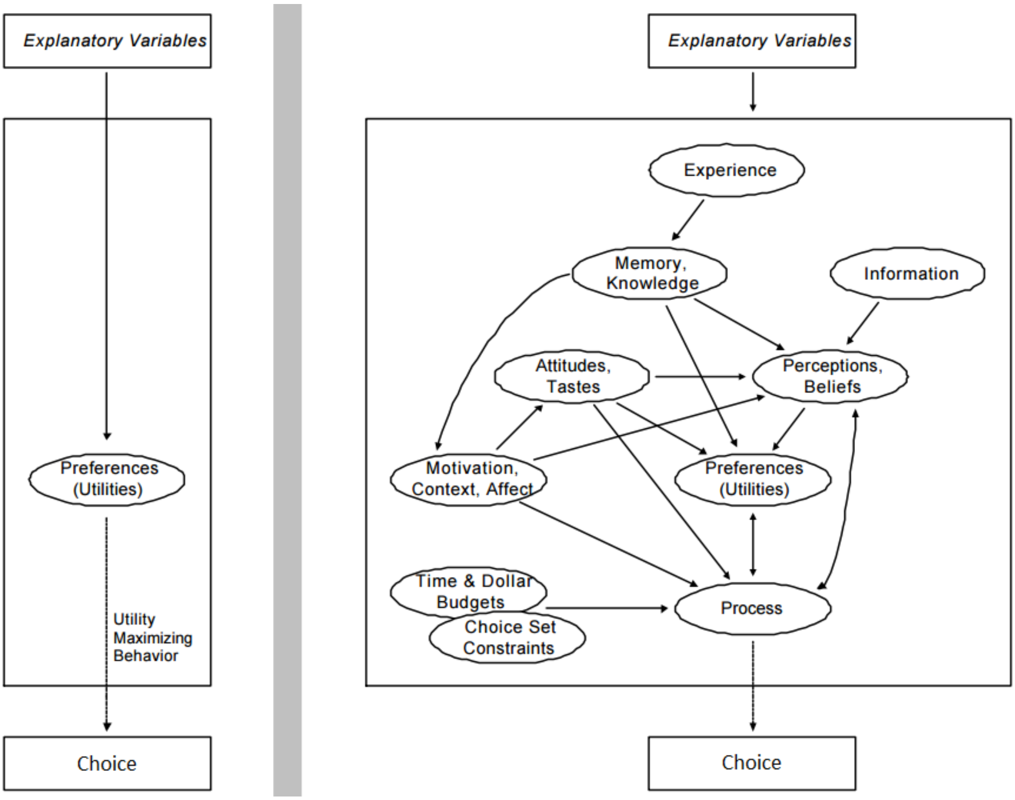


Fig. 2.8 – The gap between basic Discrete Choice Models (on the left) and the Complexity of Behaviours (on the right). Picture source: (Walker 2001)

Figure 2.8 shows that, despite the complexity of the decision-making process, Random Utility Theory describe the full process as an 'optimizing box' linking the observed inputs to the observed output and assuming that that the model implicitly captures the behavioural choice process (Walker 2001).

The question which can be raised is: does Random Utility Theory provide an adequate representation of the phenomenon? Regardless of these evident simplifications, many instances have shown that it is quite robust when used to model discrete choices (Ben-Akiva & Lerman 1985; McFadden 2001; Walker 2001; Hensher et al. 2005; Train 2009). Therefore, on one hand it is reasonable to use such as theory to model discrete choices. On the other hand, modellers should always be aware of the full assumptions underpinning Random Utility Theory and their limitations since the gap between model and reality could make predictions diverge from reality in some circumstances because of '*cognitive anomalies*' (Ben-Akiva et al. 1999).

2.6.2 Limitations of Mixed Logit Models

Mixed Logit Models have been defined as the models for the new millennium since the mathematical formulation used for these models allows several limitations of the classic multinomial logit to be overcome, as discussed in Section 2.3 (Ortuzar & Willumsen 2011). One of the most important advantages provided by Mixed Logit Models is the possibility of capturing decision-makers' heterogeneity using random parameters instead of only investigating heterogeneity systematically (this approach could provide inconsistent parameter estimations) (Chamberlain 1979; Vij et al. 2013). However, different criticisms have been presented (Vij et al. 2013). The first criticism is that the analyst has to make an *a priori* assumption about the mixture distribution for each randomly distributed coefficient (Hess & Rose 2006). Walker and Ben-Akiva (2011), argue that the correlation structure is a black box that makes the cause of the distribution not readily apparent. Finally, different studies have shown some of the deleterious effects of a wrongly specified distribution on parameter estimates and the attendant model interpretation (Hess et al. 2005; Fosgerau 2006). These criticisms highlight that modellers should be careful in the identification and interpretation of the random distributions affecting choices.

An attempt to overcome the limitation of Mixed Logit Models is provided by Latent Class Choice Models. These models are nonparametric (or semi parametric) finite mixture discrete choice models allowing decision-makers to be segmented into homogenous classes (Ortuzar & Willumsen 2011; Greene 2011). A review of their development over the years as well as the fields in which they have been applied is available in Vij et al. (2013) and Vij and Walker (2014). However, also in this case there are several other modelling issues: (a) identification of the number of classes and (b) characterization of each class. This alternative modelling formulation is not used in this thesis since the definition of a standard procedure to address these issues is still under investigation (Vij & Walker 2014).

2.6.3 Limitations of the Behavioural Data

Every dataset used to calibrate a model has limitations and those used in the three case studies introduced in Section 2.5.2 are not an exception.

In Case Study 1 (decision to start investigating and evacuating), one of the main limitations is that choices are inferred from observing the behaviour of evacuees according to the video analysis criteria described by Nilsson and Johansson (2009). Therefore, measurement uncertainty affects these observed choices. Interviews or questionnaires to investigate the decision-making process reducing this uncertainty were not conducted by Bayer and Rejnö (1999) since the main purpose of the experiment was not the investigation of the choices investigated in the case study. Other limitations of the dataset are related to the number of cameras and their resolutions. Only one camera was used and therefore partial obstructions among evacuees generate pieces of missing data. Moreover, the low resolution of the video recordings made detailed analysis impossible (Nilsson & Johansson 2009).

The main limitation of the data used in Case Study 2 (exit choice) is the low ecological validity of the online SP survey. In fact, participants were not facing a real emergency and were fully aware that they were not living an emergency. Therefore, it was impossible to instil real physiological stress in the respondents. Moreover, the awareness of participating in an experiment could bias the SPs. The respondents could conform their choice to what they think should be the 'right' answer for the researcher, instead of reporting their "natural" behaviour. Finally, the distribution of the survey using the Internet made it impossible to control the environment in which respondents filled out the survey (e.g. noisy vs. calm environments, distractions during the task).

Case Study 3 (local movement choices) used data in which the ecological validity is higher than that in Case Study 2 and lower than that in Case Study 1. The main limitation of this dataset is that participants navigated in the Virtual Environment using a joypad. Therefore, it is reasonable to think that the trajectories used were biased by this factor.

3. CASE STUDY 1: DECISION TO START INVESTIGATING AND EVACUATING

3.1 Introduction

Many studies have shown that the pre-evacuation time can be an important component of the RSET (Purser & Bensilum 1998; Kobes et al. 2010; McConnell et al. 2010). Moreover, the analysis of real emergencies have shown that there can be a correlation between pre-evacuation time and the number of deaths or injuries (Kobes et al. 2010). To date, full-scale evacuation experiments and real emergencies have been used to quantify the pre-evacuation time for different building types such as residential, commercial, cinema, etc. (Nilsson & Johansson 2009; Fahy & Proulx 2001). Other studies have been made to investigate factors characterizing the social/physical environment (i.e. external factors) and factors characterizing the evacuee (i.e. internal factors) that could influence pre-evacuation behaviour (Sherman et al. 2011; Bryan 2002; Kuligowski & Mileti 2009). However, pre-evacuation behaviours are generally less documented and quantified than movement behaviours (Kobes et al. 2010; Proulx 2002).

To date, different theories and conceptual models have been proposed to explain the decision-making process characterizing the choices made during pre-evacuation time as discussed in Section 1.1.2 (Bryan 2002; Canter et al. 1980; Kuligowski 2013). Further quantitative analyses have been done to test some of these conceptual models by using statistical analysis (i.e. multi regression analysis) (Kuligowski & Mileti 2009; Sherman et al. 2011). Despite the above mentioned theories on evacuation behaviour, most of existing engineering evacuation models still adopt simplistic assumptions and simplifications about evacuees' behaviour during pre-evacuation (Kuligowski 2013; Pan et al. 2006).

At a conceptual level, three main modelling approaches have been proposed to represent the pre-evacuation time (Kuligowski 2013). The first approach relies on the deterministic user assignment of a pre-defined time to individuals or groups or a pseudo-random number obtained from a distribution. The simulated evacuees (i.e. agents) remain stationary in their initial position until the assigned pre-evacuation time is over. The second approach involves the user assignment of sequences of pre-evacuation actions. The simulated evacuees move to different parts of the simulated building to perform their activities. Each action has a pre-defined specific duration for each evacuee. The main weakness of these first two approaches is that the behaviour is not really predicted by the models but it is a user input as illustrated in the conceptual scheme in Figure 1.3-a (Gwynne et al. 2015). This limitation has been overcome using the last approach, which is instead a predictive-based approach in which the behaviour is the actual result of the model as illustrated in Figure 1.3-b. In this last case, agents perform protective actions in accordance with different internal/external factors. Kuligowski (2013) states that the main limitation of this approach is the 'homogeneity' assumption which says "*evacuees react to particular cues in similar ways*" (i.e. lack of behavioural uncertainty).

Even though the predictive-based approach is the only one which allows pre-evacuation behaviour to be simulated, most of the pre-evacuation models employs *a priori* random or deterministic pre-evacuation times defined by the user. However, different predictive-based models have been proposed (Reneke 2013; Pires 2005; Viswanathan & Lees 2014; Liu & Lo 2011). These models are generally inspired by behavioural theories but they are not data-driven since they are not based on a regression of actual observed data. Then, their calibration appears a very complex issue that has not yet been addressed.

The main goal of this chapter is, therefore, to improve the accuracy of predictions of evacuation models by presenting a novel approach to estimate predictive-based sub-models for the simulation of pre-evacuation states (i.e. normal, investigating, and evacuating). This approach is supported by Random Utility Theory, which provides a well-defined calibration formulation as discussed in Section 3.3. Moreover, the models estimated using this approach result closer to the conceptual theories describing pre-evacuation behaviour (Canter et al. 1980; Kuligowski 2013) since their aim is to simulate the most important decision-making process affecting the pre-evacuation behaviour, namely the one defining the passage between pre-evacuation states (i.e. normal, investigating and evacuating states). This passage is ruled by both the decision to start investigating and evacuating.

The next section introduces the modelling assumptions uses to investigate the impact the decision to start investigating and evacuating on the evacuation behaviour.

3.2 Modelling Assumptions

This section introduces a modelling solution aimed at developing a pre-evacuation decision-making model based on Random Utility Theory. The agent behaviour is defined by three behavioural states inspired by those proposed by Reneke (2013), namely, normal, investigating and evacuating. The passage from these states is identified by the decision to start investigating and evacuating by using Random Utility Theory. The probabilities concerning these choices are functions of factors characterizing the social/physical environment and factors characterizing the evacuee (i.e. internal and external factors) according to the formulation introduced in Section 2.3.

The detailed list of assumption behind the proposed model can be summarised with the following list:

1 - An evacuee can have three different behavioural states:

a. *Normal State (NS)*
b. *Investigating State (IS)*
c. *Evacuating State (ES)*

This assumption is based on the model proposed by Reneke (2013), in which those three behavioural states are recommended to help classify pre-evacuation behaviour. An evacuee is in his/her NS if s/he is performing his/her pre-emergency activities whereas s/he is in his/her IS if s/he has started investigating. Finally, the evacuee is in his/her ES when is performing all the activities aimed at evacuating the building.

2 – The allowed passages are those from NS to ES, from NS to IS and from IS to ES. These passages are irreversible.

This assumption argues that once an evacuee has decided to start evacuating, s/he cannot take the decision to come back to NS or IS. At the same time, once an evacuee has decided to start investigating, s/he cannot come back to NS (see Fig. 3.1).

Moreover, this assumption argues that the passage from NS is not a condition *sine qua non* to pass to ES (see Fig. 3.1). It is worth discussing that this is a modelling assumption and not a behavioural assumption. In fact, several behavioural studies in emergencies (Canter et al. 1980; Kuligowski 2013) argue that investigation is a required step before taking the decision to evacuate. However, the time spent by an evacuee to investigate could be very short (i.e. investigation can be carried out in a time shorter than the model time-step). In those occasions, they may be ignored during the modelling stage.

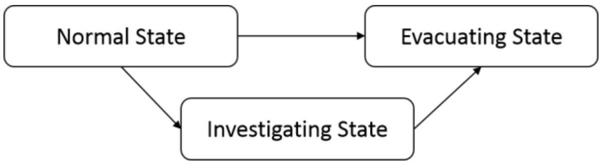


Fig. 3.1 – Proposed behavioural states based on Reneke's model (Reneke 2013);

3 - Evacuees involved in evacuation behaves rationally and their passages from NS to ES, from NS to IS and from IS to ES are ruled by binary decision-making process.

This assumption is supported by experimental and theoretical studies (Fahy et al. 2012; Canter et al. 1980) claiming that irrational behaviour, i.e., 'panic' behaviour, is extremely rare during emergencies as discussed in Section 2.1.3. The two decisions assumed to make evacuees change their state are the decision to investigate and to evacuate. The former makes evacuee pass from NS to IS whereas the latter from IS or NS to ES.

4 - The decision-making process is affected by both Environmental (external) and Evacuee (internal) Factors.

This assumption argues that an evacuee takes the decision to evacuate considering the perceived actual situation. However, these decisions can be influenced by the evacuee characteristics (e.g. previous experience, physical and mental condition, alertness, etc.) since these internal factors can influence the way in which an evacuee perceives, interpret and make a decision (Kuligowski 2008).

5 - The decision-making modelling approach proposed in this chapter follows Random Utility Theory.

Assumption (3) shows that an evacuee has to deal with different behavioural binary choices. Random Utility Theory is used in this work to represent these choices. The general assumptions of this theory (described in Section 2.1.1) are not in conflict with those of the proposed pre-evacuation model.

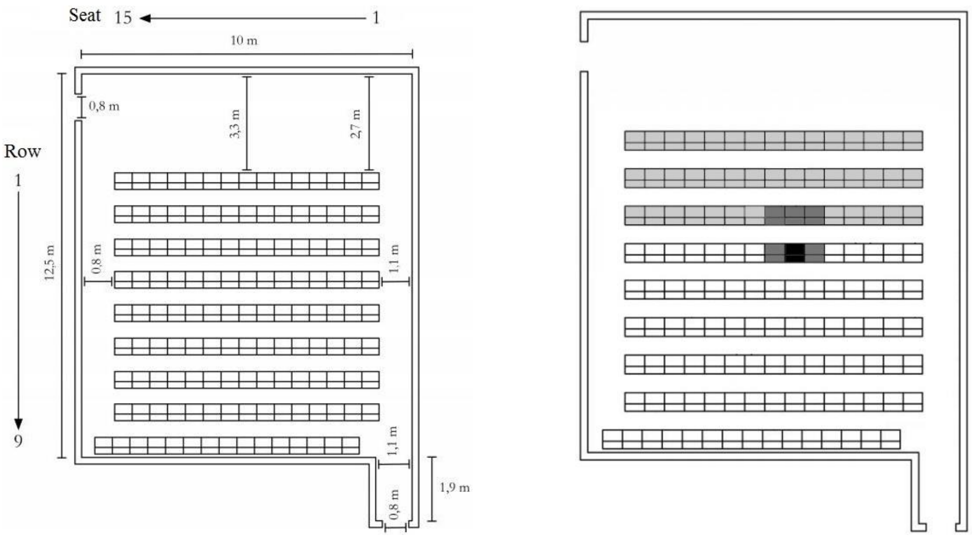
An application of the proposed methodology is made using the dataset discussed in the next section.

3.3 Dataset

A calibration of the proposed model is made by using the data collected during unannounced evacuation experiments in a cinema theatre in Sweden performed by Bayer and Rejnö (1999). The goal of these experiments was to test the influence of different alarm systems on the pre-evacuation time. Eighteen different experiments were performed with six different types of alarm systems, namely an alarm bell, an alarm tone signal, an alarm bell together with a flashing light, an alarm bell together with an information sign and two pre-recorded vocal messages. Evacuation experiments were performed in the same cinema theatre, but each participant only took part once.

3.3.1 Cinema theatre

The cinema theatre used in the experiments had one hundred and thirty-five seats (see Figure 3.2).



(a) (b)

Fig. 3.2 – (a) Schematic representation of the cinema theatre (b) Geometrical definition of closeness to the decision-maker (black square). The grey squares are the evacuees visible to the decision-maker. The darkest grey squares are the evacuee considered close to the decision-maker.

The cinema theatre consisted of nine rows with fifteen seats each. On each side of the nine rows, there were stairs from the front to the back of the cinema theatre. This meant that the participants could exit a row to both the left and right. Two doors linked the cinema theatre to the rest of the building (see Figure 3.2-a). A video camera was used to document the experiments and was placed in a dark box and mounted in the front right corner of the room. Further information regarding the procedure and recruitment of participants used during the experiments are provided by Bayer and Rejnö (1999).

3.3.2 Existing data analysis

Five of the experiments by Bayer and Rejnö (1999) have been analysed by Nilsson and Johansson (2009). The purpose of this second study was to investigate the impact of social influence on behaviour. Experiments with two types of alarms, namely an Alarm Bell (AB) and a Pre-Recorded female Message (PRM), were chosen. These alarms were chosen since they represent two different levels of ambiguity. The alarm bell is considerably more ambiguous, since it does not provide any specific information about what has happened and how participants should behave. Only experiments in which the cinema theatre was at least half-full were selected. Information concerning the participants involved in these five experiments is provided in Table 3.1.

Tab. 3.1 – Data concerning the 5 experiments analysed

Exp.	Type of alarm	Total number of participants	Participants who manifest behaviour (1)[a]	Age[b]			Gender[b]		
				Mean value	Standard deviation	Unknown[c]	Female	Male	Unknown
A1	AB	88	29	27.8	13	1	23	63	2
A2	AB	100	51	28.1	10.3	5	37	60	3
B1	PRM	113	12	26.8	6.5	1	62	50	1
B2	PRM	135	12	25.4	6.3	2	60	74	1
B3	PRM	135	15	27.9	8.8	3	59	74	2

[a] Look at others beside or behind oneself.

[b] These pieces of information were collected by an anonymous questionnaire after the experiment.

[c] Number of participants who did not stated their age in the questionnaire. Only those participants who stated their age have been included in the calculations of the mean value and standard deviation.

Nilsson and Johansson (2009) identify three distinct types of behaviour by using the analysis of the video recordings: (1) look at others beside or behind oneself, (2) start to prepare, and (3) rise. A full description regarding how these behaviours were observed during the video analysis is provided by Nilsson and Johansson (2009). All data extracted through the video analysis includes:

- A record of the three different types of behaviours and who displayed them.
- The times at which participants displayed type (2) and type (3) behaviour, i.e., each participant's recognition and pre-movement time.
- Whether participants were accompanied by others and where these people were seated.

The temporal resolution of the observed behaviour (i.e. the time-step at which a behaviour was detected) is one second.

3.3.3 Existing data analysis

This study use the data extracted through the video analysis made by Nilsson and Johansson (2009). Environmental factors are used to define the state of the decision-maker. In fact, the behavioural types defined in this previous study are used to define the choice of investigating and evacuating. The behaviour type (1) is used to define the decision to start investigating assuming that a participant passes from NS to IS once s/he has manifested the behaviour type (1). Differently, the behaviour type (2) is used to define the passage from NS or IS to ES since a participant takes the decision to evacuate once s/he has started preparing to get ready to escape.

Different internal and external factors can influence the decision-making process during the pre-evacuation time. The available data allows statistical testing of the influence of the factors listed in Table 3.2 on the decision to investigate and evacuate. All the variables introduced in Table 3.2 can be measured for each participant at each time-step since some of them are not constant during time. Table 3.2 makes a differentiation between decision-maker and evacuees. Decision-maker is the participant to which the variables are referred, while evacuees are the other participants involved in the same scenario of the decision-maker.

Only the visible evacuees and those belonging to decision-maker's personal group are assumed to influence him/her. The assumption adopted to define the visible evacuees is provided in Figure 3.2-b. These evacuees can be close to or far from the decision-maker in accordance with the assumption shown in Figure 3.2-a. Another social variable that can be investigated is the size of the decision-maker's personal group. Physical environmental factors, such as the type of alarm system and the time elapse from the beginning of the alarm, are also included in the analysis. Table 3.2 also includes internal factors such as the position of the decision-maker (RW and ST) and his/her state (NS, IS and ES). Although general statistics concerning age and gender are provided in Table 3.1, these factors are not included in Table 3.2 since those were collected after experiment by using an anonymous survey.

Tab. 3.2 – Analysed Variables

Factor ID	**Description**
AL	Dummy variable equal to 1 when the alarm system is the Alarm Bell and 0 when it is Pre-Recorded Message
TIME	Time elapse after the alarm have started
$N_{F,N}$	Total number of evacuees visible to the decision-maker and **F**ar from him/her (see Figure 2) which are in Normal (**N**), Investigating (**I**) and Evacuating (**E**) states, respectively
$N_{F,I}$	
$N_{F,E}$	
$N_{C,N}$	Total number of evacuees visible to the decision-maker and **C**lose to him/her (see Figure 2) which are in Normal (**N**), Investigating (**I**) and Evacuating (**E**) states, respectively
$N_{C,I}$	
$N_{C,E}$	
$N_{G,N}$	Number of evacuees belonging to decision-maker's personal **G**roup which are in Normal (**N**), Investigating (**I**) and Evacuating (**E**) states, respectively
$N_{G,I}$	
$N_{G,E}$	
GR	Dummy variable equal to 1 when the decision-maker has his/her person group (i.e. $N_{G,N}+ N_{G,I}+ N_{G,E} \neq 0$)
SG	Size of the personal group
RW	Number of the row where the decision-maker is sitting
ST	Number of the seat where the decision-maker is sitting
NS	Dummy variable equal to 1 when the decision-maker is in Normal State
IS	Dummy variable equal to 1 when the decision-maker is in Investigating State
ES	Dummy variable equal to 1 when the decision-maker is in Evacuating State

A new data set is created starting from data collected by Nilsson and Johansson (2009) to estimate the logit models able to predict the decision to evacuate and to seek more information. One record (i.e. observation) is included in the new data set for each decision-maker (i.e. participant) for each *relevant event*. The relevant events of a decision-maker are his/her decision to investigate and evacuate the change of state (e.g. from NS to IS, etc.) of at least one of other evacuees visible to decision-maker or belonging to his/her personal group.

