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Modeling and simulating human behavior in large-scale emergency evacuations: A comprehensive review

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ABSTRACT

Disasters pose persistent threats to human life and infrastructure, making evacuation planning vital for disaster risk reduction. The effectiveness of such efforts depends on understanding and accurately modeling human behavior. This study reviews 479 peer-reviewed articles on large-scale evacuation planning and management, classifying them along two dimensions: behavioral factors influencing key authority-issued decisions and modeling approaches incorporating these dynamics within optimization, simulation, and simulation–optimization frameworks. While demographic and route-choice behaviors are extensively studied, mode selection and road-segment designation remain largely unexplored. Optimization models commonly assume full- or non-compliance, with limited research that considers partial-compliance, leading to more realistic solutions. On the other hand, simulation-based studies capture dynamic and uncertain conditions more effectively but are dominated by rule-based behavioral proxies, particularly for departure timing and route choice, and typically limit dynamic feedback to route choice alone. Simulation–optimization approaches, while increasingly adopted, remain largely reliant on parameter-based behavioral representations rather than empirically calibrated, behavior-oriented coupling. Emphasizing the importance of embedding behavioral heterogeneity in model structures, this review develops a taxonomy, highlights research gaps, and outlines future directions for behaviorally realistic evacuation models that enhance the effectiveness and practicality of evacuation strategies in real-world crises.

Keywords: Disaster management; Mass-evacuation planning and management; Evacuee behavior; Compliance behavior; Simulation; Optimization; Simulation–optimization

1 Introduction

Disasters, both natural and human-made, cause widespread loss of life, economic damage, and societal disruption. The International Federation of Red Cross and Red Crescent Societies (IFRC) defines a disaster as an event that overwhelms a community's capacity to respond, resulting in significant human, material, and environmental losses (IFRC, 2011).

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In 2024, the Emergency Events Database (EM-DAT) (EM-DAT, 2024) recorded 393 disasters from natural hazards, causing 16,753 fatalities and affecting 167.2 million people globally. The increasing frequency and severity of such events highlight the critical need for effective disaster management strategies to mitigate their impact.

Among these strategies, evacuation planning and management is essential for protecting populations during emergencies (Bayram, 2016). A well-coordinated evacuation ensures timely relocation from high-risk areas, minimizing fatalities and congestion (Lindell et al., 2018). However, real-world evacuations often face challenges such as traffic bottlenecks, overcrowded shelters, and inefficient coordination, exacerbating disaster impacts. Many of these challenges stem from human behavior, such as panic, hesitation, and non-compliance with evacuation orders (Perry, 1979b; Drabek, 2018). Understanding and predicting evacuee behavior is essential for designing robust evacuation strategies.

Evacuation management is a complex socio-technical problem due to its large-scale nature and the severe consequences of decision-making errors. The sheer size of the problem, combined with the urgency of decision-making, makes manual planning impractical, requiring advanced models for decision support. These models must account for various logistical, infrastructural, and operational challenges. However, the inclusion of human behavior, which is difficult to predict and model accurately, adds another layer of complexity. Addressing this challenge demands both technical expertise and insights into social dynamics, as crisis-driven human behavior often deviates from rational models, necessitating a socio-technical approach to evacuation planning and management.

Mathematical models and simulations are widely used to support evacuation planning and management, enabling researchers to assess different scenarios, allocate resources efficiently, and identify potential bottlenecks. However, these models often oversimplify human behavior, treating evacuees as rational agents who follow predetermined rules. In reality, behavioral factors such as risk perception, social influence, and decision-making under stress significantly impact evacuation outcomes (Karampotsis et al., 2024). The US Department of Homeland Security (DHS) and the Federal Highway Administration (FHWA) emphasize the need to incorporate realistic behavioral dynamics into evacuation planning and management to improve decision-making and adaptability (FEMA, 1996; FHWA, 2017).

Historical disasters illustrate the consequences of failing to account for human behavior. During Typhoon Haiyan (Yolanda) in 2013, panic-driven traffic congestion and overcrowded shelters hindered rescue efforts, disproportionately affecting vulnerable populations (Group, 2017). Similarly, the 2018 wildfires in Greece and the 2019 Sulawesi earthquake and tsunami saw increased casualties due to confusion, poor coordination, and delays in evacuation (Kitsantonis et al., 2018; Irfan, 2018).

Integrating behavioral insights into evacuation models remains a challenge across all major modeling paradigms. Optimization models commonly assume that evacuees either fully comply with or entirely ignore official directives, with only limited research exploring partial compliance. Simulation-based studies capture dynamic and uncertain conditions more effectively, yet the majority rely on rule-based behavioral proxies rather than empirically grounded models, and dynamic feedback is typically restricted to route choice alone. Simulation–optimization approaches, while increasingly adopted, remain largely dependent on parameter-based behavioral representations, with a critical gap in empirical validation. Across all three paradigms, the complexity of human decision-making is often overlooked, limiting the ability of current models to capture its direct impact on evacuation effectiveness (Pel et al., 2010; Wang and Wallace, 2022; Aldahlawi et al., 2024).

This study specifically targets large-scale or mass evacuations from urban areas, which differ from site-specific facility evacuations in buildings, stadiums, or industrial sites. Large-scale evacuations involve hundreds of thousands of individuals moving across extensive regional road networks over hours or days under hazardous and dynamically evolving conditions. Accordingly, the modeling approaches suited to this setting differ from those developed for facility-scale evacuations. This study focuses exclusively on the evacuation phase and does not encompass the subsequent return or recovery stages. The research aims to contribute to the United Nations' "Climate Action" and "Sustainable Development Goals (SDGs)" (United Nations Department of Economic and Social Affairs, 2015), as well as the "Sendai Framework for Disaster Risk Reduction (SFDRR)" (United Nations Office for Disaster Risk Reduction (UNDRR), 2015), by enhancing community resilience and reducing vulnerability to disasters.

Within this defined scope, this survey is motivated by the significant need to incorporate human behavior aspects into large-scale evacuation planning and management models, as current models often overlook or simplify these critical factors. Despite growing efforts in this area, numerous reviews have examined various facets of evacuation modeling, including optimization formulations, traffic simulation, routing algorithms, agent-based social behavior, and emergency logistics. To position this review against prior work, Table 1 compares representative reviews that address emergency evacuation at large or mixed scale and that contain a substantive treatment of evacuee behavior. Reviews restricted exclusively to building or confined-space egress are excluded, as they fall outside the scope defined in Section 2.1.

The comparison is organized around five groups of dimensions. *Review scope* characterizes each review through its primary subject, whether evacuee behavior is its main organizing focus or is treated within a broader modeling or planning framework, whether it synthesizes influencing factors, behavioral modeling, or both, and the scale and hazard context addressed. *Behavioral decisions* records coverage of the six authority-issued decisions examined in this study: protective action, departure time, mode choice, destination choice, route choice, and road-segment designation. *Methodological coverage* records the extent to which optimization, simulation, and simulation–optimization studies are systematically reviewed. *Behavioral treatment* then concerns how behavior is handled within these methodological streams, covering whether influencing factors are synthesized generally, for specific decisions, or both; whether the sources of behavioral evidence are identified; whether the review examines how behavior is represented within models; and whether it addresses compliance with authority-issued instructions. *Simulation-specific characterization* applies to reviews covering simulation and records whether the reviewed studies are classified by movement mode, by simulation scale, by simulation method or tool, and by structural coupling, that is, by how influencing factors, behavioral decisions, and simulated movement are connected within a model and whether conditions arising during movement inform subsequent behavior.

Table 1. Comparison of reviews addressing human behavior in large-scale or mixed-scale emergency evacuation.

	Review scope					Behavioral decisions						Method. coverage			Behavioral treatment				Simulation-specific characterization			
Review	Primary review focus	Behav. emphasis	Behav. review scope	Scale	Hazard type	PA	DT	MC	DS	RC	RSD	Opt.	Sim.	S–O	Influencing factors	Evidence/source	Behav. repres.	Compliance	Movement mode	Sim. scale	Struct. coupling	Sim. method/tool
Southworth (1991)	Regional evacuation modeling and traffic simulation	Secondary	Behavioral modeling	Large	Multiple	✓	✓	–	✓	✓	–	✓	✓	–	Mentioned	✓	✓	–	–	✓	–	✓
Abdelgawad & Abdulhai (2009)	Emergency evacuation network design and optimization	Secondary	Behavioral modeling	Large	Multiple	✓	✓	–	✓	✓	–	✓	✓	–	Mentioned	–	✓	L	–	✓	–	✓
Pel et al. (2012)	Travel-behavior modeling in dynamic evacuation simulation	Primary	Both	Large	Multiple	✓	✓	–	✓	✓	–	–	✓	–	Both	✓	✓	L	–	✓	–	✓
Murray-Tuite & Wolshon (2013)	Highway evacuation transportation modeling and operations	Secondary	Both	Large	Multiple	✓	✓	✓	✓	✓	–	✓	✓	–	Decision-specific	✓	✓	L	✓	–	–	✓
Bayram (2016)	Large-scale network evacuation optimization and management	Secondary	Both	Large	Multiple	✓	✓	–	✓	✓	–	✓	–	–	General	–	✓	L	–	–	–	–
Huang et al. (2016)	Hurricane evacuate/stay determinants; statistical meta-analysis	Primary	Influencing factors	Large	Hurricane	✓	–	–	–	–	–	–	–	–	Decision-specific	✓	–	L	–	–	–	–
Wang et al. (2021)	Human factors and behavioral representation in evacuation models	Primary	Both	Mixed	Multiple	✓	✓	✓	✓	✓	–	–	✓	–	Both	✓	✓	L	✓	✓	–	✓
Elhami-Khorasani et al. (2023)	Human behavior and evacuation modeling in large outdoor fires	Primary	Both	Large	Outdoor fires	✓	✓	✓	✓	✓	–	–	✓	–	Both	✓	✓	L	✓	✓	–	✓
Aldahlawi et al. (2024)	Human-behavior modeling and evacuation-routing optimization	Primary	Both	Large	Multiple	✓	✓	✓	✓	✓	–	✓	✓	–	Both	✓	✓	L	✓	✓	–	✓
Templeton et al. (2024)	Social behavior and communication in agent-based evacuation models	Primary	Both	Mixed	Multiple	–	–	–	–	–	–	–	✓	–	General	–	✓	**L**	–	–	–	–
Present review	Large-scale evacuation behavior across decisions and modeling paradigms	Primary	Both	Large	Multiple	✓	✓	✓	✓	✓	✓[a]	✓	✓	✓	Both	✓	✓	✓	✓	✓	✓	✓

Coding. ✓ indicates that the dimension is systematically reviewed or classified, that is, the review devotes a dedicated section, table, or classification scheme to it. L (compliance column only) indicates limited coverage: compliance is substantively discussed but the reviewed literature is not classified by compliance treatment. – indicates that the dimension is not systematically addressed. Isolated mentions or single example studies are not sufficient for ✓.

Influencing factors. Mentioned = discussed but not systematically synthesized; General = systematically synthesized across evacuation behavior as a whole; Decision-specific = systematically synthesized for particular decisions; Both = both levels present.

Simulation–optimization. ✓ indicates that the review systematically identifies and classifies studies integrating simulation and optimization as a distinct methodological approach. Isolated integrated examples, or the separate presence of optimization and simulation studies within the same review, are insufficient.

[a] The evidence base for road-segment designation is small (two primary studies) and is reported in Section 2.2 as an identified research gap rather than as an established body of literature.

Abbreviations. PA = Protective action; DT = Departure time; MC = Mode choice; DS = Destination selection; RC = Route choice; RSD = Road-segment designation; Opt. = Optimization; Sim. = Simulation; S–O = Simulation–optimization.

Read across these dimensions, prior reviews show a consistent pattern of partial coverage. Although most address multiple hazards rather than a single hazard context, and evacuee behavior is the primary organizing focus in most of them, this breadth does not extend to the full set of decisions through which evacuation behavior is expressed: decision coverage clusters around protective action, departure time, destination choice, and route choice, while mode choice appears in fewer than half of the reviews and road-segment designation in none. Coverage of modeling paradigms is similarly partitioned, with simulation the most widely reviewed paradigm and optimization the next, yet fewer than half of the reviews cover both and none treats simulation–optimization as a distinct methodological stream. The depth of behavioral treatment varies in the same way: most reviews examine how behavior is represented within models and a majority identify the sources from which behavioral evidence is drawn, but none classifies its reviewed studies according to how compliance is treated or modeled, or by degree of compliance, so compliance remains a recurring observation rather than an organizing dimension. Among the reviews that address simulation, classification by simulation method or tool and by simulation scale is common, whereas none characterizes how influencing factors, behavioral decisions, and simulated movement are structurally linked within a model, including whether these links are unidirectional or involve feedback. No existing survey therefore combines, within a single framework, a mapping of behavioral factors across all authority-issued evacuation decisions at large scale, a treatment of compliance and non-compliance as a structuring dimension, a systematic account of how behavioral information is obtained and represented, and coverage of the three paradigms through which behavior is incorporated into evacuation models.

To address this gap, this review develops a taxonomy linking general behavioral factors and their effects on critical authority-issued evacuation decisions, as well as on compliance with and deviation from them, and provides a comprehensive assessment of how these behavioral dimensions are obtained and represented across optimization, simulation, and simulation–optimization frameworks. By reviewing evacuee behavior in large-scale emergencies across these three complementary methodological streams, this study highlights critical gaps in current evacuation models and proposes key improvements to enhance large-scale evacuation planning and save lives.

The paper is structured as follows. Section 2 details the methodology, including the selection of studies and analytical framework. Section 3 explores the behavioral factors influencing evacuation dynamics. Section 4 reviews optimization-based evacuation models incorporating human behavior. Section 5 reviews simulation-based evacuation models with explicit behavioral representation. Section 6 discusses simulation–optimization approaches designed to enhance evacuation processes. Section 7 examines the empirical validation of behavioral assumptions. Finally, Section 8 highlights critical research gaps and offers directions for future study.

2 Methodology

We begin with a broad and inclusive search using the general keyword ‘evacuee behavior’ to capture studies across a wide range of disciplines. Building on this comprehensive foundation, we then refined our focus to identify the specific behavioral factors addressed, as well as the solution methodologies and their subclasses that incorporate these behavioral effects into qualitative and quantitative analyses.

To ensure a transparent evaluation of evacuation strategies, we propose a hierarchical classification framework that categorizes key evacuation factors. This framework organizes influencing factors into general factors and decision-related

factors and classifies solution methodologies into optimization-based, simulation-based, and simulation–optimization based (S–O) methods. Additionally, the framework includes important topics such as human behavior, infrastructure constraints, and evacuation rules to show how these factors are connected and how they help solve key problems in evacuation planning and management.

2.1 Paper selection process

This review followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure a transparent and reproducible study identification, screening, and selection process. In line with this framework, we searched two major bibliographic databases, Scopus and Web of Science, to identify studies published in English between 2000 and 2025. The search was limited to articles and review papers. To reduce the risk of selection bias and capture the breadth of the literature on evacuation behavior, the search strategy was organized around three concept blocks related to evacuation context, behavioral constructs evacuee decision-making and response, and modeling approaches. The following Boolean search query was used across all databases:

> (Evacuat* OR "shelter-in-place" OR sheltering OR "emergency evacuation" OR "large-scale evacuation" OR "household evacuation" OR "neighborhood evacuation") AND ("evacuee behavior" OR "evacuation intention" OR compliance OR "protective action" OR "route choice" OR "destination choice" OR "departure time" OR "evacuation timing" OR "mode choice" OR "risk perception" OR "warning response" OR "evacuation behavior" OR "evacuation decision" OR preparedness OR "travel behavior" OR "sheltering behavior" OR "routing" OR "evacuation guidance" OR "evacuation demand" OR "staging") AND ("modeling" OR "behavioral modeling" OR "behavioural modeling" OR "optimization" OR "mathematical programming" OR "mixed integer linear programming" OR MILP OR "linear programming" OR LP OR bilevel OR "bi-level" OR "stochastic programming" OR "simulation" OR "agent-based" OR "mathematical model" OR "transportation modeling" OR "choice model" OR "logit model" OR "traffic assignment" OR "shelter location")

The database search yielded 3,041 records in total, including 1,572 from Scopus and 1,469 from Web of Science. Fig. 1 summarizes the identification, screening, eligibility assessment, and inclusion stages of the study selection process.

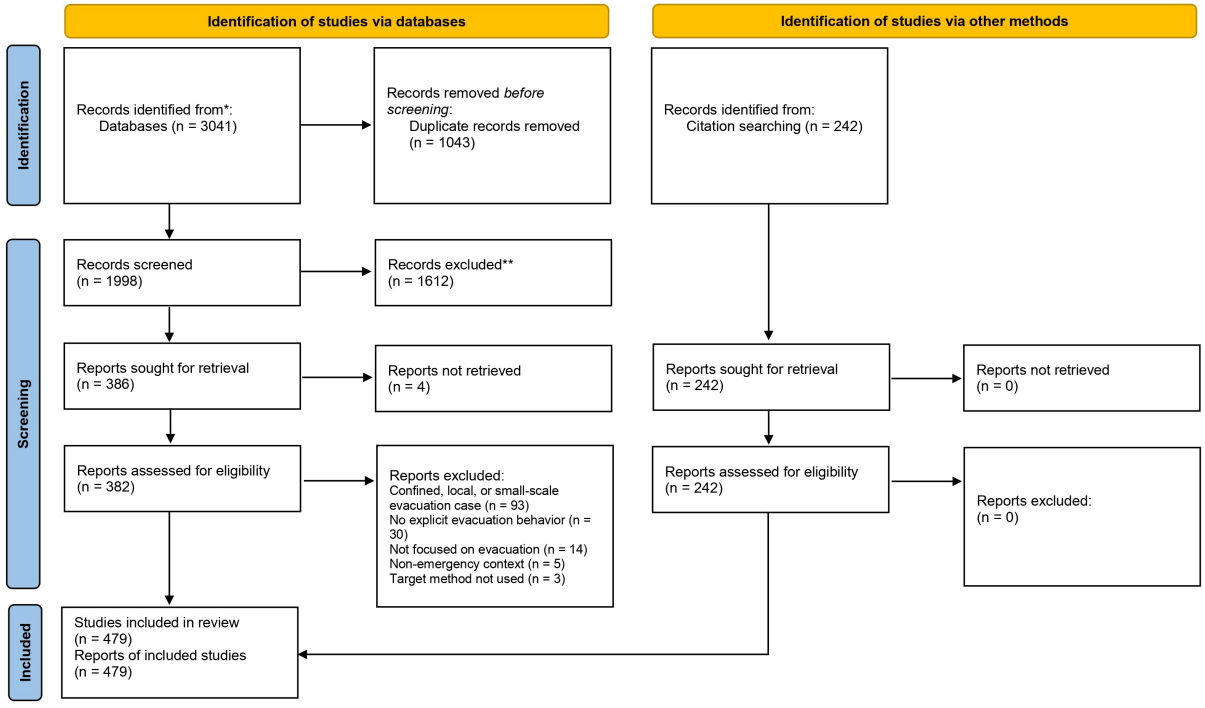


Fig. 1. PRISMA flow diagram of the paper selection process.

All retrieved records were imported into Zotero, a bibliographic reference management software, to organize the records and identify duplicate entries. After removing 1,043 duplicates, 1,998 unique papers remained for screening; this deduplicated set is available as a public Zotero library at `https://www.zotero.org/groups/6651845/large-scale_`

emergency_evacuation_behavior_review/library.These studies were eligible for inclusion if they addressed emergency evacuation and incorporated an explicit behavioral component within simulation, optimization, or related analytical modeling frameworks. Studies were excluded if they fell outside the evacuation domain; did not include a substantive behavioral component; focused exclusively on building-scale or other confined-space evacuations; examined post-disaster or recovery-phase behavior rather than behavior arising before or during evacuation; or did not concern emergency evacuation. This scope boundary applies to modeling paradigms as well as to settings. Pedestrian dynamics models, including social force and cellular automata formulations, are included when applied to large-scale outdoor urban evacuation and excluded when used to represent building egress or confined-space crowd flow. Title and abstract screening was then conducted using ASReview LAB, a machine-learning-assisted screening platform. Approximately 500 records were manually labeled on the basis of the eligibility criteria, after which the trained model was used to prioritize the remaining records according to predicted relevance. The resulting ranking was used only to support the order of screening and improve efficiency. After title and abstract screening, 386 papers from the database search were retained. Papers retained at this stage were then subjected to full-text review, during which the eligibility criteria were applied. Four papers whose full texts could not be accessed were excluded at this stage. In addition, a total of 145 papers were excluded for reasons such as confined, local, or small-scale evacuation cases; the absence of an explicit evacuation movement or behavioral component; a non-emergency context; lack of focus on evacuation; or failure to use the target method. We then conducted backward snowballing (Hirt et al., 2024), that is, screening the reference lists of retained papers to identify further eligible studies, identifying 242 additional studies that met the same criteria. As a result, the final sample comprised 479 papers, including 237 papers identified through database searching and 242 papers added through backward snowballing.

2.2 Paper classification process

After completing the paper selection process, the retrieved studies were categorized into two groups: (1) factors influencing evacuee behavior and (2) solution methodologies. Although there were 485 entries across the two categories, six papers overlapped, resulting in 479 distinct papers. Fig 2 presents the classification framework used to organize and categorize the included studies.

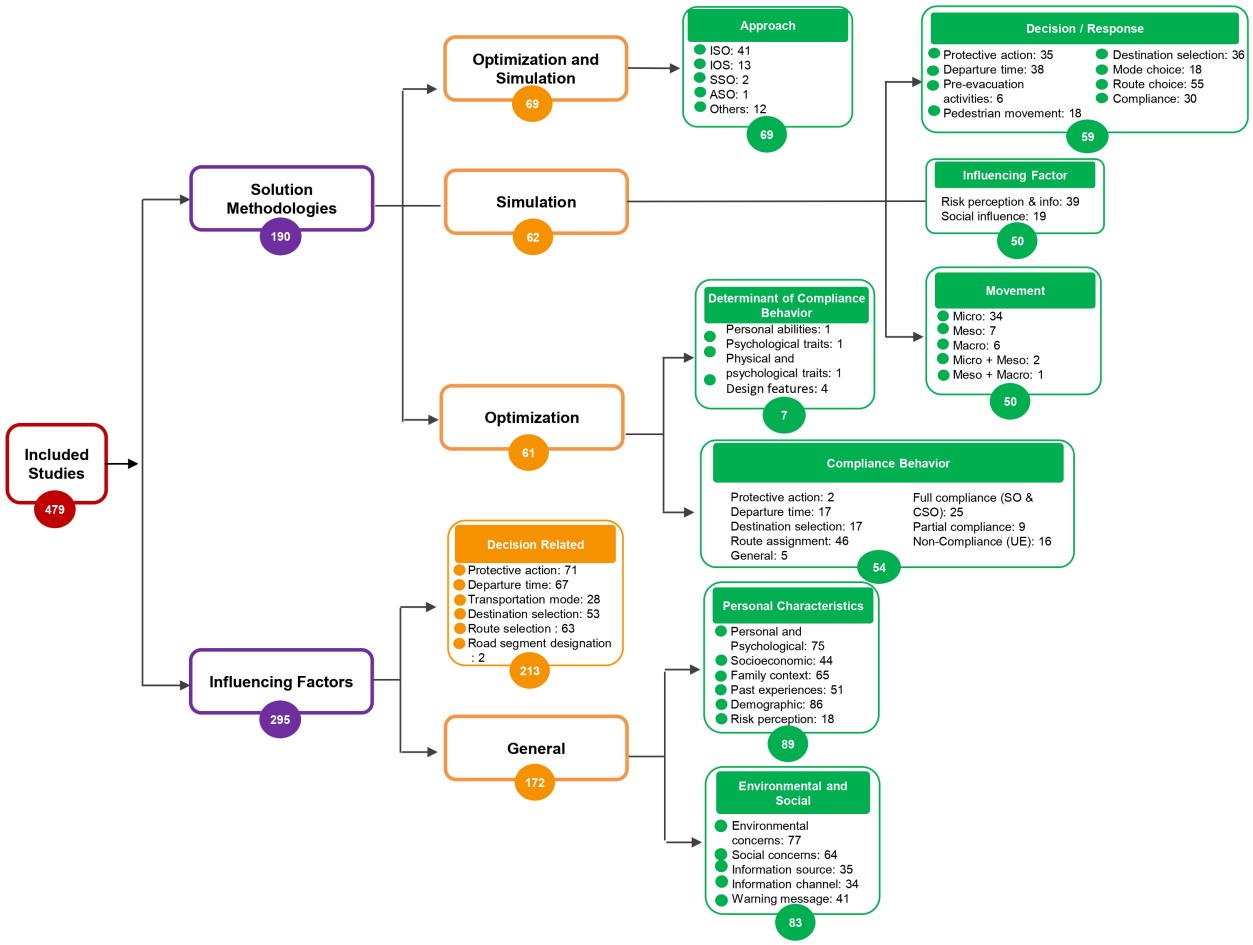


Fig. 2. Paper classification framework.

The *influencing factors* category consists of 295 papers examining the various factors affecting evacuee decision-making during evacuation. These factors are broadly grouped into two main categories: General and Decision-Related. The General category includes 172 studies and is further classified into two subcategories: environmental conditions and social context, and personal characteristics. Environmental concerns include the severity of the disaster, disaster occurrence times, weather conditions, infrastructure, and the physical environment, which are in total examined in 77 papers. Social concerns, such as social networks, cultural beliefs and norms, and language barriers, were discussed in a total of 64 papers. Additionally, information-related factors, including sources, channels, and warning messages, were analyzed in 35, 34, and 41 papers, respectively.

Personal characteristics in evacuation behavior encompass a wide range of factors, including physical and psychological traits, socioeconomic status, family context, past disaster experience, demographics, and risk perception. Physical and psychological traits were examined in 75 papers, while socioeconomic factors, including income level and access to resources, were examined in 44 papers. Family context, particularly the presence of dependents like children and pets, was analyzed in 65 papers, and past experiences with disasters were considered in 51 papers. Demographic factors, including age, gender, education level, and length of residence, were discussed in 86 papers, whereas risk perception, which shapes individual responses to evacuation warnings, was studied in 18 papers.

While a total of 172 papers were reviewed for general influencing factors, many studies examined multiple factors, leading to a cumulative count of 590 mentions. This highlights the complexity of evacuation decision-making, where environmental, social, and personal factors interact in diverse ways to influence individual responses. Building on these influencing factors, we next examine decision-related factors, focusing on how evacuees respond to key evacuation decisions.

The decision-related factors are investigated in 213 papers that specifically examine how evacuees respond to key evacuation decisions made by authorities, considering the influencing factors identified in the first category. Notably, 20 of these papers appear in both the general and decision-related subcategories, as they address how broader environmental, social, or personal factors affect evacuees' responses to specific decisions. These studies are categorized by the specific type of decision addressed and examine individuals' compliance, their alternative actions in cases of noncompliance, and the reasons behind their behavior. One of the key decisions examined is which protective action to take, such as whether to evacuate or shelter in place, which is discussed in 71 papers. Another major focus is departure time, which is a critical factor influencing evacuation efficiency and congestion. Departure time is analyzed in 38 papers. Transportation mode decisions, including whether evacuees are advised to use personal vehicles, public transit, or walk, were addressed in 28 studies. Destination selection, which concerns public shelters designated by authorities, was examined in 53 papers. Route selection, covering both pre-trip decisions and dynamic adjustments made during evacuation, was the most frequently studied topic, appearing in 63 papers. In contrast, the road segment designation decision, which refers to the assignment of road segments to manage mixed pedestrian–vehicle traffic during evacuation, was the least studied, with only two papers addressing this issue.

The solution methodologies category includes 190 papers on optimization methods, simulation, and simulation–optimization approaches, focusing on prescriptive rather than descriptive analyses. Notably, two papers are common across these three categories. Unlike standalone simulation studies that offer insights into evacuee behavior, these methods develop actionable strategies to improve evacuation planning and management. By integrating optimization techniques, they enhance decision-making efficiency, optimizing resource allocation, route planning, and shelter assignments to improve overall evacuation outcomes.

Our search has identified a total of 61 papers that incorporate human behavior into large-scale evacuation optimization models. As shown in Fig 2, these papers can be categorized according to their approach to compliance behavior. Of the 61 unique papers, 50 explicitly incorporated compliance behavior into optimization models, seven considered the determinants (drivers) of compliance behavior, and four provided general insights without direct model integration. Among the 50 model-based papers, 46 addressed route assignment, 17 focused on destination selection, 17 examined departure time, and only two analyzed protective actions, specifically compliance with evacuation orders as reflected in participation rates. Several papers considered multiple decision types; therefore, the counts across decisions exceed the number of unique papers. The majority of papers directly integrating compliance behavior into optimization models rely on classical approaches: 25 adopt system-optimal (SO) or constrained system-optimal (CSO) to assume full compliance, 16 use user-equilibrium (UE) or its extensions to capture selfish decision-making, and only nine explicitly model partial compliance, where evacuees follow instructions to varying degrees. Among the seven papers examining the determinants of compliance behavior, one addressed personal ability, another focused on psychological traits, the third considered a combination of personal and psychological characteristics, and four on structural plan/design features. The

details of this classification are discussed in Section 4 providing insight into compliance-related modeling in evacuation optimization and highlighting key research gaps for future studies.

