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Review Article

Incorporating human factors in emergency evacuation – An overview of behavioral factors and models

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ABSTRACT

Evacuation modelling has developed over time from simple engineering equations that do not consider behavioral tendencies to more sophisticated models with the potential to represent evacuation behaviors and decisions. This paper aims to lay the foundations for a more realistic representation of human factors in evacuation models, which is needed to ensure the adequacy of the infrastructure, decision processes and safety of evacuation. To provide a clearer picture of the empirical knowledge and modelling for evacuation studies, a generalized timeline is introduced. Recent behavioral evidence from empirical studies in the fields of both pedestrian evacuation and vehicular evacuations are reviewed to investigate the impact of various factors on the evacuee behavior over different phases. The consensus perspective on key behaviors that emerges is then used to review and consolidate the recent advances in evacuation modelling, in particular with respect to the formulations and techniques for representing these behaviors. Within each of these discussions, we pointed to current limitations and make corresponding suggestions on future research directions.

1. Introduction

Emergency evacuation is the process of removing people from an area of imminent or actual threat to individual safety and life to an area of safety [1]. It is a long-recognized protective strategy either prior or subsequent to a catastrophic event, which has largely evolved in recent decades and has become a key component of both social and infrastructure preparedness [2].

The evacuation process is frequently divided into the pre-travel and travel phases. The former embraces all the cues and information from the physical and social environment related to the hazard that eventually lead to the decision regarding the required action, e.g., evacuation, shelter-in-place, no action [3]. Subsequent to this decision, the travel phase then refers to the actual physical evacuation of the occupants from an area [4]. Several factors may affect the evacuation process and final outcome, including the nature and scope of the event, the features of the hazard, the features of the affected area, the notifications and information to the public, the behavior of the evacuees, as well as the planning and execution of the evacuation operational guidelines [4]. With respect to the evacuee behavior in particular, as early as Mohler [5] discussed the significance of human factors in emergency evacuation, while a more comprehensive analysis on human factors in evacuation process, focusing on possible human failures, contributing factors and prevention mechanisms, was later presented by Kennedy [6]. More recently Schatz et al. [7] and Hofinger et al. [8] addressed the issues of human factors, their associated physical, cognitive, motivational and social factors, and the need for their integration into evacuation planning and modelling. While there are differences among evacuation contexts, overall this integration has been limited and is still in its early stages, predominantly due to the lack of empirical data. More recently, IJzerman et al. [9]; for instance, highlighted the importance for social and behavioral science to utilize more tangible approaches to gain credibility when discussing policy recommendations. Similarly, more empirical evidence from a broader set of evacuation contexts is needed to support the incorporation of human behaviors, individual or/and as a collective, into evacuation modelling. Considering the lack of empirical data, new technologies, such as Virtual Reality and/or Augmented Reality, or conducting research through gaming, could be used to gather data to strengthen the models' realism.

Over time, evacuation modelling has developed from simple engineering equations that do not consider behavioral tendencies, to more sophisticated models that have the potential for representing factors that

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influence evacuee behavior and decision-making process. There is still the tendency for assumptions for uniformity and thus oversimplification with respect to the complexity of human individuals in evacuation modelling [8]. Nevertheless, the trade-off between reductionism and parsimony is always an important issue to consider. While model users may require higher level of fidelity in relation to the aim of their analysis, models also need to simple enough to be successfully used by engineers without excluding necessary aspects of human behavior [10]. Moreover, more sophisticated models always require more data for calibration and computational resources while their predictive capabilities could be disadvantaged by behavioral uncertainties [11]. In this context, this review is intended to facilitate this debate on the need for more realistic representation of evacuation behavior versus the use of simplified assumptions by presenting the recent advances in empirical evidence, in order to assist reviewing the core assumptions (i.e., theoretical foundation for the choice of factors) adopted by evacuation models. As pointed out by Haghani and Sarvi [12]; the state-of-art empirical evidence is largely dispersed and imbalanced. Most of the existing emergency evacuation studies addressing human behaviors with controlled laboratory conditions investigate a single evacuation phase only. Consequently, these studies do not sufficiently address how the behavior of evacuees may affect the overall evacuation process; in turn, the realism of existing models of the evacuation process and its implementation may be strongly limited from a human factors perspective. Nevertheless, some post-hazard field survey studies covering evacuation from start to end could offer some possibility for efficient hypothetical choice scenarios to be designed.

The aforementioned issue highlights the need to link better empirical knowledge and the engineering modelling disciplines, so as to facilitate the development and validation of behaviorally-sound evacuation modelling. To bridge this gap this paper presents a comprehensive literature review of recent empirical studies from both building evacuation (i.e., pedestrian evacuation of buildings) and large-scale community evacuation studies (i.e., vehicular evacuation of towns, cities, and metropolitan areas) offering insights to behavior; further, it points out the relevant advances in evacuation modelling in both fields. Moreover, this study for the first time discusses the overlap of the evacuation phases from the perspective of the different involved actors, i.e., evacuation coordinators and individual evacuees, and examines their interactions conjointly. The timeline serves as the grounds to link the different phases of an evacuation to the associated evacuation models. We expect this study to serve as a benchmark of the lead and lag gaps between empirical knowledge and evacuation models by grasping ideas of empirical data availability and abundance, scrutinizing the theoretical assumptions, as well as the model capabilities for incorporating various behavioral aspects. It is also anticipated that the proposed timeline and the factor categorization will inspire others to address the identified issues in the ways most suitable to their specific problems.

The remainder of the paper is organized as follows. Section 2 introduces a novel evacuation timeline, which accounts for both the evacuees and evacuation coordinators. The timeline also serves as a frame for an overview of evacuation modelling. Section 3 introduces a novel categorization of factors that affect the behavioral process in evacuation. By identifying and organizing the behaviors, choices, and actions taken by evacuees along the timeline, the impact from each category of factors is discussed based on recent empirical studies. Section 4 reviews the current advances in evacuation modelling in terms of their incorporation of these behavioral aspects. Concluding remarks and discussion are finally presented in Section 5.

2. The evacuation timeline

The literature contains a large number of evacuation timelines and sequence/phases related to evacuees (e.g., Refs. [3,6,13–18]), as well as evacuation coordinators (e.g., Refs. [1,4,19–21]). All timelines, despite some differences in the terminology and focus, are primarily developed on the two evacuation phases, i.e., *pre-travel* and *travel,* described in the introduction.

To date, the literature tends to discuss the evacuation timeline and evacuation phases emphasizing primarily the role, decisions and actions of evacuees. Further to existing literature [22–24], we propose a novel timeline in which the indispensable role of emergency coordinators is also included. We argue that there are significant interactions between these two sets of actors (i.e., evacuees and coordinators) and a clear overlap of their respective phases during an evacuation so that they should be examined in conjunction. Based on information derived from the literature [1,4,6,13,14,19,25], Fig. 1 illustrates the evacuation timeline from the perspective of both the evacuees and evacuation coordinators, considering both evacuations with advanced notice and no-notice type. The shelter-in-place action is not discussed in this paper, as it is out of the scope of the evacuation modelling.

The springs, in Fig. 1, emphasize the variable duration of each phase, which strongly depends on the type of hazard/event. Hardy and Wunderlich [26] assert that all evacuations sequences exist on a continuum between an event that could be forewarning and a no-notice event. Events with warnings, e.g., hurricanes and floods, are characterized by the advance notice (up to weeks) afforded to the evacuation coordinators as well as to the evacuees to decide whether and when to evacuate an area. Events without warnings (e.g., industrial accident, terrorist attack), on the other hand, are in general unforeseeable, and provide little time (minutes) for such decisions [19]. Further, although Fig. 1 may suggest that evacuation phases are linear, the sequence of events may not always be as such. In practice, the transition among the evacuation phases can be more diffuse and overlapping e.g., evacuees change their initial protective action, for instance, switch from shelter in place to evacuation.

2.1. The evacuation timeline - the evacuation coordinators lane

While the *pre-travel* and *travel* phases are useful for constructing the timeline, a more detailed decomposition is warranted. For the coordinators, we further divide the evacuation timeline into four steps, i.e., *decision*, *notices and instructions*, *execution and monitoring*, and finally *re-entry management*. The first two steps, are in agreement with existing literature, e.g., Urbanik [27]; Urbanik [28]; Urbanik et al. [29]. The *decision* step, spans from the occurrence of the incident till the issuance of the evacuation order. During this phase the coordinators collect intelligence from the field and consider whether to order an evacuation or advise people to shelter-in-place [4]. It is worth noting that decision and notifications may occur at different times for different areas, i.e. the timeline applies to a given area, and that movement may occur independently of orders from the coordinators. (The phases and steps for the evacuees are discussed further in Section 2.2 below.)