Table 3.3 shows an example of the features of the new data set. It represents a hypothetical decision-maker (ID=5) participating in a hypothetical experiment with alarm bell (AL=1) and located at 10th seat of the 3rd row (RW=3 and ST=10) and which is facing a hypothetical situation with 30 other visible evacuees far from him ($N_{G,N}+ N_{G,I}+ N_{G,E}$ =

30). Looking at the proposed recordings, it is possible to see that one visible evacuee starts investigating ($N_{F,I}$ =1) at five seconds from the beginning of the alarm (TIME=5s) whereas the decision-maker is still in normal state (NS=1). After eight second from the beginning of the alarm, one evacuee is investigating and three start evacuating whereas the decision-maker is still in NS. Table 3.3 shows that the decision-maker starts investigating after 13s whereas s/he take the decision to evacuate (i.e. he start preparing) after 15s.

Tab. 3.3 – Features of the new data set (The data included in this piece of data set are derived from a hypothetical situation)

Observations	ID	AL	TIME (s)	$N_{F,N}$ (pers)	$N_{F,I}$ (pers)	$N_{F,E}$ (pers)	…	RW	ST	NS	IS	ES
1	5	1	5	29	1	0	…	3	10	1	0	0
3	5	1	8	26	1	3	…	3	10	1	0	0
4	5	1	10	25	2	3	…	3	10	1	0	0
5	5	1	13	24	3	3	…	3	10	0	1	0
6	5	1	14	20	3	7	…	3	10	0	1	0
7	5	1	15	15	4	11	…	3	10	0	1	1

The result of the calibration based on this data is proposed in the following section.

3.4 Model Calibration

Two models are estimated with the data set in order to predict the probability of investigating and choosing to evacuate. Different model specifications have been tested in order to find the ones which better fit the data for both choices. In this chapter, a model specification consists of the definition of the systematic part of Equation 2.1 (V_{jq}) including/testing all the independent variables that could affect the choices under investigation. The results and descriptions of selected calibrated models are provided in the following sections. Three measures of the goodness of fit are used: the likelihood for a model only including a constant (L_0), the likelihood for the proposed model (L_M), and the adjusted McFadden R squared ($AdjR^2$). In particular, $AdjR^2$ shows that the variables included in the model give a significant improvement over the intercept model for both models (Table 3.4 and 3.6) (Hensher et al. 2005).

3.4.1 Decision to investigate

The proposed model for the decision to investigate is a classic logit model. The dependent variable used for this model is the dummy variable IS, which is equal to 1 when the decision-maker decides to investigate (see Table 3.2). The variables included in Table 3.2 (except IS and ES) or combination of those have been tested as independent variables. However, only the variables statistically influencing the decision have been kept in the model. The deterministic part of the utility function better fitting the data is shown in Equation 3.1. Equation 3.1 has both lowercase and uppercase elements. The former are the estimated parameters whereas the latter are the actual variables of the model.

$$\begin{gathered} V^{invest} = const + time \cdot TIME + n_{C,I} \cdot N_{C,I} + \\ + n_{C,E} \cdot N_{C,E} + n_{G,N} \cdot N_{G,N} + sg \cdot SG + rw \cdot RW + \\ + al \cdot AL \end{gathered} \qquad \text{Eq. 3.1}$$

Different attempts have been made to test if any parameter is randomly distributed but all those attempts failed because no parameter seems to have this feature. This could be due to the low percentage of evacuees who took this decision (see Table 3.1).

The estimated parameters are shown in Table 3.4. Since most of the variables included in the model have different units of measure, a direct comparison between the estimated coefficients would not make sense. However, a meaningful interpretation of the degree of influence of the independent variables on the probability is made by using the point elasticity method (Hensher et al. 2005; Train 2009). In fact, the elasticity (E(X)) of an independent variable X measures the change (in percentage) in the probability given a 1 percent change in X. It is worth underlining that these measurements are sample-based since they are calculated averaging the elasticity of each observation included in the data set. Table 3.5 shows the sample elasticity of all the non-categorical variables calculated by using the probability weight enumeration technique (see (Hensher et al. 2005) for further information). The dummy variables are not included in this table since these measurements cannot be meaningfully interpreted (Hensher et al. 2005).

Tab. 3.4- Logit model for the decision to investigate

Total number of Observations = 5240 L_o = -3632.091 L_M = -1233.545 AdjR^2 = 0.66			
Parameter	Coef.	Std.Er.	P-value
const	-2.131	0.289	0.000
time	0.078	0.011	0.000
$n_{c,I}$	0.430	0.059	0.000
$n_{c,E}$	0.168	0.049	0.001
$n_{G,N}$	-0.225	0.088	0.011
sg	-0.293	0.074	0.000
rw	-0.516	0.033	0.000
al	3.288	0.185	0.000

Tab 3.5 – Measurements of elasticity for the independent variables influencing the probability of investigating

Variable	TIME	$N_{C,I}$	$N_{C,E}$	$N_{G,N}$	SG	RW
Elasticity	0.863	0.232	0.138	-0.103	-0.454	-1.612

3.4.1 Decision to evacuate

The proposed model for the decision to evacuate is a mixed binary logit model. The dependent variable used for this model is the dummy variable ES, which is equal 1 when the decision-maker decides to evacuate and therefore s/he starts preparing to escape (see Table 3.2). The variables included in Table 3.2 (except ES) or combinations of those have been tested as independent variables. However, also in this case only the variables influencing the decision have been kept in the model. The proposed model is estimated by using panel data because it considers the correlation between the observations of the same individuals (Ortuzar & Willumsen 2011). The probability provided by this modelling formulation cannot be calculated using a close formulation but can be simulated using several numerical solutions (Train 2009; Hensher et al. 2005). To address this issue, a number of 200 Halton draws are used to simulate random distributed parameters (refer to Hensher et al. (2005) and Train (Train 2009) for more information on the use of Halton draws).

Equation 3.2 shows the utility function which better fits the data. Equation 3.2.has both lowercase and uppercase elements having the same meaning explained for Equation 3.1.

$$\begin{gathered} V^{evac} = const + time \cdot TIME + n_{F,N-I} \cdot \left(N_{F,N} + N_{F,I}\right) + \\ + n_{C,N-I} \cdot \left(N_{C,N} + N_{C,I}\right) + n_{G,N-I} \cdot \left(N_{G,N} + N_{G,I}\right) + n_{G,E} \cdot N_{G,E} \\ + rw \cdot RW + is \cdot IS \end{gathered} \qquad \text{Eq. 3.2}$$

where:
$time \sim N(\mu_{time}|\sigma_{time})$
$n_{G,N\text{-}I} \sim N(\mu_{nGNI}|\sigma_{nGNI})$
$n_{G,E} \sim N(\mu_{nGE}|\sigma_{nGE})$
$rw \sim N(\mu_{rw}|\sigma_{rw})$
const, $n_{F,N\text{-}I}$, $n_{C,N\text{-}I}$, is $\in \mathbb{R}$

Table 3.6 shows the estimated values for the parameters whereas Table 3.7 shows measures of sample elasticity.

3.4.3 Sensitivity Analysis

Since the measurements of elasticity would not provide useful insights for the dummy variables, their influence on the probability of choosing to investigate and evacuate is studied through a sensitivity analysis. The independent variables chosen in this analysis are both those with the highest values of sample elasticity (i.e. TIME and RW; see Table 5 and 7) and the two dummy variables (i.e. AB and IS; see Table 3.2, 3.4

and 3.6). The remaining variables of both models are kept constant and are set on the sample averages.

Tab. 3.6 – Mixed Logit Model for the decision to evacuate

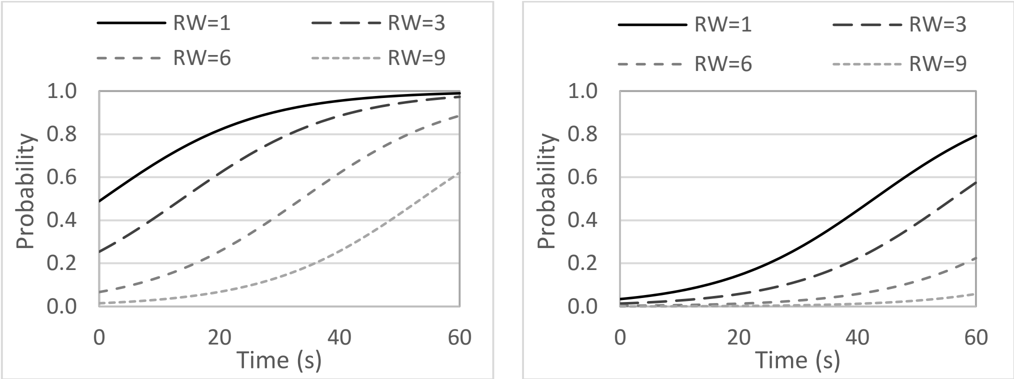
Total number of Observations = 5240 L_o = -3632.091 L_M = -1439.601 $AdjR^2$ = 0.60			
Parameter	Coef.	Std.Er.	P-value
Non-random parameters and means of random parameter			
const	-4.137	0.579	0.000
μ_{time}*	0.122	0.021	0.000
$n_{F,N-I}$	-0.034	0.007	0.000
$n_{C,N-I}$	-0.335	0.060	0.000
μ_{nGN-I}*	-0.232	0.103	0.025
μ_{nGE}*	0.633	0.121	0.000
μ_{rw}*	0.257	0.064	0.000
is	0.446	0.194	0.022
Standard deviation of random parameter			
σ_{time}	0.031	0.011	0.005
σ_{nGN-I}	0.355	0.146	0.015
σ_{nGE}	0.491	0.145	0.001
σ_{rw}	0.164	0.041	0.000

*means of the normal distributed parameters (see Equation 4.2)

Tab. 3.7 – Measurements of elasticity for the independent variables influencing the probability of evacuating

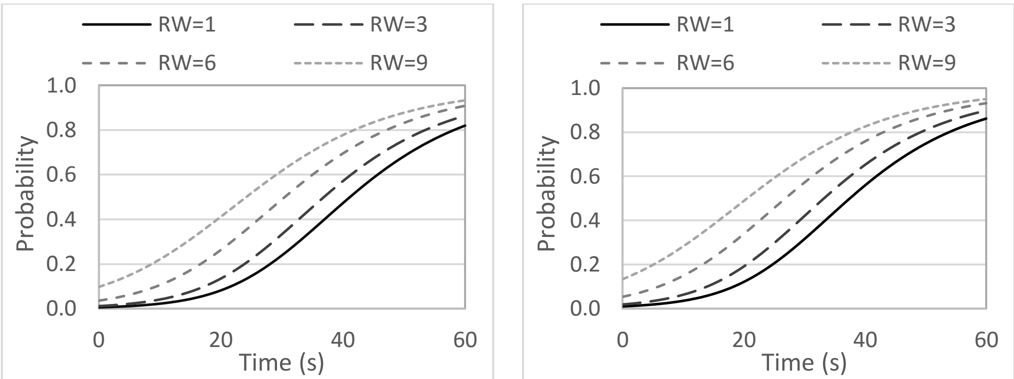
Variable	TIME	$(N_{F,N}+N_{F,I})$	$(N_{C,N}+N_{C,I})$	$(N_{G,N}+N_{G,I})$	$N_{G,E}$	RW
Elasticity	1.252	-0.419	-0.368	-0.047	0.192	0.776

Figure 3.3 shows how the probability of choosing to investigate increases with the time for two scenarios characterized by two different alarm systems, namely alarm bell (Figure 4.3-a) and Pre-Recorded Message (Figure 3.3-b). Differently, Figure 3.4 compares the variations of probability of choosing to evacuate for two different states of the decision-maker, namely NS (Figure 3.4-a) and IS (Figure 3.4-b).



(a) (b)

Fig.3.3–Variation of the probability of choosing to investigate with time and row (RW) for (a) Alarm Bell system and (b) Pre-Recorded Message system (the remaining variables are kept constant and set on the sample averages)



(a) (b)

Fig.3.4 – Variation of the probability of choosing to evacuate with time and row (RW) for decision-maker (a) in normal state and (b) in investigating state (the remaining variables are kept constant and set on the sample averages)

3.4.4 Model explanation

Given the definition of the dependent variables ES and IS of both models (see Table 3.2), the parameters having positive sign increase the probability of beginning investigating or evacuating whereas those with negative sign reduce these probabilities.

The first model predicting the decision to investigate (Table 3.4) shows that physical/social environmental and personal variables affect the probability of investigating. Among all the physical environmental variables, it is possible to see that the time (TIME) increases the probability of investigating as well as the presence of alarm bell system (AL). The latter result can be explained by the fact that an alarm bell is more ambiguous than a pre-recorded message (Nilsson & Johansson 2009). Therefore, a decision-maker is more likely to start looking for further information when the scenarios are characterized by ambiguity (Kuligowski 2011). This finding is also supported by previous studies testing the effectiveness of different alarm systems (Kuligowski & Mileti 2009; Sime 1996; Proulx & Sime 1991). The only personal factor found influencing the choice is the position of the decision-maker. In fact, the probability of investigating decreases with the increase of the row where the decision-maker is sitting. In fact, decision-makers sitting in the first rows are more likely to investigate rather than those sitting in the last rows. This result could be associated with the definition of investigating state (i.e. the decision maker is assumed to pass in investigating state whenever s/he looks at others beside or behind oneself). In fact, as one would expect, people on the back are less prone to look at others beside or behind themselves since they can observe and get information from the people in front of them. On the other hand, this observed phenomenon could also be explained by the degree of ambiguity. In fact, decision-makers sitting in the last rows have a full vision of the cinema hall and other evacuees sitting in front to them therefore they could feel less need to seek further information around them. The proposed model also confirms the findings of previous studies underlying that social influence is an important factor affecting the choice to investigate (Nilsson & Johansson 2009). In fact, a decision-maker is more likely to start investigating if evacuees close to him are already investigating ($N_{C,I}$) or preparing to evacuate ($N_{C,E}$). Moreover, s/he is less likely to investigate if members of her/his personal group are still in normal state ($N_{G,N}$). The model also shows that this probability decreases with the increase of the size of decision-maker's personal group (SG). This last variable could be seen as an indicator of social affiliation. In fact, a decision-maker could get information discussing with the members of his/her group rather than looking around to get more information. These findings are also supported by literature since different studies have proved that pre-evacuation behaviour can be affected by social factors as well as affiliation (Nilsson & Johansson 2009; Latane & Darley 1968; Sime 1996; Ronchi et al. 2014).

A comparison between the strength of the aforementioned variables is made by using the elasticity analysis. Measurements of sample elasticity shown in Table 3.5 show that in the most elastic variables are the position of the decision-maker (E(RW)=-1.612) and the time (E(TIME)= 0.863). Moreover, the most elastic variable among the social ones is the size of decision-maker's personal group (E(SG)=-0.454). The remaining social variables seem to have slightly affected the probability of investigating although these are statistically significant. These results are strongly affected by the sample under consideration. Therefore, it could be that social influences have a greater impact for different social/environmental settings.

The second model (i.e. decision of evacuating, Table 3.6) shows that many factors influence the probability of choosing to evacuating. Among those, Table 3.6 and Equation 3.2 show that some of them have normal random distributed parameters (i.e. TIME, $N_{G,N}$+ $N_{G,I}$, $N_{G,E}$, and RW). This means that these factors are perceived differently by the decision-makings. This second model shows that the probability of evacuating grows with the time (TIME). There are also two personal factors influencing this probability, namely the position of the decision-maker (RW) and her/his personal state (IS). In fact, the probability of evacuating decreases with the increase of the number of row where the decision-maker is sitting. Therefore, decision-makers located on the back part of the hall are more likely to choose to evacuate rather than those in the frontal part of the hall. Also in this case, no previous studies have been found explaining this trend. Moreover, the model shows that decision-makers who looked around to get more information are more likely to choose to evacuate rather than those who do not show this behaviour. This could be caused by the fact that decision-makers became more aware of the situation while investigating and having the need for evacuating (Canter et al. 1980). Finally, the proposed model shows that the decision to evacuate is also affected by social factors. In fact, a decision-maker is less likely to choose to evacuate if there are evacuees far from her/him ($N_{F,N}$+ $N_{F,I}$), close to her/him ($N_{C,N}$+ $N_{C,I}$) and belonging to his/her personal group ($N_{G,N}$+ $N_{G,I}$) in normal and investigating state. On the other hand, a decision-maker is more likely to choose to evacuate if members of her/his personal group have already taken this decision ($N_{G,E}$).

Measurements of elasticity are also made for this model. Table 3.7 shows sample elasticity for all the above-mentioned variables. Table 3.7 shows that the most elastic variable is the time (E(TIME)=1.252) followed by the position of the decision-maker (RW). Table 3.7 also shows that among the social influences, the influences of evacuees close to (NC,N+ NC,I) and far from the decision-maker ($N_{F,N}$+ $N_{F,I}$) are more elastic than those of evacuees belonging to decision-maker's personal group ($N_{G,N}$+ $N_{G,I}$ and $N_{G,E}$).

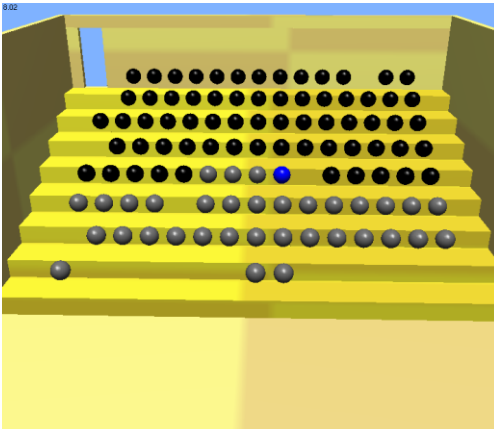
A simple sensitivity analysis of the model was made to study the effect of the dummy variables (i.e. AL and IS) on the probability of choosing to investigate and evacuate. The first pair of charts proposed in Figure 3.3 shows the probability of choosing to investigate for two scenario characterized by two different alarm systems, namely alarm bell (Figure 3.3-a) and Pre-recorded message (Figure 3.4-b). Both charts show the probability increasing with the time and the number of row in accordance with the signs of parameters shown in Table 3.4 (i.e. *time* and *rw*). However, the two charts show that there is a strong difference between the two scenarios. In fact, the probability of investigating is definitely lower when the scenario is characterised by a pre-recorded message alarm. The second pair of charts compares the probability of choosing to evacuate for two different state of the decision-maker, namely normal state (Figure 3.4-a) and investigate state (Figure 3.4-b). In both charts, the probability grows with the time but decreases with the number of row in accordance with the sings parameters shown in Table 3.6 (i.e. μ_{time} and μ_{rw}). A comparison between the two charts points out that the probability are higher when the decision-maker is already investigating. However, this difference is not as evident as that shown for the alarm system.

3.5 Model implementation

The model can be implemented as a sub-model in new and existing agent-based evacuation models regardless of their assumptions (Kuligowski et al. 2010). The implementation of the proposed sub-model can be done following two different approaches, namely event-based or time-based. The former approach assumes that a decision is taken by every decision-maker for each event changing the state of the system whereas the latter assumes that a decision is taken by every decision-maker at each time-step. Regardless of the approach in use, an implementation of the proposed model should follow the pseudo code proposed in Appendix 1. This code needs to be run for each iteration that could be defined by either a time-step or an event. This code points out that the decision to investigate precedes that to evacuate. Therefore, there could be decision-makers who can start investigating and evacuating during the same iteration. In this case, the output of the model provides a direct passage from the normal state to the evacuating one passing directly from NS to ES (see Assumption 2). Finally, it is worth highlighting that the actual state of the decision maker affects the decision to evacuate since a decision-maker already investigating has higher probability to start evacuating (see Table 3.6). Therefore, this phenomenon is taken into account in the pseudo code through the probability of evacuating (pEvac), which is affected by the decision-maker's status.

As an explanatory example, the implementation of the model is presented for a single arbitrary decision-maker. This agent represents the real decision-maker sitting at the ninth seat of the fifth row of the experiment A2 (see Table 3.1). The behaviour of the other evacuees influencing him/her is not simulated but set according to the real behaviour observed during the experiment. In other words, the behaviour of the other agents is set to match the actual behaviour during the experiment. The implementation was performed using the software package called *breve* (Klein 2003) through both a time-step approach and event based approach.

Figure 3.5 shows some snapshots taken from one simulation. The agents are represented as spheres. The simulated decision-maker is the blue sphere (Figure 3.5-8s) and it changes its colour during the simulation. The agent becomes yellow when it starts investigating (Figure 3.5-20s) and red when it decides to evacuate (Figure 3.5-22s). All the other agents in the scenario are black if they do not influence the decision-maker or grey if they do it (Figure 3.5-8s). The agents influencing the decisions change their colour becoming light grey if they are investigating and white if they choose to evacuate.