We also identified 62 simulation-based evacuation papers that explicitly represent behavioral components in large-scale evacuation studies. These papers were systematically reviewed and classified. Among them, three papers discuss the importance of integrating human behavior into simulation models. Among the remaining 59 papers, 50 integrated both movement representation and behavioral components, while the remaining nine were human-behavior-centric and focused on behavioral responses without explicitly simulating movement. In terms of movement representation, microscopic simulation was the most common approach (34 papers), followed by mesoscopic (seven), macroscopic (six), hybrid micro–meso (two), and hybrid meso–macro (one) approaches. Across behavioral dimensions, these studies represented key evacuation decisions, including route choice (55), departure time (38), destination choice (36), protective action (35), and compliance with evacuation-related decisions (30). The most common input factors were risk perception and information (39) and social influence (19). Because a single paper may address multiple behavioral dimensions, and many movement-based studies also incorporated behavioral components, these counts are not mutually exclusive. The details of this classification, together with the key findings and research gaps, are discussed in Section 5.

There are 69 papers that incorporate simulation–optimization approaches in evacuation studies. Among these, 41 papers utilized the Iterative Simulation–Optimization (ISO) method, which involves continuously refining simulation outputs through iterative optimization. Another 13 papers applied the Iterative Optimization–Simulation method (IOS), where optimization is conducted iteratively with updated simulation results. Additionally, two papers explored the Sequential Simulation–Optimization (SSO) method, where simulation–optimization is conducted in a stepwise manner rather than in an iterative loop. Only one paper examined the Alternating Simulation–Optimization (ASO) method, which suggests a different approach to integrating these two techniques. Furthermore, 12 papers were review studies that provided an overview and comparative analysis of these methodologies. These findings highlight the diversity of simulation–optimization approaches applied in evacuation research. A more detailed discussion of these methods, along with their advantages and limitations, is presented in Section 6. Next, we examine how human behaviors influence evacuation outcomes and affect the overall effectiveness of evacuation planning.

The following subsection details the primary factors influencing evacuee decision-making during emergencies.

3 Evacuee behavior during disasters

Evacuation decisions during natural disasters result from a dynamic interaction between external and internal factors. External influences include environmental conditions such as disaster severity, official warnings, and social pressures, while internal aspects encompass personal attributes like risk perception, past experiences, and emotional responses. Understanding these interactions is essential for accurately modeling evacuee behavior and improving emergency evacuation management strategies (Dash and Gladwin, 2007; Lindell and Perry, 2012).

These factors, by shaping individual behavior, critically impact the effectiveness of evacuation planning and management. Authorities play a central role in evacuation management by issuing orders, setting departure timelines, and designating destinations, routes, and transportation modes. However, some evacuees deviate from these directives due to factors

such as perceived risks, awareness levels, distrust in official guidance, past experiences, psychological influences, and sociodemographic characteristics. These deviations can lead to unexpected changes in evacuation patterns, increasing congestion, elevating safety risks, and complicating overall coordination.

These behavioral variations create challenges for evacuation planning and management, necessitating a deeper understanding of how evacuees respond to official directives. This section examines both the key factors influencing evacuee behavior and their impact on people's responses to evacuation-related decisions. It explores how individuals react under these influences and what alternative actions noncompliant evacuees take. In addition, the underlying reasons for these alternative choices are analyzed. By examining these behavioral patterns, this section highlights the complexity of human responses and the challenges they pose for effective emergency evacuation planning and management.

3.1 Factors affecting evacuee behavior

During evacuations, panic and stress often trigger unpredictable behavior, leading individuals to disregard official directives (Quarantelli, 1980). Recognizing the behavioral drivers behind such actions is crucial for improving evacuation planning and management (Ibrahim et al., 2016). A better understanding of these tendencies enables the design of strategies that facilitate safe and orderly movement.

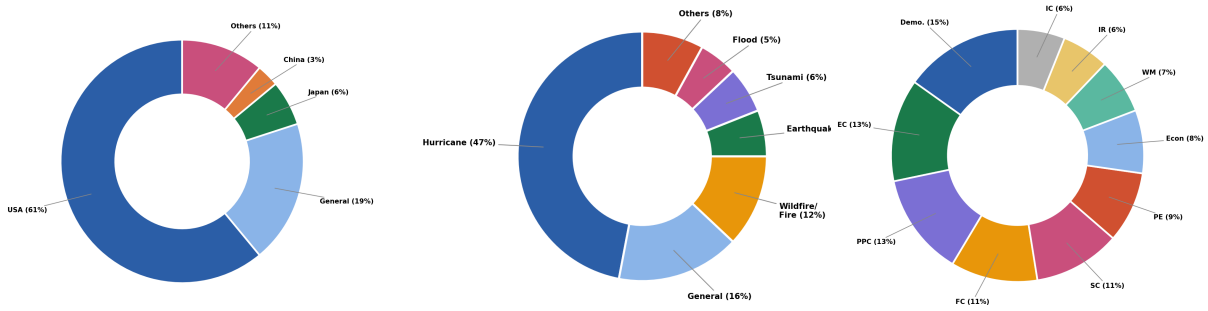
According to Lindell et al. (2018); Ibrahim et al. (2016), the factors influencing evacuation decisions are grouped into three overarching categories: Environmental context, social context, and personal characteristics. Environmental factors include disaster severity, time-of-occurrence, weather, infrastructure, and physical environment. Social factors include social networks, cultural norms, language barriers, and information dissemination (e.g., sources, channels, and warnings). Personal characteristics encompass physical and psychological traits, socioeconomic status, family context, prior-disaster experience, demographic attributes, and risk perception. A visual summary of this classification is provided in Fig. A.1 in Appendix A. Additionally, Table 2 presents a summary of these factors, detailing their influence across different phases of the evacuation process. It includes each factor's impact on behavior, whether it increases or decreases evacuation readiness, the timing of its influence (e.g., onset or during evacuation), and relevant behavioral correlations.

Table 2. Factors affecting human behavior during evacuations.

Group	Factor	Effect	Tendency	Notes
A. Environmental Concerns	Severity of Disaster	Motivates action	Increase	As severity increases, urgency rises.
	Physical Environment – Proximity	Proximity of threat	Increase	Proximity increases perceived danger.
	Physical Environment – Accessibility	Accessibility	Increase/Decrease	Difficult terrain hinders movement.
	Weather	Severe conditions	Decrease	Adverse weather hinders evacuation.
	Time	Daytime/Nighttime	Increase/Decrease	Both have advantages and disadvantages.
	Infrastructure	Familiar routes	Increase	Familiarity reduces uncertainty.
B. Social Concerns	Social Network	Information spread	Increase	Strong networks aid communication.
	Cultural Beliefs	Cultural norms	Increase/Decrease	Influence evacuation decisions.
C. Information Source	Information Sources	Trust in the message	Increase	Credible sources increase compliance.
D. Information Channels	Clarity	Clarity increases evacuation	Increase/Decrease	Traditional media is effective.
E. Warning Message	Message Clarity	Influences compliance	Increase	Clear messaging is effective.
	Timeliness	Speed of warnings	Increase	Timely information enables earlier evacuation.
F. Physical and Psychological Context	Physical Conditions	Health issues	Decrease	Disabilities may slow evacuation.
	Psychological Condition	Stress response	Increase/Decrease	Stress may hinder evacuation.
	Herd Behavior	Follow the actions	Increase	Affects choice of routes or destinations.

Group	Factor	Effect	Tendency	Notes
	Risk Perception	Risk severity and likelihood	Increase	Higher perception boosts compliance.
G. Economic Resource	Economic Status	Income variation	Increase/Decrease	Economic resources impact evacuation.
H. Family Context	Children	Traffic congestion	Decrease	Presence of children slows evacuation.
	Pets	Additional care	Decrease	Pets may cause delays.
	Household Size	Increased household size	Decrease	Larger families require more time.
I. Past Experience	Experience	Influences preparedness	Increase/Decrease	Experience affects response.
J. Demographics	Age	Physical ability	Increase/Decrease	Age affects willingness to evacuate.
	Gender	Roles/responsibilities	Increase/Decrease	Gender influences behavior.
	Education	Risk perception	Increase/Decrease	Education impacts response.
	Residence length	Trust level	Increase/Decrease	Long-term residents evacuate less.

To uncover patterns in evacuation behavior and identify which factors are well-studied versus underexplored, Table B.1 in Appendix B provides a synthesis. This overview is based on an analysis of 172 studies examining factors that influence evacuation decisions and reveals three key trends in current disaster research.



(a) Countries and papers **(b)** Types of disasters **(c)** Factors affecting human behavior

Fig. 3. Overview of human behavior research

Fig 3a, 3b, and 3c summarize the geographical distribution of the studies, the disaster types investigated, and the behavioral factors examined. As shown in Fig 3a, more than half of the reviewed studies (61%) were conducted in the United States. This concentration reflects substantial national investment in disaster research, but it may also reflect broader publication and funding asymmetries, and should not be read as indicating an absence of relevant work in other regions. Fig 3b indicates a strong emphasis on hurricanes (47%), whereas research on no-notice disasters remains limited, even though they account for 73% of disaster-related fatalities (EM-DAT, 2024). Fig 3c highlights that demographic characteristics (15%) and environmental concerns (13%) are the most frequently studied behavioral factors. While psychological and sociological studies have long explored these dimensions, their integration into operational evacuation models remains limited. Most existing models prioritize logistical elements such as traffic flow and infrastructure, without adequately addressing the complexity of human behavior. Furthermore, the literature is predominantly centered on disasters occurring in the Northern Hemisphere, pointing to the need for geographically and contextually diverse research to better inform global evacuation strategies.

3.1.1 Environmental and social context

To better understand how human behavior influences evacuation outcomes, we examine the key categories that shape individual decision-making during disasters. Building on the previously outlined classification, this section first focuses on the **environmental and social context**, which encompasses external factors that influence individuals' risk perception

and evacuation decisions (Huang et al., 2016a). These factors are organized into several subcategories, each contributing in distinct ways to evacuee responses under emergency conditions.

- **Environmental concerns:** *severity of disaster* is a critical factor in decision-making processes. Studies show that 40–60% of people evacuate when they perceive a direct threat or receive a mandatory evacuation order, demonstrating that immediate danger strongly impacts behavior (Bian et al., 2022a; Adjei et al., 2022, Bakhshian and Martinez-Pastor, 2023. Individuals often rely on visible environmental cues as indicators of danger (Lindell, 2012). In the absence of such cues, confusion can arise, leading to hesitation or reluctance to evacuate. *Physical environment*, such as geography, infrastructure, and road networks, also plays a significant role (Noltenius, 2008, Troncoso Parady and Hato, 2016, Ersing et al., 2020, Iwai, 2025). For instance, New Orleans' geography complicates evacuation logistics, requiring strategies like contraflow traffic (Wolshon, 2002). *Weather and season* further impact behavior, influencing preparation and travel times. Extreme conditions, such as winter or severe weather, can slow evacuations and increase stress (Fu et al., 2007; Pham et al., 2020; Sakamoto et al., 2020; La Greca et al., 2023). *Time of day* affects evacuation logistics; daytime evacuations face challenges like traffic congestion, while nighttime evacuations, though quicker due to less traffic, suffer from reduced visibility (Stern, 1989; Lu et al., 2014). Although both daytime and nighttime have challenges, studies on Hurricane Ike indicate that more people tend to evacuate during the daytime (Huang et al., 2012). *Infrastructure and resources*, including route familiarity and shelter availability, also shape decision-making (Dombroski et al., 2006, Lambert et al., 2013, Sadri et al., 2014b, Anyidoho et al., 2023; Mapa et al., 2026). Studies have shown a preference for private accommodations over public shelters during evacuations (Perry, 1979b; Baker, 1995; Whitehead et al., 2000; Cheng et al., 2008a; Yang et al., 2016; DiGrande et al., 2019, Morooka and Yamada, 2017; De Maio, 2013; D'Amico et al., 2024; Wang et al., 2020; Guan and Chen, 2021).
- **Social concerns:** *Social network*, where observing neighbors evacuate can prompt others to follow, driven by herd behavior (Baker, 1995; Riad et al., 1999; Kang et al., 2007; Horney et al., 2010, Jiang et al., 2021; Jin et al., 2025). *Herd behavior*, the tendency to imitate nearby actions, affects evacuation decisions and route choices (Mawson, 2005; Song et al., 2006; Adiga et al., 2013, Intini et al., 2019; Zhang et al., 2024b). The influence of this behavior increases with the number of surrounding individuals (Kinateder et al., 2018). Understanding this behavior can improve emergency response planning (Demiroluk et al., 2016, Aldahlawi et al., 2024, Reyes-Norambuena et al., 2025). For example, during Hurricane Irma, 64% of evacuees were influenced by the actions of family members or neighbors, highlighting the importance of collective action in evacuation rates (Kinateder and Warren, 2016; Sadri et al., 2017a; Collins et al., 2018, Ahmed et al., 2020, Xie et al., 2023). Modern analyses using Twitter and Facebook data further confirm that social network density directly correlates with higher compliance rates in high-risk zones (Roy and Hasan, 2021; Rashid et al., 2025). This behavior aligns with findings that approximately 30% of respondents delay evacuation to confirm warnings through observation of others' actions or seeking additional information, emphasizing the role of social cues in decision-making during emergency evacuation planning and management (Lindell and Perry, 2012, Urata and Hato, 2021; Diaz et al., 2023). *Cultural beliefs and norms* impact how different communities perceive risk and trust authorities (Fothergill et al., 1999, Toledo et al., 2018; Wambura and Wong, 2025). For example, Mexican Americans may perceive flood risks as less severe than white individuals and may be less

likely to evacuate (Perry and Lindell, 1991). Cultural ties can also encourage collective evacuation behaviors within families, as seen in underserved groups where community reliance often substitutes for official aid (Lindell et al., 2005; Blendon et al., 2007, Wong et al., 2020a; Wambura and Wong, 2025). Trust in authorities is critical, as past discrimination can diminish evacuation compliance among minorities (Elliott and Pais, 2006, Ricchetti-Masterson and Horney, 2013, Kim and Oh, 2015; Ayeb-Karlsson et al., 2019). *Language barriers*, such as during the 2007 San Diego wildfires, can hinder evacuation efforts (Lindell et al., 2018), a problem now partially mitigated by SMS alerts and localized digital notification strategies (Hou et al., 2020; Elejalde et al., 2025).

- **Information sources:** Information sources refer to the origin of information that individuals trust and consult when deciding whether to evacuate. Trustworthy sources facilitate timely responses, as observed during Hurricane Lili, where households relied on reliable authorities to guide their actions (Lindell et al., 2005, McLennan et al., 2019; Ling et al., 2021; Mahittikul et al., 2024). For instance, during Hurricane Katrina, 69% of early evacuees reported relying on official sources, such as local authorities and the media, which helped them make informed decisions (Demiroluk et al., 2016; Huang et al., 2017; Sadri et al., 2017b, Roessing-Anderson, 2023). Conversely, when individuals lack trust in these authorities or when information is perceived as inconsistent, skepticism can delay action, creating a "crying wolf" effect that diminishes future compliance(Baker, 1991, Bian et al., 2022b; Adjei et al., 2022; Tsekeni et al., 2025). This issue is particularly pronounced in areas where declining trust in government has led people to seek alternative sources, such as peer groups or real-time social media updates, to reduce perceived uncertainty (An et al., 2015, Walch, 2018, Ling et al., 2021). Recent studies emphasize that the consistency between official warnings and informal social cues is the most significant predictor of trust during rapid-onset disasters (Ling et al., 2021; Mahittikul et al., 2024).

- **Information channels:** Information channels represent the mediums through which information from sources is communicated to the public. While sources identify who delivers the information, channels focus on how the information is delivered. The effectiveness of evacuation communication depends on how well these channels convey credible and accessible information. During Hurricane Lili, local news media were found to be the most trusted channel, followed by national news, peers, local authorities, and the Internet (Lindell et al., 2005, Robinson and Khattak, 2010; Hasan et al., 2011; Sadri et al., 2017b). Studies also highlight that mass media, as a channel, can shape public perception of crises, while social media and mobile platforms can help reduce immediate concerns by providing real-time, location-based updates (Cheng et al., 2015; Diwanji et al., 2020, Roy and Hasan, 2021; Han et al., 2023; Elejalde et al., 2025; Rashid et al., 2025). Recent advancements demonstrate that smartphone applications using GPS-positioning significantly improve route-finding efficiency and reduce evacuation times, especially for individuals unfamiliar with the local geography (Muthohar et al., 2020; Han et al., 2023). Furthermore, big data analytics from platforms like Twitter and Facebook allow for the dynamic monitoring of evacuation demand, providing emergency managers with a direct channel to observe and influence behavioral responses in real-time (Roy and Hasan, 2021; Rashid et al., 2025). Emergency services must adapt their strategies to demographic and geographical factors to ensure that the best-suited channels, ranging from traditional sirens to SMS-based alerts, reach the right audiences effectively (Hou et al., 2020; Nadimi et al., 2025; Elejalde et al., 2025).

- **Warning messages:** Warnings are critical in the evacuation process and must be clear, specific (Bean et al., 2015), timely, and delivered through multiple channels for maximum reach (Mileti and Peek, 2000, Koshute, 2013, Lazo et al., 2015, Hou et al., 2020). Effective warnings depend on both content and the medium used to deliver them, ensuring that evacuees understand the urgency and act accordingly (Perry and Quarantelli, 2005, Xu et al., 2022b; Makinoshima and Imamura, 2024). For instance, 90% of residents who received clear, specific warnings about Hurricane Harvey's impact were more likely to follow evacuation orders compared to vague or generalized messages (Cheng et al., 2013, Gao et al., 2022, Bian et al., 2023; Chen et al., 2024). Recent studies on phased evacuation orders indicate that compliance is significantly higher when stakeholders' perceptions of safety and government responsibility are addressed directly within the message (Bian et al., 2023). Furthermore, the transition from receiving a warning to taking action such as often delayed by "milling" behavior can be optimized through messages that reduce perceived uncertainty and provide concrete evacuation triggers (McLennan et al., 2019; Alawadi et al., 2022; Makinoshima and Imamura, 2024). This emphasizes the need for precise and dynamic communication strategies that adapt to the evolving nature of the disaster response curve (Koshute, 2013; Bian et al., 2023).

3.1.2 Personal characteristics

Following the discussion of environmental and social influences, we now turn to the second main category shaping evacuation behavior: **Personal characteristics**. This category encompasses internal, individual-level factors that play a critical role in how people perceive risk, process information, and ultimately make decisions during emergency evacuation planning and management.

- **Physical and psychological conditions:** Disabilities can delay evacuation due to the need for extra time, assistance, or equipment, posing risks to the individuals and those providing help (Demiroluk et al., 2016, Ducy and Stough, 2021; Hostetter and Naser, 2022, Greer et al., 2023; Reyes-Norambuena et al., 2025). For example, during Hurricane Katrina, 23% of New Orleans' population had a disability, yet many were unable to evacuate due to inadequate planning that overlooked their needs. Challenges included inaccessible transportation, such as buses without wheelchair ramps, and the failure to deploy evacuation resources to areas with large numbers of disabled residents, revealing systemic barriers in disaster preparedness (Wolshon et al., 2005, Powell and Gilbert, 2006, Hasan et al., 2012; Reyes-Norambuena et al., 2025). Recent studies utilizing multi-criteria decision-making (MCDM) frameworks emphasize that integrating human factors into evacuation models is essential for enhancing the preparedness of these vulnerable populations (Reyes-Norambuena et al., 2025). In large-scale urban evacuations, delays are often attributed to insufficient transportation planning and a lack of resource allocation rather than physical exit accessibility within buildings (Christensen, 2011, Wang et al., 2021; Elhami-Khorasani et al., 2023). Poor infrastructure and uncoordinated resource deployment can exacerbate delays, especially in no-notice events where time-dependent transition probabilities are high (Guan and Chen, 2021). Stress and anxiety can impair decision-making during disasters, potentially causing immobility or disorganized evacuations (Vorst, 2010, Bernardini et al., 2016; Alawadi et al., 2020; Adjei et al., 2022). Panic, influenced by demographic factors like age and gender, can lead to unsafe evacuations (Quarantelli, 1975; Li et al., 2017, Hall et al., 2017; Urata and Pel, 2018; Nadimi et al., 2025). Anxiety and perceived uncertainty can delay evacuation until the threat is perceived as imminent, a phenomenon closely

linked to the "perceived safety" of the chosen evacuation route (Czajkowski, 2011) (Adjei et al., 2022; Grajdura and Rowangould, 2025; Ma and Lee, 2025).

- **Socioeconomic conditions:** Influence individuals' evacuation capabilities, particularly through the availability of resources (Xu et al., 2016) (Yabe and Ukkusuri, 2020) (Chang et al., 2021; Anyidoho et al., 2022). Higher income and education levels are often associated with a preference for private accommodations, whereas individuals with lower incomes are more likely to depend on public shelters (Whitehead et al., 2000) (Mozumder et al., 2008; Sadri et al., 2014a; Lim et al., 2019). Additionally, homeownership may contribute to evacuation reluctance due to emotional attachment to property (Yang et al., 2016, Sarwar et al., 2018; Golshani et al., 2020), whereas renters demonstrate a 1.33 times higher likelihood of evacuating compared to homeowners (Kulkarni et al., 2017, Bian et al., 2019; Rambha et al., 2021).
- **Family context:** Households with children, elderly, or disabled members often require additional preparation and transportation time, thereby influencing evacuation response times (Perry, 1979b; Lindell and Prater, 2007, Dixit et al., 2012, Huang et al., 2012; Lim Jr et al., 2022, Sun et al., 2024; Nadimi et al., 2025). Families typically make decisions collectively, which can further delay their responses (Sadri et al., 2017a; Wong et al., 2020a; Golshani et al., 2020). *Pets* also play a significant role in evacuation decision-making, as many pet owners refuse to evacuate without them (Dow and Cutter, 2000, Alawadi et al., 2020; Greer et al., 2023). This necessitates finding pet-friendly shelters and transportation options, which can introduce delays and increase stress levels (Heath et al., 2001). Legislative measures such as the Pet Evacuation and Transportation Standards Act (PETS), enacted after Hurricane Katrina, aim to address these challenges by promoting inclusive evacuation plans (Hunt et al., 2012; Farmer et al., 2016). The presence of *children* further shapes evacuation behavior, as parents prioritize their children's safety. This often includes retrieving children from schools, despite established procedures, which can lead to significant delays in evacuation timelines (Stern, 1989; Perry and Lindell, 1991; Baker, 1991; Lindell et al., 2005, Robinson and Khattak, 2010; Hasan et al., 2011; Diaz et al., 2023).
- **Past experiences:** Past experiences with disasters significantly influence evacuation behavior, often leading to faster and more decisive actions due to increased awareness and preparedness (Lazo et al., 2015, Wong et al., 2020b; Grajdura et al., 2021). These experiences shape individuals' perceptions of risk, trust in authorities, and preferred response strategies (Kinateder et al., 2015, Hall et al., 2017; Mahittikul et al., 2024). Empirical studies on events such as Hurricanes Lili, Katrina, and Rita reveal that individuals with prior evacuation experience tend to rely on familiar routes during subsequent evacuations (Wu et al., 2012, Syamsidik and Istiyanto, 2013; Chen et al., 2022). Notably, approximately 40% of evacuees prefer familiar routes, even when alternative paths may offer shorter travel time (An et al., 2015, Li et al., 2022b, Bakhshian and Martinez-Pastor, 2023). While positive past experiences can foster efficient evacuation behavior, negative experiences may lead to hesitation, increased anxiety, or misjudgments in response-strategies, highlighting the dual impact of past experiences on evacuation decision-making (Huang et al., 2016a, McLennan et al., 2019; Chen et al., 2021a).
- **Demographic factors:** Encompass age, gender, education, marital status, employment, and length of residence (Baker, 1991, Cheng et al., 2011; Raei et al., 2025). *Age* influences evacuation behavior, with older individuals often evacuating more slowly or choosing to stay behind (Lindell and Prater, 2000; Cahalan and Renne, 2007; Lazo et al., 2015, Urata and Pel, 2018; Chen and Cheng, 2020). *Gender* shapes risk perception and response,

with women being 1.36 times more likely to evacuate than men, as observed during disasters like Hurricane Sandy. Women often prioritize the safety of dependents, while men may stay to protect property (Fothergill, 1996; Bateman and Edwards, 2002; Neumayer and Plümper, 2007; Kulkarni et al., 2017, Bian et al., 2019; Kuligowski et al., 2022). *Education level* enhances risk perception and compliance with evacuation orders, contributing positively to overall community response (Muttarak and Lutz, 2014; Kim and Oh, 2015; Lindell et al., 2018, Chen et al., 2024; Wambura and Wong, 2025). *Length of residence* affects willingness to evacuate; long-term residents often resist due to familiarity and attachment, while newer residents are more likely to comply with orders. For instance, during Hurricane Floyd, recent residents were approximately 10% more likely to evacuate than those with over a decade of residence (Baker, 2000, Intini et al., 2019; Lim et al., 2019, Wong, 2020). International tourists tend to evacuate readily, relying on social media and local authorities and facing fewer property constraints. However, their responses may initially be slower due to unfamiliarity with local evacuation procedures (Charnkol and Tanaboriboon, 2006; Lindell and Prater, 2007; Pennington-Gray et al., 2014; Cahyanto and Pennington-Gray, 2015, Iwai, 2025; Raei et al., 2025).

- **Risk perception:** The subjective judgment of a risk's severity and likelihood plays a pivotal role in evacuation behavior (Slovic, 1987, Bian et al., 2022a; Li et al., 2022b). This perception is shaped by sociodemographic factors such as age, household size, and income (Huang et al., 2017, Rana et al., 2020, Ling et al., 2021), as well as by the credibility and frequency of warnings, which can enhance awareness or cause warning fatigue (Mileti et al., 1975; Mileti, 1999; Trettin and Musham, 2000; Paul, 2012, Adjei et al., 2022; Bian et al., 2023). Social and cultural filters further influence how individuals interpret the same risk messages (Turner, 1979, Urata and Hato, 2021; Zhang et al., 2024b). Local knowledge is also critical; for example, only 14% of Florida residents knew their home's elevation, causing many to underestimate storm surge risks and delay evacuation (Baker and Zhao, 2012, Guan and Chen, 2021; Tsekeni et al., 2025). Understanding these dynamics is essential for improving public risk-awareness and increasing compliance with evacuation strategies (Perry, 1994; Gladwin and Peacock, 1997; Riad et al., 1999; Dash and Morrow, 2000; Dash and Gladwin, 2007, An et al., 2015, Lovreglio et al., 2020, Wang et al., 2021; Elhami-Khorasani et al., 2023).

The next subsection groups these factors into compliant and non-compliant responses to evacuation orders.

3.2 Compliance/noncompliance to evacuation orders and alternative evacuee actions

Evacuation planning and management encompasses strategic and operational decisions such as whether to evacuate or shelter in place, evacuation timing, designated routes, assigned shelter, and transportation mode selection (Bayram and Yaman, 2024). These decisions are generally made with the expectation of public compliance; however, non-compliance is frequently observed in practice, posing significant challenges for planners and authorities (Lindell et al., 2018; Wong, 2020). In large-scale, city-wide or regional evacuations, the consequences of non-compliance are amplified because individual deviations propagate through the network and affect thousands of other evacuees simultaneously. To this end, researchers have examined non-compliance behavior and its contributing factors across diverse disaster contexts, as discussed in Subsection 3.1.

This subsection reviews the literature according to key evacuation decisions made by authorities. For each decision type, we identify: (1) the directive issued, (2) observed public responses, (3) noncompliant actions taken as alternatives,

and (4) contributing behavioral factors, based on empirical research and predictive approaches. We also evaluate the extent to which each decision type and disaster context has been addressed in prior studies. A summary of the findings is presented in Table 3.

Table 3. Official directives, alternative actions, and reasons for noncompliance.