The second coordinators' step encompasses the period immediately after the issuance of the evacuation order until the time that the actual evacuation of the occupants begins. During this phase notifications and instructions are issued to the public, including households' warning receipt and evacuation preparation advising them on the situation, that is the hazard, possible evacuation route(s) and evacuation centers, and recommended or mandatory actions. This phase may also allow for the involved population to begin their preparation to leave the affected area.

This third step covers the actual physical evacuation of the occupants from an area. The evacuation coordinators are mainly concerned about the evacuees' safety, evacuation transportation support, traffic management [23,30], and the access to and security of the evacuation zones. Execution and monitoring step could be further classified into mandatory and voluntary. The former is instructed when the risk to the population is considered too great to permit them to remain at their place/location. Voluntary evacuation, on the other hand, refers to evacuees that leave their location because of actual or perceived risk without being directed to do so. This step does also count for evacuation logistics, as discussed in Lindell et al. [31] and Wu et al. [32].

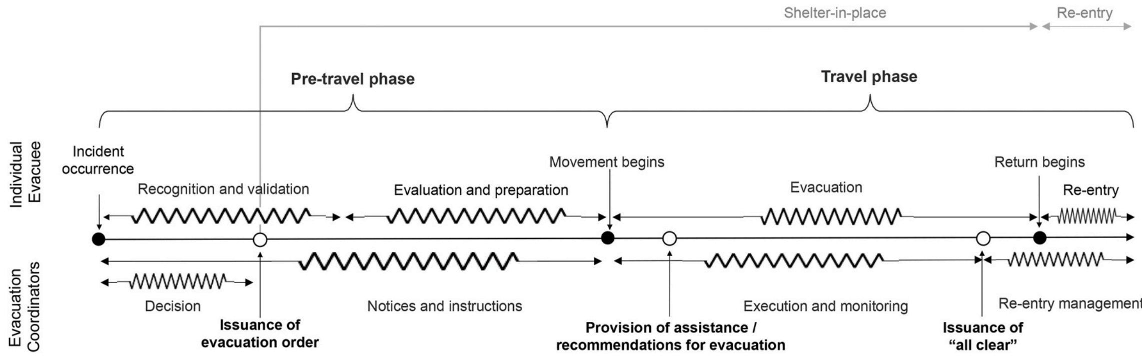

Fig. 1. The evacuation timeline for the individual evacuees and evacuation coordinators. (The black dots indicate the start of each evacuation phase from the evacuee perspective. The white dots indicate the commencement of each evacuation phase from the coordinators' perspective).

The final step of the evacuation process, that is re-entry management [33–38], includes the return to the evacuated area. In this phase the evacuation coordinators assess the affected area and issue, or not, "all-clear".

2.2. The evacuation timeline - the evacuees' lane

Similar to the evacuation coordinators, the evacuee timeline is also split into four steps, that is *recognition and validation*, *evaluation and preparation*, *evacuation*, and finally *re-entry*. The unfolding of this timeline is structured according to the Protective Action Decision Model (PADM) [23,39–41], which allows for a more comprehensive understanding of what factors affect the different stages of the evacuee decision-making process and how this effect might propagate through this process. Each phase here can be regarded as an instance of the PADM with specific protective actions (e.g., information search, protective response) investigated in the literature.

In the *recognition and validation step*, the affected population (but also others not directly affected) perceive cues from the environment or receive information. The cues may include physical signs such as smoke, flames, heat, increased level of water, or debris. Relevant information channels include messages on social media, the discussions and actions (or inaction) from others in the vicinity, and phone calls from/to family, friends or other trusted people and/or authorities. Further, the population may perceive conditions and states that are outside their usual experience, such as uncertainty, information overload, time pressure, or draw from recollections from particular past events, whether relevant or not. In this context, this step is equivalent to what is known as milling, that is to describe the process whereby individuals in unfamiliar circumstances come together to assess the situation, propose and seek coordinated actions to find a solution to their common problem [42–44].

In the second step, i.e., *evaluation and preparation*, the affected population evaluate the perceived and/or received cues and interpret the corresponding information. In addition, they define (or attempt to define) the severity of the situation and the associated risk to themselves as well as others. Finally, based on available information the population's response to the situation involves a decision on whether to evacuate, where to evacuate, how to evacuate, and when to evacuate (including the shelter-in-place option).

Once the decision to evacuate is made, the actual physical evacuation takes place. During this step the affected population executes their decisions on what to do next based on the interpretation of the cues, situations, and perceived or actual risks. If new information/cues are presented the population may discard the current actions and update their decision accordingly. The decisions may not only involve the evacuation logistics (e.g., departure time, evacuation mode, route, accommodation, destination in a large-scale community evacuation), but also relate to seeking additional information, alerting/helping others during the movement, and assisting the evacuation coordinators. Finally, the last step of the evacuation includes the safe return to the evacuated area. This phase is a less central of evacuation modelling and therefore not further discussed.

This timeline reinforces the key elements of emergency response from both the coordinators and evacuees perspectives. The evacuation phases, steps and timelines are affected by the type and size of the incident/hazard, as well as by a number of factors that affect the evacuee behavior, and to an extent the decisions and actions of the evacuation coordinators.

2.3. Overview of evacuation modelling based on the timeline

The evacuation process is a complex phenomenon due to the role of evacuees, their decisions and actions. It also encompasses the interactions between evacuees and the evacuation coordinators, the hazard conditions and environment settings. By not limiting the course of evacuation solely to evacuee decision-making, Fig. 2 introduces a framework to link the existing computational modelling based on the proposed timeline. It illustrates the three entities in an evacuation process model, namely the hazard, the evacuees, and the emergency coordinators (from top to bottom), while it also presents the interactions among them. The intended conceptual description assists in the investigation of potential interactions and factors. But it cannot be readily used as a computational prediction tool without specifying the strengths of their effects as well as their potential interactions (e.g., effect sizes), which is a potential limitation.

The top row in Fig. 2 accounts for the modelling of hazards and environmental settings, which aims at assessing the spatiotemporal pattern of the hazard and the evolving environmental conditions. Depending on the nature of the hazard, a number of hazard models have been implemented in evacuation studies, such as fire models, gas dispersion models, hydro-inundation model, and atmospheric models. For example, the spread and concentration of a chemical release can be defined by a dispersion model that includes the chemical and physical characteristics, meteorological information and the topographic characteristics in the release area [45]. The forecasting of the chemical plume along with its varying concentrations (i.e., isopleths) helps emergency planners know whom to alert and where first responders should report and develop specific action plans depending on population density, terrain, weather conditions, etc. [46]. Hence, the outcome of the modelling is crucial for determining the evacuation scope (e.g., incapacitation time in building fire), evaluating the accessibility of the network (e.g., physical barrier), engaging evacuees' decision-making and thereby impacting the effectiveness of evacuation.

This overview also ascertains the impact of emergency coordinators (i.e., authorities and entities that actively manage emergency) on shaping evacuee behaviors (bottom row). To safeguard evacuees and properties, the coordinators can opt to disseminate information, provide recommendations or binding instructions to further enhance the