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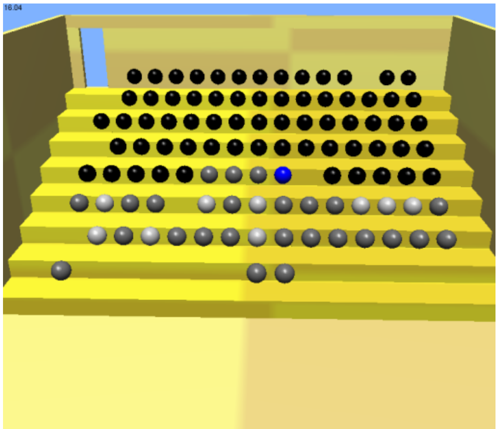

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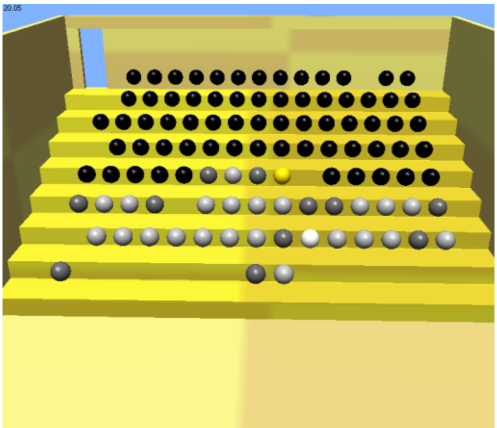

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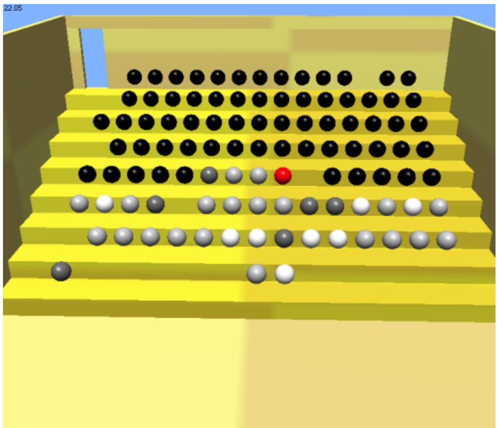


(22s)

Fig. 3.5 – Snapshots of a simulation of the proposed model for a single decision-maker (i.e. blue-yellow-red sphere) at different seconds (8s, 16s, 20s, and 22s).

Given the probabilistic approach in use, several simulations have been run for four different time-step intervals to study how they affect the results of the proposed model. The intervals chosen in the case of the time-step approach are 1s, 2s, 3s, and 4s. The intervals were chosen considering the temporal resolution of the experimental data (i.e. 1s) and the average time-step interval of the relevant events found in the analysis of the data set conducted in this work (i.e. 2.5s). For the event-based approach, the state of the decision maker is update whenever other evacuees change their states.

A simple criterion is used to study the convergence of the results and define the number of runs. The method investigates the average recognition times produced by consecutive runs (Ronchi & Nilsson 2013b). The runs are stopped when the relative error (i.e. the difference between two consecutive averages divided by the last average) is lower than 1% for at least ten consecutive runs. In addition, a minimum number of runs is conducted (i.e. forty runs). For all time-step intervals, the resulting number of runs is fifty.

The non-cumulative and cumulative frequencies of the simulated recognition times for the four time steps and for the event-based approach are shown in Figure 6 and 7. The averages of the recognition times for the four time-steps are 20.5s, 23.9s, 25.7s and 28.3s respectively. Figure 3.6 and 3.7 show that the simulated recognition times grow with the time-step interval. This result highlights that future studies are required to investigate the optimal time-step maximizing the predictability of the model.

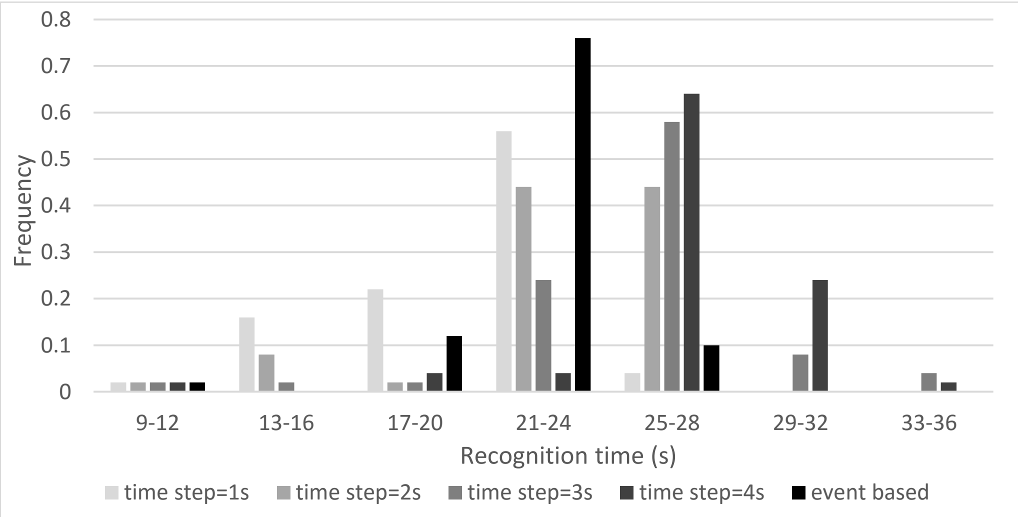


Fig. 3.6 - Non-cumulative frequencies of the simulated recognition times for time-based (time-steps equal to 1s, 2s, 3s, and 4s) and event-based approaches.

Figure 3.7 also shows that the event-based curve is the steepest one. This means that simulated data for this approach has the lowest dispersion. This is also proved by the Standard Deviations (SD) of the simulated recognition times (SD_{1s}=3.81s, SD_{2s}=3.56s, SD_{3s}=4.16s, SD_{4s}=3.65, and $SD_{event\text{-}based}$= 2.67). This result could be related to the approach used to build the new dataset, which is based on *relevant events* (see Section 3.3). However, also in this case, further studies are necessary to verify this explanation.

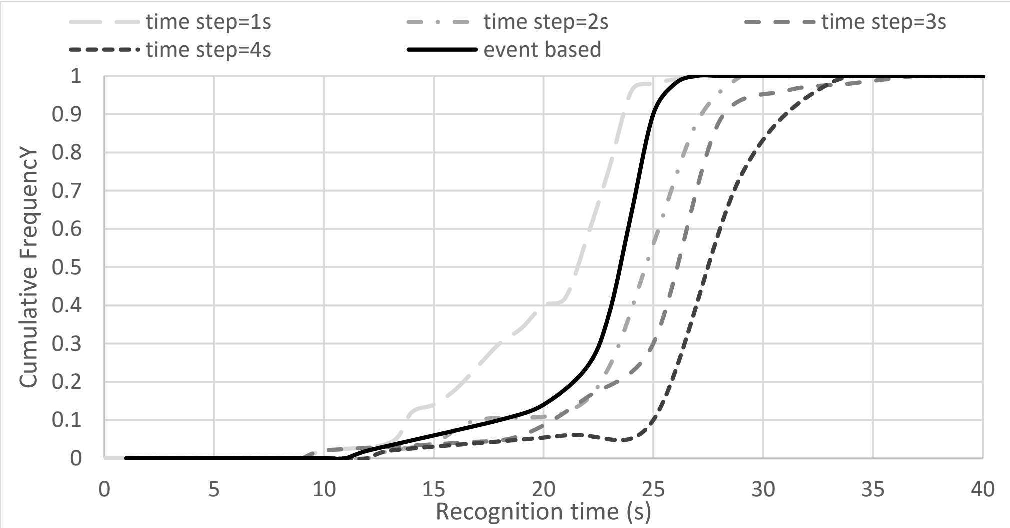


Fig. 3.7– Cumulative frequencies of the simulated recognition times for time-based (time-steps equal to 1s, 2s, 3s, and 4s) and event-based approaches.

3.6 Discussion

This chapter introduces a new predictive-based pre-evacuation model. The proposed model allows the pre-evacuation behaviour to be simulated by modelling two key decisions, namely the decision to investigate and the decision to evacuate. These two binary decisions are used to predict the state (i.e. normal, investigating, and evacuating) of each decision-maker in accordance with the external and internal factors. The proposed sub-model does not predict all activities that can take place during the investigating and evacuating states since this level of detail is out of the scope of this work. Therefore, further studies are necessary to model the decision-making process behind the planning of these activities.

This work is an attempt to improve the pre-evacuation modelling simulating the agents' pre-evacuations states using Random Utility Theory. This has been performed using data from evacuation drills carried out in a cinema theatre. Therefore, it is worth highlighting that future research is needed in order to verify the generalizability of the results for other types of scenarios.

The main difference between the model proposed in this work and existing predictive-based pre-evacuation models is that it is data-driven. In fact, this model can be easily calibrated with data from different environmental setting and evacuees by using discrete choice methods (Ortuzar & Willumsen 2011; Train 2009; Hensher et al. 2005). This allows researchers to verify the influence of internal and external factors on the decision to investigate and to evacuate by using real data. Therefore, the model can also be used to test conceptual/behavioural theories describing pre-evacuation behaviour as well as multiple regression analysis already used in other works (Kuligowski & Mileti 2009; Sherman et al. 2011). Finally, although the behavioural states based on risk perception proposed by Reneke (2013) are used in this model, its main advantage is that the passage between states is in this case based on two decisions (see Assumption 3) rather than the achievement of a pre-defined threshold of risk perception.

A key strength of this work is that a user is not asked to define a random distribution defined *a priori* for the pre-evacuation time since the decision to evacuate and the time necessary for taking this decision is estimated in accordance with the evolution of the simulated environment (i.e. predictive-based approach). This engineering model is therefore closer to the behavioural theories (Canter et al. 1980; Kuligowski 2013) describing the pre-evacuation behaviour since it focuses on the decision-making process. However, this model does not allow an evacuee in an investigating or evacuating state to return to the previous state (see Assumption 2). This limitation derives from the general time-line framework (widely used in evacuation modelling) for which the model is proposed (British Standard Institute 2004; International Organization for Standardization

1999; Proulx 2002; Purser & Bensilum 1998). In fact, the time-line model does not allow modellers to simulate evacuees that at some point of their evacuation take the decision to stop responding to the emergencies returning to their pre-alarm activities. On one hand, this assumption simplifies the modelling issue since assuming irreversible choices implies the need to study only two choices, the choice to start investigating and evacuating. On the other hand this is just a modelling assumption that could not be true for some actual emergencies since limited ambiguous information may lead evacuees to make reversible choices. The data used in this work does not allow the investigation of this issue to be investigated. However, additional data concerning human behaviour during emergencies are required to investigate this issue in future works.

A second strength of this model is that it allows both sources of behavioural uncertainty of decision-makers to be taken into account by using Random Utility Theory (see Section 2.3). Therefore, the proposed model overcomes the 'homogeneity' limitation discussed by Kuligowski (2013).

Since the proposed model is both stochastic and predictive-based, it requires more computational power for its implementation than existing non predictive-based models. In fact, a computational tool implementing the model needs to predict the probabilities of choosing to investigate and evacuate and a pseudo-random number in order to define the final choice. These calculations are made at each time-step and for each agent.

In this work an example of calibration is provided using experimental data from a cinema theatre evacuation (Nilsson & Johansson 2009). However, this approach is intended for general use since different models can be calibrated for different building types, evacuee characteristics, types of emergencies, etc. The main limitation concerning the proposed calibration is the way the observed decisions are defined. In fact, the decisions are defined by using the behavioural type defined by Nilsson and Johansson (2009) However, the passage from one state to another could be defined observing other behaviours such as eye movement. However, the poor resolution of the video recordings made this kind of detailed analysis impossible in the study by Nilsson and Johansson (2009). Another measurement issue could be behind the assumption made concerning the visible evacuees (see Figure 3.2). It could be that participants involved in the experiment had a different perception of the environment considering different combinations of visible evacuees. However, Random Utility Theory allows these measurement errors to be included in the random parameters of the model (Ortuzar & Willumsen 2011).

The proposed model can be implemented using different approaches (i.e. time-based and event-based). The first approach requires simulation that goes in time from one event to the next one, making the most efficient use of computer resources. This approach has been used to create the data set of the model (see the definition of *relevant event* in Section 3.3) implicitly assuming that decision-makers take a decision every time the environment changes its state. In contrast, the time-based approach is easier to implement at the cost of high computational burden (B. Zhang et al. 2011). However, it raises a new issue concerning the definition of a suitable time-step. In fact, too large time-step may lead to an unsuitable approximated simulation of the decisions, while too small time-step can result in unnecessary updates and higher computational cost (B. Zhang et al. 2011). In this work, an attempt of implementation is proposed for a single decision-maker using both the time-based and event-based approaches. This simple example highlights that the time-step interval could affect model results, thus sensitivity analysis studies are necessary to address this issue. Future studies are necessary to investigate the sensitivity of the model to the type of implementation in use (i.e. time-based or event-based) and the associated assumptions (i.e. definition of the time-step intervals). Moreover, it is worth mentioning that the new dataset has been built using an event-based approach. Therefore, the study of the influence of another method to build the dataset (the time-based approach) should also be carried out in the future. Finally the results of the calibrated models are affected by the layout of the scenario (i.e. participants sit on aligned seats and look ahead). Therefore, the implementation of the proposed calibrated model is recommended only for buildings with a similar layout since the same factors included in the model may affect differently the choices in other types of buildings. Hence, future studies are necessary to investigate the generalizability of the results for any cinema theatre since other factors may affect the pre-evacuation behaviour such as sample size, population characteristics, people density, etc.

4. CASE STUDY 2: EXIT CHOICE

4.1 Introduction

Decision making during the movement toward a safe place implies different choices. One of the most important concerns the escape route since this choice affect evacuees' movement phase. The literature argues that escape route can determine the effectiveness of the evacuation process in a crucial way (Ronchi 2012; Nilsson 2009; Lovreglio 2014; Fridolf, Nilsson, et al. 2013; Lovreglio, Borri, et al. 2014). The decision concerning the route to a safe place entails global and local choice (Wagoum et al. 2011; Gwynne et al. 2001). Evacuees try to select the final goal(s) of their evacuation journey through the global exit choice and then they try to achieve the selected goal making local exit choices (Reynolds 1999; Ronchi & Nilsson 2016). Even though evacuees may be familiar with the building, it is not always realistic to assume that they have a complete knowledge of the whole escape route. There could be situations in which the global evacuation route may be the consequence of local choices since different exits from the same environment may lead to very different global escape routes (Wagoum et al. 2011; Gwynne et al. 2001).

Three main approaches of representing exit choice are considered in existing agent-based evacuation models: (a) agents (i.e. simulated evacuees) head towards exits predefined by the modeller; (b) agents choose the closest exit; (c) agents choose the exit considering environmental, social and personal factors (Kuligowski et al. 2010; Schneider & Könnecke 2010; Wagoum 2012; Gwynne et al. 2000).

The first approach is clearly limited because it does not consider any evolution of the evacuating scenarios and the behaviour is an input of the model (see Figure 1.3-a). In the second one (distance-based model), the choice is context-dependent but static and based only on the building structure. It does not allow for dynamic adjustments to avoid congestion (Schneider & Könnecke 2010). The third category of models entails that each agent evaluates the features of the simulated environment and takes decisions on the basis of the perceived information. In these models, the chosen exit can change during the evacuation process if the evacuation conditions change and a range of variables can be considered (e.g. presence of smoke, visibility, familiarity with an exit). The simplest and most common model of the third category is the quickest path model, in which the agents choose the exit with the least evacuation time. Therefore, exit choice is an output of the model rather than an input (see Figure 1.3-b).

The modelling approaches to represent exit choice can be also classified into deterministic and stochastic (Lovreglio, Borri, et al. 2014). Deterministic approaches have been derived from different decision theories, such as the game theory (Lo et al. 2006; Ehtamo et al. 2010; Mesmer & Bloebaum 2014) or the utility maximization theory (Ehtamo et al. 2009; Wagoum 2012). Stochastic models differ from deterministic models (that are easier to implement but can represent only average behaviours) and they take behavioural uncertainty into account. Several stochastic approaches have been used for exit choice. For instance, Zhang et al. (2013) introduced an exit choice model in which the 'base probability' of using an exit is defined by the modeller. However, these pre-defined probabilities may change depending on the previous use of the exit and the fire condition of the next compartment connected to the exits. This approach required prior knowledge of usage probabilities, which can be difficult to obtain. This issue is overcome by random utility models since they do not require any pre-defined probability as illustrated in Section 2.3.

This work presents a case study of local exit choice during the evacuation from an enclosed environment with two exits investigating the impact of both environmental and social variables on exit choice, including presence of other evacuees, fire conditions, emergency lighting and distance from the exit. The study is based on an online stated preference survey using non-immersive VR hypothetical scenarios using videos. The main contribution of this work is to provide new experimental data, which allows for a preliminary understanding of local exit choice in emergencies when the context of choices is characterized by many environmental and social factors. Then, the aim of this study is to verify the importance of the behavioural uncertainty in local exit choice. However, because of the low ecological validity of this case study, it is necessary to test the validity of the behavioural findings of this case study using more advanced technique (i.e. immersive VR) in future study.

4.2 Modelling Assumptions

This section introduces a modelling solution aimed at developing a local exit choice model based on Random Utility Theory. Assuming that a *q* evacuee has to choose an exit between *n* possible exits, it is possible to define a utility function for each *i* exit rewriting Equation 2.1 as:

$$U_q^{i\ exit} = V_q^{i\ exit} + \varepsilon$$
$$V_q^{i\ exit} = \sum_j p_j^i F_{j,q}^i \qquad \text{Eq. 4.1}$$

where $F_{j,q}^i$ are the external factor defining the systematic utility of the *i* exit for *q* evacuees and p_j^i are the parameters defining the weight of these factors in the selection of an exit. Using the assumptions introduced in Section 2.3 for the random part (ε), it possible to the probability that to select an exit by using the multinomial formulation:

$$P_q^{i\ exit} = \frac{e^{\sum_j p_j^i F_{j,q}^i}}{\sum_k e^{\sum_j p_j^k F_{j,q}^k}} \qquad \text{Eq. 4.2}$$

Assuming that the p_j^i are randomly distributed, it is also possible to have the mixed logit formulation and its simulation as described in Section 2.3. The next section introduces the dataset used to calibrate an exit choice model to select an exit taking into account several social/physical factors.

4.3 Dataset

The exit choice model has been calibrated using data collected through an online SP survey. The procedure adopted to develop the survey includes several steps as illustrated in Figure 4.1.

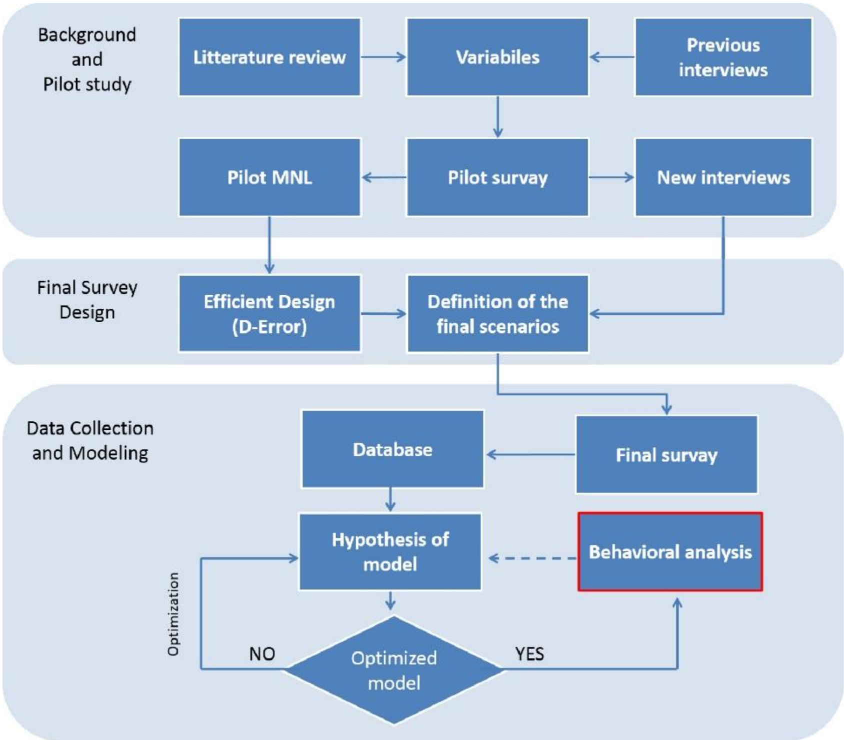


Fig. 4.1 – Methodology used to develop the survey and to calibrate the exit choice model

In the first step, the variables which may influence exit choice were identified through a literature review and analysing a set of interviews made during a previous study on exit choice (Lovreglio, Fonzone, et al. 2014). Then an on-line pilot survey presenting 12 preliminary hypothetical scenarios (using videos representing the context of choice) and involving 88 participants was carried out both to improve the representation of the scenarios and to collect information for the design of the final survey. Face-to-face semi-structured interviews with some of the respondents provided insights into the perception of the contexts of choice and the involved variables (i.e. the interviewees were asked about the factors affecting their choice to verify if they could perceive all of them). In the second step, the information collected through the pilot survey was used to define the levels of the variables characterising the scenarios in the final survey, using the Efficient Design technique explained below. Moreover, the results of interviews were used to improve the videos so that respondents could have an accurate perception of the contexts of choice. In the last stage, data collection was performed through an on-line survey. The videos representing the choice scenarios could be easily shown to respondents using the Internet.

The scenarios used in SP surveys are defined by the levels assumed by the relevant factors. When the number of variables is large, the number of the scenarios generated by the combinations of all levels of all variables becomes easily intractable. The Efficient Design (ED) technique was used to select the scenarios to be included in our survey (Rose et al. 2008; Greene 2011; Sándor & Wedel 2001; Institute of Transport and Logistics Studies 2007). The method is based on the minimization of the so called D-error, that is the determinant of the asymptotic variance-covariance matrix (i.e. the negative inverse of Hessian matrix of the log-likelihood function) to the power of 1/K, where K is number of parameters to estimate. Therefore, D-error is related to the p-values of the parameters to estimate since p-values are calculated using the variance matrix (i.e. the diagonal elements of variance-covariance matrix) (Greene 2011). To implement ED, approximated values of the model parameters ("prior" values) are needed before running the survey. Prior values can be found in literature or, if not available as in our case, obtained from a pilot study. The pilot survey can be designed by means of ED, using educated guesses on the sign and the value of each parameter to estimate.

4.3.1 Pilot and Final Scenarios

The context of choice adopted in this study was characterized by the choice between two exits, one on the left-hand side and one on the right-hand side of the decision maker. The exits were set in an enclosed environment similar to a metro station with rectangular plant (size: 23m x 18m) as shown in Figure 4.2. The scenarios were proposed using videos to make the context of choice more realistic. Moreover, videos provided respondents with information deriving from the dynamic evolution of the evacuations: for instance, the capacity of an exit can be evaluated from the number of evacuees that flow through it in a certain time. The videos were generated using Unity 3D (Personal Edition). The geometry of the metro station was directly built in Unity 3D whereas evacuees' models were downloaded from the web and their original file formats was converted using Blender. To improve the realism, a fire alarm (recorded during a school fire drill) and crowd sound were added (source: www.soundbible.com). During the experiment, decision-makers were supposed to be inside the environment and that videos were taken from their point of view.