Categorized key decision	Authorities' directive	Alternative action by noncompliant evacuees	Reasons for noncompliance	Related studies
Protective action	Evacuate	Stay at home	Concerns about traffic, limited resources (e.g., supplies, money), physical limitations (e.g., old age, disability), sociodemographic factors (e.g., long-term residency, pet ownership, absence of children in the household, larger household size, lower education level, being male and being unmarried), and lack of perceived urgency or pressure to evacuate, homeownership and property attachment (e.g., concern for belongings and livestock), lack of vehicle access, pandemic-related concerns (e.g., fear of virus exposure at shelters), confidence in building safety (e.g., pre-installed protective measures), work obligations, inadequate or ineffective warning dissemination (e.g., ambiguity, delayed delivery, and fatigue from previous false alarms), very short disaster arrival time, low self-efficacy and overestimation of available evacuation time, social influence from non-evacuating neighbors and lack of social pressure, nighttime or cold-season occurrence, absence of prior evacuation experience, and low belief in evacuation effectiveness.	(Schaffer and Cook, 1972; Mileti et al., 1975; Perry, 1979a; Carter et al., 1983; Ujihara, 1989; Jann, 1989; Bolin et al., 1996; Gladwin and Peacock, 1997; Dow and Cutter, 2000; Whitehead et al., 2000; Wolshon, 2002; Bateman and Edwards, 2002; Van Willigen et al., 2002; Urbina and Wolshon, 2003; Council, 2005; Handmer and Tibbits, 2005; Wolshon et al., 2005, Zachria and Patel, 2006; Mozumder et al., 2008, Solís et al., 2010; Hasan et al., 2011, 2012; Syamsidik and Istiyanto, 2013, Yin et al., 2016; Demiroluk et al., 2016; Xu et al., 2016; Hall et al., 2017; Morooka and Yamada, 2017; Sadri et al., 2017a,b; Sarwar et al., 2018; Toledo et al., 2018; Urata and Pel, 2018; Lim et al., 2019; McLennan et al., 2019; Hou et al., 2020; Chen et al., 2021a; Guan and Chen, 2021; Ling et al., 2021; Urata and Hato, 2021; Wang et al., 2021; Adjei et al., 2022; Anyidoho et al., 2022; Bian et al., 2022a; Li et al., 2022b, McGee and Penning-Rowsell, 2022; Elhami-Khorasani et al., 2023; Greer et al., 2023; Wong et al., 2020a, Bayram and Yaman, 2024; Chen et al., 2024; Sun et al., 2024; Wu et al., 2024; Elejalde et al., 2025; Jin et al., 2025; Ma and Lee, 2025; Nadimi et al., 2025; Rashid et al., 2025; Tsekeni et al., 2025)
	Shelter-in-place	Evacuate	Poor communication with authorities, home safety concerns, urgent medical needs, delayed or unclear official information, lack of public preparedness education, and absence of mobility constraints, high perceived risk exceeding official assessment, emotional distress and fear, proximity to threat and structurally vulnerable dwelling, desire to reunite with family, sociodemographic factors (e.g., higher income and socioeconomic status enabling mobility, being single, younger, or female), and social influence from trusted contacts and alarming messages through networks.	(Ujihara, 1989; Jann, 1989; Whitehead et al., 2000; Sorensen et al., 2004; Council, 2005; Handmer and Tibbits, 2005, Wolshon et al., 2005, Haynes et al., 2009, Hasan et al., 2011; Lambert et al., 2013; Demiroluk et al., 2016, Golshani et al., 2019a, Lim et al., 2019; Ling et al., 2021; Li et al., 2022b, McGee and Penning-Rowsell, 2022, Elejalde et al., 2025; Ma and Lee, 2025)
	No action needed (safe area)	Evacuate (shadow evacuation)	Panic, miscommunication, risk unawareness	(Lindell et al., 1983; Lindell and Prater, 2007; Dueñas-Osorio et al., 2012, Ling et al., 2021; Ma and Lee, 2025)

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Categorized key decision	Authorities' directive	Alternative action by noncompliant evacuees	Reasons for noncompliance	Related studies
Departure time	Evacuate at specific time	Delay their departure	Preparatory activities (e.g., gathering information, notifying family, collecting essentials, making intermediate trips); psychological and informational barriers (e.g., stress, unfamiliarity with hazards, limited reliable information, reliance on TV, low risk recognition, overestimation of the evacuation window, insufficient trust in official information, and waiting to observe others' decisions); demographic and socioeconomic constraints (e.g., older age, disability, lower income, male gender, long-term residency, presence of children, large household size, and lack of vehicle access); delayed, unclear, or insufficiently detailed official warnings, insufficient pressure from officials; residence outside high-risk areas, expectation of reduced hazard severity, no prior evacuation experience, shorter evacuation distances, and reduced urgency due to plans to stay with friends or at hotels; perceived traffic congestion, uncertainty about the safety of escape routes, owning multiple vehicles, low visibility, and evening or nighttime hours.	(Murray-Tuite and Mahmassani, 2003; Sorensen et al., 2004; Murray-Tuite and Mahmassani, 2004, Wolshon et al., 2005, Zimmerman et al., 2007; Chiu and Mirchandani, 2008; Kittiratanapaiboon, 2009; Chaudhari et al., 2010; Haynes et al., 2010, Dixit et al., 2012, Liu et al., 2012; Yun and Hamada, 2012; Goto et al., 2012; Suppasri et al., 2013; Hasan et al., 2013; Liu et al., 2014b, An et al., 2015, Ng et al., 2015, Bernardini et al., 2016; Hall et al., 2017; Sarwar et al., 2018; Urata and Pel, 2018; Toledo et al., 2018, Lindell et al., 2018; Gehlot et al., 2019a,a; Golshani et al., 2019b,a, McLennan et al., 2019; Golshani et al., 2020; Wong et al., 2020b; Guan and Chen, 2021; Grajdura et al., 2021; Rambha et al., 2021; Roy and Hasan, 2021, Wang et al., 2021; Grajdura et al., 2021, Anyidoho et al., 2022; Bian et al., 2022b; Chen et al., 2022; Elhami-Khorasani et al., 2023; Makinoshima and Imamura, 2024; Elejalde et al., 2025; Grajdura and Rowangould, 2025; Iwai, 2025; Jin et al., 2025; Ma and Lee, 2025; Reyes-Norambuena et al., 2025; Wambura and Wong, 2025)
	Evacuate at specific time	Evacuate earlier than instructed	Heightened risk perception (e.g., proximity to hazard, visible environmental cues), prior evacuation experience, having a plan or destination in mind, clear understanding of evacuation procedures and participation in public preparedness programs, long expected travel times, and living alone, allowing quicker decision-making and response, smartphone ownership and access to real-time information, daytime hours, higher education level and financial preparedness, vehicle ownership, concern about potential danger, delay, or rerouting.	(Sorensen, 1991; Huang et al., 2012; McLennan et al., 2013; Hasan et al., 2013; Ng et al., 2015, Sarwar et al., 2018, Gehlot et al., 2019a, Golshani et al., 2020; Grajdura et al., 2021; Guan and Chen, 2021; Anyidoho et al., 2022; Bian et al., 2022b, Jiang et al., 2022, Bian et al., 2023; Makinoshima and Imamura, 2024; Elejalde et al., 2025; Ma and Lee, 2025; Raei et al., 2025; Wambura and Wong, 2025)
Transportation mode	Evacuate as a pedestrian	Use a vehicle or bus instead	Inaccessibility of destinations by foot; benefits of vehicle use including family gathering, information access, transport capability and greater speed and convenience, psychological factors such as material attachment and perceived vulnerability, mobility limitations and household disability	(Murray-Tuite et al., 2012; Murray-Tuite and Wolshon, 2013; Sadri et al., 2014b; Liu et al., 2014a, An et al., 2015, Lindell et al., 2015; Bian and Wilmot, 2018; Togawa et al., 2018, Golshani et al., 2020; Wong et al., 2020b; Chen et al., 2021a; Elhami-Khorasani et al., 2023, Wambura and Wong, 2024, Iwai, 2025; Jin et al., 2025)
	Evacuate by vehicle	Evacuate as a pedestrian	Concerns about traffic congestion, lack of access to vehicle, demographic factors such as gender, older age, and lower education, and proximity to accessible destinations.	(Dow and Cutter, 2002; Patrick, 2005; Deka and Carnegie, 2010; Renne et al., 2011; Wu et al., 2012; Sadri et al., 2014b; Mas et al., An et al., 2015; Bian et al., 2019)
	Evacuate by bus	Use a personal vehicle	Owning a private vehicle, higher income, plans to stay with friends or relatives, fear of overcrowding, perceived comfort and shorter waiting time, need for intermediate stops, limited public transit service, desire to protect vehicular property, and presence of elderly household members.	(Wolshon et al., 2005, Wolshon et al., 2005; Sadri et al., 2014a; An et al., 2015; Troncoso Parady and Hato, 2016; Bian et al., 2019; Golshani et al., 2020)

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Categorized key decision	Authorities' directive	Alternative action by noncompliant evacuees	Reasons for noncompliance	Related studies
Destination selection	Go to the assigned public shelter	Go to homes of friends or relatives or commercial facilities	Alternatives offer flexible departure times, lower cost, no capacity constraints, and no check-in requirements, social connections and familiarity with destination, comfort and privacy of private accommodations, distrust in nearby shelters, and sociodemographic factors such as pet ownership, higher education, older age, higher income, and larger household size, lack of awareness about shelter locations, panic and confusion, mobility constraints, health and pandemic-related concerns, network congestion reducing shelter accessibility, and vehicle ownership.	(Mileti et al., 1975; Sheffi, 1985a; Prater et al., 2000; Whitehead et al., 2000; Baker, 2000; Whitehead, 2003, Wolshon et al., 2005, Smith and McCarty, 2009; Cheng et al., 2011; Lindell et al., 2011; Wu et al., 2012; Mesa-Arango et al., 2013; Wilmot et al., 2013; Wu et al., 2013; Yin et al., 2014a,a, Lambert et al., 2013; An et al., 2015; Bernardini et al., 2016; Troncoso Parady and Hato, 2016; Hall et al., 2017, Lim et al., 2016; Wong et al., 2018, Toledo et al., 2018; Bian et al., 2019, Golshani et al., 2019a, Muthohar et al., 2020; Chen and Cheng, 2020; Wong et al., 2020b, Wong, 2020; Damera et al., 2020; Wong et al., 2020c, Jiang et al., 2021, Bian et al., 2023, Chen et al., 2024; Mahittikul et al., 2024; D'Amico et al., 2024; Ma and Lee, 2025; Wambura and Wong, 2025; Jin et al., 2025; Tsekeni et al., 2025; Grajdura and Rowangould, 2025)
Route selection	If evacuating with a personal vehicle, follow the assigned vehicle route	Select an alternative route	Alternative routes may be more familiar, shorter in length or travel time, wider, less congested, more frequently used, and perceived as safer, with access to essential services, physical obstacles, or road damage along designated routes, sociodemographic factors such as older age, psychological factors such as high stress, fear, or aggression; household agreement, unclear guidance on assigned routes, and mistrust in information sources or poor communication quality, active hazards, use of real-time navigation tools, and individual risk tolerance.	(Yang et al., 1993; Leach, 1994; Hatfield, 1994; Bonsall and Palmer, 1999; Prater et al., 2000; Lickel et al., 2000; Adler, 2001; Lindell et al., 2001; Sherman et al., 2002; Arentze and Timmermans, 2005; Chiu and Mirchandani, 2008; Abdelgawad and Abdulhai, 2009, Robinson and Khattak, 2010, Deka and Carnegie, 2010; Tu et al., 2010; Knoop et al., 2010; Lindell et al., 2011; Wu et al., 2012, De Maio, 2013; Lambert et al., 2013, Hsu and Peeta, 2013; Sadri et al., 2014b; Akbarzadeh and Wilmot, 2015, Bernardini et al., 2016; Huang et al., 2017; Intini et al., 2019, Dulebenets et al., 2019; Lim Jr et al., 2019; Dulebenets et al., 2019, Muthohar et al., 2020; Wang et al., 2020; Chen and Cheng, 2020; Wong et al., 2020b, Wang et al., 2021, Wang et al., 2021; Bian et al., 2022b; Xu et al., 2022b, Lessan and Kim, 2022, Elhami-Khorasani et al., 2023, Sheu, 2024, D'Amico et al., 2024; Ma and Lee, 2025; Raei et al., 2025; Wambura and Wong, 2025; Mapa et al., 2026)
	If evacuating as a pedestrian, follow the assigned pedestrian route	Select an alternative route	Alternative routes may be shorter, wider, less congested, and offer higher capacity, poor or unclear evacuation signage; and physical damage, fear of adjacent buildings, and crowd influence.	(Older, 1968; Seneviratne and Morrall, 1985; Moussaïd et al., 2010, Bernardini et al., 2016; Troncoso Parady and Hato, 2016, Han et al., 2017, Chen et al., 2022)
Road segment designation	If evacuating with a personal vehicle, use vehicle-only road segments	Use pedestrian road segment as well	Reasons for noncompliance behavior have not been explored yet	No related study found

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Categorized key decision	Authorities' directive	Alternative action by noncompliant evacuees	Reasons for noncompliance	Related studies
	If evacuating as pedestrian, use pedestrian-only road segment	Use vehicle road segment as well	Reasons for noncompliance behavior have not been explored yet	No related study found

A core decision in evacuation planning and management is the **protective action directive**, which determines whether people should **evacuate**, **shelter-in-place**, or take **no action**, based on hazard characteristics, threat proximity, exposure risk, lead time, and transportation conditions (Lindell et al., 2018; Lindell and Prater, 2007). Among these, **evacuation** has received the most scholarly attention. Non-compliance with evacuation orders is influenced by a combination of logistical, sociodemographic, cognitive, and situational factors. Traffic congestion remains one of the most cited deterrents, with 65% of non-evacuees during Hurricane Floyd identifying it as the primary barrier (Dow and Cutter, 2000), while lack of transportation and financial constraints prevented many from evacuating during Hurricane Katrina (Wolshon, 2002). More broadly, lack of vehicle access constitutes a fundamental barrier to departure (Sarwar et al., 2018; Anyidoho et al., 2022; Sun et al., 2024). Sociodemographic characteristics further shape compliance: age (Mileti et al., 1975; Perry, 1979a; Toledo et al., 2018), gender (Bateman and Edwards, 2002; Ling et al., 2021; Sun et al., 2024), household composition (Carter et al., 1983; Gladwin and Peacock, 1997), disability (Van Willigen et al., 2002), income (Schaffer and Cook, 1972; Bolin et al., 1996), length of residence (Gladwin and Peacock, 1997), pet ownership (Whitehead et al., 2000; Mozumder et al., 2008; Solís et al., 2010; Yin et al., 2016), lower education level (Hasan et al., 2011; Sarwar et al., 2018), and larger household size (Hasan et al., 2011). Distance to shelters and trust in authorities also play a role (Whitehead et al., 2000; Solís et al., 2010). Work obligations during the evacuation period further constrain compliance (Hasan et al., 2011; Sarwar et al., 2018).

Homeownership and property attachment, including concern for belongings and livestock, can reduce willingness to leave (Hasan et al., 2011; McLennan et al., 2019; Anyidoho et al., 2022; Elhami-Khorasani et al., 2023; Rashid et al., 2025), while confidence in building safety, such as residing in a multi-floor home during flooding or having pre-installed protective measures, diminishes the perceived need to evacuate (Hasan et al., 2012; Morooka and Yamada, 2017; Lim et al., 2019; Nadimi et al., 2025). Warning communication deficiencies constitute another critical barrier. Advisory orders are often perceived as non-urgent, resulting in delayed responses or inaction, and the absence or ambiguity of official warnings further reduces compliance (Guan and Chen, 2021). Warning fatigue from previous false alarms erodes trust in future directives (Wolshon et al., 2005), while delayed warning delivery or very short disaster arrival times leave insufficient opportunity to act (Syamsidik and Istiyanto, 2013).

Cognitive and perceptual barriers also play a significant role: low self-efficacy and overestimation of available evacuation time lead individuals to misjudge their window for safe departure (Hall et al., 2017), while absence of prior evacuation experience and low belief in the effectiveness of evacuation suppress protective action (Li et al., 2022b; Jin et al., 2025).

Social dynamics further reinforce non-compliance, as the influence of non-evacuating neighbors and the absence of social pressure from close contacts encourage individuals to stay (Sadri et al., 2017a; Urata and Hato, 2021), particularly among those with weaker social networks and lower perceived exposure (Sadri et al., 2017b). Situational conditions, including nighttime or cold-season occurrence (Nadimi et al., 2025) and pandemic-related concerns such as fear of virus exposure at congregate shelters (Tsekeni et al., 2025), represent additional barriers. Across all these dimensions, lack of perceived urgency or pressure to evacuate remains one of the most consistently reported factors (An et al., 2015; Xu et al., 2016; Demiroluk et al., 2016; Urata and Pel, 2018; Hou et al., 2020; Wang et al., 2021; Chen et al., 2021a; Bian et al., 2022b; Adjei et al., 2022; Diaz et al., 2023; Greer et al., 2023; Wong et al., 2020a; Wu et al., 2024; Chen et al., 2024; Ma and Lee, 2025; Elejalde et al., 2025).

Large-scale evacuations are not always viable and may cause life-threatening congestion if poorly managed (Bayram and Yaman, 2024). During Hurricane Rita (2005), 80% of 111 deaths were evacuation-related, with traffic spanning over 100 miles (Urbina and Wolshon, 2003; Zachria and Patel, 2006). In such cases, a **shelter-in-place** directive may be issued (Sorensen et al., 2004). This approach can be effective; in Australia, 75.7% of flash flood fatalities occurred outdoors versus 12% indoors (Haynes et al., 2009). Non-compliance with shelter-in-place orders is tied to distrust, unsafe housing, or medical needs. Individuals with disabilities or secure homes tend to stay, while others may evacuate despite advice (Whitehead et al., 2000; Golshani et al., 2019a; Ma and Lee, 2025). When perceived risk exceeds official assessment, individuals are more likely to self-evacuate regardless of shelter-in-place directives (Wolshon et al., 2005; Elejalde et al., 2025), particularly those experiencing emotional distress and fear (Li et al., 2022b). Structural vulnerability, such as residing in a mobile-home or being located close to the threat, further increases the likelihood of departing against advice (Hasan et al., 2011; Demiroluk et al., 2016; Lim et al., 2019). The desire to reunite with family members at a different location is another significant motivator (Lambert et al., 2013), as is social influence from trusted contacts and alarming messages spreading through large networks (Ling et al., 2021). Demographic and socioeconomic characteristics also matter: higher income and socioeconomic status provide greater mobility and resources to self-evacuate (Hasan et al., 2011; Elejalde et al., 2025), while being single, younger, or female is associated with a higher propensity to leave rather than shelter in place (Demiroluk et al., 2016; Lim et al., 2019).

To enhance compliance, studies recommend early warnings, clear guidance, and public education (Ujihara, 1989; Jann, 1989; McGee and Penning-Rowsell, 2022). In Australia, early decisions are encouraged to reduce uncertainty (Council, 2005; Handmer and Tibbits, 2005).

A **take-no-action** directive targets populations outside danger zones to reduce congestion and conserve emergency resources. However, these can be disrupted by **shadow evacuations**, unauthorized departures by those not advised to evacuate, often driven by unclear messaging or elevated risk perception. Such actions can strain transportation systems, as seen after the Three Mile Island accident and Hurricane Ike (2008) (Lindell et al., 1983; Dueñas-Osorio et al., 2012; Ling et al., 2021; Ma and Lee, 2025). To mitigate this, authorities should clearly define risk zones, communicate consistently, and address public concerns (Lindell and Prater, 2007).

While authorities can issue evacuation orders, they have limited control over individuals' actual **departure time** (Beloglazov et al., 2016). Although most evacuate after official warnings, some leave earlier, particularly those with prior evacuation experience ((Jiang et al., 2022; Makinoshima and Imamura, 2024; Ma and Lee, 2025)), preparedness (e.g., identifying a safe destination) (Jiang et al., 2022), clear guidance on actions (Gehlot et al., 2019a), or visual cues

like smoke or flames, or deteriorating air-quality in nearby areas (McLennan et al., 2013; Raei et al., 2025). Smartphone ownership, firsthand observation of the hazard, and familiarity with community evacuation plans also facilitate earlier departure (Grajdura et al., 2021). Proximity to hazards increases perceived risk, prompting earlier departure (Huang et al., 2012; Gehlot et al., 2019a; Guan and Chen, 2021; Elejalde et al., 2025), consistent with findings linking threat severity to timing (Sorensen, 1991). Anticipated long travel times also encourage early evacuation to avoid congestion (Hasan et al., 2013; Ng et al., 2015; Gehlot et al., 2019a; Golshani et al., 2020; Bian et al., 2023). Individuals living alone may act sooner due to simplified decision-making, especially when messaging is clear (Gehlot et al., 2019a). Additionally, higher education level, vehicle ownership, and greater financial preparedness are associated with earlier departure (Sarwar et al., 2018; Ma and Lee, 2025), as are daytime hours (Anyidoho et al., 2022) and participation in public preparedness programs that increase risk-awareness (Wambura and Wong, 2025). Concern about potential danger, delay, or rerouting can also encourage some evacuees to leave before traffic management measures take effect (Bian et al., 2022b).

Many still delay evacuation after receiving official warnings due to cognitive processing and pre-evacuation tasks such as gathering information, contacting family, retrieving children, collecting essentials, or making intermediate trips (Murray-Tuite and Mahmassani, 2003; Sorensen et al., 2004; Murray-Tuite and Mahmassani, 2004; Bernardini et al., 2016; Toledo et al., 2018; Wang et al., 2021; Chen et al., 2022; Elhami-Khorasani et al., 2023; Makinoshima and Imamura, 2024; Reyes-Norambuena et al., 2025). Mothers, unemployed parents, and affluent households are more likely to retrieve children (Zimmerman et al., 2007; Chaudhari et al., 2010; Liu et al., 2012, 2014b), while commuters often return home to secure possessions (Chaudhari et al., 2010). These actions contribute to delayed departures and congestion. For instance, during the 2011 Tohoku Earthquake and Tsunami, over 80% of residents delayed evacuation for such reasons, increasing fatalities (Chiu and Mirchandani, 2008; Haynes et al., 2010; Yun and Hamada, 2012; Suppasri et al., 2013; Lindell et al., 2018).

Departure time remains highly variable and difficult to predict due to diverse pre-evacuation activities. To address this, models have estimated departure time distributions using S-curves (Radwan et al., 1985; Kalafatas and Peeta, 2009; Xie et al., 2010; Li et al., 2013; Woo et al., 2017), logistic curves (Southworth, 1991), Rayleigh (Tweedie et al., 1986), exponential (Hobeika and Kim, 1998), and Poisson-based methods (Cova and Johnson, 2003). More recent approaches apply regression, neural networks, survival analysis (Wilmot and Mei, 2004; Fu et al., 2007; Pham et al., 2020; Grajdura et al., 2021), random parameter probit models (Sadri et al., 2013), hazard-based models (Hasan et al., 2013; Gehlot et al., 2019a), and heuristic algorithms (Zhao et al., 2022).

These models predict departure timing using a set of predefined influential factors. Preparatory activities, such as gathering information, notifying family, collecting essentials, and making intermediate trips, consume time before departure begins. Psychological and cognitive barriers further contribute to delay: stress, unfamiliarity with hazards, limited reliable information, and reliance on traditional media slow decision-making (Wilmot and Mei, 2004; Fu et al., 2007; Pham et al., 2020; Grajdura et al., 2021). Low-risk recognition is a particularly strong predictor, with evacuees who do not perceive themselves at risk departing significantly later (An et al., 2015; Urata and Pel, 2018; Roy and Hasan, 2021; Iwai, 2025), and overestimation of the evacuation window compounds this effect (Wolshon et al., 2005; Hall et al., 2017). Insufficient trust in official warnings (Jin et al., 2025), unclear or insufficiently detailed warning messages (McLennan et al., 2019), and uncertainty about storm track and intensity forecasts, including hope that

evacuation may become unnecessary, contribute to hesitation (Wolshon et al., 2005; Hall et al., 2017), while insufficient pressure from officials further reduces the urgency to act (Wong et al., 2020b). Waiting to observe others' decisions before acting also delays individual departure (An et al., 2015). sociodemographic and household characteristics shape departure timing as well: older adults, individuals with disabilities, and less-educated households tend to evacuate later (Gehlot et al., 2019a; Golshani et al., 2019b; Elejalde et al., 2025), as do those with lower income and long-term residence (Grajdura et al., 2021). Male gender is also associated with later departure (Grajdura et al., 2021; Anyidoho et al., 2022). Presence of children, large household size, and absence of a mandatory evacuation order further delay departure (Dixit et al., 2012; Sarwar et al., 2018; Golshani et al., 2020; Rambha et al., 2021), while lack of vehicle access (Wambura and Wong, 2025) and owning multiple vehicles, which adds coordination difficulties, prolong the process (Rambha et al., 2021).

Evidence on insurance coverage is mixed and appears to be context-dependent. In a hurricane setting, insurance coverage has been associated with later departure, which the authors attribute to a reduced perception of financial risk from hurricane damage Jiang et al. (2022). In a wildfire stated-preference study, by contrast, full homeowners' or renters' coverage was associated with earlier intended departure (Ma and Lee, 2025).

Situational and environmental conditions present additional barriers: residence outside high-risk areas (Guan and Chen, 2021), expectation of reduced hazard severity or possible change in hurricane direction (Sarwar et al., 2018), and preference for daytime evacuation (Sarwar et al., 2018) reduce urgency, while low visibility due to smoke or nighttime conditions and evening or nighttime hours more broadly cause hesitation (Wong et al., 2020b; Grajdura et al., 2021; Anyidoho et al., 2022). Perceived traffic congestion and uncertainty about the safety of escape routes and effectiveness of traffic management measures may further discourage timely departure (Wong et al., 2020b; Bian et al., 2022b; Grajdura and Rowangould, 2025). Destination-related characteristics also influence timing: individuals staying with friends, using commercial accommodations, or traveling shorter distances often perceive less urgency and delay departure (Hasan et al., 2013; Ng et al., 2015; Golshani et al., 2019a).

Authorities not only issue evacuation orders but may also recommend **transportation modes** based on disaster type, safety concerns, evacuee location, travel distance, and commuting patterns (Murray-Tuite and Wolshon, 2013; Giovanna et al., 2016; Liu et al., 2014a). For instance, rapid-onset events like tsunamis limit mode-flexibility (Iwai, 2025), while slower-developing disasters such as hurricanes allow more considered choices. Long evacuation distances require reliable transport, whereas shorter ones permit alternatives like walking. Authorities also consider likely evacuee locations, such as home, work, or elsewhere, and their commuting behavior to assess feasible transportation modes (Murray-Tuite and Wolshon, 2013).

Transportation mode selection among evacuees is shaped not only by official guidance but also by personal preferences, perceived risk, and constraints, especially access to private vehicles. Evacuees with vehicles often follow recommendations due to flexibility, space for belongings and family, and access to real-time information, such as radio updates (Liu et al., 2014a; An et al., 2015; Lindell et al., 2015; Togawa et al., 2018; Golshani et al., 2020; Wong et al., 2020b). Some use multiple vehicles to preserve assets, while others consolidate to minimize logistical complications and stay together (Murray-Tuite et al., 2012; Elhami-Khorasani et al., 2023). The perceived speed, convenience, and independence offered by private vehicles further reinforce the preference for personal cars over public alternatives, particularly when car-ownership enables faster and more autonomous departure (Jin et al., 2025). However, not all comply with these

recommendations; some avoid driving due to concerns over severe traffic congestion. During Hurricane Floyd (1999), travel times increased up to tenfold due to storm intensity, its coastal-parallel path, high evacuee volume, and strained infrastructure (Dow and Cutter, 2002). Similarly, during Hurricane Rita (2005), fuel shortages and secondary accidents led to a 160-kilometer traffic jam (Patrick, 2005).

Those without private vehicles, including low-income individuals, older adults, people with disabilities, and others with mobility or health limitations, rely on carpooling, public transit, or walking (Deka and Carnegie, 2010; Renne et al., 2011). Carpooling is more common among unmarried evacuees, older adults, and financially-constrained individuals (Wu et al., 2012; Sadri et al., 2014b). Public transit is vital for vulnerable groups, particularly the elderly and disabled (Bian and Wilmot, 2018; Wambura and Wong, 2024), though its usefulness depends on destination type and service design. Sadri et al. (Sadri et al., 2014b) found evacuees heading to hotels used buses, while those staying with relatives often avoided evacuation buses due to baggage and accessibility issues. Yet fixed-routes, crowding, and limited service reduce transit effectiveness during emergencies (Wolshon et al., 2005). Several factors also drive evacuees' preference for personal vehicles over public transit, including perceived comfort and shorter waiting time, the desire to protect vehicular property, the need to make intermediate stops for family gathering or supplies, and the ability to reach farther destinations (Wolshon et al., 2005; Sadri et al., 2014a; An et al., 2015; Troncoso Parady and Hato, 2016; Bian et al., 2019; Golshani et al., 2020). Limited public-transit service in the area and the presence of elderly household members further discourage bus use (Sadri et al., 2014a; Bian et al., 2019). Where neither private nor public options are available, walking may be the only alternative, though it poses risks such as hazard exposure, crowding, and poor infrastructure, especially in dense urban areas (Mas et al.). Demographic characteristics also shape the propensity to walk: female evacuees, older adults, and those with lower education are more likely to evacuate on foot, as are residents in high-density areas with nearby accessible destinations (An et al., 2015; Bian et al., 2019).