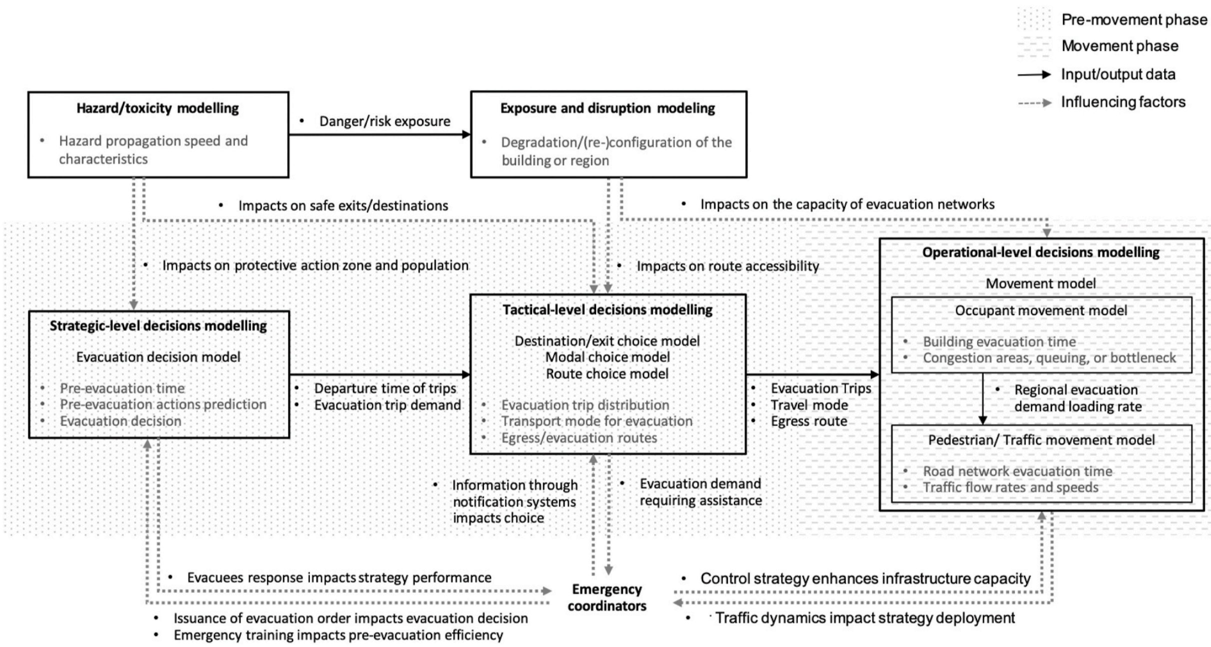

Fig. 2. Overview of modelling a regional evacuation scenario.

evacuation process. Additionally, with an in-depth understanding of critical behavioral issues, such as protective action recommendations compliance as well as shadow evacuation, the effectiveness of the disaster management policies can be strengthened. The interactions between the evacuees and emergency coordinators or building environment can be further exploited by being embedded into an optimization framework for pedestrian evacuation and design problems [47]. There has also been substantial development of simulation and optimization models that can integrate data from evacuee demand models with increasingly detailed evacuation route system models to generate evacuation time estimates [45].

As primary determinants of evacuation performance, evacuee decision-making and behaviors are represented in the middle row (the shaded areas) in Fig. 2. As the timeline unfolds, three general levels of evacuee decisions that lead to various behavioral phenomena are involved, namely *strategic*, *tactical*, and *operational* decisions [48]. In each box, a few examples are provided to illustrate the model scopes and associated outcomes, which account for the evacuees response (e.g., what decisions to make) to the hazard conditions and evacuation instructions. For example, *strategic* decision modelling is able to provide the pre-evacuation times, as well as the population taking evacuation-related actions based on the population's distinctive features. Lacking realism at this level of modelling would further impact the output accuracy of the *tactical* and *operational* levels of modelling, such as the departure times of evacuation trips, build-up and dissipation of traffic congestion, and ultimately evacuation times. Note that these decision levels (these terms) have also been applied to the decision-making of authorities (e.g., Ref. [49]); the decisions assigned to each level are different in the two cases. For instance, tactical decision-making for the authorities would include the provision of evacuation traffic management whereas for the evacuees, tactical decision-making includes destination and modal choice.

3. Factors that affect evacuation behaviors

Owing to the interdisciplinary nature of the problem, scholars from a wide range of research backgrounds have contributed to identifying the factors that influence evacuee behavior in the evacuation process. An inclusive categorization of these factors, as found in the literature, is firstly presented in this section. Organized by means of the overarching timeline and human behavior in evacuations, the influence of the factors is then discussed and compared, with a focus on recent empirical studies. The main research questions include: What are the impacting factors? And what roles do these factors play during building and regional evacuations (and the evidences)? To answer these two very broad questions, the relevant literature was primarily identified by searching literature data-bases (Google Scholar, Web of Science, Science Direct, the NIST Research Library). A set of key search terms was identified, and additional terms were added as the research progressed. The keywords used to identify relevant recent literature included: human factors, evacuation impacting factors/decision-making/behavior/actions, empirical study/evidence/data, building evacuation, large-scale evacuation, wildfire, bushfire, hurricane, evacuation timeline, pre-movement, pre-travel, pre-evacuation actions/behavior, pedestrian/evacuation dynamics. The review includes primarily post-2000 literature and few commonly referenced studies from the 1990s were also included. The selected studies were reviewed to identify the factors deemed influential in the evacuation process (i.e., a certain phase or step on the timeline). The collected studies were assessed and included if it was relevant to the topic and an important criterion was the statistical significance of impacting factors given the precision of the description of study hypothesis, quantitative data collection, and analysis methods. Since studies from a variety of fields were included at this point, some studies were excluded if there is abundant evidence for that specific type of decision-making.

3.1. Factor classification

Numerous empirical studies have addressed the questions whether and how various factors influence evacuee behavior in evacuation. These studies refer to a wide range of hazards and disasters and the behavioral process of evacuees. However, a general categorization of the factors found to impact evacuation behaviors is lacking. Here, for the first time, we introduce, such a categorization based on the three distinct facets in the evacuation process, namely the *hazard*, the *evacuees*, and the *emergency coordinators*. Compared to the few classifications in the literature [14,50,51], we provide a clearer picture of the empirical knowledge and a framework to tackle this multi-faceted topic. Table 1 presents a summary of the factors related to evacuation behavior, broadly differentiated into *individual*, *environmental*, and *interventional*

Table 1
Classification of factors relevant to evacuation.

Major factor category	Impacting Factors	Indicators or descriptions
Individual (static)	Socio-demographic	Gender, race and ethnicity, age, marital status, household size and presence of vulnerable/dependent household members, including children, the elderly, special needs individuals, and pets
	Socioeconomic	Educational attainment, employment status, household income, housing type, housing tenure, vehicle ownership
	Experience	Previous or recent evacuation experiences, frequent hazard experience, near-miss experience, etc.
	Knowledge	Understanding of hazards, emergency management policies/protocols/ procedures, familiarity with surroundings (e.g., building layout, routes, etc.)
	Abilities/ impairments	Linguistic (primary/secondary language), vision, hearing, strength, mobility, etc.
Individual (social)	Role/responsibility	Safety practices from organizational employees (e.g., department managers, safety delegates, waitresses)
	Affiliation	Social bonds, relationships, and groups, on which collaboration can be based (e. g. families, neighborhood and community groups).
Environmental	Sensory cues/ external stimuli	Smoke or fumes, heat, flames, debris, swaying, etc.
	Hazard features	Temporal (timing, duration, speed of onset, frequency, duration) and spatial (location, path, scope of impact)
	Building/ engineering environment	The physical environment facilitators/ impediments (stories, staircases, height; road furniture, traffic conditions etc.), geographic location, terrain features
	Other information and cues	Social cues, information via media and social media, personal communications (e.g. phone, e-mail)
Interventional	Official information and notices	Information, warnings, recommendations, orders (including their timing, frequency, content, channel, source, etc.)
	Authority action	Provision of evacuation (transportation) assistance, deployment of (traffic) management plans, etc.

factors.

Among the *individual* factors, two subcategories are distinguished: the *static* and *social* factors. The *static* factors are intrinsic and stable over the evacuation process. There is considerable evidence that evacuation is significantly related to *socio-demographic* factors, such as age, race, or gender, and *socioeconomic* factors, for instance, educational attainment or household characteristics. Another three personal characteristics: *hazard experience*, *knowledge*, as well as the *abilities/impairments* complete the list of the *static individual* factors. For instance, when facing different environments (e.g., buildings, transport network), evacuees tend to make use of their familiarity with the surroundings based on their knowledge, if there is any. There is a correlation/overlap between the factor classes *abilities/impairments* and *socio-demographic*; the distribution of *abilities/impairments* in a set of individuals will be related to its demographics. Both classes are included here because some studies have viewed population as a group (demographic) (e.g., foreign language barrier) while others focus on the individuals' abilities/impairments (e.g., physical strength) that would be correlated with demographic characteristics.

Apart from the above *individual* factors, the social characteristics have been receiving increased attention, due to their importance in shaping crowd behavior and important phenomena of groups [8]. Recent empirical evaluations have shown that in emergencies people are more likely to collaborate with others instead of acting individually [52] and situational altruism has been observed rather than mass panic [53]. To account for such behavior, two types of *social individual* factors are strongly involved in the evacuation process. Affiliation, which addresses the social bonds between individual evacuees (e.g. families, community organizations), and roles/responsibility that relates to their social identity.

The *environmental* factors are divided into sensory cues/external stimuli, hazard features, and building/engineering environment. Sensory cues/external stimuli such as exposure to fumes, heat, or smoke generally stimulate evacuees to take certain actions in an evacuation, often starting with information-seeking behavior. Hazard features refer to both temporal (e.g., timing, duration, moving speed) and spatial characteristics (e.g., location, impacting area, moving path) of the hazard involved. The building/engineering environment factor ranges from the layout and facilitators in buildings (e.g., stories, staircases, height) to the configurational characteristics in area networks (e.g., geographic location, terrain features, road furniture, traffic impediments).