Fig. 4.2 - Frame from one of the videos

Exit choice is influenced by environmental (concerning the physical features of the choice context), social (related to the presence of other evacuees) and personal factors (Lovreglio, Borri, et al. 2014). In this study, only social and environmental factors were included in the model specification, whereas the study of the influence of internal factors on exit choice (except gender) is left to future work. The variables considered in the survey were:

- **N**umber of evacuees **C**lose to the **E**xits (NCE);
- **FL**ow of evacuees through the exits (FL);
- **N**umber of evacuees **C**lose to the **D**ecision-**M**aker heading towards one of the exits (NCDM);
- **SM**oke near the exits (SM);
- **E**vacuation **L**ights above the exits (EL);
- **DIST**ance of the decision-maker from the exits (DIST);

Fire conditions can affect exit choice in two ways: the presence of the smoke near an exit can induce decision-makers to avoid that exit; the presence of smoke near an evacuees can affect their visibility distance. In the survey videos, the presence of smoke does not affect the visibility distance (the respondents are able to see the exit and the simulated evacuees in every video without being affect by the smoke). Therefore, only the influence of the presence of smoke near the exits, represented by a dummy variable was investigated (SM).

The evacuation light used in this case study have the evacuation sign illustrated in Figure 4.3 with a constant light source (i.e. LED). In this study, only the impact of the presence of the evacuation light (EL) was investigate whereas the impact of different luminance level and the visibility impact need to be investigated in future studies.

Fig. 4.3 – Evacuation sign (HM Government 2007)

In the pilot survey, respondents were asked to identify the exit they would choose in 12 hypothetical scenarios. The settings of the pilot survey, such as level for each variable (i.e. the set of values that variables can assume), selected hypothetical scenarios, etc., are reported in the Appendix 2 of this thesis. In accordance with the Efficient Design, positive values were assumed only for FL and EL and negative ones for NCE, NCDM, SM and DIST. The pilot study involved 88 respondents corresponding to 1056 (88 x 12) observations. The starting values of the parameters for the design of the final survey with ED were estimated by calibrating a pilot logit model (Table 4.1). 10 of the 88 respondents participated in a face-to-face semi-structured interview. Most of them stated that they could not perceive any difference between the flows though the two exits, which were actually different in some scenarios. This is confirmed by the pilot model, where the parameter associated with FL is not significantly different from zero. To improve the perception of this variable, two very different levels were chosen for the final survey (see Table 4.2). While in the pilot survey the different evacuees' flows depends only on evacuee speeds, in the final survey different flows were determined both by using different evacuee speeds and exit widths. Even though the parameter associated with DIST was not significantly different from zero (see Table 4.1), almost all interviewees stated to take into account the distance from the exits during the choice. Therefore, it is kept in the final survey.

The scenarios of the final survey are defined by different combinations of the variables and levels shown in Table 4.2. The subscript *i* represents the exit: L stands for the exit on the left, R for that on the right-hand. NCE_i varies during the videos because evacuees evacuate through the exits; the values shown in the table are those visible at beginning of each video. The two dummy variables NEAR_E and DIR define respectively the position of the decision-maker and the direction of evacuees close to the decision-maker. NEAR_E=0 if the decision-maker is closer to the right-hand exit, 1 otherwise. Similarly DIR=0 if the evacuees near the decision-maker move towards the right-hand exit, 1 otherwise (Figure 4.4).

Tab.4.1 – Pilot logit model

Parameter	Coef.	Std.Er.	P-value
NCE	-0.108	0.012	0.000
FL	0.214	0.209	0.307
NCDM	-0.049	0.021	0.020
SM	-0.985	0.123	0.000
EL	0.175	0.101	0.082
DIST	-0.011	0.030	0.718

Given the variable levels in Table 4.2, the number of the possible scenarios (full factorial design) is $4^1 3^3 2^8$=27648. 12 scenarios illustrated in Table 4.3 are selected using the Efficient Design. The 12 scenarios were divided into two blocks of 6 and each respondent was presented with one of the two blocks using the techniques explained in (Institute of Transport and Logistics Studies 2007). This allows the number of scenarios to be reduced for each respondent and so to prevent respondents' fatigue, a problem pointed out by some of the interviewees during the pilot survey where participants were asked to state their decision in 12 cases. Moreover, the scenarios were presented randomly to avoid that the collected data may be biased by the order of the scenarios.

Tab. 4.2 - Levels for each variable

Variable	Description	Levels
NCE_i* (pers)	**N**umber of evacuees **C**lose to the **E**xits	24 30 40
FL_i (pers/s)	**FL**ow of evacuees through the exits	0.6 1.2
NCDM (pers)	**N**umber of evacuees **C**lose to the **D**ecision-**M**aker	0 5 10
SM_i	**SM**oke near the exits	0 1
EL_i	**E**vacuation **L**ights above the exits	0 1
DIST (m)	**DIST**ance of the decision-maker from the exits	10 12 14 16
NEAR_E	Dummy variable equal to 0 if the decision-maker is closer to the right-hand exit, 1 otherwise	0 1
DIR	Dummy variable equal to 0 if the agents near the decision-maker move towards the right-hand exit, 1 otherwise	0 1

*the values refer to the beginning of the videos

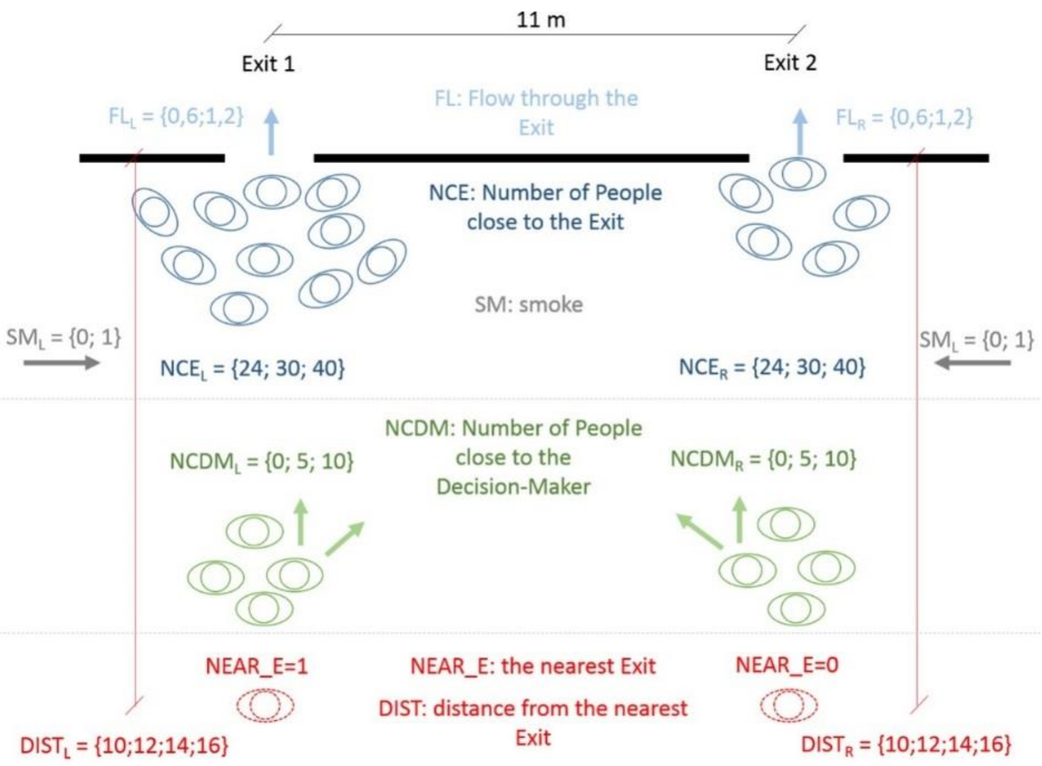


Fig. 4.4 – Context of choice

Table 4.3 – Final scenarios

Scenario	NCE_L	NCE_R	FL_L	FL_R	SM_L	SM_R	EL_L	EL_R	NCDM	DIR	DIST	NEAR_E	Block
1	24	30	1.2	0.6	0	1	1	1	10	1	14	0	1
2	40	40	0.6	0.6	1	0	1	0	5	0	16	1	1
3	30	30	0.6	1.2	0	0	0	1	10	0	10	0	1
4	24	40	1.2	0.6	1	0	0	1	0	1	10	1	1
5	40	24	1.2	1.2	0	1	0	0	0	1	12	1	1
6	30	40	0.6	1.2	1	1	1	0	0	0	16	0	1
7	40	40	0.6	0.6	0	0	0	0	5	1	10	0	2
8	40	24	0.6	0.6	0	1	1	1	5	0	12	1	2
9	24	30	0.6	1.2	1	1	0	1	10	1	16	1	2
10	30	30	1.2	1.2	1	0	1	1	0	1	14	0	2
11	30	24	1.2	0.6	1	1	0	0	10	0	12	0	2
12	24	24	1.2	1.2	0	0	1	0	5	0	14	1	2

4.3.1 Questionnaire Structure

The questionnaire, in English and Italian, was disseminated through internet over a period of two months. The survey was advertised by mail lists and social networks (LinkedIn, Twitter, and Facebook). This advertising strategy was used to collect as much data as possible from respondents coming from different parts of the world. The goal was to collect data from more than 450 respondents, which was the lower bound for the sample size suggested by the Efficient Design technique for this case study [53].

The survey included three sections. The first contained an introduction and demographic questions. In the second the videos representing the contexts of choice were shown. The respondents were instructed to make a choice at the end of the playback. It explicitly stated that "*there is no right and wrong choice and we are only interested in understanding what you would do in the situation you are faced with in the video*". This was essential because the aim of the survey was not to collect data about the "most rational/optimal" behaviour but the "natural" response to the situation. At the end of each video, respondents were directed to a new web page to choose between the left and right-hand exits. This page also included a countdown timer that gave the respondents 5s to answer the question. The countdown timer was used to prevent that excessively long reflection may lead to choices different from those in emergencies. Actually, respondents were also allowed to state their choice after the time runs out to reduce non-response, but they were not made aware of this to maintain the level of alertness. Finally, in the third section, at the end of the videos, the respondents were asked questions about the level of realism of the proposed scenarios and the level of anxiety during the experiment.

4.3.1 Respondents

The sample is made up of 1503 respondents, corresponding to 9018 (1503 participants x 6 scenarios) observations. 28.3% of participants are female. The mean age is 28.2, with standard deviations 11.4; 71% of the respondents are under 30 years old (Figure 4.5). The majority of respondents are from Europe (i.e. nationality), mainly from Italy (22%) and the UK (11%) (Figure 4.6).

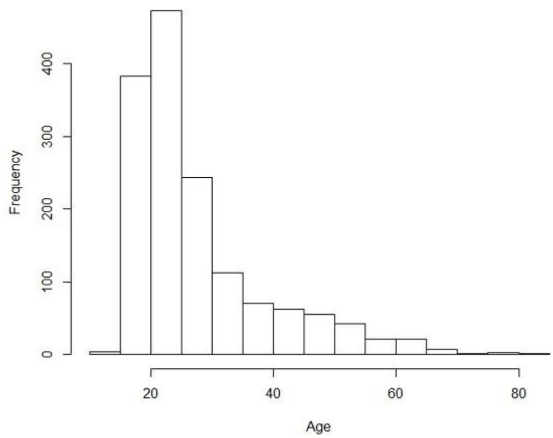


Fig. 4.5 –Age distribution of respondents

The sample demographics are explained by the dissemination channels. In fact, the age distribution reflects the age distribution of social network users (Thelwall 2008; Acquisti & Gross 2006). However, the sample is large enough to take into account differences between male and female respondents.

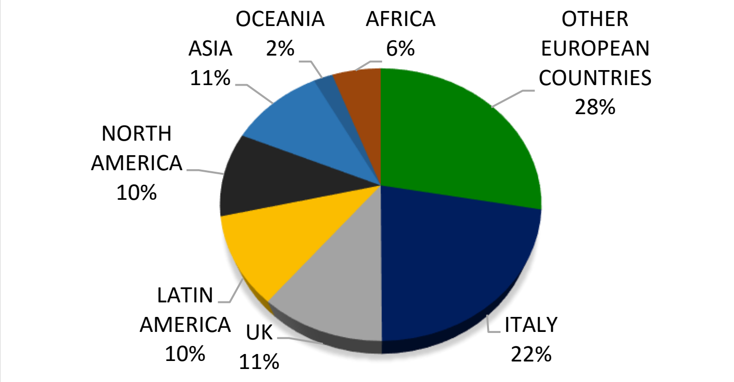


Fig. 4.6 – Geographical distribution of respondents

4.4 Model Calibration

4.4.1 Model Specification

A Mixed Logit Model is estimated using the data from the survey described in Section 4.3. The deterministic part of the utility function of the exits (V^L and V^R; where L stands for the exit on the left, R for that on the right-hand) includes all the variables described in Section 4.3.1 (see Equation 4.3). A constant is added to the utility function of the right-hand exit to check whether respondents are biased towards one of the two exits. Equation 4.3 has both lowercase and uppercase elements. The former are the estimated parameters whereas the latter are the actual variables of the model.

$$\begin{aligned} V^L &= nce \cdot NCE^L + fl \cdot FL^L + ncdm \cdot NCDM^L + \\ &\quad sm \cdot SM^L + dist \cdot DIST^L + el \cdot EL^L \\ V^R &= nce \cdot NCE^R + fl \cdot FL^R + ncdm \cdot NCDM^R + \\ &\quad sm \cdot SM^R + dist \cdot DIST^R + el \cdot EL^R + const \end{aligned} \qquad \text{Eq. 4.3}$$

where:

$nce \sim N(\mu_{nce}|\sigma_{nce})$

$fl \sim N(\mu_{fl}|\sigma_{fl})$

$ncdm \sim N(\mu_{ncdm}|\sigma_{ncdm})$

$sm \sim N(\mu_{sm}|\sigma_{sm})$
$dist \sim N(\mu_{dist}|\sigma_{dist})$
$el \sim N(\mu_{el}|\sigma_{el})$
$const \sim N(\mu_{const}|\sigma_{const})$

4.4.2 Parameter Estimation

To estimate the model, a panel data approach is used to take into account the correlation between the answers of the same respondent who makes a choice in 6 different scenarios. 200 Halton draws are used to simulate the random distribution of the variables (Train 2009; Hensher et al. 2005). Three measures of the goodness of fit are used: the likelihood for a model only including a constant (L_0), the likelihood for the proposed model (L_M), and the adjusted McFadden R squared ($AdjR^2$) as in Case Study 1.

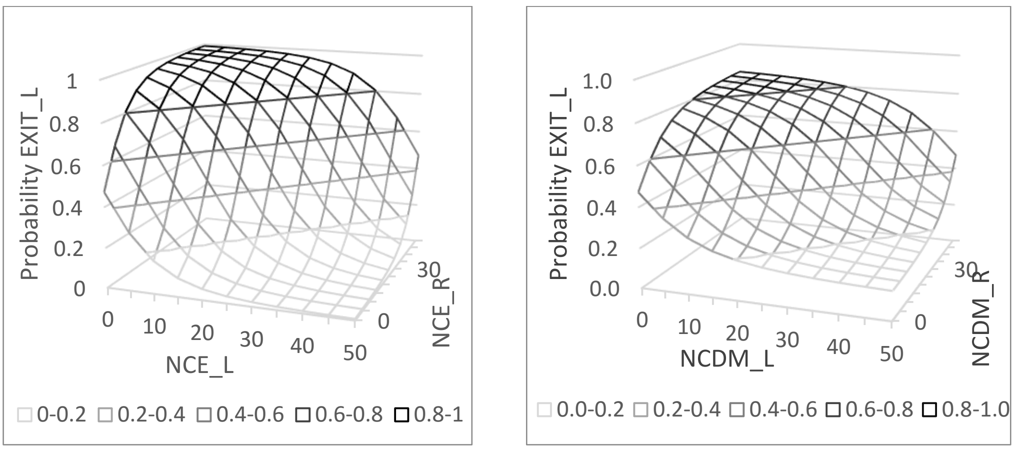
NCE changes over the duration of the videos because some evacuees leave the environment (with flow FL). In the model, the average values at the beginning and at the end of the simulation were used. Since there is a large difference between the number of female and male respondents, the interaction between a dummy variable defining the respondent gender (GEND=1 if the respondent is female) and each environmental and social variable (V_i=NCE, FL, NCDM, SM, EX or DIST) was studied to check if the gender statistically affects the choice. The model specification in Equation 4.3 does not include the interaction terms because they are not statistically different from zero (p-value>>0.05).The estimated parameters are shown in Table 4.4.

4.4.3 Sensitivity analysis

A sensitivity analysis is performed to show how the probability to choose an exit is influenced by the observed variables and their interaction. The effect of the number of evacuees near the two exits (NCE) and near the decision-maker (NCDM) is shown in Figure 4.7, whereas the influence of flow (FL), presence of smoke (SM) and emergency lights (EL), and distances (DIST) is presented in Figure 4.8. In Figure 4.7-a and 4.7-b NCE and NCDM range between 0 and 50 whereas the other variables are the same for both exits. In Figure 10, the number of evacuees close to the right-hand exit (NCE_R) is fixed to 25 while the evacuees close to the left-hand exit (NCE_L) vary between 0 and 50. All the other variables are the same for the two exits. In Figure 4.8-a and 4.8-b the flow and distance of the right-hand exit are 0.5 persons/s and 10m respectively.

Table 4.4 –Estimated model

Total number of Observations = 9018 L_o = -5419.025 L_M= -4284.297 AdjR^2 = 0.20798				
Parameter	Coef.	Std.Er.	P-value	Parameter
μ_{nce}	-0.1713	0.0107	-16.0148	0.0000
μ_{fl}	1.1455	0.1380	8.3008	0.0000
μ_{ncdm}	-0.1041	0.0090	-11.5533	0.0000
μ_{sm}	-1.0041	0.0852	-11.7836	0.0000
μ_{dist}	-0.0813	0.0114	-7.1273	0.0000
μ_{el}	1.2291	0.0853	14.4012	0.0000
μ_{const}	0.0690	0.0364	1.8950	0.0581
σ_{nce}	0.0549	0.0105	5.2446	0.0000
σ_{fl}	1.6450	0.2477	6.6411	0.0000
σ_{ncdm}	0.0826	0.0171	4.8287	0.0000
σ_{sm}	0.8860	0.1299	6.8194	0.0000
σ_{dist}	0.1972	0.0192	10.2540	0.0000
σ_{el}	1.1631	0.1228	9.4733	0.0000
σ_{const}	0.4436	0.1013	4.3804	0.0000



(a) (b)

Fig.4.7 –Sensitivity analysis for (a) NCE; (b) NCDM

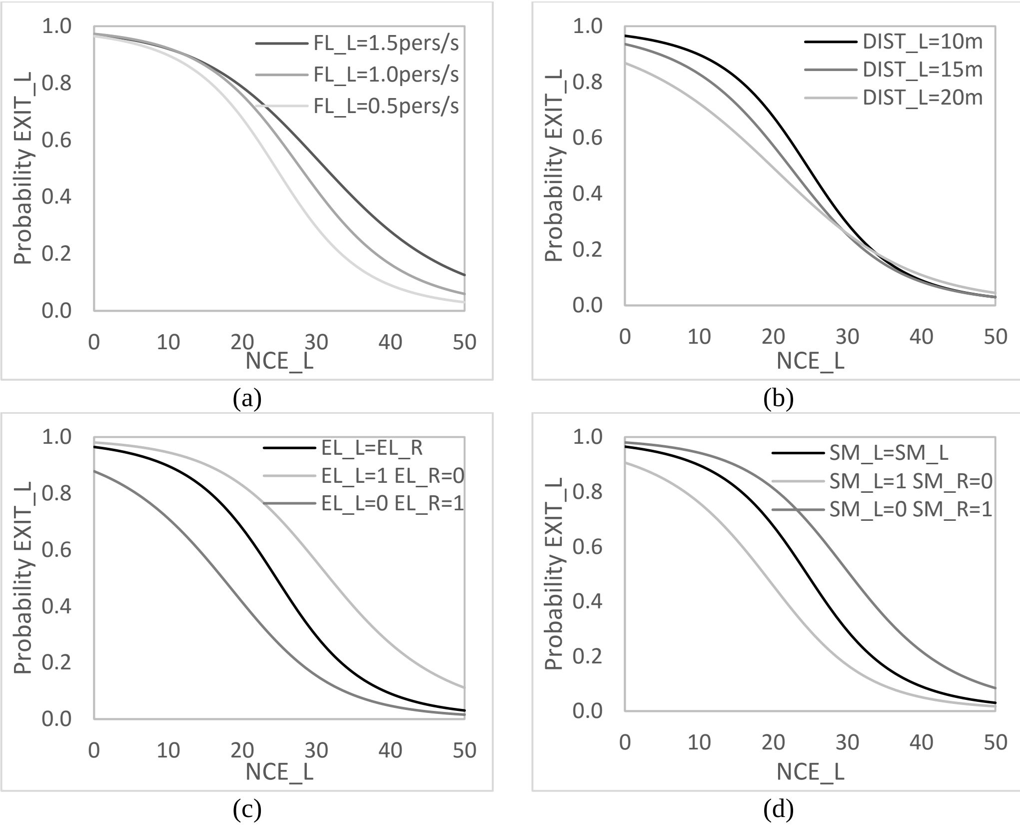


Fig. 4.8 –Sensitivity analysis for (a) FL; (b) DIST; (c) EL; (d) SM

4.4.4 Model explanation

A behavioural analysis is performed considering the averages of the parameter distributions. These behavioural findings provide an insight into the interaction of the impact of several factors on local exit choice. However, it is necessary to highlight that the behavioural results provided by the model refer to the experimental conditions given in the hypothetical scenarios and that these results are affected by the low ecological validity of the experiment. Therefore, a reader should be careful to generalize these findings for any other evacuation scenario.