As noted by Abdelgawad and Abdulhai (2009), **evacuation destination choice** is a key aspect of effective evacuation planning. Destination attributes, such as safety, comfort, medical care, food provision, and communication, significantly influence decisions (Charnkol et al., 2007). Safety concerns vary by hazard: tsunami evacuees often prioritize inland or vertical evacuation (Harnantyari et al., 2020), and many avoid destinations perceived as closer to danger, highlighting the role of geographic proximity in planning (Yamada and Yamasaki, 2021; Wang and Wallace, 2022). Perceptual and institutional factors also shape destination decisions. Some evacuees regard distant locations as safer, despite increased travel risk (Lindell and Perry, 2012), while others hold misconceptions, such as the belief that moving inland during a tsunami is sufficient without gaining adequate vertical height (Hall et al., 2017). Distrust in local shelters has been linked to non-compliance (Lambert et al., 2013; McCaughey et al., 2017; Wong et al., 2020b). Individual differences in threat appraisal, coping appraisal, past experience, and personal characteristics also shape which destination evacuees ultimately select (Mahittikul et al., 2024).

Although public shelters are officially designated, studies consistently show evacuees often prefer alternatives. Across multiple hurricanes, 44–70% stayed with friends or relatives, 7–46% used hotels, and only 2–11% relied on public shelters (Prater et al., 2000; Whitehead, 2003; Smith and McCarty, 2009; Cheng et al., 2011; Lindell et al., 2011; Wu et al., 2012; Wilmot et al., 2013; Wu et al., 2013; Yin et al., 2014a; Wong et al., 2018).

Researchers employ discrete choice models, including multinomial logit, nested logit, cross-nested logit, mixed logit, and probit formulations (Sheffi, 1985a), to predict evacuation destination decisions based on sociodemographic

characteristics, destination attributes, and perceptual or institutional influences. According to these studies, staying with friends or relatives is associated with flexibility, informal arrangements, and shared costs, especially among non-white evacuees, pet owners, older adults, and individuals with higher education (Whitehead et al., 2000; Wong, 2020; Damera et al., 2020; Bian et al., 2023). Social connections, prior familiarity with the destination, and longer residential stability further reinforce this preference, as evacuees tend to choose locations they have previously visited or where strong interpersonal ties exist (An et al., 2015; Jiang et al., 2021; Bian et al., 2019; Ma and Lee, 2025; Toledo et al., 2018). The desire for comfort, privacy, and the ability to bring pets and personal belongings to private locations also drives evacuees away from public shelters, with households with children particularly favoring private accommodations (Wolshon et al., 2005; Jin et al., 2025; Grajdura and Rowangould, 2025). Hotels are typically selected by evacuees with greater financial resources, with choices shaped by income, gender, household size, distance, and pet ownership, while delayed departure reduces hotel use (Whitehead et al., 2000; Mesa-Arango et al., 2013; Yin et al., 2014a; Lim et al., 2016; Bian et al., 2019). Public shelters are more often used by ethnic minorities, low-income groups, and late evacuees with limited options, whereas younger adults, white households, and residents near hazard-zones are less likely to use them (Mileti et al., 1975; Whitehead et al., 2000; Baker, 2000; Wu et al., 2012; Mesa-Arango et al., 2013; Wong et al., 2020c). Under panic, confusion, or unclear danger conditions, evacuees may avoid designated shelters in favor of nearby open spaces perceived as wide, less damaged, and familiar (Bernardini et al., 2016; Chen and Cheng, 2020), while lack of awareness about shelter locations and insufficient public education further reduce their utilization (Muthohar et al., 2020). Health- and pandemic-related concerns, such as fear of disease transmission in congregate shelters, have also reduced willingness to use public facilities (Chen et al., 2024; Tsekeni et al., 2025), while insufficient capacity and physical obstacles at designated areas can render them less suitable (D'Amico et al., 2024). Network congestion may further reduce the accessibility of assigned shelters (Cheng et al., 2011), and vehicle ownership enables evacuees to reach more distant alternatives, including private accommodations with family or friends (Troncoso Parady and Hato, 2016). Mobility constraints also lead disabled and carless evacuees to prefer nearby familiar destinations over more distant public shelters (Wambura and Wong, 2025).

Taken together, these findings emphasize that public shelters, while central to emergency planning, are frequently underutilized. Their use increases under authoritative directives (Lim et al., 2016) and among less-prepared households (Golshani et al., 2019a), highlighting the need for more adaptive and targeted sheltering strategies that account for behavioral heterogeneity, accessibility constraints, and evolving public health considerations.

In addition to recommending destinations, authorities often provide **evacuation routes** to manage traffic flow. Routing strategies generally fall into four categories: system optimal (SO), user equilibrium (UE), nearest allocation, and constrained system optimal (CSO). SO minimizes total travel time, UE assumes self-optimization with perfect information, NA assigns evacuees to the nearest safe location, and CSO emphasizes fairness by limiting route-length disparities (Sheffi, 1985b; Bayram et al., 2015; Bayram, 2016; Bayram and Yaman, 2018a; Bayram et al., 2023). However, evacuees frequently deviate from assigned routes, favoring personal judgment over official instructions (Wu et al., 2012). Such behavior reflects bounded rationality and incomplete or evolving information, often leading to misjudgments in travel time and congestion, thereby reducing overall system efficiency (Simon, 1957, 1972; Tong and Feiler, 2017; Bayram, 2024). This finding shows the need to incorporate pedestrian dynamics into evacuation planning, as their exclusion can lead to unrealistic models, underestimated travel times, and misaligned-response strategies.

Route choice is typically modeled using pre-trip, en route, or hybrid approaches. Pre-trip models assume fixed decisions made before departure (Florian et al., 2008), en-route models allow for real-time adjustments based on congestion or closures (Pel et al., 2009), and hybrid models combine initial planning with mid-trip adaptation (Prato, 2009).

Familiarity significantly influences route selection, with evacuees often preferring known routes over official ones, contributing to localized congestion (Deka and Carnegie, 2010; Lindell et al., 2011; Wu et al., 2012; Intini et al., 2019; Chen and Cheng, 2020; Wang et al., 2021; Bian et al., 2022c; Lessan and Kim, 2022; Elhami-Khorasani et al., 2023; Wambura and Wong, 2025; Mapa et al., 2026). Past experience also plays a key role: during Hurricane Bret (1999), 69% of evacuees relied on experience, while only 3% followed official routes (Prater et al., 2000). Similarly, Yang et al. (1993) found experienced drivers were less likely to seek external guidance. Network characteristics, such as link usage, route overlap, and real-time congestion, and sociodemographic factors like age also affect route decisions (Chiu and Mirchandani, 2008; Dulebenets et al., 2019; Lim Jr et al., 2019; Xu et al., 2022b).

As en-route and hybrid models suggest, evacuees adapt routes in response to environmental changes or access to critical services (Arentze and Timmermans, 2005; Akbarzadeh and Wilmot, 2015). During dynamic events like floods or no-notice evacuations, perceived safety, road conditions, and official recommendations shape decisions (Chiu and Mirchandani, 2008; Hsu and Peeta, 2013; Wang et al., 2020). Environmental and physical conditions along designated routes, such as proximity to active hazards, debris, and blocked streets, can compel evacuees to deviate toward perceived safer alternatives (Bernardini et al., 2016; D'Amico et al., 2024; Raei et al., 2025). These challenges have led to the rise of intelligent transportation systems (ITS), using IoT, GPS, sensors, and connected platforms to monitor traffic and optimize routing. Machine learning and optimization models support dynamic strategies to reduce congestion, yet evacuees often prioritize personal over system-wide efficiency (Lambert et al., 2013). Hence, equitable routing models aligning individual and collective interests are crucial. While real-time traffic data can increase compliance (Bonsall and Palmer, 1999; Adler, 2001; Robinson and Khattak, 2010; Huang et al., 2017), effectiveness depends on information credibility. In Texas, 9%–37% of households ignored official routes due to distrust in authorities, safety concerns, or peer influence (Lindell et al., 2001; De Maio, 2013; Muthohar et al., 2020). The growing use of real-time navigation tools may further facilitate deviation from official routes by dynamically directing evacuees toward alternatives that do not necessarily align with coordinated evacuation plans (Wong et al., 2020b). Advances in connected and autonomous vehicles offer potential for more coordinated and fair evacuations (Bayram, 2024). Individual risk tolerance also shapes route decisions, as risk-seeking evacuees are more inclined to rely on personal judgment and self-selected routes rather than following official guidance (Ma and Lee, 2025).

Household interaction also affects route decisions. Families typically act as interdependent units, and emotional contagion, driven by panic or fear, can reduce compliance and lead to suboptimal decisions (Leach, 1994; Hatfield, 1994; Lickel et al., 2000; Sherman et al., 2002). Sadri et al. (2014b) used a mixed logit model to study intra-household coordination during Hurricane Ivan in household-decision-making. More recently, Sheu (2024) proposed a framework accounting for cognitive, emotional, and social influences.

Psychological strain during evacuation also impacts in-vehicle behavior. Studies report that stress correlates with hazardous driving, such as sudden acceleration, frequent lane changes, and traffic violations, raising crash risks and disrupting flow (Abdelgawad and Abdulhai, 2009; Tu et al., 2010). Infrastructure features like road width, lane count, and headway spacing interact with such behaviors, affecting throughput (Dulebenets et al., 2019). Route-switching due

to congestion, common in large-scale events, can further destabilize networks (Knoop et al., 2010), reinforcing the need for behaviorally realistic traffic models.

While most studies focus on vehicles, pedestrian route choice remains underexplored. Early research found pedestrians favor the shortest path (Seneviratne and Morrall, 1985), while more recent work highlights the effects of route width, density, walking capacity, and distance (Han et al., 2017; Troncoso Parady and Hato, 2016). Poor or unclear evacuation signage and unfamiliarity with designated routes can cause confusion, leading evacuees to self-navigate toward alternative locations (Chen et al., 2022), while physical damage, fear of adjacent buildings, and crowd influence may further shift pedestrian route choices (Bernardini et al., 2016). Moreover, walking speed declines with age, physical condition, and crowd pressure; at densities above 3.0 persons/m^2, speeds can fall below 0.2 m/s (Older, 1968; Moussaïd et al., 2010). This finding shows the need to incorporate pedestrian dynamics into evacuation planning, as their exclusion can lead to unrealistic models, underestimated travel times, and misaligned response strategies.

The coexistence of pedestrians and vehicles during evacuations inherently results in mixed traffic conditions. Mixed traffic at intersections intensifies congestion and reduces road capacity. This issue is further amplified during evacuation, where common mixed-traffic control strategies, such as traffic signals, often fail as evacuees prioritize escape. While authorities provide routing recommendations, they typically do not assign specific road segments to vehicles and pedestrians, leaving mixed traffic unmanaged. Mixed traffic evacuation, which coordinates multiple transportation modes to optimize capacity and efficiency, aims to address these challenges (Abdelgawad et al., 2010). While various models have been developed to manage these interactions, only Li et al. (2019a) specifically explored the use of barriers to separate road segments for pedestrians and vehicles and determine their optimal locations. Using physical barriers is a practical way to enhance compliance, particularly when adherence to traffic signals is low. However, its key weaknesses are that it only partially controls mixed traffic instead of being fully managed at all entry directions of intersections and restricts vehicle movement despite already limited road capacity. Since vehicle capacity is more constrained than pedestrian capacity, further restricting vehicles can worsen evacuation delays. As a result, mixed traffic still exists at intersections, requiring local traffic management. Since such models have not yet been explored, evacuee non-compliance, whereby individuals ignore designated road segments, also remains unexamined. Future research should focus on fully separating road segments for pedestrians or vehicles at all entry of intersections and assessing evacuee compliance with these restrictions.

Our review reveals that the majority of existing studies on large-scale evacuations emphasize four primary evacuation decision areas : route selection, departure timing, destination choice, and protective actions. In contrast, transportation mode has received comparatively less attention, and road-segment designation was rarely addressed, highlighting critical gaps in the literature.

Fig 4 provides a detailed view of how papers were classified within each key evacuation decision, helping to reveal the distribution and thematic emphasis of existing research. Within the protective action category, most studies prioritize evacuation behavior (53 papers); shelter-in-place strategies have received less attention (21 papers), and shadow evacuations remain almost entirely unexplored (five papers). Furthermore, research on departure time primarily focuses on identifying effective influencing factors (35 papers), followed by departure components (19 papers) and estimation models (17 papers), while authorities' criteria remain the least explored area (two papers). In destination selection, studies give the most attention to public shelters (16 papers), followed by general effective factors (12 papers) and

friends' homes (12 papers), with commercial facilities receiving the least focus (five papers). Moreover, route selection research predominantly explores en-route models (31 papers), which allow evacuees to adjust their routes dynamically, compared to general information (10 papers) and pre-trip models that assume a fixed route choice before departure.



Fig. 4. Classification of papers for each key evacuation-related decision.

Building on these findings, the behavioral patterns and contributing factors underlying noncompliance with critical evacuation decisions have led to varying assumptions in evacuation optimization models. Section 4 examines how these models represent compliance behavior across the key decision types discussed.

4 Optimization-based modeling and solution approaches integrating evacuee behavior considerations

Two comprehensive surveys (Caunhye et al., 2012; Bayram, 2016) emphasize the significance of integrating human behavior into evacuation optimization models. Since large-scale urban and regional evacuations often involve hundreds of thousands of individuals traversing extensive road networks, optimization models must balance computational

tractability with behaviorally realistic representations of compliance. However, many existing evacuation models still fail to fully capture key behavioral factors, despite growing evidence that integrating such considerations can substantially improve the realism and effectiveness of evacuation planning (Aldahlawi et al., 2024). Based on the reviewed literature, evacuation optimization models account for compliance behavior in two main approaches: some explicitly incorporate compliance behavior into decision-making, while others focus on the underlying determinants of compliance, such as socio–demographic attributes, personal abilities, psychological traits, and structural plan/design features. Subsections 4.1 and 4.2 provide a detailed discussion of these two perspectives.

4.1 Direct integration of evacuee compliance in optimization models

Optimization models adopting the first approach explicitly embed compliance behavior within their decision-making frameworks. Table 4 summarizes these studies, highlighting their optimization approaches, disaster types, evacuation-related decisions influenced by compliance considerations, compliance degree (full, partial, or non-compliance), and key factors affecting evacuees' compliance levels.

Table 4. Overview of studies on compliance behavior and influencing factors in evacuation optimization models

Authors	**Optimization approach**	**Disaster type**	**Compliance behavior**			**Influenced decisions**
			Compliance degree	**Explicit factor**	**Methodology**	
Alçada-Almeida et al. (2009)	Multiobjective Integer Programming (p-Median-based)	Urban fire	Full compliance	N/A	SO	Shelter location and routing
Coutinho-Rodrigues et al. (2012)	Multi-objective, mixed-integer linear programming (MILP)	Urban fire	Full compliance	N/A	SO	Shelter location and routing
Goerigk et al. (2014)	Multi-objective Mixed-Integer Programming	Not specified (bomb threat, flood)	Full compliance	N/A	SO	Shelter location, bus scheduling, routing, and departure time
Bish et al. (2014)	MILP based on Cell Transmission Model (CTM)	Hurricane	Full compliance	N/A	SO	Staging (departure time), routing, and shelter assignment
Bretschneider and Kimms (2011)	MILP	Not specified	Full compliance	N/A	SO	Routing, crossing-elimination, departure time, and shelter assignment
Bretschneider and Kimms (2012)	Mixed integer dynamic network flow model	Not specified	Full compliance	N/A	SO	Routing, crossing-elimination, departure time, and shelter assignment
Hamacher et al. (2013)	MILP with dynamic network flow	Not specified	Full compliance	N/A	SO	Routing, shelter assignment, and response team location
Lim et al. (2012)	MILP with dynamic network flow	Hurricane	Full compliance	N/A	SO	Routing, shelter assignment, and departure time
Pillac et al. (2016)	MILP with dynamic network flow	Not specified	Full compliance	N/A	SO	Routing, shelter assignment, departure time, and contraflow setup
Han et al. (2006)	Nonlinear network flow optimization	Not specified	Full compliance	N/A	SO	Routing and destination assignment
He et al. (2015)	MILP with dynamic network flow	Not specified	Full compliance	N/A	SO	Routing, shelter assignment, departure time, and resource allocation
Tuydes-Yaman and Ziliaskopoulos (2014)	Linear Programming (LP) and MILP with dynamic network flow	Not specified	Full compliance	N/A	SO	Routing, shelter assignment, and staging (departure time)

Wang et al. (2012a)	Multi-objective dynamic flow-based MILP	Not specified	Full compliance	N/A	SO	Routing, contraflow setup, and shelter assignment
He et al. (2018)	MILP	Not specified	Full compliance	N/A	SO	Shelter location, contraflow setup, and routing
Kimms and Maiwald (2017)	LP over space-time expanded network	Not specified	Full compliance	N/A	SO	Routing, contraflow setup, departure time, and destination assignment
Kimms and Maiwald (2018)	Bi-objective LP based on CTM	Not specified	Full compliance	N/A	SO	Routing, departure time, and contraflow setup
Li et al. (2019b)	Hierarchical two-stage optimization model	Tsunami	Full compliance	N/A	SO	Routing (Stage 1 & Stage 2)
Bayram and Yaman (2024)	CTM-based MIP	Tornado and NBC (nuclear/ biological/ chemical)	Full compliance	N/A	SO	Evacuate or shelter-in-place, staging (departure time), and dynamic resource allocation
Liu et al. (2025)	Bi-level Mixed-Integer Optimization Model (CTM + Link Transmission)	Urban evacuation (e.g., large-scale emergencies, terrorist attacks)	Full compliance	N/A	SO	Departure time, routing, traffic signal timing, and lane configuration
Zheng and Chiu (2011)	LP based on CTM	Not specified	Full compliance	N/A	SO	Routing
Bayram et al. (2015)	Mixed-Integer Second-Order Cone Programming (MISOCP)	Earthquake	Full compliance	Distance	CSO	Routing and shelter assignment
Bayram and Yaman (2018a)	Two-stage Stochastic MISOCP	Earthquake	Full compliance	Distance	CSO	Routing and shelter assignment
Yan et al. (2018)	LP	Not specified	Full compliance	Residence time	Extended CSO	Departure time and routing
Yuan et al. (2019)	Mixed integer nonlinear program (MINLP)	Not specified	Full compliance	Residence time	Extended CSO	Departure time
Kulshrestha et al. (2011)	Nonlinear bi-level robust optimization	Not specified	Noncompliance	N/A	UE	Routing
Shen et al. (2008)	Bi-level optimization with nonlinear lower level	Not specified	Noncompliance	N/A	UE	Routing
Ng et al. (2010)	Bi-level optimization including nonlinear Bureau of Public Roads (BPR) function in the lower-level objective	Not specified	Non-compliance	N/A	UE	Routing
Karoonsoontawong and Lin (2011)	Bi-level optimization with user optimal dynamic traffic assignment in lower level	Not specified	Non-compliance	N/A	UE	Routing
Xie et al. (2010)	Bi-level optimization using CTM	Hurricane	Non-compliance	N/A	UE	Routing
Gu et al. (2025)	Bi-level optimization including nonlinear BPR function in the lower-level objective	Urban flooding	Non-compliance	N/A	UE	Routing
Zhang et al. (2024c)	Bi-level optimization with non-linear BPR-based lower-level and two-phase upper-level structure	Earthquake	Non-compliance	N/A	UE	Routing
Afkham et al. (2022)	Bi-level model with nonlinear lower level	Not specified	Noncompliance	N/A	Dynamic UE	Routing
Apivatanagul et al. (2012)	Two-stage stochastic bi-level model	Hurricane	Noncompliance	N/A	Dynamic UE	Routing
Li et al. (2011)	Stochastic bi-level model	Hurricane	Noncompliance	N/A	Dynamic UE	Routing
Li et al. (2012)	Stochastic bi-level model with scenario uncertainty	Hurricane	Noncompliance	N/A	Dynamic UE	Routing
Davidson et al. (2020)	ISE framework	Hurricane	Noncompliance	N/A	Dynamic UE	Departure time and routing

Yang et al. (2019a) and Yang et al. (2019b)	Extended ISE framework	Hurricane and inland flooding	Noncompliance	N/A	Dynamic UE	Departure time and routing
Liu and Luo (2012)	Bi-level model with nonlinear lower level	Not specified	Noncompliance	Travel time	SUE	Turning restrictions and routing
Xie and Turnquist (2009)	Bi-level stochastic optimization with probit-based traffic assignment	Nuclear	Non-compliance	N/A	SUE	Routing
Xu and Nair (2024)	Bi-level model with nonlinear lower level	Not specified	Partial Compliance	Travel time	ESUE	Routing
Xu et al. (2024)	Bi-level model with nonlinear lower level	Not specified	Partial compliance	Travel time	UE, SUE, BRUE	Routing
Wang and Wallace (2022)	Stochastic Model	Tsunami	Partial compliance	Distance and angle	Scenario-based	Shelter assignment
Sun et al. (2017)	Nonlinear optimization model	Hurricane	Partial compliance	Personal abilities, time and source of warning	Discrete choice model	Particpation rate, warning time
Yi et al. (2017)	Bi-level Stochastic Programming Model	Hurricane	hybrid (non compliance and partial compliance)	Distance, sociodemo-graphic	Discrete choice models and DUE	Departure time, destination assignment, and routing
Lessan and Kim (2022)	Nonlinear Programming (NLP); Conditional Value-at-Risk (CVaR)-based NLP with Sampling Average Approximation (SAA)	Short- or no-notice disasters (e.g., wildfires)	Full; Partial (Deterministic, Stochastic)	N/A	SO; randomly generated diversion matrix	Routing and destination assignment
Xu et al. (2025)	Two-stage stochastic evacuation optimization	Flood	Partial compliance	Distance and Direction	Scenario-based with a two-step multinomial logit attractiveness model	Shelter assignment
Bayram and Yaman (2018b)	Two-stage stochastic evacuation optimization	Earthquake	Full compliance	Distance	CSO	Shelter assignment and routing
Zeng et al. (2016)	Multistage multiobjective evacuation optimization	Not specified (traffic incident in experiments)	Partial compliance	Travel time	Probability of disutility comparison using PSL-based average utility	Route selection
Hsu and Peeta (2014)	Fuzzy logic-based optimization framework with behavior-consistent information-based control	Not specified (chemical plant accident in experiments)	Partial compliance	Travel time, risk of link failure, freeway bias, and herding behavior	Behavior-consistent mixed logit route-choice model with fuzzy logic control	Route selection

Methodology: SO = system optimal; CSO = constrained system optimal; UE = user equilibrium; SUE = stochastic user equilibrium; DUE = dynamic user equilibrium; ESUE = extended stochastic user equilibrium; BRUE = boundedly rational user equilibrium; ISE = integrated simulation and optimization; PSL = path-size logit.

Evacuation optimization models often involve critical decisions, where behavioral assumptions significantly influence model structure. One commonly adopted approach is the system-optimal (SO) routing model, which reflects a centralized planning perspective aimed at minimizing total evacuation time and reducing congestion, under the assumption of full

evacuee compliance, where individuals are assumed to strictly follow assigned routes (Wardrop and Whitehead, 1952; Sheffi, 1985a; Bayram, 2016). Although SO models are primarily defined by routing, this compliance typically extends to all evacuation-related decisions, with most models assuming universal adherence.

As shown in Table 4, System-optimal models are classified by disaster context, optimization approach, and influenced decisions. While many address general evacuation scenarios, some focus on specific contexts such as hurricanes (e.g., Lim et al., 2012; Bish et al., 2014), tsunamis (Li et al., 2019b), urban fires (Alçada-Almeida et al., 2009; Coutinho-Rodrigues et al., 2012), and nuclear, biological, and chemical (NBC) hazards (Bayram and Yaman, 2024).

The dominant methodology is mixed-integer linear programming (MILP), frequently combined with the cell transmission model (CTM) or dynamic network flow frameworks (e.g., Bretschneider and Kimms, 2012; Hamacher et al., 2013; Pillac et al., 2016; He et al., 2018), alongside linear programming (Zheng and Chiu, 2011; Kimms and Maiwald, 2017) and nonlinear formulations (Han et al., 2006). Structural extensions include bi-level programming (Liu et al., 2025) and multi-objective models (Alçada-Almeida et al., 2009; Coutinho-Rodrigues et al., 2012; Goerigk et al., 2014; Kimms and Maiwald, 2018).

All models incorporate route assignment; however, many also optimize shelter assignment (e.g., Lim et al., 2012; Bretschneider and Kimms, 2012; He et al., 2015; Pillac et al., 2016), departure timing and staging (Bish et al., 2014; Tuydes-Yaman and Ziliaskopoulos, 2014; He et al., 2015; Kimms and Maiwald, 2017), contraflow operation (Pillac et al., 2016; Kimms and Maiwald, 2017; He et al., 2018; Kimms and Maiwald, 2018), crossing-elimination (Bretschneider and Kimms, 2011, 2012), and shelter location (Alçada-Almeida et al., 2009; Coutinho-Rodrigues et al., 2012; Goerigk et al., 2014). A few studies also consider evacuate-or-shelter-in-place decisions, dynamic resource allocation (Bayram and Yaman, 2024), and traffic signal timing (Liu et al., 2025). Although SO models are theoretically tractable and serve as useful benchmarks for large-scale network optimization, their real-world applicability is limited due to the fact that full compliance is rarely observed in mass evacuations.

To better represent individual-level autonomy, many models adopt the user-equilibrium (UE) paradigm. In this framework, evacuees are assumed to minimize their individual travel times based on perceived conditions, leading to decentralized yet equilibrium outcomes (Wardrop and Whitehead, 1952; Sheffi, 1985a). From a behavioral standpoint, this reflects a different form of compliance, whereby evacuees follow their own preferences rather than official directives.

Several studies apply UE principles through bi-level modeling. Shen et al. (2008) and Kulshrestha et al. (2011) formulate models in which upper-level decisions, such as shelter location or assignment, are optimized, while evacuees independently select routes at the lower-level based on user equilibrium. Gu et al. (2025), Ng et al. (2010), and Zhang et al. (2024c) also employ bi-level models with deterministic UE routing at the lower-level, incorporating the BPR function to represent traffic congestion. While Ng et al. (2010) address a general evacuation scenario with shelter assignment modeled at the upper-level, Gu et al. (2025) focus on urban flooding, assigning origin zones to pre-designated evacuation exits. In contrast, Zhang et al. (2024c) propose a two-phase upper-level approach for earthquake evacuation: the first phase minimizes the number of new shelters, and the second minimizes total evacuation time by optimizing shelter location and assignment decisions.

Similarly, Xie et al. (2010) and Karoonsoontawong and Lin (2011) apply deterministic UE to model route choice at the lower-level and incorporate upper-level strategies involving lane reversal. Both models simulate time-dependent

traffic dynamics using the CTM within a deterministic bi-level optimization framework. Extending these foundations, dynamic UE has been increasingly incorporated into evacuation models to better capture evacuee decision-making under evolving hazard and network conditions. Apivatanagul et al. (2012) and Li et al. (2011) introduced early stochastic bi-level frameworks optimizing evacuation, shelter-in-place, and shelter location strategies, with evacuees dynamically selecting routes based on changing travel conditions. Li et al. (2012) further advanced stochastic bi-level evacuation modeling by developing a shelter location model that integrates evacuee dynamic route choice across multiple hurricane scenarios. Extending this line of research, Davidson et al. (2020) introduced the integrated scenario-based evacuation (ISE) model, integrating multiple hazards and building on the earlier formulations of Apivatanagul et al. (2012) and Li et al. (2011). Yang et al. (2019a) and Yang et al. (2019b) operationalized the ISE framework in real-world hurricane case studies, emphasizing adaptive and repeated evacuation strategies. More recently, Afkham et al. (2022) applied a bi-level dynamic UE model to wildfire evacuation, modeling self-evacuee route choice combined with infrastructure allocation under fire-spread uncertainty.

Several studies propose behaviorally enriched extensions of classical UE models. Xie and Turnquist (2009) and Liu and Luo (2012) both employ deterministic bi-level models with stochastic user equilibrium (SUE) at the lower-level to represent evacuee route choice under uncertainty. In Xie and Turnquist (2009), stochasticity arises through probabilistic route selection to support integrated planning of shelter allocation and lane control. Liu and Luo (2012) further enhance behavioral realism by applying random utility theory to model evacuees' perceived travel costs and probabilistic route decisions, thereby accounting for perception errors and bounded-rationality. Xu and Nair (2024); Xu et al. (2024) present an expanded stochastic user equilibrium (ESUE) framework that integrates random regret minimization (RRM) with bounded rational user equilibrium (BRUE), and evaluate it alongside other models including deterministic UE, SUE, BRUE-1, BRUE-2, and a non-equilibrium baseline. Their findings show that behaviorally realistic models, particularly SUE, BRUE, and ESUE, achieve lower evacuation time, congestion, and infrastructure costs, thereby enhancing robustness and realism in evacuation modeling.

These models often rely on optimistic assumptions about awareness, rationality, and access to information. The challenge lies in designing evacuation plans that guide behavior under such imperfect conditions.

To address these challenges, researchers have developed constrained system-optimal (CSO) models, which relax the assumption of full compliance by incorporating fairness-based constraints. Bayram et al. (2015) and Bayram and Yaman (2018a) introduce models that restrict route assignments to paths whose lengths do not exceed a specified threshold relative to the shortest available route. Compliance is assumed if this condition is satisfied. These models focus primarily on distance-based fairness and operate under known compliance behavior. Bayram and Yaman (2018b) extend this framework to a stochastic setting for earthquake evacuation in Istanbul, simultaneously incorporating uncertainty in demand, road capacity degradation, and shelter disruption, while preserving the CSO tolerance constraint to ensure route acceptability across scenarios.