In contrast to previous classifications this paper proposes a new category of factors, referred to as *interventional*, to capture the external influences from evacuation coordinators. This includes both information and actions from crisis response authorities, namely *Official information and notices* (involving timing, content, sources, channels) and *authority actions* (e.g., phased evacuation, provision of mobility assistance, deployment of traffic management plans).

It is worth mentioning that the causal relationships between impacting factors and evacuation process have become disentangled and yet the modelling remains complex. Classifying them into categories does not enable independent and adequate thematic analysis on each category. On the contrary, the factors that potentially influence evacuation usually interact with each other with entangling effects (e.g., the need for mediating or moderating variables such as risk perception) and can be affected by the decision making process itself [14]. Nonetheless, together with the proposed timeline, this classification greatly facilitates the identification of specific effects of impacting factors during evacuation in the next subsection.

3.2. Impact of factors throughout the evacuation process

As pointed out by Lindell et al. [45]; the fundamental principles revealing people's behavior during different phases of the evacuation process are crucial for evacuation plans. Knowledge of how the factors influence the evacuee behavior and subsequently the actions in evacuation can allow researchers to realistically represent the behavioral aspects for modelling purposes, further to support evacuation coordinators in the elaboration and implementation of management strategies. Table 2, using the overarching timeline, presents recent empirical evidence on the impact of each category of factors grouped by the specific decision-making/behaviors they affect. The reviewed empirical studies have also been compiled into 42 extracted behavioral statements (including the impacting factors as well as the type of hazard), listed in the Appendix, to further facilitate the understanding of evacuee behavior. These statements elaborate how the identified factors (i.e., statistically significant) impact the behavior or actions in evacuation within the context of the individual study. Compared to the "behavioral facts/statements" consisting of mini-theories in Kuligowski and Gwynne [94]; Kuligowski et al. [95]; these statements are solely findings from quantitative studies but not the assumption in modelling analysis necessarily.

Among the studies on the *pre-travel* phase, the field of behavioral sciences related to human psychological response to imminent emergency conditions and decision making under time-pressure and safety concerns plays a significant role. Evacuees typically engage in

Table 2
Classes of factors that affect evacuation.

Factor class	Timeline	*Pre-travel* phase			*Travel* phase
		Recognition and Validation Step	*Evaluation and Preparation* Step		*Evacuation* Step
	Main actions	Information seeking and milling	Pre-evacuation actions	Evacuate decision-making	Wayfinding/Route finding, walking/driving behaviors
Socio-demographic		Spence et al. [54] [a] Spence et al. [55] [b] Lachlan et al. [56] [b] Zhao et al. [57] [a] Spence et al. [58] [b]	Zinke et al. [59] [a] Yin et al. [60] [b]	Whitehead et al. [61] [b] Whitehead [62] [b] Lindell et al. [31] [b] Liu et al. [63] [b] Sadri et al. [64] [b] Yin et al. [60] [b] DeYoung et al. [65] [b] Lim et al. [66] [a] Maghelal et al. [67] [b] Toledo et al. [68] [b]	Sadri et al. [69] [b] Dulebenets et al. [70] [b]
Socioeconomic		Zhao et al. [57] [a] Spence et al. [58] [b]	Yin et al. [60] [b]	Whitehead et al. [61] [b] Whitehead [62] [b] Lindell et al. [31] [b] Hasan et al. [71] [b] Sadri et al. [64] [b] Yin et al. [60] [b] Lim et al. [66] [a] Maghelal et al. [67] [b]	Sadri et al. [69] [b]
Experience		Gu et al. [72] [b]	Zinke et al. [59] [a]	Hasan et al. [73] [b] Stein et al. [74] [b] Cahyanto et al. [75] [b] Sadri et al. [64] [b]	Wu et al. [32] [b]
Knowledge		Gu et al. [72] [b]	Zinke et al. [59] [a] Bode and Codling [76] [a]	Deka and Carnegie [77] [b] Stein et al. [78] [b] Downey et al. [79] [b] Cahyanto et al. [75] [b] Kim and Oh [80] [b] Lim et al. [66] [a]	Wu et al. [32] [b] Kinateder et al. [81] [a]
Abilities/impairments			Zinke et al. [59] [a]		
Affiliation			Aguirre et al. [82] [a]	Liu et al. [63] [b] Toledo et al. [68] [b]	
Role/responsibility			Aguirre et al. [82] [a]		
Sensory cues/external stimuli		Zhao et al. [57] [a]	Kuligowski and Mileti [83] [a] Bode and Codling [76] [a]	Durage et al. [84] [b] Lim et al. [66] [b] Zhang et al. [85] [b]	
Hazard features				Whitehead et al. [61] [b] Whitehead [62] [b] Lindell et al. [86] [b] Lim et al. [66] [a]	
Building/engineering environment		Zhao et al. [57] [a]	Kuligowski and Mileti [83] [a]	Lindell et al. [86] [b] Cheng et al. [87] [b] Lindell et al. [31] [b] Huang et al. [88] [b]	Ma et al. [89] [a] Sadri et al. [69] [b] Dulebenets et al. [70] [b]
Other information and cues			Nilsson and Johansson [90] [a]	Stein et al. [78] [b] Huang et al. [88] [b] Stein et al. [74] [b]	Kinateder et al. [91] [a] Kinateder et al. [81] [a]
Official information and notices				Whitehead et al. [61] [b] Whitehead [62] [b] Stein et al. [78] [b] Huang et al. [88] [b] Lindell and Perry [41] [b] Hasan et al. [71] [b] Lim et al. [66] [a] Zhang et al. [85] [b] Carter et al. [92] [b]	Sadri et al. [69] [b]
Authority action				Burnside et al. [93] [b] Kim and Oh [80] [b] Carter et al. [92] [b]	

[a] Building evacuation (i.e., pedestrian evacuation of buildings).
[b] Large-scale community evacuation studies (i.e., vehicular evacuation of towns, cities, and metropolitan areas).

information-seeking and milling in the *recognition and validation* step, as already introduced in Section 2.2. Milling refers to the process whereby individuals come together to assess the situation, propose and seek coordinated actions to find a solution to their common problem [42]. Subsequently, in the *evaluation and preparation* step they carry out pre-evacuation actions and decide whether to evacuate or not.

The evacuation process is initiated by the impacted population receiving information related to hazards. Table 2 shows the significant role of the *individual* factors on affecting information-seeking and milling, including the *socio-demographic* factors [54,55], as well as experience and knowledge [40,72]. Regarding the impact of the *socioeconomic* factors, a number of studies on the "knowledge gap hypothesis" [56,58,96] offers supporting evidence on the effect of socioeconomic status on information-seeking patterns (e.g., types of information), information sources, and message accuracy. Despite being hazard-specific and to some extent controversial (e.g., Ref. [58]), these findings provide clues and suggest approaches for further studies of information-seeking behavior in different situations. Valuable insights are provided for improving future risk and crisis communication efforts in information dissemination and interpretation across diverse audiences, especially to serve better the vulnerable and minority communities or populations that are diverse in terms of culture and attitudes. All of these *individual* factors shape further the cognitive human activities (e.g., perception, appraisal and assessment) as a result of their interaction with cues of both environmental and social contexts.

After receiving, heeding, and comprehending the hazard-related information, the impacted population is likely to continue with the initiation of protective decision-making (i.e., *evaluation and preparation* step). Depending on the urgency, as a result of the hazard features, certain problem-focused actions or emotion-focused actions are witnessed during this step, especially in the hazards with a longer lead time (e.g., hurricane, bushfire). While the *static individual* factors continue to affect the evacuee behavior, the influence of the *social individual* factors are emerging. Physical impairments and vigilance [59], for instance, impact significantly the evacuee responses initiated along the chronology of the unfolding hazard. Compared to the previous cognitive process, i.e., *recognition and validation*, the *evaluation and preparation* step involves more variables from the field of social-psychological research; as pointed out by Kuligowski [97]; perceptions of danger and the need for protective action are largely socially determined. The pre-evacuation actions (e.g., continuation of normal activities; seeking out friends, relatives, neighbors, and coworkers; gathering materials and supplies) are influenced by social relations [82] and restrained by situational impediments and facilitators [39,41,83]. The implementation of such pre-evacuation actions during hazards can reduce the potential for injury and loss-of-life if appropriate, decrease pre-evacuation times, or lead to delayed evacuation.