In general, the probability to choose an exit decreases when the number of evacuees close to it (NCE) increases, i.e. the decision-makers perceive a large number of evacuees using an exit as an impedance. In other words, respondents demonstrate crowd avoidance behaviour with the evacuees near the two exits. The same tendency can be seen in the interaction with evacuees near the decision maker (NCDM). However, the distribution of NCDM implies that crowd avoidance behaviour is sometimes replaced by the herding behaviour. In fact, in Figure 4.9 it can be seen that the probability is high when the parameter associated with NCDM is positive. This means that there are respondents for whom the fact that many other evacuees head towards one of the two exits is an incentive to select the same exit. This can be explained by the fear to be negatively judged by other evacuees by choosing the 'wrong' alternative (normative social influence (Lovreglio, Fonzone, et al. 2016)), and/or by the attitude to consider other people's decisions as a proof of the correctness of a choice (social proof theory) (Cialdini 1993; Lovreglio, Fonzone, et al. 2016; Lovreglio, Fonzone, et al. 2014). In the Figure 4.9, it is also evident that NCE and NCDM have different distributions, i.e. there is a difference in the way respondents perceive these two variables, related to the same factor, the presence of other evacuees. This could be explained by the proxemics approach, which argues that the closer other people are to a decision-maker, the more the decision-maker is affected by them (Hall 1966). This phenomenon has been also observed in other previous VR experiments (Bailenson et al. 2003; Bailenson et al. 2008) showing that the social interactions are affected by the distances.

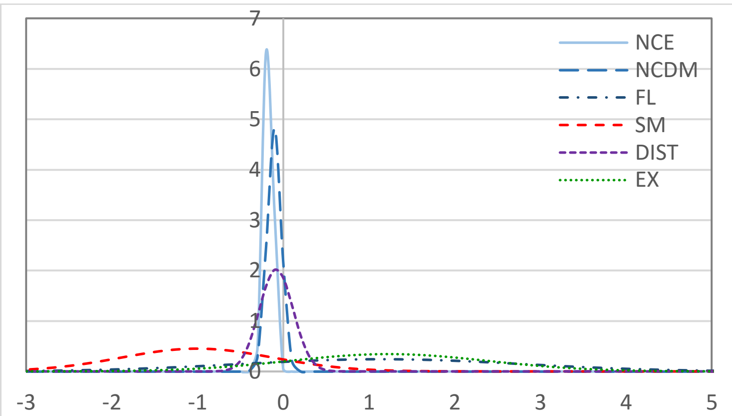


Fig. 4.9 –Random distribution for (a) NCE and NCDM; (b) FL; (c) SM and DIST; (d) EL

The exit distance is generally perceived as disutility as normally expected. However, the random distribution of the distance is characterised by a very large dispersion, i.e. several respondents choose the furthest exit (Figure 4.9). This could be because the two exits are not too far away from each other and therefore some participants did not consider distance as an important factor as most other did.

Considering the averages of the random parameters in Figure 4.9, it is possible to argue that overall the respondents perceive the flow through the exits as a utility because higher flow rates allow faster evacuation whereas the presence of smoke have a negative impact on the choice since it could harm the decision-maker. Then, the presence of emergency lights increases, on average, the probability to choose an exit because it improves the functional affordance of the exit (Lovreglio, Ronchi, et al. 2015; Ronchi, Nilsson, et al. 2015). However, Figure 8 shows that the parameters associated to FL, SM and EX have very large dispersions, as indicated by the standard deviations in Table 4. As a consequence, there is high probability that, for a specific decision-maker, the concerned parameters assume a sign different from that of the average decision-maker. The high dispersion can be due to a combination of the high level of heterogeneity in the preferences and respondents not considering these factors to make their choices (as it has been observed for the exit distance). This modelling issue may be solved using bounded distributions such as a lognormal one. However, this may reduce the model fit as well as lead to less accurate estimation of the mean value of the parameter (Hole & Kolstad 2011; Hess et al. 2005). Even though some solutions have been proposed, this is still an open modelling issue for discrete choice modellers, which needs to be investigated deeply in the future (Vij et al. 2013).

The constant included in the utility function of the right-hand exit is not statistically significant (p-value = 0.07 > 0.05). This means that the right-hand exit is not chosen systematically more than the left-hand one under the social/physical conditions described in Table 3.

Further information can be provided analysing the results of the sensitivity analysis. In the scenarios in which the variables are equal to zero for one door and equal to 50 for the other, the probability of selecting the left-hand side door is very close to 1 and 0 in Figure 4.7-a, whereas in Figure 4.7-b the probability surface has the maximum and minimum equal to 0.85 and 0.12 respectively. Comparing the two charts, it can be seen that NCE influences (negatively) the probability to choose an exit more than NCDM. In other words, a decision-maker is more willing to choose the less congested exit when the other evacuees are closer to the exit (NCE) than when they are close to them (NCDM) in the conditions given in the hypothetical scenarios used in this study.

In Figure 4.8, the number of evacuees close to the right-hand exit (NCE_R) is fixed to 25 while the evacuees close to the left-hand exit (NCE_L) vary between 0 and 50. All the other variables are the same for the two exits. In Figure 4.8-a and 4.8-b the flow and distance of the right-hand exit are 0.5 persons/s and 10m respectively. Figure 4.8-a and 4.6-b show the existence of situations in which flow and distance are not determinant in the exit choice because the social factors are predominant. These situations occur when the curves in the figures tend to overlap. For instance, Figure 4.8-a shows that for low values of NCE_L (NCE_L<10), the flow does not influence the choice. In these conditions, the left-hand exit is almost free and definitely freer than the right-hand one (NCE_R=25) and therefore the decision-maker may reckon that he can escape quicker by using it, even though the capacity of the exit is low. For low values of NCE, the flow is difficult to evaluate for the decision maker, and so it can be assumed that the flow rate is the same for the two exits, leaving the number of evacuees as the only decision variable. In Figure 4.8-b, it can be seen that for high values of NCE_L (NCE_L>30) the distance from the left-hand exit does not affect the choice probability, since this exit is so crowded that the decision maker tends to avoid it anyway. When the number of close evacuees is the same for the two exits as in Figure 4.8-c (NPE_L=NPE_R=25), the probability to choose the left-hand exit depends on the presence of the emergency lights. The probability varies from 0.26 when there is not light on the left-hand exit but there is one on the right-hand one (EL_L=0 and EL_R=1), to 0.70 in the opposite case (EL_L=1 and EL_R=0). Figure 4.8-c also suggests that the decision-maker can neglect the information given by the emergency light. In fact, in the situation with emergency light on the right-hand exit only, one would expect that the decision-makers avoid the exit on the left-hand side. Instead, the plot shows the left-hand exit has high probability to be chosen for medium-small values of NCE_L. That can be explained by the informational social influence (Nilsson & Johansson 2009), which predicts that the presence of other evacuees close to an exit indicated that that exit is an available alternative. Finally, Figure 4.8-d shows how the presence of smoke can affect the choice considering different number of evacuees near the exits. In the condition given in the hypothetical scenarios, it seems that the presence of smoke close to an exit is less important than the choice of other evacuees. In fact, when there is smoke near the left-hand exit and the other exit is clear (SM_L=1 and SM_R=0), the decision-makers prefer the former alternative if it is relatively uncongested (NCE_L approaching zero).

4.5 Discussion

This chapter introduces an exit choice based on Random Utility Theory, which allows the probability of a decision-maker to choose an exit to be predicted by considering six environmental and social variables. The model is estimated using the data collected through an on-line SP survey designed through Efficient Design. The results of this model need to be carefully investigated considering the low etiological validity and that these refer to the given experimental conditions.

The findings show that presence of smoke, distance of the exit, number of evacuees near the exit or close to the decision-maker but moving towards the exit have a negative influence on the probability of the exit to be chosen. On the contrary, emergency lighting and flow of evacuees through the exit have a positive influence.

The model shows that the perception of the variables and/or their relevance/weights in the decision makers is not constant among respondents, but the parameters associated to all the independent variables are normally distributed (i.e. Perceptions and Preferences Behavioural Uncertainty). Note that different parameters distribution can be tested using the mixed logit approach. In the absence of evidence on the distributions in this case, the normal one was selected since it is the most commonly used (Hess et al. 2005). However, this aspect should be investigated in future work.

Compared to the existing literature, this study has the advantage to investigate the influence of more variables simultaneously expanding the current understanding of local exit choice in emergencies. In Table 4.5, the proposed model is compared to the existing ones. All the models have been fitted using our dataset – that is definitely larger than all the others - for a fair comparison. It can be seen that the fit of the model in terms of adjusted R^2 indicator (which includes a penalty for each parameter included in the model) is much better than the others, proving the need for considering all the environmental and social variables together. The table also shows the mean values of the parameters (the parameters are proven random in all the cases) in each model specification. It can be seen that there is a remarkable difference between the parameter of FL (the exit flow rate) in the specification proposed by Haghani et al. and in our model. The under-specification of the former model may lead to wrong design choices whenever evacuation scenarios include smoke and emergency lighting. In fact, a design based on Haghani et al.'s results may overestimate the possibility of inducing evacuees to select an exit by make it larger. However, the model specification proposed by Haghani et al. may still be correct in evacuations which do not involve smoke and emergency lighting.

Tab 4.5 – Comparison between the proposed model and the existing ones.

	Model specification						Survey features		RsqAdj*
	NCE	FL	NCDM	SM	EL	DIST	Sample size	Video	
(Duives & Mahmassani 2012)	Yes (-0.087) **	No (-)	No (-)	No (-)	No (-)	Yes (-0.055)	117	no	0.089
(Lovreglio, Borri, et al. 2014)	Yes (-0.134)	No (-)	Yes (-0.076)	No (-)	No (-)	Yes (-0.088)	191	yes***	0.126
(Haghani et al. 2014)	Yes (-0.089)	Yes (1.615)	No (-)	No (-)	No (-)	Yes (-0.082)	53	no	0.125
Proposed model	Yes (-0.116)	Yes (0.609)	Yes (-0.077)	Yes (-0.762)	Yes (0.856)	Yes (-0.053)	1503	yes	0. 208

* Referring to the models fitted with the dataset collected in our survey.

** Mean of the parameter distribution.

*** The degree on realism is definitely lower than that in the videos used in this study.

Methodologically, a strength of this case study compared with the existing stated preference studied listed in Table 4.5 is the use of non-immersive VR to represent choice scenarios. This improves substantially the realism of the context the respondent has to evaluate, and so it increases the validity of the results. Our sample, made up of 1,503 respondents from different parts of the world, is much larger than those used so far to investigate the local exit choice process in stated preference study (see Table 4.5). Even though some demographics of our sample are homogeneous (most of the participants are under 30), our sample is more heterogeneous than previous studies listed in Table 4.5 in terms of nationalities. This heterogeneous gives the possibility of exploring general features of the decision making process, which could be bounded by cultural attributes as in the existing dataset. However, the results may be biased by the other demographic characteristics of the sample, in particular by the fact that most of the respondents are under 30 year. In this work, no significant difference between the choices of female and male respondents has been found. However, the influence of other demographic variables (i.e. age, nationality, etc.) should be analysed in future studies.

This study was not designed with the purpose of recruiting a specific population target but with the purpose of collecting data from more than lower bound of the Efficient Design to investigate the behavioural uncertainty in local exit choice. However, using *a posteriori* analysis of the sample demographics it is possible to identify population target investigate in the survey. This model can be used for any building with population target similar to the one identify (i.e. university building, etc.). The methodology and the survey developed in this work can be used in future studies to investigate the behaviour of specific population targets defined *a priori*.

Finally, in the research field, the parameters estimated in of this study can be used as a starting point for future Stated Preference studies based on Efficient Design and using more advanced technique such as immersive VR.

5. CASE STUDY 3: LOCAL MOVEMNT CHOICES

5.1 Introduction

The simulation and modelling of pedestrian navigation has received great attention during the last two decades in the field of evacuation dynamic (Kuligowski et al. 2010). Those models can be classified into two classes: macroscopic and microscopic models (Kachroo et al. 2008a). To date, different modelling solutions have been used to model the individual behaviour of pedestrians, which can be divided into continuous, e.g., the social force model (Helbing et al. 2000) or network models, e.g., cellular automata (Torrens 2009), etc. There is not a definitive modelling approach that can be suitable for all possible scenarios to be simulated by fire engineers and crowd managers (Kuligowski et al. 2010). In fact, a specific modelling approach can be more appropriate to address a specific issue but not accurate enough to investigate several other issues. For instance, the scale of the evacuation problem (e.g., buildings versus large-scale evacuations), the infrastructure types, computational costs can be discriminant for the choice of a modelling approach rather than another (Kuligowski et al. 2010; Kachroo et al. 2008b).

Despite the ‘proliferation’ of models and the improvements in modelling techniques, the calibration of navigation models for microscopic pedestrian simulation is an issue to which a definitive standard solution has yet to be defined (Guo et al. 2010). Different calibration approaches have been used, which can be divided into macroscopic and microscopic (Schadschneider et al. 2001). Macroscopic approaches may allow the parameters of the models to be calibrated by using fundamental diagrams (Schadschneider et al. 2001) or evacuation time estimations (Guo et al. 2012). In contrast, the microscopic approaches allow a model to be calibrated through the use of experimental trajectories (Schadschneider et al. 2001; Hoogendoorn & Daamen 2009). This second approach is more reliable, but it requires a more sophisticated fitting procedure (Schadschneider et al. 2001).

There are two general numerical methods for parameter estimation which can be used: least-squares estimation (LSE) and maximum likelihood estimation (MLE) (Greene 2011). LSE identifies the set of parameters which minimizes the sum of the squares of the residuals (i.e. the difference between the observed points and the ones predicted by the model) whereas MLE is based on maximizing likelihood function (i.e. the probability of the model getting observed data by using defined parameter values). However, additional dedicated measures of relative distance error can be found in the literature (e.g. Least Absolute Deviations) (Bloomfield & Steiger 1983). Unlike LSE, which is primarily a descriptive tool, MLE is a preferred method of parameter estimation in statistics and it is an indispensable tool for many statistical modelling techniques, in particular in non-linear modelling with non-normal data (Myung 2003; Ortuzar & Willumsen 2011). In fact, MLE has many optimal properties in estimation (i.e. sufficiency, consistency, efficiency, and parameterization invariance) which are discussed by Green (2011) and Myung (2003).

Different combinations of calibration approaches and numerical methods have been used to estimate the parameters for different pedestrian navigation models. For example, Berrou et al. (2007) used macroscopic approaches to calibrate the Legion model studying pedestrian flow and density fluctuations at bottlenecks. Chu (2009) proposed a macroscopic calibration for a cellular automaton evacuation model using LSE. Seer et al. (2014) proposed a calibration of the social force model (Helbing et al. 2000) through a microscopic method and LSE using data collected by Microsoft Kinect. Johansson et al. (2007) introduced a microscopic method to calibrate pedestrian-simulation models by using an ad-hoc relative distance error, and applied the method to the social force model. Antonini et al. (2006) proposed a microscopic pedestrian model based on discrete choice modelling, and calibrated it by the MLE using an experimental dataset of pedestrian trajectories. Hoogendoorn and Daamen (2007) introduced microscopic approach to estimate the NOMAD model by using MLE. Guo et al. (2010) proposed an approach based on the LSE to calibrate their logit-type pedestrian model using sample data on the deviation angles, step velocities, and walking speed-density relations obtained from experiments. Another approach is that used by Guo et al. (2012) based on the comparison between simulated evacuation times and observed evacuation times by using LSE.

This work introduces a new methodology for the calibration of pedestrian floor field cellular automaton models. These models are fine network microscopic models based on logit formulation which have been greatly developed after the pioneering works by Burstedde et al. (2001), and Kirchner and Schadschneider (2002). In fact, different authors have developed floor field cellular automaton models to predict pedestrian behaviour in different situations (i.e. emergency and non-emergency, indoor and outdoor scenarios) (Schadschneider 2002; Papadimitriou et al. 2009; Pelechano & Malkawi 2008; Kirchner et al. 2003). However, the main limitation of these models is that they may not be calibrated with experimental data and whether they are, they are not completely calibrated by using observed data (i.e. most of the time only a few parameters are calibrated). The present work introduces a methodology to estimate all the parameters included in these models by defining a likelihood function and using observed trajectories (i.e. microscopic approach). Moreover, the proposed methodology allows different model specifications to be compared in terms of fitting. A calibration example is presented in order to make a comparison between different model specifications using quantitative criteria.

5.2 Modelling Assumptions and Likelihood Function

The proposed methodology is applied to the existing floor field cellular automaton models for pedestrian dynamics. The basic structure of these models is the multinomial logit probability formulation described in Section 2.3. Since many different formulations and solutions have been proposed, the aim of following subsection (i.e. 5.2.1) is to generalize these formulations in order to build a general likelihood function as described in subsection 5.2.2.

5.2.1 Floor Field Cellular Automaton Models

The existing floor field cellular automaton models for pedestrian dynamics (Burstedde et al. 2001; Kirchner & Schadschneider 2002) assume the classical fine network discretization, in which the walkable space is divided into cells which can either be empty or occupied by exactly one pedestrian. To date, different cell shapes (i.e. triangular, square, hexagonal, etc.) have been used (Torrens 2009). A squared mesh is used in this work given its simple implementation, although the methodology can be applied for any cell shape. Another assumption that need to be taken into account is the definition of the neighbourhood defining the possible movements for a pedestrian (e.g., Moore or von Neumann) (Gwizdałła 2015). In the present work, a Moore neighbourhood is used since it allows more movement directions (i.e. 8) if compared with the von Neumann neighbourhood (i.e. 4). However, it is also possible to use the proposed methodology assuming the von Neumann movement directions.

Each agent can be located in one single cell (C_{ij}) at each time-step or more than one cell can be occupied by a single agent (whenever the cell size is smaller than the pedestrian size) (Guo et al. 2012; Kirchner et al. 2004). In the present work, the cell size matches with the pedestrian size (i.e. each agent can be located in one single cell) in order to have a simpler formulation, although the methodology can be applied when the cell size does not match the pedestrian size.

Each agent can move to one of its unoccupied neighbour cells (C_{rs} where r=i-1, i+1, s=j-1, j+1) or wait at its current one at each discrete time step interval (Figure 5.1). These transition rules are based on probabilities (p_{ij}) which are functions of the floor field. The floor field can be divided into two parts, namely Static and Dynamic (Burstedde et al. 2001; Kirchner & Schadschneider 2002).

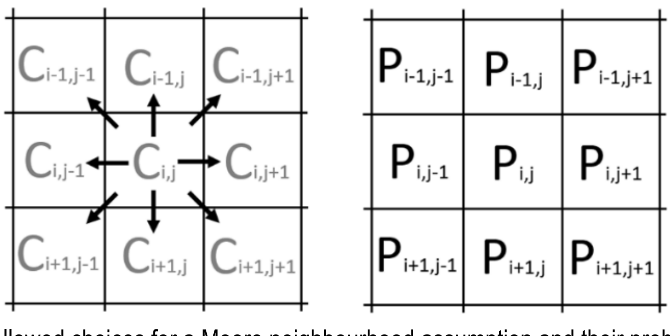


Fig. 5.1 - Allowed choices for a Moore neighbourhood assumption and their probabilities.

The static floor field is generally used to define regions of space which are more attractive (i.e. pedestrians' goals), such as an emergency exit or shop windows (Kirchner & Schadschneider 2002). It does not evolve with time and it does not depend on the presence of other pedestrians. It depends only upon the space and the goal of the *q* pedestrian and the presence of fixed obstacle (i.e., walls) (Burstedde et al. 2001). The value of *S* for $\boldsymbol{C_{ij}}$ for *q* pedestrian can be generalized as follows:

$$S_{ij}^{q} = f_s(\boldsymbol{C_{ij}}, g^q, \boldsymbol{x^o} | \boldsymbol{\theta_S}) \qquad \text{Eq. 5.1}$$

where:

$\boldsymbol{C_{ij}} = \{x_{ij}, y_{ij}\}$is the cell defined by the x_{ij} and y_{ij} spatial components;

g^q is the goal of the *q* pedestrian;

$\boldsymbol{x^o}$ is a vector including information concerning the location of fixed obstacles;

$\boldsymbol{\theta_S}$ is the vector of the parameters defining the function $f_S()$.

In pedestrian modelling, different strategies have been developed to predict pedestrian goals (i.e. exit and path choice) (Lovreglio, Fonzone, et al. 2015). For instance, different path strategies (i.e. shortest time versus shortest way strategy (Kirik et al. 2011)) can be included in Equation 5.1.

An example of a 20x20 cells room with two exits (i.e. exit 1 and exit 2) and no obstacles (Figure 6.2-a) can be used to clarify the meaning of Equation 5.1. In this case, the static floor field can have a different formulation according to the three possible goals of the *q* pedestrian (i.e. goal 1: exit 1, goal 2: exit 2, and goal 3: exit 1 or exit 2).

Assuming Euclidean distance as a criterion to define the static floor field, Equation 5.1 assumes three different formulations:

$$\begin{cases} S_{ij}^{q}(goal\ 1) = \sqrt{(x_{ij} - x_{E1})^2 + (y_{ij} - y_{E1})^2} \\ S_{ij}^{q}(goal\ 2) = \sqrt{(x_{ij} - x_{E2})^2 + (y_{ij} - y_{E2})^2} \\ \quad S_{ij}^{q}(goal\ 3) = \min(S_{ij}^{q}(E1), S_{ij}^{q}(E1)) \end{cases} \qquad \text{Eq. 5.2}$$

where x_{E1}, y_{E1}, x_{E2} and y_{E2} are the spatial coordinates defining the position of exit 1 and exit 2 respectively. Figure 5.2 shows the result of these formulations.

This example does not include the influence of fixed obstacles. However, a pedestrian could prefer to not get too close to an obstacle (e.g., a wall) given the so-called "effective width" principle (Pauls 1980). This can be represented by adding an extra term in Equation 5.2 that makes pedestrians less likely to occupy cells close to the wall or obstacles, or using different metrics (i.e. Manhattan, Dijkstra (Dijkstra 1959), etc.) (Alizadeh 2011; Kirchner & Schadschneider 2002).