Yan et al. (2018) extend the CSO framework by incorporating social fairness through location-based risk prioritization. Their model, based on the CTM, integrates dynamic traffic assignment and evacuation scheduling with centrally assigned routes and no individual decision-making. A weighted objective function enables planners to balance fairness and efficiency by prioritizing populations in higher-risk areas. Although compliance is not behaviorally modeled, it is implicitly addressed through the assignment of acceptable, priority-based evacuation plans, making the model a

fairness-aware extension of the CSO framework. Similarly, Yuan et al. (2019) extend the CSO framework by introducing residence-time constraints to regulate departure timing at the residential level. Full compliance is assumed, conditional on residence times remaining within a predefined tolerance, reflecting the expectation that evacuees will follow assigned schedules if delays are perceived as fair. By ensuring temporal equity across zones and avoiding excessive delays in low-risk areas, the model improves the acceptability of authority-directed evacuation plans.

While constrained system-optimal (CSO) models introduce fairness-based constraints, they still assume full compliance when limited conditions are satisfied, offering only a partial reflection of real-world evacuee behavior. To better capture varying levels of adherence, recent studies have proposed models that explicitly incorporate partial compliance. Figure 5 shows the publication timeline of the nine partial-compliance studies identified in Table 4: no such model was published before 2014, with one appearing in 2011–2015 (Hsu and Peeta, 2014), three in 2016–2020 (Zeng et al., 2016; Sun et al., 2017; Yi et al., 2017), and five in 2021–2026 (Wang and Wallace, 2022; Lessan and Kim, 2022; Xu and Nair, 2024; Xu et al., 2025).

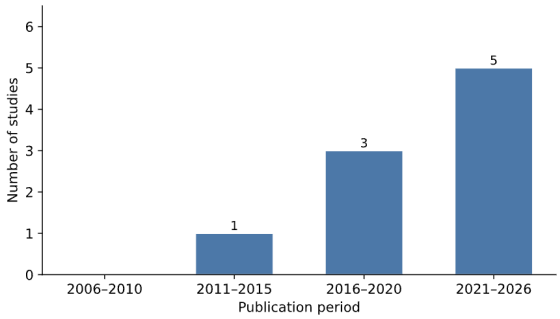


Fig. 5. Number of partial-compliance optimization studies by 5-year publication period ($n = 9$).

Among these, Lessan and Kim (2022) addresses behavioral uncertainty in short- and no-notice events such as wildfires. The authors introduce a diversion matrix to represent deviations from assigned routes and evaluate system performance across four cases. Case I assumes full compliance. Case II optimizes under full compliance but evaluates performance under observed deviations. Case III integrates a fixed, known diversion matrix into the optimization. Case IV captures uncertain compliance by generating multiple diversion matrices from a uniform distribution and solving a two-stage stochastic nonlinear program using sample average approximation (SAA) and conditional value-at-risk (CVaR). In all cases, the objective is to minimize total evacuation time. Arc travel times are modeled using the Bureau of Public Roads (BPR) function:

$$t_{ij}(x_{ij}) = t_{ij}^0 \left(1 + \alpha \left(\frac{x_{ij}}{c_{ij}}\right)^{\beta}\right) \tag{1}$$

where t_{ij}^0 is the free-flow travel time, c_{ij} is arc capacity, α is the calibration parameter reflecting the sensitivity of travel time to congestion, β is the exponent that controls the steepness of the congestion effect, and x_{ij} is the total flow on arc (i, j), calculated as:

$$x_{ij} = \sum_{r,s} \sum_{p \in P_{rs}} f_{rsp} \cdot \delta_{ijp} \tag{2}$$

where δ_{ijp} indicates whether arc (i, j) is included in path p. In Case III, flows are adjusted by applying a fixed diversion matrix to the instructed flows:

$$f_{rsp} = \sum_{l \in P_{rs}} \theta_{l,p} \cdot y_l \tag{3}$$

where y_l is the instructed flow on path l, and $\theta_{l,p}$ represents the proportion of evacuees diverting from path l to path p. These adjusted flows are used in the BPR function to compute congestion effects.

Case IV introduces stochasticity by drawing multiple diversion matrices ξ^m from a uniform distribution. For each scenario m, the total evacuation time is denoted as $W(f, \xi^m)$, and the objective is to minimize the Conditional Value-at-Risk (CVaR) at confidence level λ:

$$\text{CVaR}_\lambda = \min_\eta \left\{ \eta + \frac{1}{M(1-\lambda)} \sum_{m=1}^{M} [W(f, \xi^m) - \eta]^+ \right\} \tag{4}$$

where η is the Value-at-Risk threshold, M is the number of scenarios, and $[\cdot]^+ = \max(\cdot, 0)$ denotes the positive part operator.

This formulation captures the risk of extreme non-compliance and highlights the robustness of Case IV under uncertainty. Although this approach introduces compliance-uncertainty, the diversion matrices are randomly generated rather than data-driven, and the model focuses exclusively on routing decisions. Zeng et al. (2016) take a different approach by modeling partial compliance through an advanced traveler information system (ATIS) that provides real-time route guidance which evacuees may or may not follow. Travelers are classified into three groups: ATIS-equipped compliant users (class 1), ATIS-equipped non-compliant users (class 2), and users without ATIS (class 3), with route choices represented using a path-size logit (PSL) model with class-specific dispersion parameters. For each origin–destination pair w, the compliance rate governing route choice is computed as the probability that following the ATIS-guided route yields lower generalized travel cost than independently chosen alternatives:

$$\varphi_w = \Pr(U_1^w \le U_2^w) \approx \sum_{r \in R_w} \sum_{k \in R_w^r} P_{2r}^w \cdot P_{1k}^w \tag{5}$$

where U_1^w and U_2^w are the random perceived disutilities for compliant and non-compliant users, P_{ir}^w is the Path-Size Logit route choice probability for class i on path r, and $R_w^r = \{l \mid u_l^w \le u_r^w\}$ is the subset of paths whose generalized cost does not exceed that of path r. This rate, together with the ATIS penetration rate λ_w, splits demand across classes:

$$q_{1w} = \varphi'_w q'_w + q_w \lambda_w \varphi_w, \quad q_{2w} = (1 - \varphi'_w) q'_w + q_w \lambda_w (1 - \varphi_w), \quad q_{3w} = q_w (1 - \lambda_w) \tag{6}$$

where q'_w and q_w are evacuation and general traffic demands and φ'_w is the evacuation compliance rate. The class-specific demands enter a multiobjective bilevel framework that maximizes evacuation travel time reliability and minimizes expected network travel time under stochastic link capacity degradation. Results confirm that higher compliance and penetration rates improve overall evacuation network performance. Similarly, Hsu and Peeta (2014) develop a behavior-consistent information-based control framework that iteratively adjusts prescribed route guidance to reduce

the gap between planned and realized route proportions. Route guidance is disseminated as discrete linguistic messages, ranging from "strongly recommended" to "should not be used." All evacuees at the same origin receive identical guidance to ensure social equity. Evacuee responses are predicted through a mixed logit route choice model:

$$v_{sk} = \sum_{\varsigma} v_s^{\varsigma} \cdot F(X_{sk}^{\varsigma},\ h_{sk}) \tag{7}$$

where v_s^{ς} is the forecasted evacuation demand at origin s in time interval ς, $F(\cdot)$ is the mixed logit route choice function, X_{sk}^{ς} is a vector of route attributes capturing estimated travel time, risk of link failure, freeway bias, and herding behavior, and h_{sk} is the linguistic guidance message assigned to route k at origin s. The framework minimizes the total discrepancy between the system-optimal desired proportions and the behaviorally predicted proportions:

$$\min \sum_{s} \sum_{k} |SO_{sk} - E_{sk}| \tag{8}$$

where SO_{sk} is the desired route proportion from the system-optimal dynamic traffic assignment and $E_{sk} = v_{sk} / \sum_{\varsigma} v_s^{\varsigma}$ is the predicted proportion under the current guidance. Because the mixed logit model introduces nonlinearity and the guidance messages are discrete, the problem is solved using a fuzzy logic control framework that iteratively evaluates the gap between desired and predicted proportions, determines whether each route's message should be strengthened or weakened through fuzzy inference rules, and updates accordingly until the predicted proportions stabilize. Numerical experiments on a network under a chemical plant accident scenario demonstrate that this approach substantially reduces the gap between realized and system-optimal route proportions compared to both the absence of guidance and the direct mapping of system-optimal proportions to linguistic messages without accounting for behavioral responses.

However, beyond routing, destination assignment also presents challenges when evacuee behavior is not explicitly modeled (Abdelgawad and Abdulhai, 2010). Wang and Wallace (2022) propose a two-stage stochastic optimization model for assigning each demand point i to a single pick-up point j, accounting for partial compliance. The first stage determines assignments, while the second stage evaluates scenario-based compliance realizations $s \in S$, with $\phi_{is} \in [0, 1]$ representing the proportion of compliant evacuees. Non-compliant evacuees $(1 - \phi_{is})$ follow either a deterministic BEST strategy—choosing the most attractive point—or a probabilistic BETTER strategy—shifting among more attractive alternatives. Pick-up point attractiveness under scenario s is:

$$\rho_{ijs} = \omega_i \cdot \exp\left(-\iota_i^s \cdot \frac{t_{ij} - \sigma_i}{\sigma_i}\right) + (1 - \omega_i) \cdot \exp\left(-\zeta_i^s \cdot \frac{\psi_i - a_{ij}}{\psi_i}\right) \tag{9}$$

where t_{ij} and a_{ij} are travel time and directional angle; σ_i, ψ_i are the minimum and maximum values for demand point i; ι_i^s, ζ_i^s are scenario-specific sensitivity factors; and $\omega_i \in [0, 1]$ balances the importance of time and direction. Under BETTER, evacuees initially assigned to j' but choosing j follow:

$$\mu_{ijj's} = \begin{cases} \frac{\rho_{ijs}}{\sum_{k \in \Gamma_{ij's}} \rho_{iks}}, & \text{if } \rho_{ijs} > \rho_{ij's} \\ 0, & \text{otherwise} \end{cases} \tag{10}$$

where $\Gamma_{ij's}$ includes pick-up points more attractive than j'. The model minimizes a weighted sum of expected overflow and travel time, with constraints for assignment, capacity, and compliance. Results show the BETTER strategy enhances robustness by enabling flexible redistribution and reducing both overflow and delay. Xu et al. (2025) extend this line of research to flood evacuation by jointly optimizing shelter assignment and shelter-in-place site deployment under stochastic non-compliance within a two-stage stochastic programming framework. In this context, shelter-in-place refers not to staying at home but to pre-deployed nearby facilities such as high-rise buildings or elevated platforms that provide immediate local refuge without long-distance evacuation. Unlike Wang and Wallace (2022), who optimize pick-up point assignment without considering shelter-in-place, Xu et al. (2025) integrate shelter-in-place as an alternative strategy that mitigates non-compliance by reducing the number of evacuees directed to distant shelters. Before disasters, shelter-in-place sites of varying capacity are deployed at selected demand points; after disasters, evacuees are guided either to a nearby site or to a remote shelter, and non-compliant evacuees redirect toward more attractive alternatives. Non-compliance is modeled using the distance-and-direction-based attractiveness formulation of Wang and Wallace (2022) (Equation 9), extended to capture heterogeneous behavior across multiple evacuee types through type-specific sensitivity parameters. A dam-break flooding case study demonstrates that accounting for stochastic non-compliance leads to spatially decentralized shelter-in-place deployment, reducing the negative impacts of behavioral uncertainty on shelter overflow and evacuation costs.

Another essential aspect of evacuation planning is *compliance with evacuation orders*, commonly referred to as the *participation rate*, which is central to Sun et al. (2017). They develop a dynamic optimization model that improves hurricane evacuation by delivering targeted-warnings through multiple channels, including official authorities, the National Weather Service (NWS), media, and social networks. Evacuees are categorized into two groups: those with access to private vehicles, who can flexibly determine their departure time and destination, and those reliant on public transit, who face capacity and scheduling-constraints requiring centralized-coordination.

The model seeks to maximize total evacuation participation over a multi-period horizon by incorporating time- and source-dependent compliance behavior. A key parameter, p_{ijt}, denotes the proportion of evacuees of type i who respond to a warning from source j at time t. These response rates are based on behavioral research and expert input and vary according to timing, source credibility, and evacuee characteristics such as vehicle ownership and household structure. The response rate is integrated through the binary decision variable x_{ijkt}, defined as 1 if a warning is issued to evacuees of type i in zone k from source j at time t, and 0 otherwise. The number of evacuees who respond is modeled as $x_{ijkt} \cdot p_{ijt} \cdot n_{ikt}$, where n_{ikt} is the population of that group in that zone and time, dynamically updated based on prior departures. This dependency introduces nonlinearity into the objective function.

To solve the model, the authors implement a greedy time-step heuristic: warning decisions are optimized period by period, the population is updated accordingly, and the process repeats. This sequential method efficiently produces near-optimal results while accounting for evolving compliance patterns.

Unlike earlier studies that model compliance with a single evacuation decision—such as routing, destination selection, or participation—Yi et al. (2017) proposes a more comprehensive framework that integrates multiple evacuation decisions. Their bi-level stochastic optimization model simultaneously considers route choice, destination selection, and evacuation timing under hurricane uncertainty. Route choice is modeled using dynamic user equilibrium, capturing noncompliant, self-routing behavior. In contrast, compliance with assigned evacuation timing and destinations is

explicitly modeled using discrete choice approaches. Behavioral variation is represented through scenarios $s \in S$, each reflecting different hurricane paths and timings.

Evacuation timing is estimated using a sequential binary logit model, following Fu and Wilmot (2004). For each origin z, time period t, and scenario s, the probability that a household evacuates at time t, given that it has not evacuated earlier, is:

$$P^s_{z,t}(\text{evac}) = \frac{\exp(\kappa' X^s_{z,t})}{1 + \exp(\kappa' X^s_{z,t})} \tag{11}$$

where $X^s_{z,t}$ includes explanatory variables such as the presence of an evacuation order, log-distance to the hurricane, low-income status, work obligations, and race. The coefficient vector κ is fixed, while scenario-specific inputs generate evacuation probabilities that vary across s. These are calibrated using estimates from Gudishala and Wilmot (2012).

Destination selection follows a nested logit model adapted from Mesa-Arango et al. (2013), distinguishing between public shelters and exits from the study area. The joint probability of shelter use and evacuation is:

$$P^s_{z,t}(\text{shelter}, \text{evac}) = P^s_{z,t}(\text{shelter} \mid \text{evac}) \cdot P^s_{z,t}(\text{evac}) \tag{12}$$

with the probability of exit treated as the complement. The model is solved using progressive hedging, enabling adaptive planning across multiple scenarios. While the model is notable for its comprehensive structure, partial compliance is not consistently integrated across all decision dimensions.

Although the models in this subsection integrate evacuee compliance behavior into evacuation optimization frameworks, the following subsection 4.2 reviews studies that embed the underlying drivers of compliance directly into the optimization process itself.

4.2 Behavioral driver-based compliance modeling in evacuation optimization

Although most evacuation models represent compliance behavior, particularly by emphasizing the extremes of full compliance and non-compliance, a subset of studies embeds the underlying factors influencing compliance, such as physical constraints, psychological states, and structural plan/design features, directly into the optimization framework.

Personal capabilities, particularly mobility limitations and physical vulnerabilities, play a central role in shaping evacuees' ability and willingness to comply with evacuation directives. Hsiao et al. (2021), for example, present two optimization models for shelter-in-place deployment during dam-break floods, a no-notice scenario where evacuation is restricted to walking. Key decisions include whether to open a shelter at a given location, which capacity to select (small, medium, or large), and how to assign evacuees, classified as general public or elderly, to shelters within acceptable walking distances (500m and 300m, respectively). The first model aims to maximize the total number of evacuees assigned to shelters, where w_k is the weight assigned to population class k to prioritize vulnerable groups:

$$\max \sum_k \sum_j \sum_i n_i w_k v_{ijk} \tag{13}$$

Here, v_{ijk} is the proportion of class-k evacuees from node i assigned to shelter j; n_i is the population at node i. The second model extends this by incorporating spatial risk, using d_i, defined as the reciprocal of the distance (in meters)

from node i to the river, to prioritize high-risk areas:

$$\max \sum_{k} \sum_{j} \sum_{i} n_i w_k d_i v_{ijk} \tag{14}$$

While the first model favors maximizing total coverage with large shelters in dense areas, the second targets high-risk zones with smaller shelters, enhancing protection for vulnerable groups. By integrating vulnerability weights, spatial risk, and mobility constraints, this framework supports equitable, accessible evacuation strategies.

Psychological influences, though difficult to quantify, are also explicitly modeled in some studies. For instance, Hu et al. (2014) present an optimization model for post-disaster evacuation and resettlement, using the 2008 Wenchuan earthquake as context. The model determines when and where to open shelters, schedule evacuations, assign evacuees, and deploy mental health workers across disaster sites. At each time t and disaster site s, individuals are classified into three psychological states: *susceptible* ($x^S_{t,s}$), who have not yet panicked; *infective* ($x^I_{t,s}$), who have panicked and seek evacuation; and *removed* ($x^R_{t,s,d}$), who have been transported to resettlement site d. State transitions result from panic spread driven by social exposure and stressors such as congestion, hazards, and waiting time. The number of newly panicked individuals is determined as:

$$x^{NIP}_{t,s} = \tau_{t,s} \cdot x^I_{t,s} \cdot \frac{x^{NIP}_{t,s} + x^S_{t,s}}{x^I_{t,s} + x^{NIP}_{t,s} + x^S_{t,s}} \tag{15}$$

Following the susceptible–infective–removed (SIR) formulation of Hu et al. (2014), this equation is defined as an implicit function $x^{NIP}_{t,s} = \zeta(x^I_{t,s},\ x^{NIP}_{t,s} + x^S_{t,s})$, where the fraction on the right-hand side represents the proportion of the susceptible-plus-newly-panicked population relative to the total disaster-affected population at site s. The newly panicked individuals are included in this proportion because, consistent with the SIR contagion mechanism, they simultaneously expand the pool of individuals subject to social exposure from infective (panicked) victims. The equation is thus solved implicitly at each time step. The panic spread strength $\tau_{t,s}$ depends on the panic degree χ_t, which increases with waiting time in affected areas, and government intervention $\gamma_{t,s}$, defined as:

$$\gamma_{t,s} = \nu \cdot \frac{e_{t,s}}{x^I_{t,s} + x^{NIP}_{t,s} + x^S_{t,s}} \tag{16}$$

where $e_{t,s}$ is the number of deployed mental health workers and ν is a treatment coefficient representing the number of evacuees one worker can support per time unit. Newly panicked individuals $x^{NIP}_{t,s}$ join the infective group in the next period and contribute to the psychological penalty cost, formulated as Equation (17):

$$f_{\text{Psych}} = \sum_{t} \chi_t \cdot \sum_{s} \left(x^I_{t,s} + x^{NIP}_{t,s} - \nu \cdot e_{t,s} \right) \tag{17}$$

This penalty increases when mental health worker deployment is insufficient relative to evacuee psychological needs. The model minimizes psychological, deployment, transportation, and shelter costs using a weighted objective. Several concepts regulate psychological dynamics: intervention capacity constraints ensure site-level support limits are not exceeded, while resource constraints restrict the total number of deployable mental health workers.

To address compliance-influencing factors more holistically, Dulebenets et al. (2020) developed a multi-objective evacuation planning model that jointly optimizes departure time, route, and shelter assignment to minimize six evacuee

burdens: evacuation time (travel duration), mental demand (cognitive workload), physical demand (discomfort), temporal demand (urgency pressure), effort (perceived difficulty), and frustration (emotional stress). The model was reformulated into a single-objective function aggregating total burden, calculated as the number of individuals per vehicle, including carpooling groups, multiplied by the sum of these burdens. Burdens are quantified using linear regression models based on a driving-simulator study with 115 participants, identifying key influencing factors: evacuation time is shaped by age, driving frequency, and decision-making speed; mental demand by education, health, and reaction ability; physical demand by health status, chronic conditions, and vision; temporal demand by time-of-day and evacuation experience; effort by driving ability and physical condition; and frustration by income, education, and past evacuation history. Critical constraints ensure that individuals with health or mobility limitations are only assigned to special-needs shelters. By embedding burden estimation and personal attributes into both objectives and constraints, the model supports human-centered, behaviorally realistic evacuation planning that enhances compliance and equity.

Beyond personal capabilities and psychological influences, recent studies enhance compliance by embedding structural plan/design features directly into the optimization formulation. Rather than modeling evacuee characteristics, these models provide evacuation plans that are inherently easier to follow, thereby reducing the behavioral gap between planned and realized evacuations.

Even et al. (2015) introduce convergent evacuation plans, in which all assigned routes form a tree converging toward safe zones, ensuring that evacuees never encounter forks requiring independent route choices. This is achieved by imposing a convergence constraint that restricts the outdegree of each node to at most one:

$$\sum_{e \in \delta^+(i)} x_e \leq 1 \quad \forall i \in \mathcal{N} \tag{18}$$

By eliminating all divergence points from the network, the model removes a documented source of driver hesitation and congestion during evacuations. Simulations confirm that convergent plans outperform non-convergent alternatives even when hesitation delays at forks are as small as 0.75 seconds.

Hafiz Hasan and Van Hentenryck (2021) extend this structural approach within a unified zone-based evacuation planning framework, where all evacuees from the same residential zone are assigned a single route. This design is widely adopted by emergency services to simplify communication and increase compliance. The authors consider three problem-variants: a basic formulation, a convergent variant imposing the convergence constraint above, and a non-preemptive variant. The non-preemptive formulation is particularly relevant to compliance, as it ensures that the evacuation of a zone, once initiated, proceeds without interruption at a constant departure rate, making the schedule easier for authorities to enforce. These findings demonstrate that structural plan-design features, including convergent routing that eliminates driver hesitation at forks and non-preemptive scheduling that simplifies enforcement, can effectively enhance the realizability of evacuation plans without requiring explicit behavioral modeling of individual evacuees. Building on this framework, Hasan and Van Hentenryck (2021) evaluate the same formulations through microscopic SUMO simulations on a large-scale flood case study in Australia. Their results confirm that plans incorporating convergence and non-preemption constraints achieve higher fidelity when validated at the microscopic level, despite producing lower theoretical evacuation rates at the macroscopic level. Extending this perspective to multimodal tsunami evacuation, Bayram et al. (2026) develop a risk-aware mixed-integer second-order cone programming (MISOCP) for Istanbul under full compliance. The model embeds two structural features aimed at improving plan realizability. First, pedestrian

routing is constrained to be convergent, extending the convergent-tree principle of Even et al. (2015) and Hasan and Van Hentenryck (2021) from vehicles to pedestrians. Second, a road-segment designation mechanism classifies each arc as pedestrian-only, vehicle-only, or mixed-use, eliminating the modal ambiguity that causes hesitation and unplanned route choices at shared intersections.

Across both subsections, a common methodological characteristic emerges: the optimization models reviewed here incorporate human behavior through exogenous parameters, fixed compliance assumptions, or externally imposed design constraints, including compliance rates, equilibrium conditions, diversion probabilities, discrete-choice coefficients, mobility limits, psychological cost terms, and structural plan features. While these approaches offer tractable representations of compliance within mathematical programming frameworks, they do not endogenously couple evacuee decision-making with movement dynamics through interaction rules or adaptive behavioral mechanisms. This boundary should be recognized when interpreting the scope of optimization-based contributions to behavioral realism in evacuation planning. The growing integration of simulation techniques, reviewed in the following section, reflects a shift toward capturing more dynamic, emergent, and context-dependent human behaviors, and the combined use of optimization and simulation frameworks offers promising directions for more realistic and adaptable evacuation models.

5 Simulation-based evacuation models with behavioral representation

Traffic simulation models play a central role in large-scale evacuation planning, enabling systematic analysis of clearance times, network congestion, and life-safety outcomes under hazardous conditions that cannot be directly observed or experimentally reproduced (Pel et al., 2012). However, the reliability of these analyses depends on how realistically the underlying models capture evacuee behavior, understood as a sequence of behavioral responses to authority-issued evacuation decisions, as discussed in Section 3.2. As demonstrated by large-scale disaster events such as the 2004 Indian Ocean tsunami and Hurricane Katrina, models that fail to account for this behavioral complexity may yield planning recommendations with limited validity and transferability (Mas et al., 2015; Templeton et al., 2024). To systematically review the literature in this domain, we examine 59 peer-reviewed papers that combine simulation modeling with explicit behavioral representation in large-scale evacuation contexts. These papers are reviewed through using the analytical framework shown in Figure 6 and classified in Table 6.

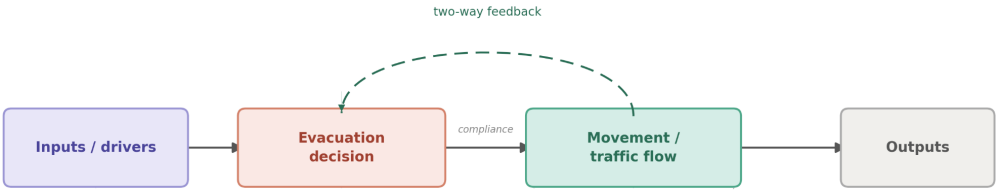


Fig. 6. Analytical framework for behaviorally informed evacuation simulation.

The framework decomposes the evacuation simulation process into four linked components: inputs and drivers, evacuation decisions, movement and traffic flow, and outputs (Figure 6). On the input side, the reviewed studies primarily capture two behavior-shaping factors: risk perception and information, and social influence. These inputs

feed into the evacuation decision component, which encompasses the critical decision types discussed in Section 3.2, including protective action, departure time (including pre-evacuation activities), destination or shelter choice, mode choice, and route choice. The transition from behavioral decision-making to network loading is mediated by compliance, shown on the link connecting the decision and movement components. Compliance constitutes the critical interface between behavioral modeling and operational simulation, governing the degree to which prescribed behavior translates into actual movement demand. The movement and traffic flow component captures how evacuees traverse the system, whether through vehicular traffic, pedestrian movement, or mixed settings. The outputs component summarizes resulting system performance across three categories of metrics: traffic efficiency metrics, life-safety outcomes, and behavioral outcomes. Finally, the network-state feedback arrow identifies studies in which evolving traffic conditions, such as congestion, delay, or route conditions, update evacuees' subsequent choices in real-time, closing the loop between behavior and system dynamics.

Based on which framework components each paper engages and how the decision and movement components are coupled, the 59 papers are classified into three structural types. Human-centric (H) models ($n = 9$, 15%) engage only the input and decision components without any movement simulation. Integrated one-way (I1) models ($n = 19$, 32%) link a behavioral demand model to a movement simulator unidirectionally: behavioral outputs drive network loading, but prevailing traffic conditions do not feed back into behavioral decisions during the simulation run. This architecture is operationally tractable and sufficient for evaluating fixed evacuation plans, but precludes representation of adaptive behavioral responses to observed congestion. Integrated two-way (I2) models ($n = 31$, 53%) implement a network-state feedback loop, allowing dynamic traffic and hazard conditions to update behavioral decisions in real-time. Key findings from I2 papers confirm that this coupling has material consequences: shelter congestion information redirects destination choice over time, false or corrected information triggers shelter switching mid-evacuation, and congestion or road damage updates route decisions dynamically (Uenae et al., 2020; Takahashi et al., 2022; Chang et al., 2022, 2024b). However, the feedback remains partial in most I2 papers, with the majority updating only route choice dynamically while leaving departure timing and destination selection fixed, which limits the model's capacity to capture the full co-evolution of behavioral demand and network supply. The feedback represented in these models operates at the level of aggregate network state, in which congestion, travel time, road damage, or shelter occupancy inform subsequent decisions. This differs from behavior–motion coupling, in which local perception, interpersonal interaction, collision avoidance, and speed adaptation jointly determine movement at the individual level. Within the large-scale evacuation studies reviewed here, no model couples evacuee decision-making with movement dynamics in this manner, which parallels the boundary identified for optimization models in Section 4.2. The I2 classification should accordingly be understood as denoting system-level feedback within large-scale network evacuation rather than behavior–motion coupling.