A substantive body of empirical studies in transportation has examined how evacuees make decisions during evacuation, including crowd evacuation modelling, (in-building) exit choice modelling for pedestrian evacuations, travel demand modelling, trip distribution modelling, and traffic assignment modelling for vehicular evacuations. Table 2 shows the diverse range of evacuation decisions as determined by a combination of *individual*, *environmental*, and *interventional* factors. Baker [50] in his seminal review of variables affecting hurricane evacuation decisions concluded that five predictors define the decision to evacuate: the risk level of a location, notices and actions by public authorities, housing type, personal perception of risk, and storm features. Using Baker's summary as the foundation for further hypotheses, a number of recent empirical studies have been carried out to further assess various factors that affect evacuation-related decisions and the bivariate relationships between them. Results are mostly in agreement with Baker [50] and suggest that official warnings/actions, sensory cues, hazard features are consistently significant predictors of evacuation decisions, whereas the influence of other factors varies from study to study. Huang et al. [98] contributed to the household evacuation study by providing rigorous estimates of effect sizes in their statistical meta-analysis. Apart from confirming Baker [50]'s conclusions, they also suggested that future research should be conducted to improve the functionalization of certain factors, accounting for the intercorrelations among covariates, and possibly the identification of additional mediators (e.g., risk perception, expected personal impact) of indirect factors' effects. For additional information, readers may refer to the individual papers listed in Table 2, and the reviews by Folk et al. [99]; Huang et al. [98]; Murray-Tuite and Wolshon [100]; Pel et al. [16]; Sorensen [101]; Sorensen and Sorensen [102]; Thompson et al. [103].

In the evacuation decision-making literature, compliance of the impacted population with protective action recommendations from the evacuation coordinators (e.g., evacuate or shelter-in-place, destination, timing) is one of the most intensively examined issues. Compliance behavior plays a key role in the success of operational response efforts. While the role of most *socio-demographic* and *socioeconomic* factors with regard to evacuation-related decisions is highly hazard-specific, race was identified to be significantly associated with evacuation order compliance [65]. Specifically, minority respondents and those responsible for the elderly are less likely to have a high evacuation threshold compared to white respondents and respondents who do not look after the elderly. The effects on evacuation compliance from other *static individual* factors including past experience and knowledge, examined in fewer empirical studies, remain inconsistent and inconclusive [74,75,78,80]. The importance of *social* factors (e.g., reactions from their relatives, friends, and neighbors, social isolation, social ties, and cohesion) in shaping the evacuation compliance behavior has also been put forward [74,93,104–106]. Recently, attention was paid on understanding the interactions between evacuation coordinators and evacuees. Notices and actions given by the evacuation coordinators are one of the most influential predictors of evacuation compliance [50] and yet impacted by the evacuees' perceptions of the source's expertise and trustworthiness [45]. These should be developed and implemented to enhance the public perception of the legitimacy of authorities, confidence in the government, as well as knowledge about emergency management policies [80,92].

For evacuees, the *pre-travel period* ends when they start to evacuate. This marks the transition from pre-evacuation actions to evacuation movement (e.g., wayfinding and routing). Please note that movement can take place after an extended period of time since the evacuate decision-making especially in events with substantial forewarning such as hurricanes, due to evacuation preparation tasks [86,107] or preferred departure time [86,88,108]. Based on the empirical evidence listed in Table 2, socio-demographic and socioeconomic factors (e.g., household geographic location, number of children, evacuees income and age) continue to influence the route and destination choices [69]. It is worth noting that familiarity plays a prominent role in ascertaining the determinants of wayfinding/routing behavior. Kinateder et al. [81] argued that occupants have the tendency to evacuate buildings through a familiar exit. Similarly, Wu et al. [32] speculated that evacuees seek most often familiar routes in network evacuation, which echoes previous findings from Deka and Carnegie [77]. *Social* and *environmental* factors should be considered for the estimate of evacuation times but with as there are relatively few empirical analyses on those factors impact on wayfinding/routing behaviors. The motion characteristics of the evacuees play also role in affecting the evacuation process. However, research on empirical adaption effects in movement behaviors (e.g., speed adjusting, pedestrian/vehicle overtaking) following an emergency situation is very limited [109]. Some studies have made efforts towards the empirical underpinning of theoretical framework by exploring the influence of various factors. Dulebenets et al. [70] identified age, space headway, and the evacuation route geometric characteristics as the most statistically significant factors that influence major driving performance under emergency. For in-building evacuation movement, Ma et al. [89] looked into the speed, merging, and overtaking behaviors of evacuees in an ultra high-rise building evacuation. The building geometry characteristics are reported to mainly impact the behaviors, while the impact of age and gender is inconclusive and more experimental work is required.

Our review highlights the wide range of disciplines contributing to investigating the impact of factors on emergency evacuation, including psychology and behavioral sciences, ergonomics, safety, and transportation. A minor finding is that current empirical knowledge on human behavior in the different phases of evacuation process is imbalanced. The fragmentation lies in the fact that during different phases the actions taken require different disciplinary understanding and amount of data. For example, there is more empirical evidence to lay the foundations of utility theory embedded in evacuate-or-not decision modelling. In contrast, the available empirical studies on the aspects of predicting the "pre-travel/movement time" and/or "choice of activity" are not sufficient to draw definitive conclusions. These observations underline the need for more empirical studies in certain fields to substantiate the validity of behavioral assumptions or theory. Another future extension is to investigate the cross-side network effects (i.e., moderating and mediating effects) among the impacting factors. Future work should be conducted to improve the functionalization of certain factors, accounting for the intercorrelations among covariates, and the identification of additional mediators (e.g., perception of risk, self-efficacy) of indirect factors' effects [110]. Although empirical evidence derived from past emergency incidents could offer great insights for developing dedicated models in different contexts, the findings are largely dispersed, in some cases even mixed and contradictory [12]. It should be noted that the empirical evidence cannot cover the entire range of phenomena in order to develop models with extensive range of applicability. The intent of Table 2 is to indicate the links between factors and the diverse protective and decisions that have been investigated in the literature. When constructing an evacuation simulation for a specific evacuation context, such links would have to be examined in terms of relevance for that context. The question is whether the mechanism underlying the effect examined in the study's evacuation context is applicable to the (different) evacuation context of interest. The sample size and reported significance of the effect for the context reported in the study would certainly need to be considered. Further, the lack of reliable and well-conditioned data for model validation or calibration purposes still exists.

4. Modelling

A comprehensive modelling framework consisting of three general levels of decision-making is used to organize the evacuation modelling studies, as described in Section 2.3. The evacuees first decide what to do (and the order or timing of these actions) at the *strategic level* decision-making. With such overarching decisions made, the *tactical level* concerns a series of subsequent decisions including destination choice, exit choice, route choice etc. Finally, the *operational level* describes the moving behavior such as avoiding collisions and steering around obstacles. This taxonomy of behavior, as summarized in Table 3, has gained widespread acceptance in the pedestrian crowd modelling literature [12], as well as in traffic evacuation modelling [111].

The processes at the strategic and tactical levels are usually considered to be exogenous to the traditional pedestrian or traffic simulations and thus out of their scope. Meta-analyses or reviews in the field of evacuation modelling focus mainly on operational level (i.e., pedestrian or traffic simulation). Several scholars, including Santos and Aguirre [112]; Papadimitriou et al. [113]; Schadschneider et al. [48]; Zheng et al. [114]; Ronchi and Nilsson [115] have reviewed a multitude of crowd movement models to lay the methodological foundation for the development of building evacuation tools/simulations. Similarly, in the field of transportation evacuation modelling, Alsnih and Stopher [116] reviewed a variety of traffic assignment-simulation tools for evacuation applications. Recently, Duives et al. [117] and Pel et al. [16] discussed the applicability of these models to the representation of the evacuation movement phenomena in the fields of pedestrian and transportation evacuation research, respectively.

To complement the above-mentioned literature on operational level modelling, the following sections examined the recent advances of evacuation modelling with a focus on their capability of capturing decision-making processes, with a focus on the strategic-level modelling and the integrated modelling among different levels. Utilizing the three-levels taxonomy of behavior, the decision-making associated behind a wide spectrum of phenomena identified in the empirical studies are discussed.

4.1. Models for strategic-level decisions

The strategic-level decisions are notably associated with the *pre-travel* phase, where evacuees typically engage in information-seeking and milling and carry out a wide range of pre-evacuation actions such as collecting and/or securing items, instructing/alerting others to evacuate, gathering families. As summarized in Table 4, the current models incorporating these behaviors mainly focus on estimating pre-evacuation/pre-movement time and evacuation, due to their significant effect on evacuation performance for both building (i.e., pedestrian) and transportation (vehicular) evacuation.