The *dynamic floor field* is a virtual trace left by the pedestrians through dynamic formulations defining its diffusion and decay (Kirchner & Schadschneider 2002). Therefore, it depends upon the space and the position ($\boldsymbol{C_{ij}^{p}}$) of other *p* pedestrians (p≠q, p=1,…,P), the personal characteristics of the *q* pedestrian (i.e. gender, age, etc.) and other *p* pedestrians (i.e. leader, etc.) and other factors affecting the *q* pedestrian (e.g., fire (Li et al. 2008)) . The value of the dynamic floor field for $\boldsymbol{C_{ij}}$ for a *q* pedestrian can be generalized as follows:

$$D_{ij}^{q} = f_D\left(\boldsymbol{C_{ij}}, \boldsymbol{C_{ij}^{p}}, \boldsymbol{x^{q}}, \boldsymbol{x^{p}}, \boldsymbol{x^{f}} \middle| \boldsymbol{\theta_D}\right) \quad p = 1, \dots, P \qquad \text{Eq.5.3}$$

where:

$\boldsymbol{x^{q}}$ is the vector including personal characteristics of the *q* pedestrian;

$\boldsymbol{x^{p}}$ is the vector including personal characteristics of the other *p* pedestrians;

$\boldsymbol{x^{f}}$ is the vector including other factors;

$\boldsymbol{\theta_D}$ is the vector of the parameters defining the function $f_D()$.

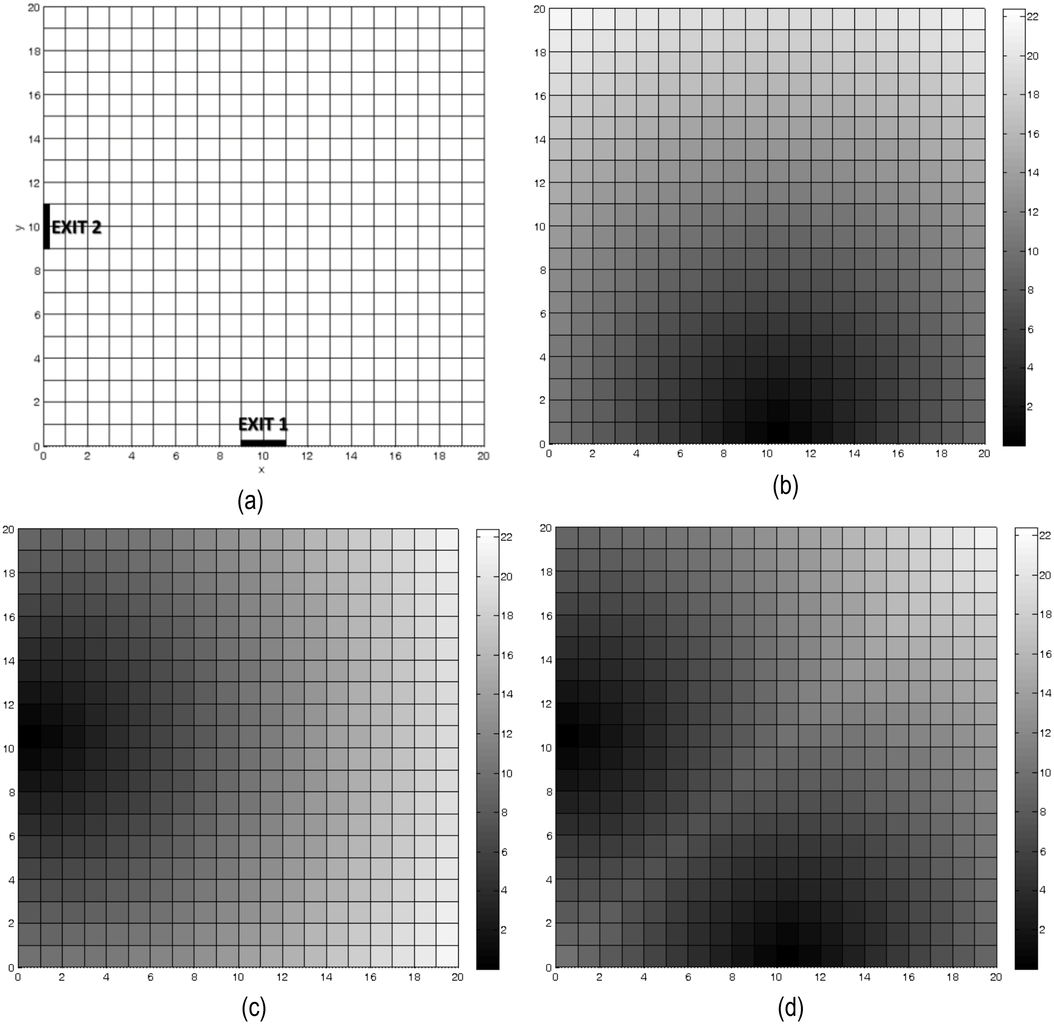


Fig. 5.2 – Static floor fields for 20x20 cells room with two exits for a pedestrian having (a) Exit 1, (b) Exit 2 and (c) both of them as goal.

In this work, the dynamic floor field is assumed to include all the interactions of a pedestrian with all the dynamic elements included in the environment (e.g. other pedestrians, fire, smoke, etc.). Therefore, Equation 5.3 can include all the social interactions affecting pedestrian behaviours such as leader-follower behaviours, and proxemics behaviour (Ezaki et al. 2012).

The probability of q pedestrian choosing the ***C_{rs}*** cell is here represented using a multinomial logit formulation (Burstedde et al. 2001; Kirchner & Schadschneider 2002):

$$p_{r,s}^{q} = \frac{e^{(k_S S_{r,s}^{q} + k_D D_{r,s}^{q} + f_{r,s}(\boldsymbol{x^n}|\boldsymbol{\theta}_N))}(1-\gamma_{r,s})\delta_{r,s}}{\sum_{(r,s)} e^{(k_S S_{r,s}^{q} + k_D D_{r,s}^{q} + f_{r,s}(\boldsymbol{x^n}|\boldsymbol{\theta}_N))}(1-\gamma_{r,s})\delta_{r,s}} \qquad \text{Eq. 5.4}$$

$$r = i-1, \dots, i+1;$$
$$s = j-1, \dots, j+1$$

where:

k_S is a parameter defining the weight of $S_{r,s}^{q}$for the choice of $\boldsymbol{C_{rs}}$ which could depend on the personal characteristics of the q pedestrian (i.e. $k_S(\boldsymbol{x^q})$);

k_D is a parameter defining the weight of $D_{r,s}^{q}$for the choice of $\boldsymbol{C_{rs}}$ which could depend on the personal characteristics of the q pedestrian (i.e. $k_D(\boldsymbol{x^q})$);

$f_{r,s}()$ is a function including the other n factors ($\boldsymbol{x^n}$) influencing the choice (i.e. inertia(Guo et al. 2012), direction of the q pedestrian (Yue et al. 2010), etc.);

$\boldsymbol{\theta_N}$ is the vector of the parameters defining the function $f_{r,s}()$;

$\gamma_{r,s}$ is a dummy variable equal to zero when $\boldsymbol{C_{rs}}$ is occupied by another pedestrian and to one when it is empty;

$\delta_{r,s}$ is a dummy variable equal to zero when $\boldsymbol{C_{rs}}$ is a blocked cell (i.e. if there is an obstacle such as a wall) and to one otherwise.

Further assumptions can be added to the ones listed above to make the model closer to reality (see, for instance, the non-homogeneous cellular automata framework proposed by Was and Lubas (2014), the different walking abilities investigated by Fu et al. (2015) the modified dynamic floor field model proposed by Guo et al. (2015)). Two other key issues of this modelling framework that need to be discussed are conflict resolution (when more than one pedestrian compete for the same cell) and multi-velocities (Fu et al. 2015). Different solutions have been proposed to solve both issues (see (Fu et al. 2015; Weifeng & Kang Hai 2007; Burstedde et al. 2001)) and can be added to the general formulation described above. The proposed methodology is applicable for different types of formulation as far as the multinomial logistic assumption shown in Equation 5.4 is kept.

In this section, a general formulation has been used to define $f_S()$, $f_D()$, and $f_{r,s}()$ although they can have different formulations. Once $f_S()$, $f_D()$, and $f_{r,s}()$ have been defined, $\boldsymbol{\theta_S}$,$\boldsymbol{\theta_D}$,$\boldsymbol{\theta_N}$, k_S and k_D need to be calibrated. This issue is addressed in this work by using navigation data (e.g. experimental data-sets or pedestrian trajectories from actual observations) and MLE by using the formulation described in the following section.

5.2.2 Likelihood function

Let $\boldsymbol{T^q} = \{\boldsymbol{C_1^q}, \dots, \boldsymbol{C_t^q}, \dots, \boldsymbol{C_n^q}\}$ be the n-vector including all the observed cells occupied by a *q* pedestrian for each consequential time step (t=1,…,n) to achieve his goal g^q and interacting with other *p* pedestrians (*p*=1,…,*P*) occupying $\boldsymbol{T^p} = \{\boldsymbol{C_1^p}, \dots, \boldsymbol{C_n^p}\}$ cells during the same time steps. Therefore, the probability of *q* pedestrian passing from $\boldsymbol{C_i^q}$ to $\boldsymbol{C_{i+1}^q}$can be defined using Equation 5.5:

$$P(\boldsymbol{C_i^q} \rightarrow \boldsymbol{C_{i+1}^q}) = \\ = p^q(\boldsymbol{C_i^q}, \boldsymbol{C_{i+1}^q}, g^q, \boldsymbol{C_i^p}, \boldsymbol{x^o}, \boldsymbol{x^q}, \boldsymbol{x^p}, \boldsymbol{x^f}, \boldsymbol{x^n} | \boldsymbol{\theta_S}, \boldsymbol{\theta_D}, \boldsymbol{\theta_N}, k_S, k_D) \\ p = 1, \dots, P \qquad \text{Eq. 5.5}$$

This probability depends on the position of the *q* pedestrian ($\boldsymbol{C_i^q}, \boldsymbol{C_{i+1}^q}$), his/her goal ($g^q$), the position of all other *p* pedestrians ($\boldsymbol{C_i^p}$) and all the variables ($\boldsymbol{x^o}, \boldsymbol{x^q}, \boldsymbol{x^p}, \boldsymbol{x^f}, \boldsymbol{x^n}$) defined in Equation 5.3 and 5.4 which can be observed and collected (i.e., known values). Therefore, the probability of having the $\boldsymbol{T^q}$ trajectory can be defined as the product of the single choices ($\boldsymbol{C_i^q} \rightarrow \boldsymbol{C_{i+1}^q}$) (i.e. panel data (Train 2009)):

$$P(\boldsymbol{T^q}) = \prod_{\boldsymbol{i=1}}^{\boldsymbol{n-1}} P(\boldsymbol{C_i^q} \rightarrow \boldsymbol{C_{i+1}^q}) \qquad \text{Eq. 5.6}$$

However, some of the parameters ($\boldsymbol{\theta} = \{\boldsymbol{\theta_S}, \boldsymbol{\theta_D}, \boldsymbol{\theta_N}, k_S, k_D\}$) defining the $P\left(\boldsymbol{C_i^q} \rightarrow \boldsymbol{C_{i+1}^q}\right)$ can have their own random distribution (i.e. random parameter models (Train 2009; Greene 2011; Hensher et al. 2005)). Therefore, the unconditioned probability can be defined as (Train 2009):

$$\bar{P}(\boldsymbol{T^q}) = \int P(\boldsymbol{T^q}|\boldsymbol{\theta}) f(\boldsymbol{\theta} \,|\, \boldsymbol{\alpha}) \, d\boldsymbol{\theta} \qquad \text{Eq. 5.6}$$

Where *f()* is the probability density function of $\boldsymbol{\theta}$ parameters whereas $\boldsymbol{\alpha}$ is the vector of the parameters characterizing the probability distribution *f()*. Since Equation 5.7 has not a closed formulation, it is possible to use a Monte Carlo approach to simulate $\bar{P}(\boldsymbol{T^q})$ (Train 2009; Hensher et al. 2005). Let $\boldsymbol{\bar{\theta}_i}$ be one of the R draws from $f(\boldsymbol{\theta} \,|\, \boldsymbol{\alpha})$, the simulation of $\bar{P}(\boldsymbol{T^q})$ can be calculated using the following equation:

$$\dot{\boldsymbol{P}}(\boldsymbol{T^q}) = \frac{1}{R} \sum_{i=1}^{R} P(\boldsymbol{T^q}|\boldsymbol{\theta_i}) \qquad \text{Eq. 5.7}$$

The likelihood function associated with the Q observed *q* pedestrians can be written as:

$$L(\boldsymbol{\theta_S}, \boldsymbol{\theta_D}, \boldsymbol{\theta_N}, k_S, k_D) = \prod_{\boldsymbol{q=1}}^{\boldsymbol{Q}} \dot{\boldsymbol{P}}(\boldsymbol{T^q}) \qquad \text{Eq. 5.8}$$

The variables of this function are the parameters that need to be calibrated (i.e., $\boldsymbol{\theta_S}, \boldsymbol{\theta_D}, \boldsymbol{\theta_N}, k_S, k_D$). These parameters can be estimated by maximizing *L()* by using several optimization methods (Greene 2011). For convergence reasons, it is more common to use the log-likelihood function rather than the likelihood function itself (Hensher et al. 2005):

$$LogL(\boldsymbol{\theta_S}, \boldsymbol{\theta_D}, \boldsymbol{\theta_N}, k_S, k_D) = \sum_{\boldsymbol{q}=\mathbf{1}}^{\boldsymbol{Q}} \boldsymbol{log}(\dot{\boldsymbol{P}}(\boldsymbol{T^q})) \qquad \text{Eq. 5.9}$$

5.3 Dataset

A dataset is here presented to provide an application of the proposed methodology. This is made using pedestrian navigation data (i.e. pedestrian trajectories) collected in a VR experiment. More information about the experiment can be found in Ronchi et al. (2015). In the present case study, the scope is to analyse pedestrian navigation of single pedestrians in the proximity of emergency exits in case of evacuation, i.e., the trajectories adopted by evacuees when approaching emergency exits.

5.3.1 The VR experiment

The VR experiment was carried out in VR laboratory of Lund University (Sweden) in 2014, where participants were immersed in a VR environment. The VR laboratory consists of a main hall (200 m^2 with a 7 m high ceiling) and a room for development and instruction to participants. The laboratory includes a Cave Automatic Virtual Environment, i.e. the Black Box. This technology consists of a back projection system with three screen segments, each 4 m wide. In addition, the VR environment is also projected on the floor (see Figure 5.3). The VR environment is projected using polarized light to generate a 3D view of the environment. Participants navigated the VR environment using a joypad and their position is monitored in real time by the navigation software. The VR environment consisted of a portion of a road tunnel based on the design of a real world project and it was drawn using a 3D modelling software (SketchUp), and imported into the game engine Unity3D.

Fig. 5.3 - Test participant navigating through the tunnel evacuation scenario in the Cave Automatic Virtual Environment system.

5.3.2 Participants

A total of 96 participants took part in the experiment (68 male and 28 female). Test participants' age ranged from 19 to 64 years old (average=25.15 years and standard deviation=7.4 years). Most of them were of Swedish nationality (90.6%). The sample was mainly made of students (81 people, i.e., 84.4% of the participants), while the rest of the sample included people of different ages and professions (e.g. lecturers, technicians, managers, etc.).

5.3.3 Experimental procedure

Once the participants had arrived in the Cave Automatic Virtual Environment, they were briefly instructed on the equipment in use for the experiment (i.e. how to navigate the VR environment with the joypad). Then the navigation in the tunnel was started. Participants were asked to navigate a VR three-lane tunnel in the Cave Automatic Virtual Environment system (see Figure 5.3 and 5.4). Participants were initially located in the proximity of their car (outside the car) and their position was in the middle of two exits (Exit 1 and Exit 2 in Figure 5.4). The VR scenario had a total length of 200 m, where 100 m is the distance between the exits, which are distant 50 m from the ends of the VR scenario. Participants had to reach one of the two emergency exits navigating individually (i.e. the participants do not interact with each other or with any other agent in the scenario).The navigation ended once they had reached an emergency exit.

5.3.4 Pedestrian navigation

The maximum speed during the navigation in the VR scenario was fixed to 1.3m/s in order to match a typical average walking speed of an adult population (Korhonen et al. 2010), whereas the position of each participant in the virtual environment was recorded at a time-step equal to 0.5s. In the present study, two regions of interest have been defined in the proximity of the exit (see Figure 5.4) given the scope of the analysis (i.e. the study of pedestrian evacuation navigation in the proximity of an emergency exit).

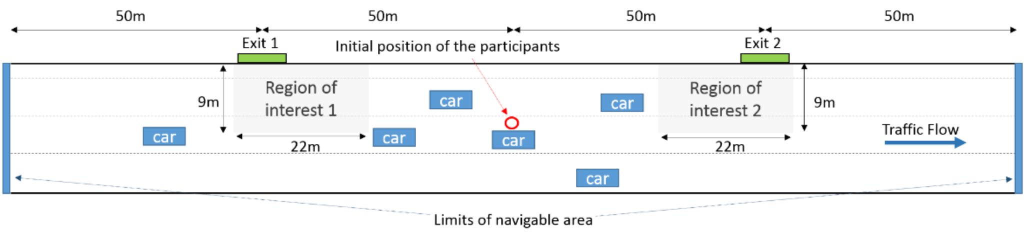


Fig.5.4 - Schematic representation of the layout of the tunnel during the experiments. The elements within the tunnel (cars, exits, etc.) are off scale to facilitate the reading of the figure.

Nine participants eventually used Exit 1, while eighty-five participants used Exit 2. Figure 5.5 shows the observed trajectories in the regions of interest. It should be noted that data from the two regions of interests have been merged in Figure 5.5 to facilitate the visualization of the trajectories. The coordinates of the centre of the exit are X=0 m and Y=0 m in the new local system of reference referring to the participants using that exit.

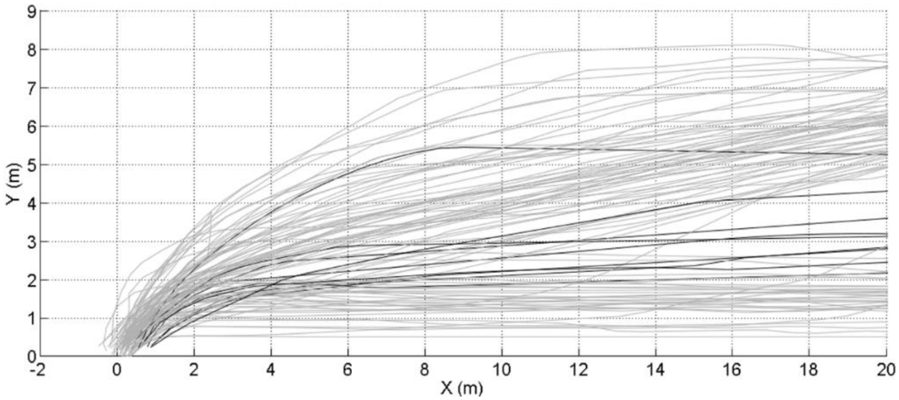


Fig 5.5 – 96 trajectories of the participants in the merged region of interest. The trajectories of 9 participants (black lines) reaching Exit 1 are mirrored and overlapped to those of the remaining 87 participants (grey lines). The trajectories are plotted in a local system of reference (X parallel to longitudinal axis of the tunnel, Y orthogonal to longitudinal axis of the tunnel) having origin centre of the exit. All measures are expressed in metres.

Two-dimensional square cells were employed to sub-divide the space in the regions of interest. The size of each cell is 0.333x0.333m^2 since the maximum number of people can stand in a square metre is 9 (Zhang et al. 2011). Frequencies of participants moving through each cell were calculated. Figure 5.6 shows the frequency of use for each cell.

The cells occupied by each participant at each time step have been analysed. Figure 5.7 shows an example of cells occupied based on a sample hypothetical trajectory. Therefore, it is possible to build up a dataset detecting all the choices made by each participant at each time step. In fact, each participant is assumed to occupy one cell (i.e. starting cell) and to occupy one of 9 possible cells (i.e. to move to one of the 8 neighbouring cells or to remain in the starting cell) every time step. Therefore, it is possible to define the choices made by detecting his/her starting and final position every time step (i.e. $\boldsymbol{T^q}$, see Section 5.2.2). A total of 6239 choices were collected. Therefore, once a pedestrian model has been specified, it is possible to use this dataset to estimate parameters maximizing Equation 10.

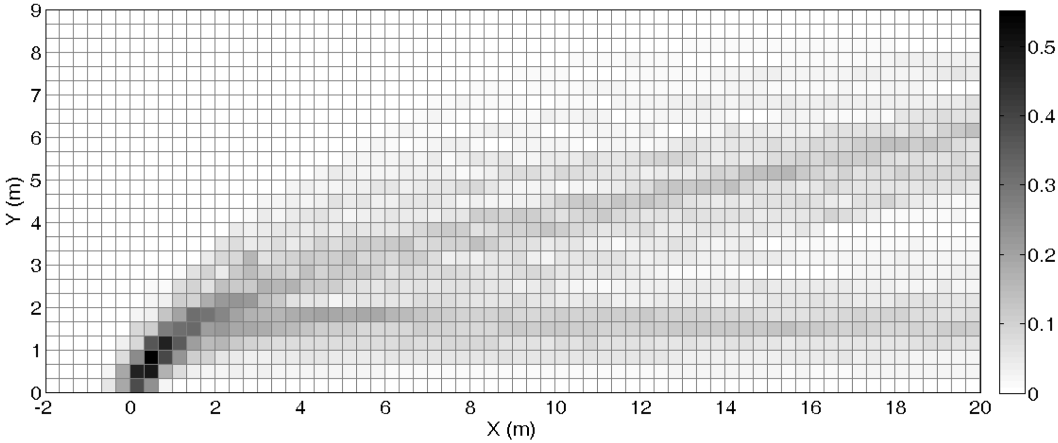


Fig 5.6 – Frequencies of participants moving through each cell of the region of interest. A participant was only counted once after entering a cell, so that participants standing in a cell would not be weighted more than participants who moved through a cell without waiting.