Across all paper types, three methodological categories are used to represent individual evacuation decisions (Table 6). Category 1 (empirical-statistical) generates decisions from models estimated on behavioral survey or revealed-preference data, Category 2 (cognitive-process-based) represents the formation and dynamic updating of decisions through explicit reasoning frameworks, and Category 3 (rule-assumption-based) approximates decisions through exogenously imposed heuristics. As shown in Figure 7a, rule-based methods account for the largest share of implementations (approximately 52%), followed by empirical-statistical approaches (30%) and cognitive-process-based methods (18%), indicating that the majority of individual decisions in evacuation simulations are still governed by assumed heuristics rather

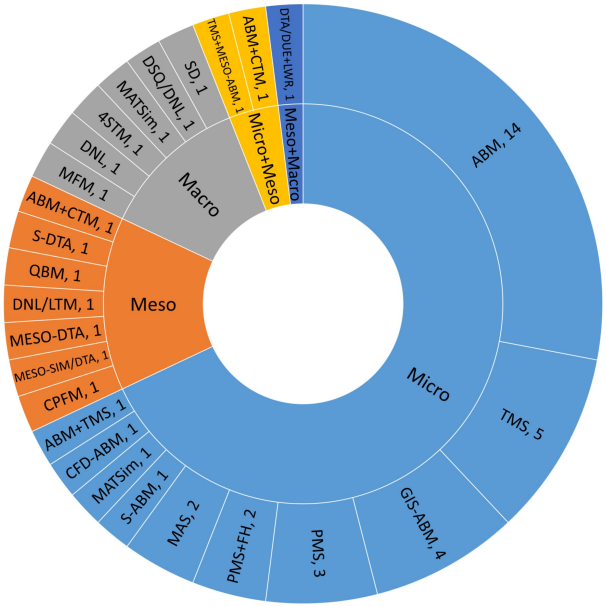
than behaviorally grounded models. This reliance on rule-based proxies is particularly problematic in large-scale simulations, where small behavioral inaccuracies at the individual level can compound into large aggregate errors across networks with hundreds of thousands of agents. However, the dominance of each category varies substantially by decision type. Protective action is the most methodologically balanced decision, with empirical (13), cognitive (12), and rule-based (10) methods appearing in roughly equal measure. Departure time and route choice are both dominated by rule-based proxies, accounting for 24 of 38 and 31 of 55 implementations, respectively, which indicates that the decisions most consequential for network loading are also those least grounded in behavioral evidence. Destination selection similarly relies predominantly on rule-based assignment (20 of 36), while its empirical share (13) considerably exceeds its cognitive share (three). Mode choice presents a notable gap: while empirical and rule-based methods are each applied in nine studies, cognitive methods are entirely absent, making it the only decision type never modeled through a process-based framework across the entire body of reviewed literature. Pre-evacuation activities, covered in only six studies, are primarily addressed through empirical methods (four), with minimal cognitive (one) and rule-based (one) representation. Non-compliance follows the broader pattern of rule-based dominance (18 of 30), with empirical (6) and cognitive (6) methods contributing equally but modestly.

The movement simulation component is distributed across three simulation scales, as illustrated in Figure 7b. Microscopic simulation models individual entities and their interactions, making it suitable for capturing detailed human behaviors during evacuation (Dawson et al., 2011). Mesoscopic simulation aggregates individuals with similar behavior to balance realism and computational efficiency, while still retaining key behavioral patterns without modeling individuals separately (Hoogendoorn and Bovy, 2001). Macroscopic simulation treats traffic flow at the system level without individual differentiation, offering a more abstract but computationally efficient representation (Hoogendoorn and Bovy, 2001). Among the reviewed papers, microscopic simulation dominates ($n = 34$, including two mixed micro-meso papers). Microscopic resolution, however, spans several distinct modeling paradigms, and three conceptually different families are represented within this group. The first, traffic microsimulation, resolves individual vehicles through car-following and lane-changing rules, so that the modeled entity is a vehicle rather than an evacuee. The second, comprising agent-based and GIS-integrated agent-based models, resolves individual evacuees as decision-making agents, although their movement is typically abstracted to traversal of network links. The third, pedestrian microsimulation, additionally resolves physical movement dynamics such as local density effects, speed adaptation, and interpersonal spacing. Agent-based formulations account for the majority of microscopic studies in the reviewed corpus, while pedestrian microsimulation appears in a small number of studies. Microscopic classification therefore indicates the resolution at which movement is represented, and the distinction among these families identifies the extent to which pedestrian movement behavior is structurally modeled. At this scale, the most frequently applied methods include agent-based modeling (ABM, 14 papers), traffic microsimulation (TMS, five papers), GIS-integrated ABM (GIS-ABM, four papers), pedestrian microsimulation (PMS, three papers), and combined pedestrian and flow hybrid frameworks (PMS+FH, two papers), alongside single-paper applications of MATSim, CFD-ABM, S.ABM, MAS, and ABM+TMS. Mesoscopic models ($n = 7$, plus one meso-macro hybrid) apply methods including the stochastic pedestrian cell transmission model (SPCTM), mesoscopic dynamic traffic assignment (MESO-DTA), mesoscopic simulation with dynamic traffic assignment (MESO-SIM/DTA), dynamic network loading and link transmission models (DNL/LTM), queue-based models (QBM), stochastic dynamic traffic assignment (S-DTA), and coupled agent-based and cell transmission models (ABM+CTM) to large-scale regional vehicular evacuation scenarios where full microscopic simulation

is computationally prohibitive. Macroscopic models ($n = 6$) employ dynamic network loading (DNL), mean-field models (MFM), the four-step traffic model, MATSim, and system-dynamics frameworks, offering analytical tractability suited to studying policy levers, such as contraflow and departure staging , while nine papers model only the behavioral decision component without any movement simulation, corresponding to the H-type classification discussed above.

Decision/response	#papers	C1	C2	C3
Protective Action	35	13	12	10
Departure Time	38	9	4	24
Pre-Evacuation Activities	6	4	1	1
Destination Selection	36	13	3	20
Mode Choice	18	9		9
Route Choice	55	12	12	31
Non-compliance	30	6	6	18

(a) Behavioral representation by decision type.



(b) Simulation scales and methods.

Fig. 7. Methodological structure of the reviewed studies.

Table 5 summarizes the principal simulation tools available for evacuation modeling, classified by resolution scale; each tool is cited using its official developer website or technical user manual where available, and for legacy tools or specialized academic frameworks without active web platforms, the original foundational research articles are provided as primary references.

Table 5. Simulation tools available for evacuation modeling, classified by resolution scale.

Simulation tool	Microscopic	Mesoscopic	Macroscopic	Reference/source
Paramics	✓			(Cameron and Duncan, 1996)
SUMO	✓	✓		(DLR, 2024)
CORSIM	✓			(, FHWA)
TRANSIMS	✓	✓	✓	(Smith et al., 1995)
DynaMIT-E	✓	✓		(Ben-Akiva et al., 2002)
AReBIC	✓			(Papadimitriou et al., 2011)
MASON	✓			(Luke, 2024)
MDTCPD-VRP	✓			(Zheng et al., 2015)
AnyLogic	✓	✓	✓	(AnyLogic, 2024)
VISSIM	✓	✓		(Group, 2024)
AIEva	✓	✓		(Lim et al., 2015)
NetLogo	✓	✓	✓	(Wilensky, 1999)
AIMSUN	✓	✓	✓	(Aimsun, 2024)
PyroSim	✓	✓		(Engineering, 2024)

However, the adoption of these tools across the reviewed studies does not reflect the breadth of available platforms. Custom or in-house agent-based models are the most frequently adopted overall (15 papers), followed by NetLogo (Wilensky, 1999) (six papers), AnyLogic (AnyLogic, 2024) (five papers), and MATLAB/Repast (three papers each), while several established tools such as CORSIM, Paramics, AIMSUN, and PyroSim appear in only one or two studies, indicating substantial room for broader adoption of established simulation platforms in behavioral evacuation research.

Table 6. Comparison of evacuation simulation studies

					Traffic flow based		Behavioral component				
Author	**Disaster type**	**Mode**	**Structural type**	**Influencing factor**	**Scale**	**Method**	**Decision**	**Behavior representation**	**Compliance behavior**	**Simulation tool**	**Output**
Han et al. (2025)	Hurricane	Vehicle	I1	RTI	Micro	TMS	RC	C3	–	TransModeler	TEM
Yin et al. (2014b)	Hurricane	Multimodal	H	OW	–	–	PA+DT+DS+MC+RC+PD	C1	EOC	Custom C++ ABM	BO
Takahashi et al. (2022)	General	Pedestrian	I2	SNS+HFB+ID	Micro	MAS	DT+DS+RC	C3	–	R	TEM+BO
Keykhaei et al. (2024)	Earthquake	Multimodal	I2	–	Micro	ABM	RC	C2+C3	–	NetLogo	TEM
Yang et al. (2020)	Rainstorm	Pedestrian	I1	RP	Micro	ABM	RC+PD	C2	–	Custom ABMS	BO
Uenae et al. (2020)	General	Pedestrian	I2	SNS	Micro	MAS	DS+RC	C3	–	R	TEM+BO
Chang et al. (2024b)	Earthquake	Pedestrian	I2	–	Micro+Meso	ABM+CTM	DS+RC	C2+C3	RC	Custom ABM	TEM
Yuan and Puchalsky (2015)	General	Multimodal	I2	–	Meso+Macro	DTA/DUE+LWR	DT+DS+MC+RC	C3	–	VISUM	TEM
Yang et al. (2019c)	Hurricane	Household	H	OW+SNI+ID	–	–	PA+DT+RC	C1+C3	EOC	Custom ABM	BO+TEM
Makinoshima et al. (2016)	Tsunami	Multimodal	I2	–	Micro	ABM	PA+DT+DS+MC+RC	C3	–	Custom Fortran	TEM+LSO
Sopha et al. (2021)	Volcano	Multimodal	I1	HFB	Micro	ABM	PA+DT+DS+MC+RC	C3	–	AnyLogic	TEM
Zhao et al. (2025)	Flood	Population	H	RP+OW+SNS+TCA	–	–	PA	C2	–	Custom LLM	BO
Wang et al. (2012b)	General	Pedestrian	I2	PS	Macro	SD	RC	C3	–	STELLA+DYNAMO	BO+TEM
Huang et al. (2016b)	General	Multimodal	I2	–	Meso	ABM+CTM	MC+RC	C1+C3	–	MATLAB	TEM
Pel et al. (2011)	General	Vehicle	I2	RTI	Macro	DSQ/DNL	DT+DS+RC	C2+C3	DTC	MATLAB	TEM
Gillet et al. (2024)	Volcano	Multimodal	I1	RP+OW	Micro	ABM	PA+DT+DS+MC+RC	C1+C3	EOC	GAMA+ESCAPE	TEM
Lee et al. (2021)	Hurricane	Population	I2	RP+OW+TCA	Micro	GIS-ABM	PA+DT+DS+RC	C2	EOC	AnyLogic	BO
Zeng et al. (2020)	General	Vehicle	I2	RTI	Meso	S-DTA	RC	C1+C3	RC	Custom impl.	TEM
Gao and Wang (2021)	Hurricane	Population	H	RP+OW	–	–	PA+DT	C2	EOC	Custom ABM	BO
Siam et al. (2022)	Wildfire	Multimodal	I1	–	Micro	ABM	PA+DT+DS+MC+RC	C1+C3	EOC	NetLogo	LSO
Liang et al. (2015)	Hurricane	Vehicle	I2	–	Micro+Meso	TMS+ABM	PA+DT+DS+RC	C3	–	MATLAB+VISSIM	TEM
Tamima and Chouinard (2016)	Earthquake	Household	I1	–	Micro	TMS	DT+DS+RC	C1	–	OREMS	TEM
Ukkusuri et al. (2017)	Hurricane	Household	I2	–	Micro	ABM+TMS	PA+DT+DS+MC+RC+PD	C1	RC	Repast Simphony	TEM
Watts et al. (2019)	Hurricane	Population	H	RP+OW+SNI+ID	–	–	PA+DT	C2	EOC	NetLogo	BO
Choi et al. (2024)	Tsunami	Pedestrian	I2	OW+HFB	Micro	GIS-ABM	PA+DT+DS+RC	C2+C3	EOC	GAMA	TEM+BO
Jumadi et al. (2018)	Volcano	Population	I1	RP+OW+SNI	Micro	GIS-ABM	PA+DT+RC	C2+C3	EOC	AnyLogic	BO
Roy et al. (2022)	Hurricane	Household	H	RP+SNI	–	–	PA+DT	C1+C2	EOC	Repast Simphony	BO
Widener et al. (2013)	Hurricane	Household	H	RP+SNI	–	–	PA+RC	C2+C3	EOC	AnyLogic	BO
Harris et al. (2025)	Hurricane	Household	I2	RP+OW	Micro	ABM	PA+DT+DS+RC	C2	EOC	FLEE 2.0	BO+TEM
Gehlot et al. (2019b)	Hurricane	Household	I2	–	Micro	TMS	PA+DT+DS+MC+RC	C1	EOC	Repast Simphony	TEM

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(continued from previous page)

					Traffic flow based		Behavioral component				
Author	**Disaster type**	**Mode**	**Structural Type**	**Influencing factor**	**Scale**	**Method**	**Decision**	**Behavior representation**	**Compliance behavior**	**Simulation tool**	**Output**
Silva et al. (2025)	Flood	Population	I1	RP+OW	Micro	ABM	PA+DT+DS+MC+RC+PD	C3	–	LifeSim	LSO
Chen et al. (2023)	Tsunami	Population	I1	–	Micro	ABM	PA+DT+DS+MC+RC	C1+C3	EOC	Julia	LSO
Liu and Lim (2016)	Flood	Household	I1	–	Micro	GIS-ABM	DT+DS+MC+RC	C3	–	ArcGIS+Repast	TEM
Moradi et al. (2025)	General	Population	I2	–	Meso	MATSim	PA+DT+DS+MC+RC	C2	–	MATSim+BDI	TEM+BO
Handford and Rogers (2012)	General	Vehicle	I2	HFB	Meso	QBM	RC	C2+C3	RC	Custom C++	TEM+BO
van der Gun et al. (2016)	General	Household	I2	–	Meso	DNL/LTM	PA+DS+MC+RC+PD	C1	RC	OmniTrans	TEM
Bian et al. (2024)	Hurricane	Household	H	RP	–	–	PA+DT+DS+MC+RC	C1	EOC	TransCAD	BO
Epstein et al. (2011)	General	Vehicle	I1	OW	Micro	CFD-ABM	PA+DS+RC	C3	EOC	Custom C++ ABM	LSO+TEM
Robinson and Khattak (2012)	Hurricane	Vehicle	I2	RTI	Meso	MESO-DTA	PA+DT+RC	C1+C3	RC	Cube Avenue	TEM
Shi et al. (2021)	Wildfire	Population	H	RP	–	–	PA+RC	C2	EOC	Vensim PLE	BO
Borowska-Stefańska et al. (2022)	Flood	Vehicle	I1	–	Macro	4STM	PA+DS+MC+RC	C3	–	VISUM+ArcGIS	TEM
Du et al. (2023)	Flood	Household	I2	–	Micro	MATSim	PA+DT+DS+RC	C3	–	MIKE21+MATSim	TEM
O'Shea et al. (2020)	Flood	Population	I1	OW+ID	Micro	S-ABM	PA+DT+RC	C3	EOC	LISFLOOD+NetLogo	BO+LSO
Chen et al. (2021b)	General	Vehicle	I2	RTI+PS	Macro	DNL	PA+DT+RC	C2+C3	–	EVAQ	TEM+BO
Feng and Lin (2022)	Hurricane	Household	I2	OW	Macro	MFM	PA+DT+DS+RC	C1	DC	Custom flow model	TEM
Tamminga et al. (2011)	Flood	Vehicle	I2	–	Micro	TMS	DT+DS+RC	C3	–	S-Paramics	TEM
Do and Noh (2016)	General	Vehicle	I1	–	Micro	TMS	PA+RC	C3	RC	TransCAD	TEM
Fang and Edara (2013)	Hurricane	Vehicle	I1	–	Meso	MESO-SIM/DTA	DT+DS+RC	C3	RC	DynusT	TEM
Zhang et al. (2020)	Hurricane	Vehicle	I1	–	Micro	ABM	PA+DT+DS+RC	C1+C3	–	TRANSIMS	TEM
Chang et al. (2022)	Earthquake	Pedestrian	I2	–	Meso	CPFM	DS+RC	C2	RC	Custom SPCTM	TEM+BO
Kuligowski et al. (2025)	Fire	Pedestrian	I1	–	Micro	PMS	DT+RC	C3	–	Pathfinder	TEM
Mostafizi et al. (2019)	Tsunami	Pedestrian	I1	–	Micro	ABM	PA+DT+DS+RC	C3	–	NetLogo	LSO
Takabatake et al. (2017)	Tsunami	Pedestrian	I2	HFB	Micro	ABM	DT+DS+RC	C3	–	Artisoc	TEM+LSO
Lalith et al. (2022)	Tsunami	Multimodal	I2	–	Micro	ABM	DT+DS+MC+RC	C3	–	Custom HPC ABM	TEM
Wang et al. (2016)	Tsunami	Multimodal	I1	–	Micro	ABM	PA+DT+DS+MC+RC	C3	EOC	NetLogo	LSO
Zhao et al. (2026)	General	Pedestrian	I2	HFB	Micro	PMS	RC	C1	–	AnyLogic	TEM+BO
Sun et al. (2021)	Earthquake	Pedestrian	I2	HFB+PS	Micro	PMS	RC	C1+C3	–	GIS+MAS	TEM+BO
Bernardini et al. (2021a)	Flood	Pedestrian	I2	RP	Micro	PMS+FH	RC	C3	–	FlooPEDS	TEM
Bernardini et al. (2021b)	Flood	Pedestrian	I1	RP	Micro	PMS+FH	DS+RC+PD	C3	–	Delft3D+MassMotion	TEM+LSO

Output: TEM = Traffic efficiency metrics; BO = Behavioral outcomes; LSO = Life-safety outcomes.

Compliance: EOC = Evacuation order compliance; RC = Route compliance; DTC = Departure-time compliance; DC = Destination compliance.

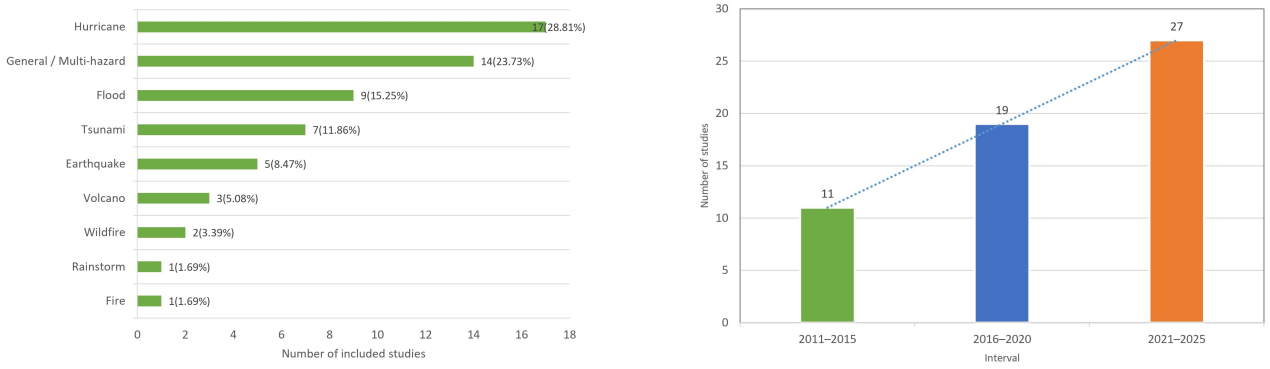
Decision: PA = Protective Action; DT = Departure Time; DS = Destination Selection; MC = Mode Choice; RC = Route Choice; PD = Pre-Evacuation Decisions.

Influencing factor: RP = Risk perception; OW = Official warnings/orders; RTI = Real-time traffic info (VMS/ATIS); SNS = Social media/SNS; TCA = Threat & coping appraisal; SNI = Social network influence; HFB = Herding/following behavior; PS = Panic spread; ID = Information diffusion.

Structural type: H = Human-centric; I1 = One-way integrated; I2 = Two-way integrated (network-state feedback).

Behavior representation: C1 = Empirical/statistical based; C2 = Cognitive/process based; C3 = Rule/assumption based.

Table 6 classifies the reviewed evacuation simulation studies by author, disaster type, transportation mode, structural type (H, I1, or I2), influencing factors, simulation scale, simulation method, evacuation decisions modeled, behavioral representation category (C1, C2, or C3), compliance type, simulation tool, and output. Several descriptive patterns emerge from this classification. In terms of hazard coverage, hurricane evacuation dominates ($n = 17$, 28.81%), followed by general or multi-hazard contexts ($n = 14$, 23.73%) and flood ($n = 9$, 15.25%), while rapid-onset hazards such as tsunami, earthquake, and wildfire collectively account for fewer than 15 papers (Figure 8a). This distribution reflects the historical availability of post-event behavioral data in hurricane-prone regions and implies that behavioral-simulation findings are disproportionately conditioned on slow-onset, vehicle-dominated contexts, limiting their direct transferability to pedestrian-dominant hazards. Publication volume has grown consistently: 11 papers in 2011–2015, 19 in 2016–2020, and 27 in 2021–2025 (Figure 8b), confirming that behavioral integration in evacuation simulation has become a mainstream methodological concern over the past decade. In terms of transportation mode, the reviewed studies are distributed relatively evenly across pedestrian (23.73%), vehicle (22.03%), household (20.34%), mixed-mode (16.95%), and general population (16.95%) contexts. However, a pronounced asymmetry exists in how each mode is simulated: pedestrian evacuation is modeled almost exclusively at the microscopic scale (78.57% of pedestrian papers), reflecting the fine-grained spatial and behavioral resolution required to capture crowd dynamics, exit choice, and density-dependent movement. Vehicular evacuation, by contrast, is more evenly distributed across microscopic (38.46%), mesoscopic (30.77%), and macroscopic (23.08%) scales, reflecting the wider range of network sizes and planning horizons addressed in vehicle-based studies.



(a) Distribution of reviewed studies by disaster type.

(b) Distribution of reviewed studies by publication period.

Fig. 8. Descriptive characteristics of the reviewed simulation-based evacuation studies.

Compliance behavior is explicitly modeled in 30 of the 59 reviewed papers (51%). Among these, evacuation-order compliance is the most frequently represented type (19 papers), followed by route compliance (nine papers), while departure-time compliance and destination compliance each appear in only one paper. This concentration on the binary evacuate-or-stay decision leaves non-compliance with recommended departure schedules, assigned destinations, and designated routes, behaviors widely documented in post-event surveys, largely unrepresented in current simulation frameworks.

Regarding simulation outputs, traffic efficiency metrics such as clearance time, delay, and network throughput appear in 42 of 59 papers, while behavioral outcomes are reported in 24 and life-safety outcomes in only 10, with 26 papers reporting traffic metrics exclusively. This imbalance suggests that behavioral representation is primarily used to calibrate demand inputs rather than to evaluate safety implications. The findings reinforce this concern: evacuation time is highly sensitive to departure timing and congestion-aware routing (Tamminga et al., 2011; Chang et al., 2024b; Kuligowski et al., 2025), mortality depends critically on participation rates, milling time, and shelter location (Wang et al., 2016; Mostafizi et al., 2019; Chen et al., 2023; Silva

et al., 2025), and the balance of demand across shelters is strongly affected by information quality and destination assignment rules (Uenae et al., 2020; Sopha et al., 2021; Takahashi et al., 2022) , yet these safety and behavioral dimensions remain underreported.

Despite the methodological gaps identified throughout this subsection, spanning hazard coverage, decision representation, behavioral grounding, compliance modeling, multimodal interaction, feedback scope, and output emphasis, the reviewed studies collectively demonstrate that behaviorally informed simulation models capture meaningful interactions between evacuee decisions and system performance. Yet these studies assess how a given plan performs rather than searching over possible plans to identify which performs best. Addressing this limitation requires coupling behavioral simulation with optimization frameworks that search over authority-issued decisions while accounting for the adaptive behavioral responses those decisions induce, which we focus in the following subsection.

6 Simulation–optimization approaches integrating evacuee behavior considerations

Simulation is not inherently designed to identify optimal decisions in a solution space. Instead, it is primarily used to evaluate the outcomes of predefined strategies under complex and uncertain conditions. Optimization models, on the other hand, are built to generate prescriptive solutions. However, their reliance on simplified assumptions often limits their ability to capture system uncertainty and behavioral complexity. Evacuation behavior clearly illustrates this limitation. Decisions made during emergencies are influenced by a wide range of psychological, social, experiential, and demographic factors, which are difficult to model using the simplified abstractions required for tractability in optimization models. While simulation is better suited to reflect these dynamic and context-dependent aspects of human behavior, it lacks the capacity to prescribe optimal decisions on its own.

To address these limitations, S–O approaches have gained prominence by combining the behavioral realism of simulation with the prescriptive capabilities of optimization. As shown by Carson and Maria (1997), this integration allows simulation to handle complex dynamics while optimization guides decision-making.

Literature identifies four coupling frameworks based on the interaction between simulation and optimization: **Iterative Optimization-based Simulation** (IOS), **Iterative Simulation-based Optimization** (ISO), **Sequential Simulation-Optimization** (SSO), and **Alternating Simulation-Optimization** (ASO). These vary by coupling intensity: black-box, grey-box, or integrated. In ISO, simulation acts as a stochastic black-box evaluator; the optimizer (e.g., GA, PSO) explores the decision space $\mathcal{X}$ and submits candidate vectors $x \in \mathcal{X}$ to receive performance estimates $f(x, \omega)$ without altering the underlying optimization model. Conversely, ASO creates a bi-directional interaction where simulation outputs dynamically update the optimizer's constraints or parameters for subsequent iterations, establishing a closed-loop dialogue. IOS employs tight algorithmic coupling with optimization embedded within the simulation loop at time steps t, while SSO follows a decoupled pipeline where simulation generates datasets for a separate, subsequent optimization phase. These distinctions are summarized in Table 7.

A critical distinction in the reviewed literature lies in how human behavior is structurally integrated into these S–O frameworks. This study distinguishes between parameter-based representations and behavior-oriented modeling. Parameter-based approaches treat evacuee response as exogenous constants, such as fixed compliance rates or pre-defined reaction times, fed into optimization models. In contrast, behavior-oriented frameworks employ rule-based or interaction-based mechanisms, where decisions emerge dynamically from agent interactions during simulation Nagarajan and Shaw (2021). While the majority of current S–O

studies rely on parameter-based assumptions for computational efficiency, there is an emerging shift toward behavior-oriented coupling in high-fidelity agent-based models. To operationalize these behavioral rules within an S–O framework, the selection of an appropriate simulation fidelity is paramount.

A comprehensive understanding of S–O requires examining both of its main components: simulation and optimization, each of which includes multiple methodological variations.

Beyond the traffic-focused tools listed in Section 5, alternative paradigms such as discrete event simulation (DES), system dynamics (SD), and Monte Carlo simulation (MCS) provide broader perspectives. DES is effective for representing system behavior over time in movement networks (Na and Banerjee, 2019), while SD supports strategic decision-making in feedback-driven environments (Zhang et al., 2021). MCS addresses uncertainty through probabilistic sampling, which is critical for the validation and sensitivity analysis of optimization outputs.

S–O methods are applied iteratively to address complex decision-making, as illustrated in Fig 9, and Table 7 compares these frameworks in terms of their functional logic, application contexts, and advantages.

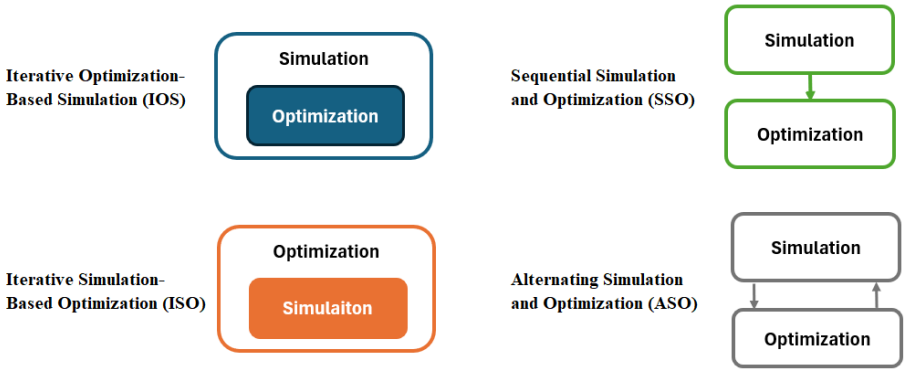


Fig. 9. Iterative simulation–optimization methods.

Table 7. Comparison of S–O articulation frameworks.

Method	Functional logic	Mathematical articulation & data exchange	Key advantage
Iterative Optimization-Based Simulation (IOS)	Optimization is executed repeatedly during the simulation run to adapt to evolving states.	**Tight Algorithmic Coupling:** Simulation pauses at interval t to pass real-time state variables (e.g., density, speed) to an embedded optimization sub-routine.	Offers high responsiveness to emergent behaviors and real-time dynamic conditions.
Iterative Simulation-Based Optimization (ISO)	Optimization algorithm proposes solutions evaluated through multiple simulation replications.	**Black-Box Coupling:** Optimization submits a decision vector $x \in \mathcal{X}$ to the simulator, which returns a stochastic performance estimate $f(x, \omega)$ as feedback.	Enables global search and systematic refinement of complex or stochastic strategies.
Sequential Simulation-Optimization (SSO)	Simulation is performed first to explore system behavior, followed by a separate optimization phase.	**One-Way Data Flow:** Simulation results are used to construct a static response surface or a feasibility database that informs subsequent optimization constraints.	Reduces computational complexity by decoupling the two heavy computational phases.
Alternating Simulation-Optimization (ASO)	Simulation and optimization are alternated, with each phase updating the other's parameters.	**Bi-Directional Feedback:** Continuous information exchange where simulation outputs update the optimizer's search direction and vice-versa throughout the process.	Provides maximum flexibility for adaptive planning in highly uncertain environments.