In building evacuation modelling, despite the complexity in predicting detailed behavior of individual occupants, the pre-evacuation time is reasonably amenable to prediction and quantitative description [118]. To date, at least three approaches have been used for estimating pre-evacuation times in building evacuation.

The first approach expresses the estimates as average values derived from empirical data. However, the derived explicit values usually vary due to the used observational data sets. The values show wide dispersion, depending on the type of building and activities people are engaged in. Therefore, such estimates have been analyzed using time probability distributions [118–121]. For this approach, a rather limited set of design scenarios related mainly to the *environmental* factors, such as type of building, warning provision, evacuees being alert or asleep can be considered. Some of the influence of social cues can be implicitly taken into consideration since certain building types are often associated

Table 3
Modelling human behavior in terms of levels of decisions.

Decision level	Strategic	Tactical	Operational
Decisions	"what-to-do actions" "the choice of activity" (e.g., when to initiate the activity, whether to help others or not)	"where-to-go" (e.g., the choice of route or exit)	"how-to-get-to-target" actions (e.g., momentary choice to avoid collision)
Model scope	Activity pattern choice, departure time choice	Exit choice, route choice, destination choice	Walking behavior, driving behavior, crowd/traffic dynamics

Table 4
Strategic-level modelling.

	Pedestrian evacuation	Vehicular evacuation
Primary decisions	Pre-evacuation actions (e.g., seek information, inform other people or alert, collect property etc.), necessity to evacuate, time of departure	
Applied models	Pre-evacuation time estimate model	Travel demand models (e.g., Hazard-based duration model, Cox model)
Modelling approach	Empirical data Multiple regression analysis	
Impacting factors considered	*Individual* factors (static) *Environmental* factors *Interventional factors*	*Individual* factors (static, social) *Environmental* factors *Interventional* factors

with specific social settings, such as a theatre [90]. In spite of the lack of explicit representation of evacuee behavior, this approach provides a simple and transparent method for evaluating pre-evacuation time and is widely used. It is also argued that the additional complexity of the most advanced models may not yield significantly different results [122]. Yet, an extensive database is required for the entire range of scenarios to serve design and regulation purposes [123].

The second approach adopts more advanced regression statistical analysis to gain stronger predictive capability. Kuligowski and Mileti [83] as well as Sherman et al. [124] used linear regression (or path analysis technique) to investigate any *individual* and *environmental* factors that could influence the pre-evacuation actions and delay in the World Trade Center evacuation studies. Apart from the conventional linear and polynomial predictive methods in the multi-variable setting, Liu and Lo [125] proposed an alternative approach based on artificial neural network to simulate human behavior in fire. Though this approach is capable of investigating the relationship between pre-evacuation responses and a variety of impacting factors, mostly *individual* and *environmental* factors, it is difficult to capture all of the influences of human behavior using this technique since there is likely to be some amount of unexplained variance associated with the model equations. Also, this approach does not explain the mechanism (e.g., interpersonal and social processes) involved in how these behaviors occur as pointed out by Kuligowski and Mileti [83].

The third set of approaches deploy models derived more directly from cognitive science and decision science. Such models are built upon behavioral assumptions and theories, such as risk perception, random utility theory, cumulative prospect theory, etc. A dynamic decision-making process defined by multiple behavioral states (e.g., normal, investigating, evacuating) and the passages between stated are based on pre-defined threshold of risk perception [126] or ruled by binary decision-making process [127]. The time necessary for taking pre-evacuation actions is estimated in accordance with the evolution of the process. Various factors can be incorporated, including not only static factors such as *individual (static, social)*, *interventional factors* but also dynamic *environmental* factors. Besides, these models have great potential to be implemented as a sub-model to incorporate processes of information flow and/or the emergence of leadership in existing agent-based evacuation models using an event-based or time-based approach (e.g., Ref. [128]). Nevertheless, the level of detail associated with each state is currently low and decontextualizing is required for higher transferability of the model [129,130]. Alas, the current studies are focusing more on conceptual model development due to the difficulties of collecting human cognitive performance data for validation.

As to transportation evacuation modelling, the strategic-level decisions affect predominantly the number of evacuating households over time as an input to further traffic simulation. The evacuation demand models are generally classified based on whether the participation and departure time choices are modelled as sequential decisions (i.e., two-step approach) or conducted simultaneously (i.e., one-step approach) [16,100]. For the two-step approach, techniques such as conventional participation rate, logistic regression, and neural network models are commonly used for predicting evacuation decision [131], while the departure time choice is estimated by applying an exogenous response curve based on certain distribution assumptions [132]. The drawback of this approach is that no clear behavioral basis is incorporated into the response curves, which are exogenous input based on expert judgment instead of endogenously determined by the impacting factors within the model. As Lindell and Perry [23]; Lindell and Prater [133]; and Lindell et al. [45] have criticized, departure time curves are based on arbitrary assumptions instead of empirical data.

The other one-step approach repeatedly predicts evacuees' decision of evacuating or postponing as hazards approach. Fu and Wilmot [134] successfully captured the empirical behavior findings presented by Baker [50]; particularly the impact of dynamically changing factors such as *environmental* factors (e.g., prevailing hazard, road network conditions), and *interventional* factors (e.g., evacuation order issuance) are incorporated. To further capture the heterogeneity in the evacuation behavior, Hasan et al. [71] developed a probabilistic model using a hazard-based modelling approach, taking the *socioeconomic* factors (e.g., race, income and education level) into consideration. Although this one-step approach is advocated for dynamic evacuation demand prediction, it relies heavily on extensive real data for calibration compared to the first approach. To have a reliable evacuation response model, more empirical data from different sites and scenarios would be needed, in order to better calibrate and compare current state-of-the-practice and state-of-the-art evacuation response models, as well as to enhance the transferability of their results.

4.2. Models for tactical-level decisions

The tactical-level modelling encapsulates a variety of topics, as listed in Table 5, including exit choice modelling in building (i.e., pedestrian) evacuation studies, destination choice modelling and route choice modelling in transportation (i.e., vehicular) evacuation studies.

The most commonly used modelling approach is the discrete choice method, which is based on certain behavioral populates (e.g., expected utility theory, prospect theory, bounded rationality). Recent advances include the nested logit [64,135] and the mixed logit models [136,137]. Murray-Tuite and Wolshon [100] presented a detailed summary of the development of destination choice and mode choice models from transportation evacuation studies. These econometric models provide increasing modelling flexibility, allowing the inclusion of various factors and even correlations in unobserved factors. Nevertheless, the challenge still lies in the incomplete picture of the cognitive and behavioral aspects of decision-making. As pointed out by Haghani and Sarvi [136]; the knowledge about the actual behavior of people in different evacuation scenarios based upon empirical data is still limited; this hinders the development and calibration of theoretically simple tactical-level decision models that can be embedded in the operational level of modelling (i.e., in movement models).

As an alternative, Lo et al. [138]; Ehtamo et al. [139] and Mesmer and Bloebaum [140] utilized game theory to rationalize the interaction among evacuees in their decision-making. The impact of *individual* factors (e.g., knowledge), as well as environmental factors (e.g., social cues, external stimuli, fire conditions) are considered. However, the fidelity of this decision model varies according to the number of modelled players (i.e., evacuees) and is subject to limits on computational capabilities.

4.3. Models for operational-level decisions

The operational-level decisions characterize the actual moving behavior of the evacuees (e.g., walking/driving). The modelling approaches are more systematically documented compared to those for the strategic and tactical levels, owing to the well-established literature of crowd motion simulation models and traffic flow models. The modelling approaches can be roughly categorized into macroscopic and

Table 5
Tactical-level modelling.

	Pedestrian evacuation	Vehicular evacuation
Primary decisions	Wayfinding (towards an exit)	Evacuation trip destination Transportation mode Evacuation route
Applied models	Exit choice model	Destination choice model Route choice model Mode choice model
Modelling approach	Game theory approach Discrete choice method	Discrete choice method
Impacting factors considered	*Individual* factors *Environmental* factors *Interventional* factors	

microscopic (and mesoscopic) models, based on the representation of crowd/traffic: macroscopic models deal with aggregate variables (e.g., speed, density, and flow) whereas at the microscopic level, individual trajectories are modelled by the individual's characteristics and the interaction among evacuees which influence their movement. Several broadly used approaches/models are listed in Table 6.