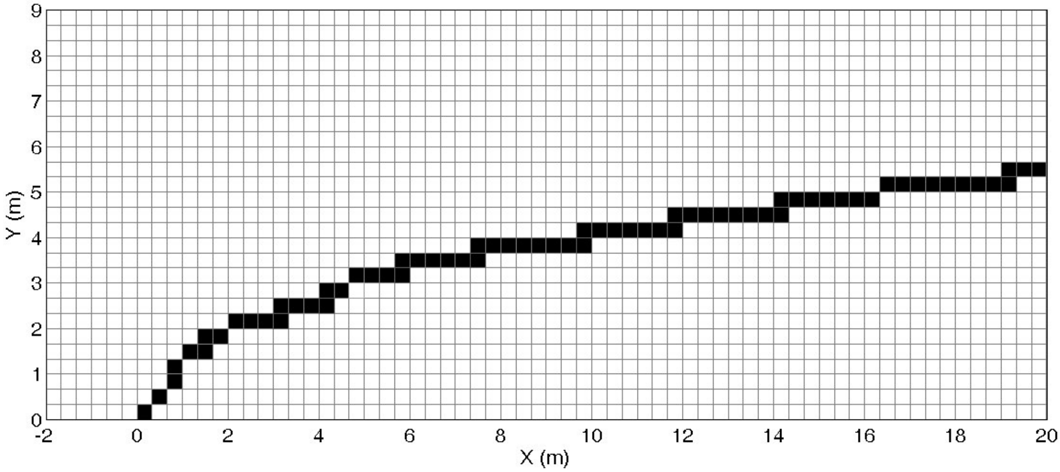


Fig. 5.7 – An example of cells occupied at each consequential time step following a sample hypothetical trajectory.

5.4 Model Calibration

5.4.1 Model Specification

In this experiment, the participants navigated in an environment which did not included any other *p* pedestrians (i.e. individual navigation) or factors ($\boldsymbol{x^f}$) that can affect the participants. Therefore, only the parameters included in static floor field (Equation 5.2) and the cellular automaton model (Equation 5.4) can be calibrated.

In this work, the static floor field is assumed to have the following formulation:

$$S_{ij}^{q} = \sqrt{(x_{ij} - x_E)^2 + z\,(y_{ij} - y_E)^2} \qquad \text{Eq. 5.11}$$

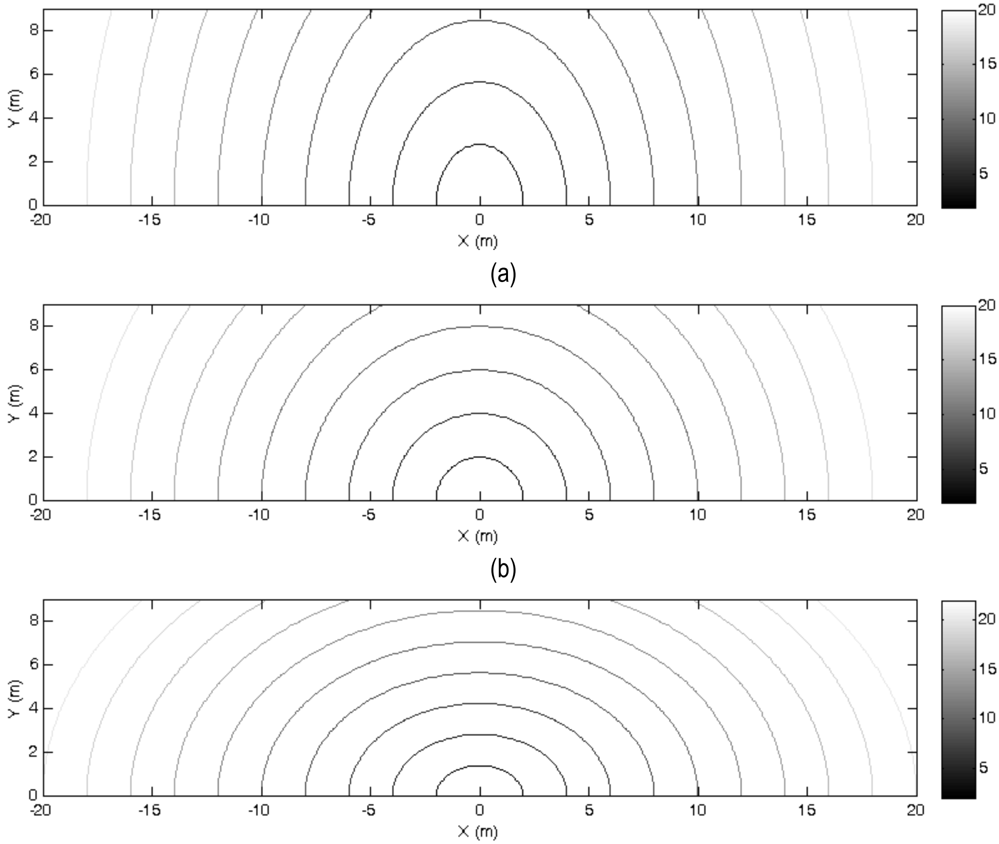
This function is not influenced by the goal of the pedestrian since there is a single goal (i.e. the evacuation exit defined by the coordinates: x_E and y_E). Then, it is a generalization of the widely used Euclidean metric (i.e. radial floor field). This metric is chosen in this example since there is no obstacle in the region of interest (Alizadeh 2011; Kirchner & Schadschneider 2002). In fact, if *z* (i.e. distortion parameter) is equal to one then the field is defined by the Euclidean distance. Figure 5.8 shows the static floor field for *z* equal to 0.5, 1 and 2 respectively.

The cellular automaton model used in this model is defined by the following equation:

$$p_{r,s}^{q} = \frac{e^{(k_s S_{r,s}^{q})}(1-\gamma_{r,s})\delta_{r,s}}{\sum_{(r,s)} e^{(k_s S_{r,s}^{q})}(1-\gamma_{r,s})\delta_{r,s}}$$

$$r = i-1, \dots, i+1; \qquad \text{Eq. 5.12}$$
$$s = j-1, \dots, j+1$$
$$k_s \sim N(\mu_k, \sigma_k)$$

The model proposed in Equation 5.12 assumes that pedestrians could have different interactions with the static floor field. In fact, k_s is assumed normally distributed. The dynamic floor field has been not included in Equation 5.12 since the exemplary dataset in use does not include interactions between pedestrians.



(a)

(b)

(c)

Fig.5.8 – Static floor field defined by Equation 11 for (a) z=0.5, (b) z=1, and (c) z=2

Then, the log-likelihood function defined by Equation 5.10 can be calculated for the proposed case study by using the information concerning the cells occupied by each participant at each time step.

Both conflict resolution and multi-velocities described in Section 5.2.1 are not taken into account in this work. In fact, the former cannot be investigated since participants navigate individually without competing. The latter is not taken into account because the participants navigate at the maximum velocity (i.e. 1.3m/s) during almost the entire navigation. However, the model takes into account the possibility that a pedestrian can stop or reduce his/her speed since s/he is allowed to occupy the same cell for more than one time iteration (see Equation 5.4).

5.4.2 Parameter Estimation

Different nested models (i.e. models in which the degree of complexity can be decreased by imposing a set of constraints on the parameters) are estimated in this work by using several assumptions for the *z* parameter introduced in Equation 5.11 (see Table 5.1).

Case 1 in Table 5.1 corresponds to a static floor field defined by the Euclidean distance assuming *z* equal to one. The second case assumes that the *z* corresponds to any possible constant value. In cases 3-4, it is assumed that the *z* is function of the *X* (i.e. longitudinal distance from the exit) corresponds to different polynomial formulations (i.e. degree of a polynomial = 1, …,2). The formulation of k as function of X has been selected since, in general, pedestrians tend to move following the longitudinal direction of the tunnel when they are far from the exit and they start modifying their trajectories once they are ‘close’ to it (Fridolf, Ronchi, et al. 2013).

Tab. 5.1 – Assumptions for k parameter (see Equation 5.11)

Case	Formulations
1	$z = 1$
2	$z = a$
3	$z = a + b \cdot abs(X)$
4	$z = a + b \cdot abs(X) + c \cdot X^2$

In this work, the Quasi-Newton method called Broyden–Fletcher–Goldfarb–Shanno (BFGS) is employed to find the value of the parameters maximizing the log likelihood function (Greene 2011). This method allows the Hessian to be estimated for the optimal solution. Therefore, it is possible to verify whether the parameters defining floor field and cellular automaton model are statistically different from zero by using t-test (Greene 2011).

The estimated parameters for the 4 cases are shown in Table 5.2. Considering the model specification proposed in this study (see Equation 5.11 and 5.12 and Table 5.1), the parameters that need to be estimated are: μ_k (i.e. the mean value of the normal distribution defining k_s, see Equation 5.12), σ_k (i.e. the standard deviation of the normal distribution defining k_s, see Equation 5.12), *a*, *b* and *c* (i.e. parameters defining the functional dependence of *z* from *X*, see Table 5.1). Table 5.2 also includes the value of the log-likelihood (LL) for a model in which all parameters are null (see case 0). In this case, a pedestrian randomly selects the next cell. This value has been estimated in order to calculate the adjusted McFadden R squared (AdjR^2). AdjR^2 suggests the level of improvement over the intercept model (i.e. case 0) offered by the given models (i.e. cases 1-4) (Hensher et al. 2005). Since the estimated models are nested, it is possible to use the likelihood ratio test (LRT) to compare the fit of those models. Each model was compared with the previous one in order to verify whether the increased degree of complexity fits significantly better the data (i.e. case 1 is compared with case 0, case 2 with case 1 and so on).è’

5.4.3 Model explanation

Table 5.2 shows that the model defined by case 1 (i.e. radial floor field) results in the lower fitting of the data with an AdjR^2 equal to 0.357. Differently, the models proposed in cases 2-4 demonstrate that there is a better agreement when the *z* parameter has a value lower than 1 (Figure 5.9). Moreover, the models defined in cases 3 and 4 show that this parameter decreases with the distance from the X axis. This result is in line with the fact that the z parameter tends to zero for very high value of X. In fact, setting z=0 in Equation 5.11 the floor field is defined by parallel lines which are orthogonal to the X axis whereas the stream lines are parallel to the X axis. In other words, results show that a modified Euclidean metric ($z \neq 1$) performs better than the classical Euclidean metric ($z=1$) when there are no obstacles in the navigation.

Tab. 5.2 – Estimated parameters for the four cases

	0	1	2	3	4
LL	13708.0	-8816.0	-8199.6	-8192.2	-8171.8
μ_k*	-	-6.0440	-8.3190	-8.3690	-8.3700
p-val	-	0.0000	0.0000	0.0000	0.0000
σ_k*	-	0.0000	0.0000	0.0000	0.0000
p-val	-	1.0000	0.9990	1.0000	1.0000
a	-	1.0000	0.2940	0.3380	0.4270
p-val	-	fixed	0.0000	0.0000	0.0000
b	-	-	-	-0.0030	-0.0190
p-val	-	-	-	0.0000	0.0000
c	-	-	-	-	$3.0 \cdot 10^{-4}$
p-val	-	-	-	-	0.0000
AdjR^2	-	0.3570	0.4010	0.4020	0.4040
LRT**	-	0.0000	0.0000	0.0000	0.0000

* k_s is assumed normal randomly distributed, i.e. $k_s \sim N(\mu_k|\sigma_k)$.
** each model is compared with the previous one: LRT($case_i$ vs. $case_{i-1}$) (i.e. case 1 is compared with case 0, case 2 with case 1 and so on)

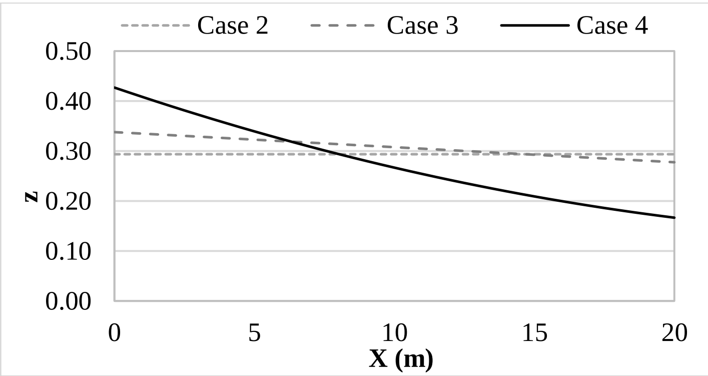


Fig. 5.9 – Variation of *z* parameter along the longitudinal distance from the exit (i.e. X) for case 2 (i.e. *z* is assumed constant), case 3 (i.e. *z* decreases linearly with X) and case 4 (i.e. *z* decreases quadratically with X) defined in Table 1.

Table 5.2 shows that the model which better fits the observed trajectories in terms $AdjR^2$ is that described by the case 4. However, since $AdjR^2$ does not predict whether this model makes a significant contribution respect to the others, the likelihood ratio test is used to compare the estimated nested models. The results of this test show that all models (i.e. cases 1-4) improve the fitting of the data if compared with the previous case (see LRT in Table 5.2). Therefore, the model described by case 4 best fits the data. This model assumes that the z parameter changes following a quadratic function of X passing from 0.43 for X=0m to 0.17 for X=20m (Figure 5.9). Figure 5.10 shows the level lines and streamlines for the floor field defined by the case 4. The streamlines show that a pedestrian does not move following a radial path (i.e. following a linear path) but s/he prefers to walk increasing his/her steering with the decrease of the longitudinal distance (i.e., X) from the exit following a curved path.

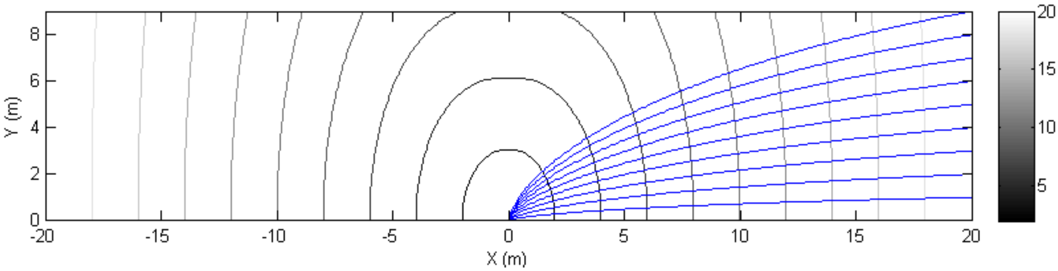


Fig. 5.10 – Estimated static floor for case 4 (see Table 2) in grey and streamlines in blue.

Finally, Table 5.2 shows the improvements of $AdjR^2$ for cases 3 and 4 are marginal, even though they are statistically significant. Therefore, a modeller could prefer a simpler model (i.e., case 2) to save computational power.

5.5 Discussion

The methodology proposed in this chapter allows all the parameters defining a floor field cellular automaton model to be calibrated by using observed experimental trajectories (i.e. microscopic calibration). In fact, the parameters defining both static and dynamic floor field (see Equation 5.2 and 5.3) and the cellular automaton model (see Equation 5.4) are selected by maximizing the log-likelihood function defined in Equation

5.10. The proposed methodology is based on MLE since it is deemed to be more suitable for this optimization problem if compared with LSE (i.e. logistic regression) (Greene 2011).

Covariance matrix of the parameters are also estimated by using the hessian of the log-likelihood function (Greene 2011). Therefore, it is possible to verify whether the estimated parameters are statistically different from zero by applying a statistical test (e.g. t-test). This is a strength of the methodology since it introduces quantitative criterion to prove the statistical need for new parameters included in their navigation models (Chu 2009; Schadschneider & Seyfried 2010).

A strength of the proposed methodology is that it allows different model specifications to be compared (i.e. to test the fitting of different models with experimental data) by using different statistical methods. The likelihood-ratio test can be used if the models under consideration are nested whereas different statistics (e.g. Akaike's information criterion, Bayesian information criterion, etc. (Greene 2011)) can be used to compare non-nested models. Therefore, this methodology allows the comparison of both static and dynamic floor fields (see Equation 5.2 and 5.3) as well as cellular automaton models (see Equation 5.4).

The present methodology can also be used to compare the same model using different datasets (i.e., real experiment versus VR experiment; non-emergency versus emergency situations, etc.). This overcomes a limitation of the present study, i.e. the sources of uncertainties in experimental data-sets (e.g., VR navigation may not correspond to real pedestrian navigation, given the use of joypad, there may be uncertainties in the collection of trajectories in a real evacuation experiment, etc.). Moreover, the type of navigation (i.e. non-emergency versus emergency situations) can affect the value of the estimated parameter in different manners.

The present work improves the classical logit formulation of the cellular automaton models by introducing random parameters (i.e. mixed-logit model) using the random parameter formulation discussed in Section 2.3.

The proposed methodology requires observed data which can be difficult to collect (Lovreglio, Ronchi, et al. 2014; Chu 2009). A solution to this issue could be the creation of an open data-set to test different models as it is commonly done in the image processing field (e.g. FERET database (Phillips et al. 1998)). However, this may open a discussion concerning the quality of the datasets themselves (which involves the validity of the data-collection methods, uncertainties) and if those datasets can be used to represent behavioural uncertainty (i.e., the uncertainty caused by the presence of human factors) (Lovreglio, Ronchi, et al. 2014; Ronchi et al. 2013). One key issue that needs to be addressed in future studies is the investigation of criteria to define the reliability of the datasets to be used for model calibration (Gwynne et al. 2005). This involves several issues such as the uncertainty and limitations associated with the data collection methods used in the production of the dataset. In addition, a dataset should be representative of a specific scenario (e.g. type of building) and of a specific segment of population defined by demographic variables (e.g. age, gender, nationality, etc.). Therefore, an open research question is: 'how many and what type of trajectories are required to define a dataset reliable for a specific situation and population?'. Future studies could reply to this question by applying the proposed methodology to existing open datasets. At the moment, examples of open datasets concerning pedestrian trajectories have been released by the University of Wuppertal (experimental data-sets) (Seyfried et al. 2010; J Zhang et al. 2011; Jun Zhang et al. 2011; Steffen & Seyfried 2009) and non-experimental datasets (i.e. pedestrians were engaged in their daily activities without being aware of being recorded) collected at the Informatics Forum of the University of Edinburgh (Majecka 2009). Any dataset could be tested with the proposed methodology as far as it includes information about both trajectories and velocities and the time resolution is small enough to investigate which cell of the pedestrian's neighbourhood is selected at each time step (see Section 5.3.2).

In the exemplary implementation, different hypothetical static floor fields have been tested (see Equation 5.11 and Table 5.1). Floor fields are studied modifying the Euclidean metric using a distortion parameter (z). In this work, different polynomial formulations are compared. However, future works could investigate several other formulations (e.g.

exponential one). In fact, it could be that the formulation for z, which better fits the observed trajectories, can change in accordance with the navigation environment or pedestrian characteristics.

A limitation of this work concerns the data used for the exemplary application of the modelling framework proposed. In fact, the dataset does not allow the calibration of a dynamic floor field and conflict model since the participants navigate individually in the tunnel without interacting with other pedestrians. In fact, pedestrian navigation data in VR were obtained assuming fixed walking speeds of individuals, which did not include pedestrian interactions. Therefore, future studies are necessary to collect new datasets including more realistic pedestrian navigations and social interactions between pedestrians in order to calibrate both static and dynamic floor fields. Other future studies could address the same issue by using existing pedestrian datasets (Seyfried et al. 2010; J Zhang et al. 2011; Jun Zhang et al. 2011; Steffen & Seyfried 2009; Majecka 2009) overcoming the limitation of this work (i.e. limited sample size, the use of data only from VR). Moreover, these datasets could be useful to study different solutions for multi-velocities. In fact, this issue is not investigated in this work since the participants navigated using the maximum speed during most of their paths.

In the proposed exemplary calibration case study, a new formulation based on the random parameters is used (Equation 5.12). This formulation assumes that pedestrians have a different interaction with the static floor field by using a normal random distribution for k_S. Results show that the standard deviation of this parameter is not statistically different from zero for any of the cases (see Table 5.2). This means that this parameter is constant among the participants. Despite this tendency, the randomness of the observed trajectories (see Figure 5.5) can still be modelled since the classical floor field cellular automaton models implement a stochastic formulation (see Equation 5.4). This absence of heterogeneity for k_s (i.e. it is constant among the participants) can be due to limited number of participants involved in the navigation or be associated with the use of VR data. Future studies are needed to investigate this issue using different types of datasets (e.g., real evacuation data) and larger samples.

6. CONCLUSIONS

This thesis aims at developing new decision-making models to improve existing evacuation models by overcoming part of their weaknesses. Several authors (Groner 2004; Kuligowski 2013; Gwynne et al. 2015) have highlighted that the main issue of existing evacuation models is their scarce ability to predict evacuees' decision-making about when, where and how they move to reach a safe place during an emergency. In fact, evacuees' behavioural actions are often an input of several existing evacuation models rather than an output of these models (Kuligowski et al. 2010; Gwynne et al. 2015). To overcome such a limitation, this thesis has investigated the advantages and disadvantages of the use of Random Utility Theory to develop new evacuation decision-making models for the simulation of the evacuees' decision-making process. To pursue this goal, an analysis has been performed comparing the assumptions underpinning this theory and the behavioural assumptions in evacuation decision-making processes.

From a theoretical point of view, Section 2.1 has shown that Random Utility Theory assumptions do not conflict with the existing knowledge on evacuees' decision-making processes and that this theory can be used to develop new evacuation decision-making models for several reasons. First, this theory is suitable for microscopic approach (i.e. agent-based approach) to simulate the evacuation process since it provides a mathematical framework for disaggregated behavioural models (Cascetta 2009; Ortuzar & Willumsen 2011). Second, the analysis has highlighted that most of the decisions taken during evacuation are discrete and Random Utility Theory can be used to simulate these discrete evacuation choices since it provides one of the most used/flexible mathematical frameworks to develop discrete choice models. However, the literature has proved that this framework can still be used for modelling continuous choices by transforming them into equivalent discrete choices. This transformation may introduce some limitations. For instance, dividing the space into discrete cells as described in Chapter 5 does not allow proper investigation of scenarios characterized by high density. In fact, this approach assumes that all people are the same size as the grid cell and therefore the maximum density is an input value rather than an output of the model. Another solution to model continuous choices can be the use of a continuous spatial choice model, i.e. an extension of the discrete choice models for decision involving continuous variables (Ben-Akiva & Watanatada 1981).However, the pros and cons of such an approach have not been investigated in this thesis. Third, the paradigm of rational behaviour is in line with the findings on human behaviour in fire showing that evacuees act rationally without really panicking. However, Section 2.1.3 points out that in situations characterized by time pressure and complex decision making tasks (i.e. many possible alternatives to be analysed), evacuees may not choose the best option among those available but the one which can satisfy minimum criteria (Simon 1956; Gwynne et al. 2015). Therefore, in these circumstances a random utility model needs to be coupled with a sub-model extracting a partial choice set from the complete choice set depending on the time available to process the information. This modelling issue has not been investigated in this thesis and it could be a further development of this work as suggested in the following Section 6.2. Finally, from a modelling viewpoint, the mathematical framework derived from Random Utility Theory allows the simulation of the behavioural uncertainty related to human behaviour in fire.