The frameworks summarized in Table 7 offer different trade-offs between computational intensity and model responsiveness. **IOS** is particularly suited for real-time operational adjustments where the system must react to emergent behaviors like network congestion. In contrast, **ISO** excels in strategic planning where the goal is a robust global solution under fixed stochastic conditions. While **SSO** provides a computationally efficient alternative by isolating heavy simulation runs from the optimization—ideal for preliminary feasibility studies. **ASO** represents the most flexible integration. Unlike the fixed structures of ISO, ASO's feedback loop allows the planning model itself to evolve alongside simulation results, making it highly effective for uncertain environments where decision objectives may shift as new behavioral data becomes available.

From the broader set of studies discussed in Section 2, we focus specifically on those that incorporate S–O approaches. The reviewed literature is categorized using a comprehensive set of classification criteria, including author names and publication years (Ref.), simulation-optimization frameworks (Frame.), objective functions (Obj. function), disaster or hazard types (Hazard), solution tools (Software), and traffic simulator fidelity (Fid.)—microscopic, mesoscopic, or macroscopic. Additional classification criteria include publishing journals (Journal), human behavior and response during evacuation (Hum. behavior), simulation methods (S.M.)—agent-based, discrete event, or Monte Carlo—and optimization methods (O.M.). Furthermore, the studies are evaluated based on their integration strategy (Int.), specifically distinguishing between parameter-based (P) and behavior-oriented (B) approaches to reflect the structural coupling of human dynamics within the S–O framework. Finally, each modeling study is assessed according to the empirical validation of its behavioral component (E.V.), indicating whether the behavioral parameters were validated against real-world data (Y), partially grounded in empirical evidence (P), or based solely on theoretical assumptions (N). This assessment addresses the quality of behavioral evidence incorporated in each study, as shown in Table 8.

Table 8. Overview of S–O studies integrating behavioral factors in evacuation planning.

Ref.	Frame.	Obj. function	Hazard	Software	Fid.	Journal[1]	Hum. behavior	S.M.[2]	O.M.[3]	Int.[4]	E.V.[5]
Islam et al. (2023)	Review	Review Paper	Both	Review	Review	TRIP	Mode Choice	-	-	-	-
Gan et al. (2016)	ISO	Min. total time	Bushfire	iWays	Micro	SMPT	Route Choices	A.B.	S.H.	B	N
Amideo et al. (2019)	Review	Review Paper	Both	Review	Review	EJOR	Route Choices	-	-	-	-
Takabatake et al. (2017)	ISO	Min. loss of life	Tsunami	Artisoc	Micro	IJDRS	Route Choices	A.B.	-	B	P
Yuan et al. (2017)	ISO	Min. clearance time	Hurric.	SCTO	Micro	TR-Part C	Transp. Mode	A.B.	-	P	P
Murray-Tuite and Wolshon (2013)	Review	Review Paper	No-not.	Review	Review	TR-Part C	Social Networks	-	-	-	-
Zhang et al. (2009)	ISO	Min. suffering	Hurric.	TRANSIMS	Micro	WSC	Route Choices	A.B.	-	B	N
Afshar and Haghani (2008)	ISO	Min. trip time	Notice	Custom	Meso	TRR	Route/Shelter	-	-	P	N
Balakrishna et al. (2008)	ISO	Min. evac. time	No-not.	DynaMIT-E	Micro	TRR	Route Choices	A.B.	S.H.	P	P
Chang and Edara (2016)	ISO	Min. travel time	Hurric.	DTA	Meso	IJTE	Route Choices	-	G.A./TS	P	N
Chang and Edara (2018)	ISO	Min. overlap	Hurric.	AReBIC	Micro	IJDRR	Route Choices	A.B.	S.H.	B	Y
Chang and Edara (2017)	ISO	Min. overlap	Hurric.	AReBIC	Micro	IEEE IV	Route Choices	A.B.	S.H.	B	Y
Chavhan and Venkataram (2019)	ISO	Min. delay	Both	Custom	Micro	IEEE TETCI	Route Choices	A.B.	-	B	N
Nakanishi et al. (2020)	ISO	Min. travel time	Storm	Java	Micro	IJDRR	Route/Mode	A.B.	S.H.	P	P
Swamy et al. (2017)	IOS	Max. effectiveness	Hurric.	Python	Micro	SEPS	Route/Shelter	D.E.S.	P.S.O.	P	N
Abdelgawad and Abdulhai (2010)	IOS	Min. vehicle time	Both	MDTCPD	Micro	TRR	Transp. Mode	D.E.S.	G.A.	P	N
Crainic et al. (2018)	Review	Review Paper	Both	Review	Review	EJOR	Route/Mode	-	-	-	-
Alahi Kawsar et al. (2019)	IOS	Max. cost func.	Both	-	-	JITS	Social Networks	-	S.H.	B	N
Cabrera et al. (2022)	IOS	Min. evac. time	Both	-	Macro	EJTL	Shelter Choices	D.E.S.	C.G.	P	N
Zong et al. (2014)	IOS	Min. evac. time	Both	MATLAB	Micro	COR	Social Networks	D.E.S.	P.S.O.	B	N
Farahani et al. (2020)	Review	Review Paper	Both	Review	Review	EJTL	Transp. Mode	-	-	-	-
Wang et al. (2023)	ISO	Max. satisfaction	Gas	AnyLogic	Micro	FACETS	Panic/Route	A.B.	P.S.O.	B	N
Joo et al. (2013)	ISO	Min. evac. time	Fire	AnyLogic	Micro	SMPT	Route Choices	A.B.	-	B	N
Chen et al. (2006)	ISO	Min. clearance	Hurric.	VISSIM	Micro	NHO	Route/Time	A.B.	-	P	P
Shi et al. (2009)	ISO	Min. evac. time	Fire	AIEva	Micro	Auto. Constr.	Panic/Familiar.	A.B.	-	B	N
Cova and Johnson (2002)	ISO	Min. evac. time	Fire	Paramics2	Micro	EPA	Route/Time	D.E.S.	S.H.	P	P
Lu et al. (2005)	ISO	Min. egress time	Both	DYNASMART	Micro	LNCS	Route/Time	D.E.S.	S.H.	P	N
Han et al. (2006)	ISO	Min. travel cost	Both	DYNASMART	Micro	Interfaces	Route/Shelter	A.B.	-	P	N
Wang et al. (2023)	ISO	Max. expected utility	No-not.	NetLogo	Micro	JASSS	Route/Shelter	A.B.	S.H.	B	N
Hsu and Peeta (2013)	ISO	Max. expected utility	No-not.	DYNASMART	Macro	Transp.	Social/Route	D.E.S.	S.H.	B	N
Chiu et al. (2007)	ISO	Min. travel time	No-not.	DYNASMART	Micro	IIE Trans.	Panic/Route	D.E.S.	E.M.	B	N
Zou et al. (2005)	ISO	Min. interrupt.	Hurric.	CORSIM	Micro	JTRB	Route Choices	-	-	P	N
Sfeir et al. (2018)	ISO	Min. evac. time	Hurric.	AIMSUN	Micro	SMPT	Route Choices	A.B.	M.C./CG	P	P
Li et al. (2022a)	ISO	Min. gas risk	Hurric.	Pathfinder	Micro	PSEP	Social Networks	A.B.	S.H.	B	N
Rivers et al. (2014)	ISO	Max. flows	Both	MassMotion	Micro	TR-Proc	Social/Route	A.B.	-	B	N
Lahmar et al. (2006)	SSO	Min. evac. time	Hurric.	CORSIM	Micro	ITSC	Route Choices	A.B.	E.M.	P	N
Maassen (2012)	SSO	Min. danger	Hurric.	SUMO	Micro	PhD	Panic/Route	A.B.	T.S.	B	N
Liu et al. (2016)	ASO	Min. evac. time	No-not.	NetLogo	Micro	FAR	Route Choices	A.B.	P.S.O.	B	N
Song et al. (2013)	ISO	Min. generalized cost	Both	VISUM	Macro	SBS	Route/Time	A.B.	G.A.	P	N
Amaran et al. (2016)	Review	Review Paper	Both	Review	Review	4OR	Evac. Time	-	-	-	-
Tekin and Sabuncuoglu (2004)	Review	Review Paper	Both	Review	Review	IIE	Evac. Time	-	-	-	-
Figueira and Almada-Lobo (2014)	Review	Review Paper	Both	Review	Review	SMPT	Evac. Time	-	-	-	-
Liu et al. (2023)	ISO	Max. shelter serv.	Earthq.	NetLogo	Micro	NH	Social/Panic	A.B.	P.S.O.	B	N

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Table 8 – continued from previous page

Ref.	Frame.	Obj. function	Hazard	Software	Fid.	Journal	Hum. behavior	S.M.	O.M.	Int.	E.V.
Cheng et al. (2008b)	IOS	Min. evac. time	Both	GIS based	Micro	ICIA	Social Network	A.B.	P.S.O.	B	N
Bo et al. (2007)	IOS	Min. evac. time	Both	GIS based	Micro	CIS	Social Network	A.B.	P.S.O.	B	N
Wei et al. (2012)	IOS	Min. evac. time	No-not.	Cell-Auto.	Micro	IEEE Geoinf.	Social Network	A.B.	S.H.	B	N
Zhang et al. (2024a)	IOS	Min. evac. time	No-not.	Cell-Trans.	Meso	SMPT	Route Choices	-	S.H.	P	N
Zheng et al. (2021)	IOS	Min. evac. time	Both	MATLAB	Macro	JAIHC	Social/Route	A.B.	S.H.	B	N
Xu et al. (2022a)	IOS	Min. evac. time	Fire	PyroSim	Micro	JBE	Social/Panic	A.B.	S.H.	B	N
Kimms and Maassen (2011)	ISO	Min. total danger	No-not.	SUMO	Micro	SOBRA	Panic/Route	A.B.	G.A.	B	N
MA et al. (2013)	ISO	Min. evac. time	No-not.	MATLAB	Micro	JATIT	Route Choices	A.B.	G.A.	P	N
Chang et al. (2024a)	IOS	Min. evac distance	Gen.	Prob-spec	Micro	CIE	Shelter Choice	A.B.	S.H.	B	N
Lopez-Carmona and Garcia (2021)	ISO	Max. safety/eff.	Urban	Python	Micro	IEEE Access	Route Choice	A.B.	S.H.	P	N
Fu et al. (2014)	IOS	Min. travel time	Urban	MATLAB	Micro	IEEE ITS	Route Choice	A.B.	G.A.	P	N
Huang et al. (2016c)	ISO	Min. evac. time	Earthq.	MATLAB	Micro	NH	Route Choice	A.B.	G.A.	P	N
Ma et al. (2013)	IOS	Min. time/risk	Flood	Python	Micro	IJCA	Route Choice	A.B.	S.H.	P	N
Chebika et al. (2025)	ISO	Min. evac. time	Flood	NetLogo	Micro	OCM	Route Choice	A.B.	S.H.	B	N
Yazici and Ozbay (2008)	ISO	Min. clearance time	Hurric.	CORSIM	Micro	TR-Rev	Route Choice	D.E.S.	S.H.	P	P
Romano et al. (2025)	ISO	Max. flow	Urban	AnyLogic	Micro	SCIRES	Social Net.	A.B.	S.H.	B	P
Even et al. (2015)	ISO	Min. clearance time	Flood	Custom	Micro	AAAI	Route/Sched.	A.B.	MIP/SH	P	N
Nagarajan and Shaw (2021)	ISO	Min. travel time	Tsunam.	NetLogo	Micro	IJDRR	Panic Behav.	A.B.	S.H.	B	N
Takabatake et al. (2025)	ISO	Min. loss of life	Tsunam.	Python	Micro	RESS	Route Choice	A.B.	E.M.	B	P
Cao et al. (2024)	ISO	Min. evac. time	Fire	Python	Micro	IJDRR	Social Net.	A.B.	P.S.O.	B	N
Hafiz Hasan and Van Hentenryck (2021)	ISO	Min. total time	Wildf.	Custom	Mac/Mic	Networks	Compliance	A.B.	S.H.	P	P
Hasan and Van Hentenryck (2021)	ISO	Max. throughput	Wildf.	Custom	Micro	Networks	Route Choice	A.B.	S.H.	P	N
Islam et al. (2022)	ISO	Min. delay	Urban	Custom	Micro	IJCAI	Congest. resp.	A.B.	S.H.	B	N
Huertas et al. (2020)	ISO	Max. efficiency	Urban	MATLAB	Micro	OR Spec	Ped. Dynam.	A.B.	S.H.	B	N
Zambrano et al. (2020)	ISO	Min. evac. time	Build.	AnyLogic	Meso	TEM	Perception	A.B.	S.H.	B	N
Kim et al. (2017)	ISO	Min. evac. time	Tsunam.	MATSim	Micro	TR-B	Route Choice	A.B.	HND	P	N

[1] **Journals:** AAAI: AAAI Conf. on AI; Auto. Constr.: Autom. Constr.; CIE: Comput. Ind. Eng.; CIS: Comput. Inf. Syst.; COR: Comput. Oper. Res.; EJOR: Eur. J. Oper. Res.; EJTL: EURO J. Transp. Logist.; EPA: Environ. Plan. A; FAR: Front. Archit. Res.; IEEE Access: IEEE Access; IEEE ITS: IEEE Trans. Intell. Transp. Syst.; IJCA: Int. J. Comput. Appl.; IJCAI: Int. Joint Conf. Artif. Intell.; IJDRR: Int. J. Disaster Risk Reduct.; IJDRS: Int. J. Disaster Risk Sci.; IJTE: Int. J. Transp. Eng.; JAIHC: J. Ambient Intell. Humaniz. Comput.; JASSS: J. Artif. Soc. Soc. Simul.; JATIT: J. Theor. Appl. Inf. Technol.; JBE: J. Build. Eng.; JITS: J. Intell. Transp. Syst.; JTRB: J. Transp. Res. Board; LNCS: Lect. Notes Comput. Sci.; NH: Natural Hazards; Networks: Networks; OCM: Ocean Coast. Manag.; OR Spec: OR Spectrum; RESS: Reliab. Eng. Syst. Saf.; SBS: Soc. Behav. Sci.; SCIRES: Sci. Rep.; SEPS: Socio-Econ. Plan. Sci.; SMPT: Simul. Model. Pract. Theory; SOBRA: Springer Optim. Best Real Appl.; TEM: IEEE Trans. Eng. Manag.; TETCI: IEEE Trans. Emerg. Top. Comput. Intell.; TR-B/C: Transp. Res. Part B/C; TR-Rev: Transp. Res. Rec.; TRIP: Transp. Res. Interdiscip. Perspect.; TRR: Transp. Res. Rec.; WSC: Winter Simul. Conf.

[2] **S.M. (Sim. Method):** A.B.: Agent-Based; D.E.S.: Discrete Event Sim.; M.C.: Monte Carlo.

[3] **O.M. (Opt. Method):** C.G.: Column Gen.; E.M.: Exact Method; G.A.: Genetic Alg.; HND: Heuristic Net. Design; MIP: Mixed-Integer Prog.; P.S.O.: Particle Swarm; S.H.: Spec. Heuristic; T.S.: Tabu Search.

[4] **Int. (Integration): P**: Parameter-based (Static constants); **B**: Behavior-oriented (Dynamic/Emergent rules).

[5] **E.V. (Empirical Validation of Behavioral Component): Y**: Behavioral parameters validated against real-world data; **P**: Partially validated (some behavioral parameters are empirically grounded, others rely on assumptions); **N**: No empirical validation reported (parameters based solely on theoretical assumptions or prior literature); **-**: Not applicable (review papers).

As shown in Table 8, 74% of the reviewed studies adopt microscopic simulation. Among these, agent-based modeling (ABM) is the most common technique, applied in 67% of the papers. Mesoscopic and macroscopic simulation each account for only 6% of the reviewed literature, indicating a strong preference for methods that capture individual-level behaviors.

While the 'H.B.' (Human Behavior) column identifies the factors considered in the literature, in the vast majority of these cases, these factors are implemented as exogenous parameters or compliance assumptions rather than dynamic, rule-based decision-motion coupling mechanisms. Approximately 83% of these reviewed studies utilize parameter-based representations, where behavioral factors like route choice or compliance are treated as static input variables to maintain computational feasibility. Only 17%, primarily those utilizing advanced ABS such as Hasan and Van Hentenryck (2021) and Cao et al. (2024), transition toward behavior-oriented modeling by defining explicit interaction rules between individuals and their environment.

Regarding alternative simulation methods, 13% of the reviewed studies employ DES to model human behavior and simulation optimization. Despite the increase in the total number of papers, the relative share of DES has slightly decreased, as recent studies such as Islam et al. (2022) and Hasan and Van Hentenryck (2021) lean towards custom agent-based frameworks to handle complex spatial dynamics. None of the reviewed studies use SD for individual behavior modeling. MCS is applied in only 1% of the papers, primarily for model validation purposes. This shows that researchers mostly prefer methods like ABS and DES that can represent individual actions and network-level constraints in detail, while SD and MCS are rarely used for modeling human behavior.

Among human behavior factors, route choice remains the most frequently studied, appearing in 58% of the reviewed studies. This highlights its critical role in mitigating congestion and enhancing overall evacuation efficiency, particularly in agent-based models where individuals dynamically choose between paths under evolving conditions. Recent studies by Islam et al. (2022) and Hasan and Van Hentenryck (2021) further emphasize how route selection is heavily influenced by real-time congestion and network delays. Social networks follow at 19%, often captured through herd behavior models or the simulation of group decision-making. For instance, in the studies by Cheng et al. (2008b) and Bo et al. (2007), social ties are embedded in agent behavior rules, while Cao et al. (2024) and Romano et al. (2025) have recently demonstrated how peer-to-peer influence significantly alters crowd flow. Other factors such as panic behavior (10%), transportation systems (12%), evacuation time (6%), and shelter choice (10%) also play substantial roles. Notably, Chang et al. (2024a) integrated prioritized shelter preferences into the S–O loop, and Hafiz Hasan and Van Hentenryck (2021) introduced "zonal compliance" as a key behavioral factor in wildfire evacuations. Environmental familiarity (1%) remains the least explored factor. These findings suggest that while route dynamics and social behavior continue to dominate the literature, critical dimensions of individual decision-making—such as the psychological impact of panic, environmental familiarity, and adaptive responses to zonal instructions—require more robust integration into emerging simulation-optimization frameworks.

Approximately 43% of the reviewed studies employ problem-specific heuristics to address complex scenarios, a trend reinforced by recent models where traditional algorithms struggle with computational scalability (Hasan and Van Hentenryck, 2021; Islam et al., 2022). Exact methods are used in only 3% of the papers due to their computational intensity. In 26% of the studies, the primary focus remains on the simulation framework and results rather than on the optimization technique, highlighting a greater emphasis on application outcomes over methodological advancements.

Regarding optimization techniques, S–O methods incorporate a variety of approaches. Genetic algorithms (GA), used in 7% of the studies, are favored for their ease of implementation and ability to optimize complex problems (Abdelgawad and Abdulhai, 2010; Song et al., 2013). Particle swarm optimization (PSO) is applied in 9% of the papers for route optimization (Zong et al., 2014; Swamy et al., 2017). Tabu search (TS) appears in 3% of the studies. Although simulated annealing (SA) is known for exploring solution spaces through probabilistic methods, it is not employed in the reviewed evacuation studies

due to its limited suitability for dynamic behavioral models (Amaran et al., 2016). Column generation (CG) is used in 3% of the papers, for evacuation path generation (Cabrera et al., 2022) and resource allocation (Kim et al., 2017). These findings suggest that problem-specific heuristics and population-based algorithms are more widely used than exact methods or classical metaheuristics, likely due to their flexibility in adapting to the complexities of evacuation scenarios.

Among the hybrid methodologies, IOS models, accounting for 19% of the reviewed studies, begin with optimization, followed by simulation to evaluate the outcomes. These models, typically GIS-based and microscopic, focus on route planning and congestion management. Cheng et al. (2008b) and Bo et al. (2007) incorporated social network structures to reflect peer influence and group movement, demonstrating how evacuees tend to follow familiar individuals, thereby affecting traffic dynamics. Wei et al. (2012) employed a cellular automata-based microscopic model to capture herding behavior and non-compliance, emphasizing the need for real-time re-optimization as evacuees prioritized peer actions over official instructions. In addition, IOS approaches have also been applied by (Abdelgawad and Abdulhai, 2010; Zong et al., 2014; Swamy et al., 2017; Alahi Kawsar et al., 2019; Zheng et al., 2021; Cabrera et al., 2022; Xu et al., 2022a; Zhang et al., 2024a).

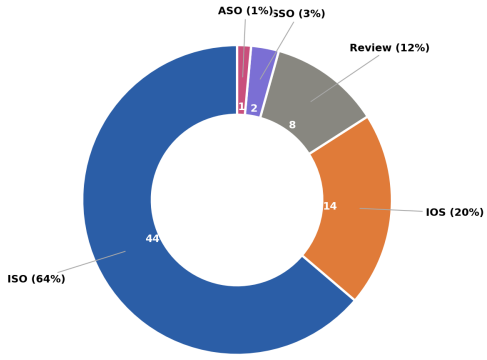
ISO stands out as the most widely adopted approach, appearing in 59% of the reviewed studies, primarily because the optimization process drives the generation of candidate strategies, while simulation acts as a feedback mechanism to evaluate and refine these strategies. This optimization-driven structure allows ISO to systematically search a wide solution space, incorporate diverse constraints, and adapt decisions based on simulation outputs in large-scale environments. The robustness of this framework is evidenced by a vast body of literature including Gan et al. (2016); Takabatake et al. (2017); Yuan et al. (2017); Zhang et al. (2009); Afshar and Haghani (2008); Balakrishna et al. (2008); Chang and Edara (2016, 2018, 2017); Chavhan and Venkataram (2019); Nakanishi et al. (2020); Wang et al. (2023); Joo et al. (2013); Chen et al. (2006); Cova and Johnson (2002); Lu et al. (2005); Han et al. (2006); Hsu and Peeta (2013); Chiu et al. (2007); Zou et al. (2005); Sfeir et al. (2018); Li et al. (2022a); Rivers et al. (2014); Song et al. (2013); Liu et al. (2023); Kimms and Maassen (2011); MA et al. (2013); Chang et al. (2024a); Fu et al. (2014); Huang et al. (2016c); Ma et al. (2013); Chebika et al. (2025); Yazici and Ozbay (2008); Romano et al. (2025); Nagarajan and Shaw (2021); Takabatake et al. (2025); Cao et al. (2024); Hafiz Hasan and Van Hentenryck (2021); Hasan and Van Hentenryck (2021); Islam et al. (2022); Huertas et al. (2020); Zambrano et al. (2020); Kim et al. (2017). Addressing the scalability limitations of exact mathematical programming, Even et al. (2015) introduced a two-stage ISO framework that decouples route design from evacuation scheduling. This approach employs a conflict-aware path-generation heuristic to eliminate delays at intersections, ensuring that optimized plans remain operationally convergent and feasible in large-scale urban networks. Representing the urban-scale methodologies, Hasan and Van Hentenryck (2021) demonstrates the pinnacle of ISO application by optimizing zonal evacuation schedules for massive wildfires, where high-fidelity simulation evaluations are used to ensure the operational feasibility of prescriptive plans in sprawling networks.

SSO models proceed sequentially, first executing simulation to understand system dynamics and then employing optimization. Lahmar et al. (2006) used CORSIM to adjust routes and control strategies based on congestion. Maassen (2012) combined SUMO with heuristic optimization to simulate panic-induced disruptions via crowd density thresholds, linking behavioral stress to dynamic rerouting.

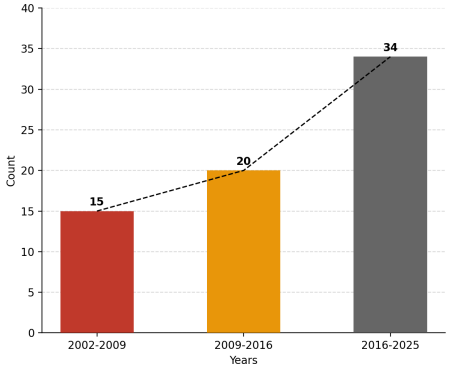
ASO models alternate between simulation and optimization steps, allowing for continuous feedback and adaptive planning. Liu et al. (2016) developed an agent-based model in NetLogo to capture decentralized decisions and spontaneous rerouting during no-notice evacuations.

Regarding S–O method types, Table 8 and Fig 10a show that 13 studies used IOS, 41 applied ISO, two employed SSO, and one used ASO. The remaining 12 studies are methodological reviews that do not implement a specific simulation-optimization coupling framework.

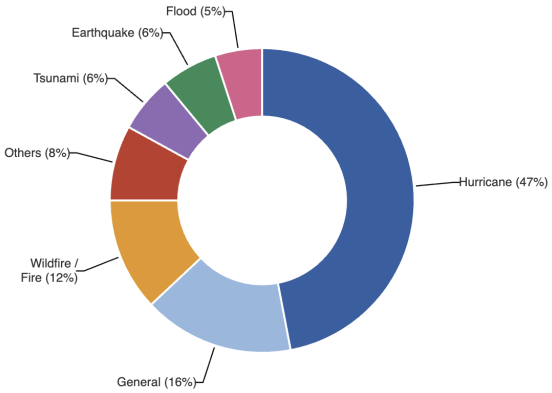
The dominance of the ISO framework, accounting for 59% of the reviewed studies, stems from its superior ability to bridge the gap between prescriptive optimization and stochastic simulation. Unlike sequential models, ISO's iterative feedback loop allows for a systematic search of wide solution spaces while simultaneously incorporating granular human behaviors. This scalability and flexibility make it the preferred choice for recent large-scale applications, where simulation-based performance metrics are used to continuously refine optimization parameters (Hasan and Van Hentenryck, 2021; Islam et al., 2022). The robustness of this approach is further demonstrated in high-demand scenarios involving up to 0.1 million agents, proving its unique suitability for modeling complex network constraints and real-time behavioral adaptations in large-scale emergency contexts (Even et al., 2015; Kim et al., 2017; Huertas et al., 2020).



(a) Usage distribution of S–O optimization methods



(b) Yearly distribution of S–O studies



(c) Types of disasters

Fig. 10. Overview of S–O method usage, temporal trends, and disaster types.

As shown in Fig 10b, interest in S–O approaches has grown significantly, with 59% of the 69 reviewed studies published between 2016 and 2025. This upward trend reflects a growing emphasis on urban-scale, data-driven, computational methods that combine optimization and simulation to improve network-level evacuation planning and management and disaster response. The recent surge in publications totaling 41 studies in the final period shows the need for interdisciplinary collaboration across engineering, behavioral sciences, and emergency evacuation planning and management to develop more adaptive and effective large-scale evacuation strategies. As illustrated in Fig 10c, hurricane scenarios dominate the reviewed literature, accounting for 47% of all studies, followed by general or multi-hazard contexts at 16% and wildfire/fire at 12%. This distribution reflects the historically high research attention toward large-scale, notice-based evacuations, while flood, tsunami, and earthquake scenarios

remain comparatively underrepresented, highlighting clear opportunities for future simulation-optimization research in these hazard domains.

7 Empirical validation of behavioral assumptions

Optimization-Based Evacuation Models. The empirical grounding of behavioral components in the reviewed optimization models varies considerably. Most SO and UE-based formulations rely on established traffic assignment theory without validating compliance assumptions against observed evacuation data. Among partial-compliance models, Yi et al. (2017) calibrate behavioral parameters using empirically estimated discrete choice models, and Sun et al. (2017) derive response rates from behavioral research and expert-input, while others rely on randomly generated deviations (e.g., Lessan and Kim, 2022), theoretically-assumed fairness thresholds (e.g., Bayram et al., 2015; Bayram and Yaman, 2018a,b), endogenously computed but uncalibrated compliance rates (Zeng et al., 2016), or assumption-based attractiveness parameters (Wang and Wallace, 2022; Xu et al., 2025). Hsu and Peeta (2014) estimate their route choice model from synthetic behavioral data rather than real-world observations. Among models embedding compliance-enhancing factors, Dulebenets et al. (2020) calibrate their parameters through a driving-simulator experiment with 115 participants, whereas Hu et al. (2014) employ theoretically motivated but uncalibrated panic dynamics. Even et al. (2015) validate plan performance through mesoscopic simulations, while Hasan and Van Hentenryck (2021) provide microscopic validation using the SUMO traffic simulator, both offering indirect empirical support for structural plan-design features. While a few optimization studies demonstrate meaningful empirical grounding through calibrated choice models, simulator experiments, or microscopic validation, the majority of behavioral components remain theoretically assumed.