For building evacuation modelling, to formulate crowd movements in continuum models, fluid dynamic analogies are usually adopted to estimate the quantitative relations of speed and surrounding crowd density [141]. *Individual* factors could only be implicitly considered by implementing adaptations to the macroscopic flow functions. However, the interactions among specific individuals and en-route strategic or tactical decisions can hardly be coupled with this model. Though this approach cannot predict the behavior of individual pedestrians, they might replicate certain collective phenomena such as some effects of (non-aggressive) rush or competitiveness [142] or imitative behavior [143]. Nevertheless, the macroscopic models proposed are not capable of simulating all relevant behavioral processes and characteristics that crowds show, as pointed out by Hoogendoorn et al. [144].

In contrast, the cellular automata model and social force model are microscopic, which are capable of capturing crowd dynamics through representing the pedestrians' behavioral rules and decisions at the individual level. The social force model developed by Helbing et al. [145]; in which the individual movements are described by means of repulsive and attractive forces, turns out as a good analogy to reproduce substantial self-organization effects. Recently, a number of studies have further refined the cooperation mechanism among individuals in the original social force model, by incorporating leadership effect [146], guided pedestrian [147], and information dissemination [148]. On the other hand, in cellular automata models, the individual's motion decision depends on a number of *environmental* factors (e.g. their relative location towards the destination, infrastructure, others, and objects). Continuous efforts have been made on individual's decision-making in cellular automata models [149–151]. Moreover, cellular automata models have been integrated with strategic/tactical level modelling, such as exit choice [152] and wayfinding [153], to predict the movement behaviors more accurately. Thanks to the versatility, these models are easy to adapt and have excellent fitting capabilities that they could reproduce almost any observation with adjustment and recalibration. On the other hand, the model's predictive power or transferability of results is relatively low due to the fact that quantitative agreement with empirical data often requires rather sophisticated movement equations [154]. In more recent years, new microscopic alternatives from pedestrian simulation have been added to the evacuation application owing to their full flexibility and great precision of tracking individuals. One example is the optimal steps model proposed by Seitz and Köster [155] which has effectively employed the social psychology aspects including self-categorization theory and social identity theory to simulate collective crowd behavior (e.g., Refs. [156,157]). For a more detailed assessment of pedestrian movement modelling techniques, a few reviews can be found in the literature, including Duives et al. [117]; Papadimitriou et al. [113]; Zheng et al. [114]. Most recently, both Drury [158] and Templeton and Neville [159] provided an overview of theoretical insights from crowd psychology and discussed their implementation into pedestrian dynamics research.

Table 6
Operational-level modelling.

	Pedestrian evacuation	Vehicular evacuation
Primary decisions	Changing speed Collision avoidance	Changing speed Car following Lane-changing/overtaking
Applied models	Crowd/pedestrian motion model	Network traffic flow model
Modelling approaches	Continuum model (Macro) Social-force model (Micro) Cellular automata model (Micro)	Dynamic network loading model - Macroscopic model (flow-based) - Mesoscopic model (packet-based) - Microscopic model
Impacting factors considered	*Individual* factors *Environmental* factors *Interventional* factors	*Environmental* factors *Interventional* factors

As transportation evacuation studies, operational-level modelling (i.e., dynamic network loading model) are more closely integrated with tactical-level modelling (e.g., route choice model), as appear in dynamic traffic assignment (DTA) problems [160]. Compared to building evacuation studies, the behavioral model development for traffic dynamics in emergency situations is understudied. Most transportation evacuation simulations still reply on the model structure and parameter settings for normal situations because of the difficulty in validating for evacuations [100]. Recent contribution lies in the consideration for mixed pedestrian–vehicle flows into dynamic network flow models [161], as well as the integration with tactical level models with more realistic assumptions, such as incorporating en-route route choice into DTA model [162–165]. Since current empirical knowledge of driving behavior during emergency conditions is very limited (e.g., Refs. [166,167]), microscopic driving model development or adjustment for the case of emergency evacuation is scarce. While the advances in representation of very detailed behavior gains traction, a standard verification and validation document is vital for the assessment of the key requirements that evacuation models need to meet in order to be used in evacuation design. Ronchi and Nilsson [115] and Ronchi [17] have presented a broad analysis about the methods used for the validation of fire evacuation model results.

5. Concluding comments

Modelling emergency evacuation has been widely discussed in the literature. However, existing methodologies do not thoroughly account for the impact of human behavior in the evacuation process. This paper presented a literature review on human factor considerations associated with emergency evacuations. By proposing an evacuation timeline that addresses both the evacuees' and evacuation coordinators' perspectives, recent empirical evidence from diverse evacuation contexts is brought together. The impact of various factors on the evacuee behavior over different phases is discussed in detail, in order to give a perspective on the current consensus on human behaviors to be modelled in evacuation studies. Further, this review also structures the current state-of-the-practice in evacuation modelling, with a focus on the treatment of evacuee behaviors. The recent advances in different model formulations and techniques to replicate evacuation behaviors are reviewed and consolidated.

Despite the fruitful literature highlighted in this article, significant research endeavors still remain. Although a growing amount of new empirical evidence becomes available and supports the development of cognitive-behavioral frameworks to model individuals' pre-movement behaviors, data for large scale evacuations with much shorter warning periods is still scarce. Data insufficiency and limited transferability remain significant challenges for behavioral studies and evacuation modelling. Moreover, the evacuation models are becoming increasingly complex in an attempt to reproduce the new empirical observations, while the research and theory from social science, cognitive science, or psychology may not be available with scientific scrutiny to ground the models in realistic assumptions. The evacuation models can only be of great value for emergency planning and intervention if they have predictive validity, which is inextricably linked to empirical investigations of emergency evacuations. We expect that this study will promote the interdisciplinary efforts in evacuation modelling, involving the expertise of social scientists, engineers, fire scientists, computer scientists, and emergency planners, among others. We also anticipate that this study will support model developers and users in identifying and incorporating prominent human factors aspects in evacuation modelling.

Declaration of competing interest

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

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Appendix

Behavioral statements extracted from the references in Table 2.

Information seeking and milling

1. Differences for age and gender were found for the usefulness of source of information, including television, print media, and the Internet [54]. (Socio-demographic - terrorism)
2. Differences were indicated in crisis preparation and information seeking on the basis of race [55]. (Socio-demographic - hurricane)
3. Differences in the informational needs or preparations were not detected among knowledge gaps (i.e., socioeconomic status) but across sex and ethnicity [58]. (Socio-demographic and socioeconomic - hurricane)
4. Patterns of information-seeking are similar between experts and novices but experts conducted a more efficient search than novices, where their knowledge and experiences in emergency management may play a critical role [72]. (Knowledge and experience - general)
5. People's behavioral reactions at the recognition stage may be dependent on numerous factors including human characteristics such as gender, education level, building characteristics (e.g. pre-fire activities—the usage of the building) and fire characteristics (flame, smoke spread, etc.) [57]. (Socio-demographic, socioeconomic, building/engineering environment, hazard features – building fire)

Pre-evacuation actions

6. Individual characteristics such as physical impairments, preliminary experience with similar situations or infrastructure influenced the speed of evacuation [59]. (Experience, knowledge – underground evacuation)
7. Larger households and those with college graduates were more likely to engage in activities that required travel; households choosing to drive their own vehicles were more likely to participate in out-of-home activities; and the number of people older than 64 had a negative impact upon engaging in out-of-home activities [60]. (Socio-demographic, socioeconomic - hurricane)
8. The level of risk people takes by collecting objects before evacuating is affected by three factors: knowledge of a building, a change in the behavior of other simulated evacuees, and a change in how they are attached to the objects they can collect (potential gain versus loss). The only factor that significantly increases the average number of objects participants collect is loss aversion [76] (Knowledge, sensory cues – building fire)
9. Intimate relations in groups reduce the chances of people being injured in fire when conditions are not extremely lethal [82]. (Affiliation - building fire)
10. The results indicate that people respond more like their neighbor with regards to time [90]. (Other information and cues – building fire)
11. In general, longer pre-evacuation times were predicted by witnessing a higher number of environmental cues, being on a lower floor in the building, obtaining more information, seeking additional information, and performing a higher number of pre-evacuation actions [83]. (Sensory cues and building/engineering environment – terrorism)

Evacuation decision making:

12. Race indicated significant group differences in terms of stated evacuation thresholds for both voluntary and mandatory evacuation future orders. Significant predictors in the logistic regression that examined thresholds of evacuation for a mandatory order were: having ignored an order in the past, age, and race [65]. (Socio-demographic - hurricane)
13. The most important predictor of evacuation is storm intensity. Households are more likely to evacuate when given evacuation orders, when they perceive a flood risk, and when they live in mobile homes. Non-white households, pet owners and those with more education are less likely to go to either a motel/hotel or shelter, preferring instead to stay with friends or family [61]. (Socio-demographic, socioeconomic, and hazard features - hurricane)
14. The mandatory evacuation order and whether they lived in a mobile home are significant predictors for evacuation behavior. Respondents who perceive their wind risk to be medium or high do not evacuate more than others, but respondents who perceived their flood risk to be medium or high do. Also, pet ownership acts as a constraint on evacuation behavior given the its negative coefficient. Female are more likely to evacuate. Race and education have no statistically significant effect on evacuations [62]. (Socio-demographic, socioeconomic, hazard features, evacuation order issuance/warning - hurricane)
15. Analyses revealed that some demographic variables are significantly related to evacuation logistics. Specifically, older respondents left earlier but larger households and those located farther from the coast tended to leave later. Demographic characteristics including gender, age, race, as well as education and income were all significantly correlated with use of a personal vehicle [31]. (Socio-demographic, socioeconomic, building/engineering environment)
16. It is found that the variables related to household location, destination characteristics, socioeconomic characteristics, and evacuation notice are key determinants of the departure time [71]. (Socioeconomic, official warnings - hurricane)
17. The results of this study confirm that parents expect to gather children under emergency conditions, which needs to be accounted for in evacuation planning; failure to do so could cause difficulties in executing the pick-ups, lead to considerable queuing and rerouting, and extend the time citizens are exposed to high levels of risk. Another significant factor affecting child pick-up behavior/expectations was household income when controlling for distance [63]. (Socioeconomic, affiliation - general)
18. Results show that evacuation decision is determined by a combination of household characteristics and capacity-related factors (gender, educational level, presence of children, and number of years living in the residence, house ownership, number of house floor levels, type of house material), as well as hazard-related factors (distance from source of flood, level of flood damage, and source of warning) [66]. (Most of the factors - hurricane)
19. The findings suggest that location in highly vulnerable areas, concerns about reaching destinations safely, income, and having

multiple vehicles were important determinants of splitting, with additional sociodemographic factors displaying marginal significance as well [67]. (Socioeconomic, building/engineering environment - hurricane)
20. It show that the evacuation decisions and travel patterns are affected by the presence of children in the household and that household members tend to meet and group together before evacuating, which strongly supports the need for household-level evacuation models and to capture the dependence of children's behavior on that of their parents [68]. (Socio-demographic, affiliation - wildfire)
21. Although not highly significant, the indicator variable for previous major hurricane experience results in a lower probability to evacuate. However, there exist inconsistent findings in the literature related to the influence of previous experience on the evacuation decision [73]. (Experience - hurricane)
22. Tourists with higher hurricane knowledge are less likely to evacuate than those with low hurricane knowledge. Those without past experience with hurricane impacts are more likely to evacuate than those that experienced hurricane impacts in the past [75]. (Knowledge, experience - hurricane)
23. Maintaining situational awareness of the rapidly changing circumstances is critical to sound decision making [79]. (Abilities/impairments - hurricane)
24. Through sensitivity analysis of six influencing factors, we found that appealing evacuees who already knew the pre-warning information to exclaim when they evacuate, strengthening personal curiosity threshold and alertness to emergencies, or improving interpersonal trust in oral communication are very helpful in increasing regional evacuation efficiencies [66]. (Abilities/impairments, sensory cues/external stimuli, evacuation warning - building fire)
25. Evacuation decisions are influenced by a heterogeneous set of parameters, including perceived risk from wind, influence of media and neighbors, knowledge about the evacuation status of one's neighborhood, and awareness of evacuation zone [78]. (Knowledge, other information and cues - hurricane)
26. Stated preference household survey data revealed that there is a strong preference for private vehicle and that the choice of other modes was related to familiarity with a particular transit option and the unavailability of a personal vehicle [77]. (Knowledge - hurricane)
27. As indicated in the responses, appearance of visible environmental cues, such as funnel clouds, had a high rating average for giving warnings to both the household and driving populations [84]. (Sensory cues – tornado)
28. Evacuation decisions tended to be strongly correlated with geographic characteristics (i.e. coastal proximity). Personal experience and evacuation impediments were not significantly correlated with evacuation decisions [86]. (Building/engineering environment - hurricane)
29. Among the factors associated with the selection of evacuation destination/accommodation, it is found that increased distance from the evacuees' homes and higher risk were negatively associated with the likelihood of selecting that location for the accommodations (e.g., peers' homes and commercial establishments). The destination socioeconomic and demographic characteristics are also impacting the destination choices, such as greater population and the metropolitan location for peer's [87]. (Building/engineering environment - hurricane)
30. It is found that expected personal impacts and perceived evacuation impediments have a direct effect on evacuation decision, other variables (official warnings, coastal proximity, and social cues) have unpredicted direct effects. Expected personal impacts are determined by perceived storm characteristics, but there are also unpredicted positive direct effects of official warning, hurricane experience, and social cues, as well as unpredicted negative direct effects of education, risk area, and unnecessary evacuation [88]. (Building/engineering environment, Other information and cues, evacuation order issuance/warning - hurricane)
31. The wording and content of evacuation orders (message), person delivering the message (source), and distribution medium (channel), can heavily influence not only the number of people that evacuate, but also the urgency at which they leave, the areas from which they depart, and the destinations that they chose [41]. (Evacuation order - hurricane)
32. It is concluded that the recommendations or orders by government officials (as well as the language and method of dissemination) affected evacuation rates more than any other factor. Residents who use the advice of public officials as important sources of information are more likely to evacuate [93]. (Evacuation order issuance/warning and authority action - hurricane)
33. The mode choice decisions of evacuees, who are likely to use different non-household transportation modes, are influenced by several determining factors related to evacuees' socio-demographic, household characteristics, evacuation destination and previous experience [64]. (socio-demographic, socioeconomic, and experience – hurricane)
34. Households with higher income and education attainment were more likely to evacuate. Households using their own vehicles were more likely to evacuate earlier compared to those relying upon transit or a friend/relative. More household members over 64 years old contributed to increased likelihood of early departure [60]. (Socio-demographic, socioeconomic - hurricane)
35. For hurricane Ike survey participants, having experienced evacuation in the previous notable hurricane event is a significant factor in predicting compliance with the orders. For hurricane Rita, significant factors include having a greater number of neighbors evacuating prior to the hurricane's landfall; the level of influence by the media; and having correct identification of the evacuation status of their location [74]. (Experience, Other information and cues - hurricane)
36. Research in policy implementation shows that public confidence in government agencies and knowledge of policies being implemented are critical in securing compliance from target populations [80]. (Knowledge, authority action - general)
37. Perceived illegitimacy of responders could result in public antagonism and non-compliance with recommended protective behaviors, which could delay necessary actions being taken. Failure to communicate effectively during the initial response to an incident could create a perception of responder illegitimacy, which could prevent the development of shared social identity between emergency responders and crowd members [92]. (Evacuation order issuance/warning and authority action - general)

Wayfinding/Route finding, walking/driving behaviors:

38. Several important factors including household's geographic location, number of children, evacuees' income and age, evacuation timing and medium of evacuation notice influence household's evacuation routing decision. Moreover, low income people who experience heightened levels of risk perception, tend to follow routes recommended by officials or update their routes on the way to their destinations [69]. (Socio-demographic, socioeconomic - hurricane)
39. The socio-demographic characteristics of individuals (e.g., age, gender, racial group, health conditions) and roadway geometric characteristics (e.g., number of lanes, and space headway) may substantially impact the driving ability of individuals throughout

the emergency evacuation process [70]. (Socio-demographic, building/engineering environment - general)

40. The results show that exit familiarity and neighbor behavior influence evacuation behavior, and that social influence increases with the number of neighbors [81]. (Knowledge, other information and cues – general in-building)
41. Social influence (i.e., passive behavior of others) does not only affect behavior activation but also more subtle choices, such as route choice, during evacuation. There were no group differences regarding destination choice. Participants in the social influence group were more likely to choose a route similar to the virtual agent. Participants in the control group were more likely to choose a longer route along the tunnel walls [91]. (Other information and cues – tunnel fire)
42. This study confirmed previous findings that evacuees take multiple cars, rely on familiarity with the route based on past experience and traffic conditions to choose their evacuation routes, and are most likely to choose the homes of friends/relatives as their shelter accommodations [32]. (Knowledge, building/engineering environment - hurricane)

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