In this thesis, the formulation provided by Mixed Logit Models has been used. This formulation allows the two sources of behavioural uncertainty that may affect evacuees' choices to be taken into account as discussed in Section 2.1.4. This modelling framework has then been merged in Section 2.7 with the general conceptual decision-making model identified in the introduction of this thesis (Figure 1.7). This allows the identification of the practical advantages deriving from the use of Random Utility Theory since it can provide a mathematical formulation in line with the conceptual understanding on how evacuees make choices during emergencies.

The second objective of this thesis is to reduce the gaps between real and simulated evacuations. This objective is fulfilled by developing a methodology based on Random Utility Theory (Section 2.2) linking conceptual decision-making models with existing or new behavioural data. In detail, this procedure allows the verification of whether/how a factor affects the decision-making process and the intensity of such an influence. Moreover, the proposed methodology allows the comparison of the impact of different factors on the choices. The proposed modelling methodology has been tested to investigate three different decisions in the case studies described in Chapters 3-5. Chapter 3 investigated the use of Random Utility Theory to model the decision-making process behind the decision to start investigating and evacuating whereas exit choice and the local movement choices were studied in Chapters 4 and 5, respectively. Therefore, this thesis provides an introduction to the possible applications of Random Utility Theory to model human behaviour in fire. Many other decision making processes can be investigated through the modelling approach used in this thesis as discussed in Section 6.2.

The final objective of this thesis is the identification of the data collection techniques and research methods, which can be used to collect behavioural data aimed at calibrating decision-making models. This goal was pursued in Section 2.4, analysing the existing state-of-the-art on data collection approaches. The advantages and disadvantages of different research strategies (i.e. combinations of data collection techniques and research methods) have been discussed. The impact of a research strategy on the final modelling results has been investigated by selecting three different research strategies for the three case studies. The decision to start investigating and evacuating has been investigated by combining observations and announced evacuation drills (Chapter 3) as well as exit choice using an online Stated Preferences survey (Chapter4). Finally, the local movement choices have been studied using observed pedestrian trajectories of participants in a Virtual Reality experiment.

The behavioural data used in Chapter 3 have the highest ecological validity since the evacuees were not aware of being participants in an experiment. Despite the undeniable advantage of this dataset, the main issue of this type of dataset (i.e. unannounced evacuation drills) is that the choices are inferred by researchers observing the behavioural of evacuees. For instance, in Chapter 3 the passage from behavioural states is identified using the different behavioural observations made by Nilsson and Johansson (2009). This research strategy may lead to high measurement uncertainty for both the choice (i.e. dependent variable) and external factors (i.e. independent variable). In fact, it is not easy to define which external information was internalized by each evacuee before making his/her decision. For example, in Chapter 3 each evacuee was surrounded by other evacuees and a consistent approach/rules to assess who is actually affecting his/her behaviour was not clearly defined. These issues could be solved in future experiments using more complex research strategies, e.g. interviewing the participants in unannounced evacuation drills after the experiments and linking the data from the video analysis with the data from the interviews (Lovreglio, Borri, et al. 2015).

The behavioural data used in Chapter 4 have the lowest ecological validity since these data were collected using hypothetical scenarios in the form of videos through an online survey. Despite this limitation, the research strategy adopted in Chapter 4 provides preliminary findings on the context of choice characterized by many social and environmental factors. In fact, Stated Preference surveys give researchers an insight into the interaction between several independent variables thank to the very high control of the hypothetical scenarios. These preliminary results could be very useful as a starting point for future studies based on Efficient Design and using more advanced techniques such as immersive VR.

Chapter 5 introduces behavioural data with a lower ecological validity than that in the first case study and higher than in the second case study. VR experiments represent a frontier new trend for researchers investigating human behaviour in fire (Nilsson & Kinateder 2015). However, the use of a joypad could strongly affect the navigation findings provided by this research strategy and could represent the main technical limitation of this emerging technology. An open research question regarding this technology is whether the data collected using Virtual Reality experiments can be considered equivalent to that collected using classical laboratory experiments (Nilsson & Kinateder 2015).

The last concern about all the investigated datasets regards the external validity of the findings. In fact, the generalization of the behavioural findings of the investigated case studies is a critical issue that can be addressed by applying the proposed methodology to many other case studies with different evacuee characteristics/demographics and evacuation settings. For instance, most of the participants in the experiments in case studies 1 and 3 were Swedish and this factor may affect the way in which they select an option during emergencies. In case study 2, most of the participants were under 30 and this could have an impact on their exit choice. Therefore, future studies using this methodology should recognize general behavioural paths depending on evacuee characteristics/demographics. Moreover, the three case studies investigate the behaviour in different evacuation settings (cinema theatre, underground station and road tunnel) and these layouts may have an impact on the behavioural findings of this thesis.

6.1 Implications of the Results

The improvement of existing evacuation models by developing new decision-making models and procedures to calibrate these models has several implications in the real world.

This work has implications mainly in performance-based design analysis. This analysis, which has been described in the introduction of this thesis, is applied mainly to evaluate the safety conditions of new and existing buildings during fire emergency. In fact, evacuation models have been used in several engineering contexts to improve the design of buildings such as stadia (Graat et al. 1999; Fang et al. 2011; Zhang et al. 2007), high-rise buildings (Pelechano & Malkawi 2008; Fahy 1994; Ronchi & Nilsson 2013a), stations (Shi et al. 2012; Jiang et al. 2010), tunnels (Ronchi 2012; Fridolf et al. 2015), music festival areas (Ronchi, Uriz, et al. 2015) and also to improve means of transport such as the design of ships (Galea et al. 2004; Gwynne et al. 2003; Klüpfel et al. 2000), trains (Capote et al. 2012) and aircraft (Galea & Perez Galparsoro 1994; Kirchner et al. 2003).

Moreover, evacuation models have been used to evaluate and compare the effectiveness of different evacuation systems and strategies. For instance, Ma et al. (2012) and Ronchi and Nilsson (2013b) compare different evacuation strategies for high-rise buildings based on the use of either horizontal or vertical egress components or a combination of the two using a discrete and a continuous evacuation model, respectively. Koo et al. (2013) present new evacuation strategies for a heterogeneous population evacuating high-rise building environments and compare them with a traditional simultaneous evacuation strategy.

The improvements in evacuation models have also had an impact on forensic analysis and analysis of what-if scenarios. In fact, evacuation models can be used to investigate/reconstruct the behavioural processes which occurred and identify failures, inefficiencies and possible improvements. For instance, Purser (2009) and Jiang et al. (2003) combined the results of an evacuation model and a CFD model to analyse the real case of the Mont-Blanc tunnel fire which occurred in the year 1999 and the Gothenburg fire incident in 1998, respectively. Kuligowski et al. (2011) used a multiple evacuation modelling approach to frame an understanding of actual evacuation findings on September 11, 2001.

A further implication of this work is on crowd management in buildings and transportation systems in case of emergency. In fact, the possibility of using real-time evacuation simulations or pre-simulated evacuation scenarios could be useful to manage an emergency by selecting the most effective strategy using dynamic way-finding or other messaging strategies to give evacuees instructions. This use of evacuation models is still at an initial stage of research (Galea et al. 2015). However, experiments such as the one carried out at the Sant Cugat Station in Barcelona have shown that the combination of an evacuation model and a Dynamic Signage System could reduce the evacuation time supporting the evacuees' wayfinding decisions in complex structures (Galea et al. 2015).

Beyond the general implications of this thesis listed above, it is possible to identify the implications of the results of each case study.

The first case study (Chapter 3) is an attempt to improve the representation of the pre-evacuation phase. The need for reliable predictions of the pre-evacuation time is a key issue for fire building planners and designers since this time could greatly affect the total evacuation time as shown by many studies (Purser & Bensilum 1998; Kobes et al. 2010; McConnell et al. 2010). Therefore, evacuation models have to take into account pre-evacuation time in order to make more reliable predictions of the safety conditions of buildings during fires. This is generally done in existing models by delaying agents before the actual evacuation, making them stay in their starting positions, i.e. the pre-assumed fixed time approach (Kuligowski et al. 2010). Alternatively, a more reliable pre-evacuation model, such as the one introduced in this thesis should help researchers understand emergent behaviours as well as how evacuees use a building and navigate into it to perform their protective activities (e.g. alerting other people, collecting their belongings, etc.) before the actual movement toward a safe place. Therefore, a reliable pre-evacuation model can help planners and designers to understand how design solutions (e.g. different alarm systems, notification strategies, etc.) can affect these activities and subsequently the pre-evacuation time.

The second and third case study (Chapters 4 and 5) investigate local exit choice and local movement. The improvement of the existing understanding of how evacuees select their route (i.e. identification of the factors affecting the choice and assessment of the impact of each factor on the choice) and how they navigate interacting with physical and social obstacles could have a direct impact on more precise hazard assessment (i.e. the evaluation of evacuees' life safety). In fact, evacuees' life safety can be greatly affected by their exposure to toxic products. This exposition and the derived evacuee dose of a toxic gas absorbed depend on the position of the evacuees in space over time, in relation to safe and dangerous locations in a given scenario (Ronchi, Kinateder, et al. 2015). Finally, a better understanding of exit choice can have an impact on how to compare different exit design solutions and identify the one having the highest effectiveness in relation to a design goal.

6.2 Future Research

Several limitations have been identified and discussed in Section 2.6. These limitations refer to Random Utility Theory, modelling formulation used in this thesis (i.e. Mixed Logit Models) and the behavioural data used in each case study. Therefore, future research is necessary to overcome these limitations. From a modelling point of view, this can be done by reducing the gap between behavioural theory and discrete choice models, developing a more complex theory including the paradigm of '*Homo Psychologicus*'. In fact, several studies have proved the existence of '*cognitive anomalies*' whenever decision-makers use a variety of ''quick and dirty'' heuristics to make a choice (Ben-Akiva et al. 1999; Kuligowski 2013). The paradigms of '*Homo Exonomicus'* and '*Homo Psychologicus*' have converged into an integrated approach called Dual Process Theory highlighting the existence of both a rational–analytical system and an intuitive–experiential system (Epstein et al. 1996; Starcke & Brand 2012). Therefore, a future challenge is the understanding of when both systems are used to make a choice and the developing of a more comprehensive and validated modelling formulation accounting for both systems. An additional modelling challenge is the development of a sub-model taking into account the fact that people tend to settle on a choice rather than find the optimal choice when they select an alternative among several others (Gwynne et al. 2015). This sub-model should be able to extract a partial choice set from the complete choice set depending on the time available to process the information and the evacuees' skills.

In this work, Mixed Logit Models have been used to simulate decision-makers' heterogeneity through random parameters. However, more advance modelling techniques, such as latent class models and hybrid choice models, can be used in future works to segment the decision-makers into latent classes and to investigate the impact of several latent factors on their choices. The main issue in the calibration of such a complex model is the need for adequate behavioural data including much more information on the evacuees (Lovreglio, Borri, et al. 2015). This limitation related to the behavioural data can be overcome in future studies by developing more complex research strategies aimed at having both high validity of the data and experimental control.

This thesis has investigated the use of Random Utility Theory for three selected evacuee choices in specific evacuation scenarios. Future research needs to investigate the generalization of the behavioural findings of this work. This can be done by developing further models for several other evacuation scenarios to verify whether it is possible to identify general behavioural paths affecting evacuee behaviour. Moreover, the modelling approach proposed in this thesis can be used in the future to investigate several other decisions affecting evacuee behaviour. For instance, Random Utility Theory can be used to model all the decisions identified in Section 2.1.2 and not yet investigated in this thesis, such as the actions taken to seek further information, the selection of pre-evacuation activities, etc. Moreover, the time line model described in Section 1.1.1 assumes that that an evacuation always takes place. However, there may be other behaviours that can occur such as fighting the fire, warning other people, waiting for assistance (Canter et al. 1980) or sheltering in place. The modelling solution introduced in this work can also be used to investigate all these further decisions.

This thesis investigates the advantages and disadvantages of the use of Random Utility Theory to model evacuees' decision-making process. However, it is necessary to mention that several other theories/methods have been used to address this issue in previous studies during the last decade. For example, Pan et al. (2007) use a deterministic Decision-Rule approach to define the actions taken by agents during evacuations based on perceived cues and agent's psychological factors (i.e., perceived importance, uncertainty and urgency). Ethamo et al. (2009) investigate the use of Deterministic Utility Model to simulate evacuees' exit choice. Many other studies (Sharma et al. 2008; Dell'Orco et al. 2014; Tomé et al. 2009; Lo et al. 2009) have been carried out to study the advantage of using a Fuzzy Logic approach to model uncertainty in behaviour that results from stress. Application of the Game Theory have been also introduced into the literature to investigate exit choice (Lo et al. 2006; Mesmer & Bloebaum 2014; Ehtamo et al. 2010) and collision avoidance among agents (Tanimoto et al. 2010; Zheng & Cheng 2011b; Zheng & Cheng 2011a; Shi & Wang 2013). Finally, other navigation models inspired by insect behaviour, i.e. Particle Swarm Optimization (Zheng et al. 2012; Izquierdo et al. 2009), and based on Heuristic Approaches (Degond et al. 2013; Moussaïd et al. 2011) have been introduced into the literature. Therefore, future studies are necessary to compare the use of RUT with other theories/methods used to model human behaviour in fire, highlighting the advantages and limitations of each theory and providing recommendations on its use. The behavioural statements introduced by Gwynne et al. (2015) represent a valuable reference point to evaluate the behavioural validity of the assumptions underpinning different theories/methods. Finally, future works also need to assess the possibility of merging different theories/methods to improve the predictability and validity of the final evacuation model.

Finally, this thesis represents a step forward toward the future generation of evacuation models, namely self-predictive models. This new generation of models are aimed at reducing the impact of the user on the final results provided by the models. At the moment, several evacuee choices -such as pre-evacuation time - are defined by the users before the simulation rather than predicted by the model. Therefore, this approach is strongly affected by the decisions made by the users and can lead to either too optimistic or too conservative estimation because of the lack of behavioural data to choose appropriate input settings (Kuligowski 2013). Furthermore, these modelling tasks can be aggravated by the absence of well-defined instructions in codes and regulations (Ronchi 2012). Reducing the impact of users on the outputs of evacuation models can be achieved by letting evacuation models simulate all the key factors affecting the evacuation process such as evacuees' decision-making. However, this new generation of self-predicting model relies on model input calibration. Therefore, researchers should be careful in calibrating these new models and stating for which scenarios the model has been calibrated and when it can and cannot be used. This thesis provides some means to cope with these new challenges using Random Utility Theory. However, many other future efforts are still necessary to develop a full self-predictive evacuation model.

APPENDIX

Appendix 1: Pseudo Code

```
Set agents to list of all agents included in the scenario
For each agent in agents

        Set  state(agent) to current state of the agent (i.e. normal, investigating or
        evacuating)

        # decision to investigate#
        If state(agent) = normal
                pInv = probability of investigating
                rn1 = get a random number from 0 to 1
                if rn1 <pInv
                        newState(agent) = investigating
                        print'agent start investigating'
                else
                        newState(agent) = state(agent)
                end if
        end if

        # decision to evacuate#
        If state(agent) = normal  or state(agent) = investigating
                pEvac = probability of evacuating
                rn2 = get a random number from 0 to 1
                if rn2 <pEvac
                        newState(agent) = evacuating
                        print'agent start evacuating'
                else
                        newState(agent) = state(agent)
                end if
        end if

end for each
```

Appendix 2: Pilot Survey

The levels of the variables and the hypothetical scenarios of the pilot survey are shown in Table A1 and A2, respectively.

Table A1 - Levels for each variable included in the pilot survey

Variable	Description	Levels
NCE_i* (pers)	**N**umber of evacuees **C**lose to the **E**xits	0 5 10 20
FL_i (pers/s)	**FL**ow of evacuees through the exits	0.6 1.2 1.5
NCDM (pers)	**N**umber of evacuees **C**lose to the **D**ecision-**M**aker	0 5 10
SM_i	**SM**oke near the exits	0 1
EL_i	**E**vacuation **L**ights above the exits	0 1
DIST (m)	**DIST**ance of the decision-maker from the exits	10 12 14 16
NEAR_E	Dummy variable equal to 0 if the decision-maker is closer to the right-hand exit, 1 otherwise	0 1
DIR	Dummy variable equal to 0 if the agents near the decision-maker move towards the right-hand exit, 1 otherwise	0 1

*the values refer to the end of the videos

Table A2 – Pilot scenarios

Scenario	**NCE_L**	**NCE_R**	**FL_L**	**FL_R**	**SM_L**	**SM_R**	**EL_L**	**EL_R**	**NCDM**	**DIR**	**DIST**	**NEAR_E**
1	20	0	0.9	0.9	1	1	0	0	5	1	1	20
2	10	20	0.6	1.2	0	1	0	0	5	1	0	10
3	10	0	1.5	1.2	0	1	0	1	0	0	1	10
4	5	20	1.5	0.6	0	1	1	0	0	1	0	5
5	20	5	0.6	1.2	0	0	1	1	0	0	1	20
6	10	10	0.6	0.6	1	1	1	1	5	1	1	10
7	5	10	1.2	0.9	0	0	0	1	5	1	0	5
8	5	0	1.2	1.5	0	0	1	0	5	1	1	5
9	0	20	0.9	1.5	1	0	0	1	0	0	0	0
10	0	5	1.5	0.6	1	0	1	1	5	1	0	0
11	20	10	1.2	0.9	1	0	0	0	0	1	1	20
12	0	5	0.9	1.5	1	1	1	0	0	0	0	0

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Educational background

Jan/2013-April/2016
PhD Student in Civil Engineeringat Scuola Interpolitecnica, Politecnico di Torino, Politecnico di Milano and Politecnico di Bari (Italy)
Supervisors: Prof. Dino Borri (Politecnico di Bari, Italy)
Dr. Enrico Ronchi (Lund University, Sweden)

Visiting periods:

Jun/2015-Dec/2015
Visiting Research Student at Lund University (Sweden)
Division of Fire Safety Engineering
Supervisor: Dr. Enrico Ronchi

Jan/2015-May/2015
Visiting Research Student at Edinburgh Napier University (UK)
Transport Research Institute
Supervisor: Dr. Achille Fonzone

Aug/2014-Dec/2014
Visiting Research Student at Lund University (Sweden)
Division of Fire Safety Engineering
Supervisor: Dr. Enrico Ronchi and Prof. Daniel Nilsson

Jul/2013-Aug/2014
Visiting Research Student at Edinburgh Napier University (UK)
Transport Research Institute
Supervisor: Dr. Achille Fonzone

Collaborations with researchers working at:
Lund University (Sweden), Edinburgh Napier University (UK), Cantabria University (Spain), National Research Council Canada (Canada), Dundee University (UK), ARUP (UK), Utrecht University (Netherland)

Oct/2010-Oct/2012
Master of Science in Civil Engineering at Politecnico di Bari (Italy)
Mark: 110/110 cum laude
Subjects: Building Science, Geotechnics, Transportation

Oct/2007-Oct/2010
Bachelor of Science in Civil Engineering at Politecnico di Bari (Italy),
Mark: 110/110 cum laude
Subjects: Building Science, Geotechnics, Hydraulics, Hydrology, Material Science, Transportation

Professional Achievements

Peer-reviewer for *Fire Safety Journal*, *Transportation Research Part A*, *Reliability Engineering & System Safety* and *Physics Letters A*
Member of IAFSS
Chartered Civil Engineer in Italy

Scholarships and Grants

May/2014
Winner of 7,000€ research fund by SIPD, Politecnico di Milano Torino and Bari

April/2014
Grant of 50,000SEK by C.M Lerici Foundation (Stockholm, Sweden) aimed at founding the Visiting Research period at Lund University

Jun/2012
Winner of 8,000€ scholarship by Autostrade per l'Italia (Rome, Italy).
This scholarship was awarded to the three best students from Politecnico di Bari

Technical skills and competences

Discrete Choice Modelling (Python Biogeme, NLogit)
Evacuation and Pedestrian Modelling and Simulation (FDS+Evac, Pyrosim and Pathfinder)
Virtual Reality experiment (Unity3D)
Statistics (SPSS, R, Matlab)
Programming languages: Matlab, C#, Visual Basic.NET, PHP, Javascript (Ajax and jQuery) and SQL (ability to create websites and online questionnaires)
Video analysis experiences using Aforge.NET
Operating systems: Windows, OpenSuse and Ubuntu (Linux) with basic knowledge of Shell and Bash Scripting

Language skills

Italian: Mother Tongue
English: Fluent (IELTS: 7; European level: C1)

Other research interest

CFD, agent-based modelling, behavioural modelling, econometrics, image/video processing, data analysis, artificial intelligence

Other interest

Cooking, Playing classic and acoustic guitar

List of publications

Journal papers:

Lovreglio R., Fonzone A., dell'Olio L., 2015, A Mixed Logit Model for Predicting Exit Choice during Building Evacuations, under review for *Transportation Research Part A*

Lovreglio R., Fonzone A., dell'Olio L., Borri D., 2015, A Study of Herding Behaviour in Exit Choice during Emergencies based on Random Utility Theory, *Safety Science*, Vol. 82, pp. 421–431, DOI: 10.1016/j.ssci.2015.10.015

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<u>Conference papers:</u>

Lovreglio R., Ronchi E., Nilsson D., 2015, A Mixed-Ordered Approach to Investigate Correlations Among Different Affordances in Fire Evacuation, *6th Human Behaviour in Fire Symposium* , Cambridge, UK

Lovreglio R., Borri D., Ronchi E., Fonzone A., dell'Olio, L., 2015, The need of latent variables for modelling decision-making in evacuation simulations, *IX International Workshop on Planning and Evaluation*, Bari, Italy

Mayeux A., **Lovreglio R.**, Saleh W., Fonzone A., 2015, Illegal pedestrian crossing at signalised junctions in urban areas: The impact of spatial factors, *TRB 94th Annual Meeting*, Washington, D.C., DOI: 10.13140/2.1.1534.7520

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