Simulation-Based Evacuation Models. A similar pattern emerges in the simulation literature, where the empirical grounding of behavioral components follows a clear hierarchy tied to the three methodological categories. Empirical-statistical models (Category 1) provide the strongest foundation, deriving parameters from post-event surveys or revealed-preference data. Cognitive-process-based models (Category 2) are theoretically grounded but typically calibrated against limited or context-specific evidence. Rule-assumption-based models (Category 3), which constitute the largest share, impose exogenous heuristics without calibration against observed behavioral data. This imbalance is most pronounced for the decisions with the greatest operational consequences: departure time and route choice are predominantly governed by rule-based proxies, while protective action is the only decision type with roughly balanced representation across all three categories. Mode choice is never modeled through a cognitive framework, and non-compliance is dominated by rule-based assumptions. While meaningful empirical progress has been made for protective action decisions, departure time and route choice, which are the most consequential decisions for network-level performance, remain largely governed by assumed heuristics.

Simulation-Optimization Based Evacuation Models. These frameworks inherit behavioral assumptions from both their simulation and optimization components, and as the preceding discussion indicates, neither component is typically well-calibrated. Since simulation-optimization models do not generally introduce additional empirical validation of these inherited assumptions, they face a compound validity challenge. Across the reviewed studies, these findings converge into a consistent picture. Only a very small proportion (3%) provides strong empirical validation by calibrating simulation kernels with real-world disaster data, such as observed traffic counts from actual hurricane events (Chang and Edara, 2017, 2018). A further 18% offers partial validation by grounding selected behavioral parameters in empirical evidence. For example, departure time distributions derived from post-event surveys (Takabatake et al., 2017; Nakanishi et al., 2020), demand curves calibrated against historical traffic observations (Yazici and Ozbay, 2008; Cova and Johnson, 2002), or compliance rates informed by

prior field studies (Hafiz Hasan and Van Hentenryck, 2021). However, the large majority (79%) rely entirely on synthetic behavioral proxies, such as idealized full compliance or fixed herd-following rules, without any empirical calibration (Zhang et al., 2009; Liu et al., 2023; Nagarajan and Shaw, 2021). This persistent validity gap across optimization, simulation, and simulation-optimization frameworks suggests that while these studies contribute significantly to methodological advancement, their operational reliability in real-world large-scale evacuations remains fundamentally limited by the lack of behavioral validation. Closing this gap will require systematic integration of empirically calibrated behavioral models into evacuation planning frameworks.

8 Conclusion and future research directions

Effective evacuation is vital for reducing disaster risk, as climate change, rapid urbanization, and global digital interconnectivity increase the frequency and complexity of emergencies. However, evacuation strategies are often designed under the assumption of full public compliance, despite the frequent occurrence of non-compliance, creating significant challenges for planners and authorities. To address this reality, this study comprehensively reviews research on integrating human behavior into large-scale evacuation modeling. Understanding how individuals respond to key decisions made by authorities, and the factors influencing those responses, provides the foundation for realistic and actionable planning. Building on this, the study examines two complementary dimensions: the behavioral perspective, which identifies drivers of evacuee compliance, and the modeling perspective, which embeds these insights into evacuation optimization, simulation, and simulation–optimization frameworks. Beyond synthesizing prior work, the study evaluates its progress and limitations in capturing real-world complexities, including uncertainty, equity, real-time data integration, and the protection of vulnerable populations. Finally, it highlights opportunities to integrate advanced methodologies, such as digital technologies, artificial intelligence, and other emerging tools, and to translate academic research into operational practice for data-driven and actionable evacuation planning.

8.1 Key insights from the literature

Research on influencing factors in evacuation behavior is extensive and highlights key insights. Factors such as demographic characteristics and family context are the most frequently studied and shape evacuation decisions. Combined with decision-related studies, these investigations demonstrate progress in understanding compliance behavior across critical decisions points. Most research focuses on route choice, departure timing, destination selection, and protective actions, particularly evacuation behavior. Identifying the factors guiding choices is essential for developing strategies that enhance adherence to instructions and translate behavioral insights into actionable evacuation plans.

Most optimization models integrating compliance behavior focus on routing and adopt idealized, binary assumptions: SO for full compliance, UE for non-compliance, and CSO models that add behavioral realism through fairness constraints, assuming evacuees comply fully once these are met. CSO models represent the first progress toward behaviorally aware optimization. More recent studies explicitly address partial compliance, often for specific disasters and incorporating uncertainty, revealing the operational impacts of varying compliance rates and producing more realistic and equitable solutions. A smaller group of models embeds determinants of compliance, such as physical or psychological considerations, directly into optimization frameworks, offering solutions that are both realistic and equitable.

Simulation-based studies demonstrate that behaviorally informed models capture meaningful interactions between evacuee decisions and system performance, and the growing volume of research in this area confirms that behavioral integration has become a mainstream methodological concern in evacuation simulation. Two-way integrated models (network-state feedback)

which allow evolving network and hazard conditions, such as congestion or blockages, to dynamically update individual choices, produce substantively different outcomes compared to static or one-way architectures, with direct implications for shelter management, route guidance, and real-time planning. Across all three structural categories discussed in Section 5, rule-based methods dominate how individual decisions are represented, and this reliance is most pronounced for departure timing and route choice. This creates a notable tension: the decisions with the greatest influence on network loading are precisely those least grounded in behavioral evidence.

Simulation–optimization approaches build on these developments by combining the prescriptive strength of optimization with the ability of simulation to capture complex, dynamic processes. ISO methods are especially effective, systematically exploring wide solution spaces and adapting decisions based on simulation outputs. Similar to influencing-factor studies and optimization models, S–O approaches often prioritize route choice as the key decision variable, emphasizing its critical role in mitigating congestion and improving evacuation efficiency.

8.2 Gaps and opportunities for future research

Although recent advances highlight promising progress in integrating behavioral insights into both optimization and S–O frameworks, our synthesis also reveals several critical gaps. Addressing them is essential to move beyond models toward behaviorally realistic, adaptive, and actionable approaches for real-world crises.

- **Behavioral Coverage Across Decisions:** Existing behavioral studies and modeling frameworks focus predominantly on route choice, while transportation mode is rarely addressed and road-segment designation is almost absent. Most of the routing studies prioritize vehicle-based evacuation and overlook multimodal strategies, despite the operational challenges of mixed traffic. This lack of road-segment assignment for managing mixed flows also leaves non-compliance behavior underexplored. In the simulation literature, this imbalance is equally pronounced: mode choice has never been modeled through a cognitive or process-based framework, and road-segment designation is entirely absent from simulation-based studies. Furthermore, protective actions such as shelter-in-place and shadow evacuation receive minimal attention. Future research should therefore adopt an integrated framework that captures a broader range of decisions such as transportation mode selection, road-segment designation, and diverse protective responses to better reflect real-world evacuation behavior.

- **Modeling Compliance and Its Drivers:** Partial compliance appears in only a few optimization studies, typically for a single decision type, and these often rely on simplified or randomly generated behavioral inputs. Moreover, only a limited number of models embed underlying drivers of compliance, such as physical factors like mobility constraints for vulnerable populations or psychological considerations. In the simulation literature, compliance modeling is similarly limited, remaining concentrated on the binary evacuate-or-stay decision while non-compliance with recommended departure schedules, assigned destinations, and designated routes, behaviors widely documented in post-event surveys, is largely unrepresented. More broadly, rule-based methods dominate how individual decisions are represented across all simulation categories, particularly for departure timing and route choice, which remain the least grounded in behavioral evidence. Our quality-of-evidence assessment further reveals a critical validity gap" in the literature, where approximately 59% of the reviewed S–O frameworks rely on synthetic or unvalidated behavioral proxies. This heavy reliance on theoretical assumptions, rather than empirically calibrated kernels, limits the operational reliability of prescriptive evacuation strategies. To advance this area, future research should integrate influencing factors with partial compliance into unified frameworks, prioritizing the transition from "synthetic behavior"

to "calibrated behavior" by utilizing real-world datasets such as GPS trajectories, video analytics, and post-disaster surveys to ensure that optimization outputs are grounded in observed human reality.

- **Hazard Types and Geographic Contexts:** Most of the reviewed studies focus on hurricanes in the United States, leaving sudden-onset hazards, such as tsunamis, earthquakes, and wildfires, as well as compound disasters, underexplored. This U.S.-centric focus also means that regional differences in infrastructure, governance, and culture remain largely unaddressed. Expanding research to cover a wider range of hazards and geographic contexts is therefore essential for developing globally relevant and life-saving evacuation strategies.
- **Equity and Vulnerability Considerations:** Vulnerable groups, including the elderly, disabled, low-income populations, and those without access to private vehicles, are rarely incorporated into optimization or simulation–optimization models. While a few studies explore their destination and mode choices or prioritize them through mobility constraints, most models focus on average population behavior, leaving the specific challenges of these groups underrepresented. This limitation is compounded by the predominant focus on traffic efficiency metrics in simulation outputs, while life-safety and compliance-driven consequences remain underreported, leaving the field without adequate tools to assess whether evacuation strategies achieve their primary goal of saving lives and serving all population groups equitably. Future research should explicitly integrate vulnerable populations into evacuation modeling and planning to ensure strategies that are both equitable and effective.
- **Real-Time Data Integration and Human-in-the-Loop Approaches:** Most existing models are static and cannot ingest live data or adapt strategies as a disaster unfolds, despite the highly dynamic nature of emergencies. This limitation is evident in the simulation literature, where most two-way integrated models dynamically update only route choice, leaving departure timing, destination selection, and mode choice predetermined, which limits representation of how evacuees adapt under evolving conditions. Extending dynamic feedback mechanisms to jointly update multiple decision dimensions is a critical step toward more adaptive simulation architectures. Future models should incorporate real-time data streams, including ITS, IoT sensors, satellite imagery, mobile devices, and social media, and support human-in-the-loop decision-making so that strategies can be adjusted interactively, enabling adaptive and resilient evacuation planning. More fundamentally, feedback in existing models operates at the level of network state rather than through behavior–motion coupling. Representing local perception, interpersonal interaction, and speed adaptation within large-scale evacuation models remains an open methodological challenge.
- **Uncertainty in Evacuation Planning:** Evacuation planning is characterized by deep uncertainty arising from complex human behavior, rapidly changing environmental conditions, and incomplete or imperfect information. While some optimization models that include compliance consider uncertainty, mostly using stochastic approaches, most of simulation–optimization models remain deterministic, relying on simplifying assumptions misaligned with real-world conditions. Robust-optimization approaches can be effectively used to address this critical issue, which is mostly overlooked in the existing literature. Future research towards this direction can have a very significant practical impact to offer stronger performance in ensuring reliable evacuation planning.
- **Integration of Emerging Technologies and Advanced Methods:** Digital technologies, including AI, machine learning, ITS, digital twins, and satellite imagery, are still underutilized in evacuation modeling Bayram (2024) .

  A Digital Twin is defined as a dynamic virtual replica of a physical system, such as an urban road network, synchronized through real-time data exchange. Rather than serving merely as a 3D visualization tool, a DT can function as a bi-directional synchronization platform that continuously integrates live data streams from ITS, mobile devices, IoT sensors, drones, and satellites. Evacuation planning can embrace this technology by shifting from static models to

live-responsive systems where a DT acts as a high-fidelity simulation engine, enabling planners to test and deploy optimization strategies in a virtual environment that mirrors the real-time state of the physical city, while providing real-time situational awareness and dynamic routing recommendations as events evolve. ITS and IoT sensor networks can enable real-time traffic and hazard data collection during evacuations, which, combined with machine learning and data analytics, can be transformed into dynamic route guidance and congestion management decisions Bo et al. (2007). Autonomous- and connected-vehicle technologies can further support coordinated, system-optimal routing by centralized traffic management authorities Fagnant and Kockelman (2015); Mahmassani (2016). Satellite imagery and remote sensing can complement these tools by enabling rapid post-disaster damage assessment and real-time updates to evacuation network models Joyce et al. (2009). These tools can enrich behavioral prediction, enable real-time traffic assignment, detect blocked roads or hazards, and support congestion management. Methodologically, hybrid models that combine agent-based simulation with robust-optimization, stochastic programming, or reinforcement learning offer substantial potential but are rarely applied.

- **Strengthening Academic–Practitioner Collaboration:** Progress is limited by a persistent gap between academic research and operational practice. In the simulation domain, this gap is further reflected in the heavy reliance on custom or in-house agent-based models, with many established simulation platforms rarely adopted, pointing to a need for greater standardization and reproducibility. Collaborative, co-designed modeling efforts involving local emergency managers, transportation agencies, NGOs, community organizations, and international bodies (e.g., UNDRR, IFRC) are essential. In addition to high-level agencies like FEMA or FHWA, partnerships with local authorities and grassroots organizations will enable models that reflect diverse realities. Standardized datasets, transparent modeling protocols, and interoperable simulation platforms can help bridge this divide and ensure that models are directly usable in practice.
- **Reframing Evacuation as a Socio-Technical Challenge:** Evacuation is not solely a logistics problem but a complex socio-technical system shaped by human factors and infrastructure. Future research should integrate behavioral science, communication, sociology, and ethics into the design of algorithms and models. Such multidisciplinary approaches will produce tools that are not only accurate but also fair, trusted, and implementable in real-world decision environments.

Together, these gaps highlight a research agenda where computational rigor must be matched with behavioral realism, inclusivity, and practical insights. Advancing in these directions will require a new generation of adaptive, data-rich, and human-centered evacuation models that are designed hand-in-hand with practitioners, rather than in isolation from them.

8.3 Bridging the academic–practitioner divide

Evacuation planning and management cannot remain a purely academic exercise. The complex realities of large-scale emergencies demand stronger, continuous collaboration between researchers, operational agencies, local authorities, international organizations, NGOs, and community stakeholders. While academic research has generated increasingly sophisticated models, these tools will only achieve real impact if they are co-designed, validated, and adapted with those responsible for decision-making in the field.

The framework proposed by Lindell et al. (2018) shows this principle: effective evacuation planning integrates engineering, social science, emergency management, and policy insights. Building on this perspective, our review highlights several priorities for closing the gap between research and practice:

Practitioners need:

- Practical tools grounded in validated models and informed by reliable, real-world data.
- Strategies tailored to context, recognizing that tsunami, earthquake, wildfire, hurricane, or compound hazards require distinct approaches.
- Guidance on public communication, coordination of multimodal transportation, and adaptive shelter allocation under deep uncertainty.

Academics must:

- Ground their models in empirical-behavioral data and stakeholder feedback rather than relying on simplified assumptions.
- Design for usability, transparency, and operational constraints to ensure models can be applied in the field.
- Extend collaboration beyond U.S.-based agencies (e.g., FEMA, FHWA) to include diverse organizations such as Turkey's Disaster and Emergency Management Presidency (AFAD), Japan's Cabinet Office, European Civil Protection, local municipalities, and community groups.

Academic–practitioner partnerships need to evolve from one-off consultations into long-term, collaborations. Early and sustained involvement of practitioners in model design, scenario development, data collection, and validation is essential. Approaches such as co-designed simulations, stakeholder workshops, and post-event reviews can ensure that models reflect operational realities and build trust for real-world adoption.

The rapid expansion of digital technologies, including ITS, mobile data, social media, IoT sensors, and satellite imagery, creates unprecedented opportunities for real-time coordination between modelers and field-level responders. Decision-support systems should move beyond prescribing shortest paths toward recommending strategies that balance efficiency, safety, equity, and feasibility given current behavioral and infrastructure conditions. Advanced approaches such as reinforcement learning, and dynamic traffic assignment under partial compliance will only reach their potential when combined with the expertise of practitioners who understand local-level constraints and priorities.

Bridging this divide requires institutional mechanisms for sustained dialogue, shared data platforms, joint funding initiatives, and multidisciplinary research programs. By fostering these collaborations, models can evolve from academic prototypes into trusted, actionable systems that help protect lives during crises.

8.4 Toward a multidisciplinary, inclusive research agenda

The next generation of evacuation modeling will depend on interdisciplinary collaboration, bringing together operations research, transportation engineering, behavioral science, data analytics, artificial intelligence, and emergency management practice. The goal is to build models that are scientifically rigorous, behaviorally authentic, technologically advanced, and directly usable in decision-making environments.

Key research priorities include:

- **AI-enabled adaptive decision support:** Leveraging machine learning and reinforcement learning for adaptive routing and shelter allocation that responds to uncertainty, partial compliance, and changing conditions on the ground. These methods can also learn from past evacuation data to anticipate likely human responses.

- **Inclusive and climate-resilient planning:** Placing equity and inclusivity at the core of model design to ensure that strategies account for vulnerable populations, multimodal mobility, and the disproportionate risks posed by climate-related and compound disasters in different regions of the world.
- **Open data and benchmarking:** Promoting standardized, openly available datasets, common benchmarks, and replicable scenarios to make models comparable across hazards and regions, accelerating innovation and enabling independent validation.
- **Institutionalized co-design:** Establishing long-term, multidisciplinary research programs where academics, practitioners, and policymakers jointly design, test, and refine evacuation models, ensuring that methods remain relevant and trusted in real-world settings.

8.5 Final remarks

This review calls for a fundamental rethinking of how evacuations are modeled, simulated, and managed. They must no longer be treated solely as technical optimization problems, but as human-centered, socio-technical challenges shaped by the interplay of human behavior, institutional constraints, and rapidly advancing digital technologies. The evidence synthesized here highlights both how far the field has come and how much more remains to be done to align models with the realities of complex, fast-evolving crises.

Ultimately, embedding human behavior into evacuation modeling is not only a technical challenge but also a societal responsibility. Building the next generation of evacuation systems will require sustained collaboration between researchers, local authorities, emergency managers, and communities across diverse hazard types and geographic contexts. Only by combining rigorous methods with inclusive, real-time, and practitioner-informed approaches can evacuation models evolve into trusted decision-support systems that protect those most at risk and function effectively under the pressures of real disasters.

CRediT authorship contribution statement

Shiva Moslemi: Methodology (PRISMA framework and paper selection, paper classification), Investigation, Writing – original draft (Optimization, Simulation, Decision-related factors), Formal analysis; Ada Arıkanoğlu: Methodology (paper classification), Writing – original draft (Simulation–optimization, General factors), Investigation, Formal analysis; Vedat Bayram: Conceptualization, Writing – original draft, Writing – review and editing, Supervision, Project administration, Funding acquisition; Barış Yıldız: Conceptualization, Writing – review and editing, Supervision.

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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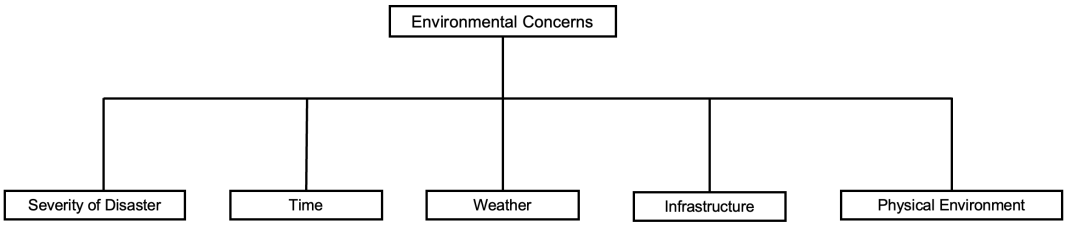
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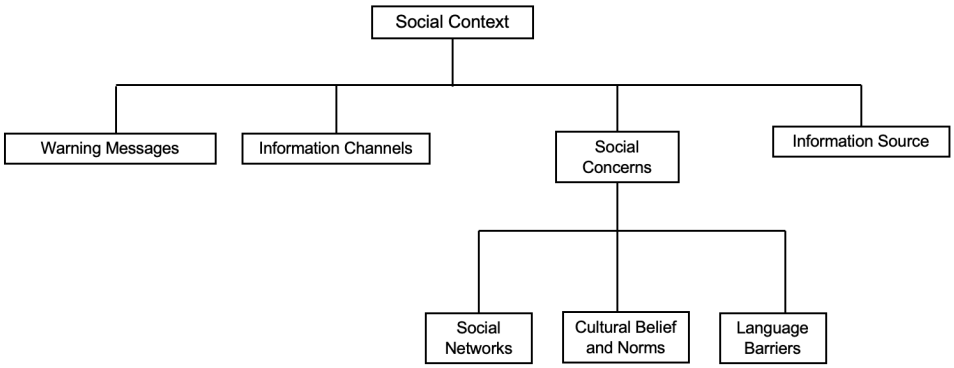
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A Classification of factors affecting evacuee behavior

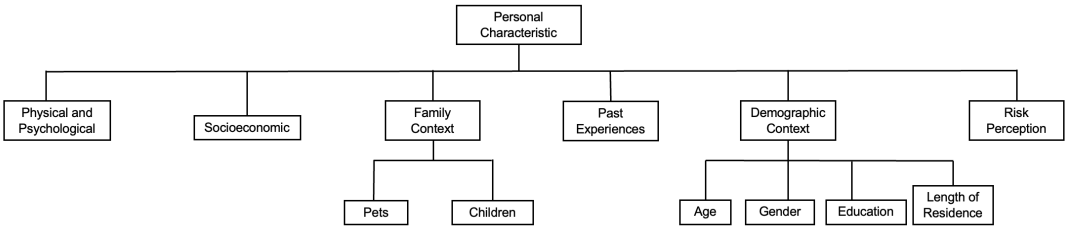
Based on the classification by Lindell et al. (2018) and Ibrahim et al. (2016), evacuation behavior is shaped by three main domains: environmental, social, and personal factors. Environmental factors include disaster severity, time of occurrence, weather, infrastructure, proximity, and accessibility—conditions that affect perceived risk and the logistical feasibility of evacuation. Social factors relate to the influence of social networks, cultural norms, language barriers, and the communication of warnings through trusted sources and clear channels, that guide information processing and compliance. Personal characteristics encompass health status, psychological responses, economic resources, family structure, such as the presence of children or pets, prior disaster experience, and demographics such as age, gender, education, and length of residence—factors that influence both capacity and motivation to evacuate.



(a) Environmental factors



(b) Social factors



(c) Personal factors

Fig. A.1. Factors affecting human behavior during evacuation

B Studies on human behavior

Each study is categorized by author, country, disaster type, and the key behavioral elements observed. These behavioral elements include social concerns (SC), information resources (IR), information channels (IC), family context (FC), past experience (PE), demographic factors (Demog.), and environmental concerns (EC).

Table B.1 summarizes three key dimensions of the literature: (1) the countries where studies on evacuation behavior are concentrated, (2) the types of disasters that are examined most frequently, and (3) the specific behavioral factors addressed in these studies. By systematically presenting this information, the table enables the identification of dominant research patterns and highlights gaps that require further investigation.

Table B.1. Summary of studies on human behavior across different disaster types.

Author	Country	Disaster type	Human behavior
Baker (1991)	USA	Hurricane	SC, IR, IC, FC, PE, Demog.
Dash and Gladwin (2007)	USA	Hurricane	SC, WM, PPC, FC, PE, Demog.
Perry (1979b)	General	General	SC, IR, IC, WM, FC, PE
Dow and Cutter (2000)	USA	Hurricanes	EC, IR, FC, PE
Perry and Lindell (1991)	USA	Flow and Hazardous Material Incidents	SC, IR, WM, EC
Perry and Quarantelli (2005)	General	General	SC, IC, WM, PPC, FC, Demog
Mawson (2005)	General	General	SC, IC, WM, PPC, FC, Demog
Stern (1989)	Israel	Radiological Emergency	EC, IC, PPC, FC
Quarantelli (1975)	General	General	SC, IC, PPC
Dombroski et al. (2006)	USA	Radiological Emergency	EC, IC, PPC, EC, FC, Demog.
Lindell et al. (2005)	USA	Hurricane	EC, IR, IC, EC, FC, PE, Demog.
Sadri et al. (2014b)	USA	Hurricane	IC, FC, EC
Lindell and Prater (2007)	USA	Hurricane	SC, WM, FC,
Lazo et al. (2015)	USA	Hurricane	SC, IR, WM, EC, FC, PE, DC
Wolshon (2002)	USA	Hurricane	EC, FC, PE
Ersing et al. (2020)	USA	Hurricane	EC, IC, SC, PE
Tinsley et al. (2012)	USA	Hurricane	EC
Noltenius (2008)	USA	Hurricane	EC, SC
Wilson and Cales (2008)	USA	Hurricane	EC
Chakraborty et al. (2005)	USA	Hurricane	EC, SC, FC, Demog., EC
Jumadi et al. (2018)	Indonesia	Volcanic Crisis	EC, SC, IR, IC, WM, PPC, FC
La Greca et al. (2023)	USA	Hurricane	EC
Pham et al. (2020)	USA	Hurricane	EC, IR, FC, Demog.
Sakamoto et al. (2020)	China / Japan	COVID-19 / Earthquake	EC
Fu et al. (2007)	USA	Hurricane	EC
Nogami (2022)	Japan	Rainstorm	EC, IR, IC, PPC, FC
Jang et al. (2022)	Korea	Nuclear Power	EC, FC, IR
Lindell et al. (2011)	USA, Cuba	Hurricane	EC, SC, WM, PPC, PE, Demog.
Johnson Jr and Zeigler (1986)	USA	Nuclear Power	EC, IR, FC
Lu et al. (2014)	USA	Fire	EC, Demog.
Baker (1995)	USA	Hurricane	IR, WM, PPC, PPC, Demog.
Whitehead et al. (2000)	USA	Hurricane	SC, EC, FC, Demog.
Cheng et al. (2008a)	USA	Hurricane	EC, Econ., FC, Demog.
Yang et al. (2016)	USA	Hurricane	EC, PPC, Econ, PE, Demog.
Sadri et al. (2014b)	USA	Hurricane	EC, Demog.
Murray-Tuite and Mahmassani (2004)	General	General	EC, FC

Table B.1 continued from previous page

Author	Country	Disaster type	Human behavior
DiGrande et al. (2019)	USA	Hurricane	EC, Econ., Demog.
Horney et al. (2010)	USA	Hurricane	EC, SC, Econ, FC, Demog.
Lindell et al. (2005)	USA	Hurricane	SC, WM, FC
Riad et al. (1999)	USA	Hurricane	SC, PPC
Xie et al. (2023)	General	General	SC
Kinateder et al. (2015)	General	General	SC
Fothergill (1996)	General	General	SC, PPC, Econ., Demog.
Perry and Lindell (1991)	General	General	SC
Ayeb-Karlsson et al. (2019)	Kenya / Philippines	Flood / Typhoon	SC, IR, PE
Kim and Oh (2015)	USA	Hurricane	SC, Econ, FC, PE, Demog
Blendon et al. (2007)	USA	Hurricane	SC, FC
Bolin et al. (1998)	General	General	SC, Econ, FC, Demog
Bateman and Edwards (2002)	USA	Hurricane	SC, Econ, FC, Demog
Elliott and Pais (2006)	USA	Hurricane	SC, PPC, Econ.
Walch (2018)	India / Philippines	Cyclone / Typhoon	IR, PE
Cheng et al. (2015)	Japan	Earthquake	IC, Demog
Diwanji et al. (2020)	USA	Hurricane	IC, Demog
Christensen (2011)	General	General	PPC
Xu et al. (2022a)	USA	Fire	PPC
Ducy and Stough (2021)	USA	Fire	PPC, FC, Demog.
Drabek and Stephenson III (1971)	USA	Flood	PPC, FC
Munro et al. (2017)	UK	Flood	PPC, Econ, Demog.
Gist and Lubin (2013)	General	General	PPC
Meyer et al. (2014)	USA	Hurricane	PPC, Econ., FC, Demog.
Czajkowski (2011)	Cuba, Mexico, United States	Hurricane	PPC, FC
Wang et al. (2021)	General	General	SC, PPC
Li et al. (2017)	General	General	SC, PPC
Vorst (2010)	General	General	SC, PPC
Regnier (2008)	USA	Hurricane	IR, PPC
Yabe and Ukkusuri (2020)	USA	Hurricane	Econ., Demog.
Hu et al. (2017)	China	Earthquake	Econ.
Harris et al. (2022)	USA	Hurricane	SC, PPC, Econ.
Lindell and Prater (2000)	USA	Earthquake	SC, PPC, Econ.
Golshani et al. (2019b)	General	No-notice emergency	EC, PE, Demog.
Kinateder et al. (2015)	USA	Fire	PPC, PE
Demuth et al. (2016)	General	Hurricane	PPC, Econ, FC, PE
Lindell et al. (2011)	USA	Hurricane	Econ., FC, PE, Demog.
Wu et al. (2012)	USA	Hurricane	FC, PE
Huang et al. (2016a)	USA	Hurricane	EC, SC, FC, PE
Jamshed et al. (2019)	Pakistan	Flood	SC, PPC, FC
Hunt et al. (2012)	USA	Hurricane	FC, Demog.
Heath et al. (2001)	USA	Flood	FC, Demog.
Liu et al. (2014b)	USA	No-notice emergency	FC, Demog.
Liu et al. (2012)	USA	No-notice emergency	EC, FC, Demog.
Nakanishi et al. (2019)	Japan	Flood	SC, FC, Demog
Neumayer and Plümper (2007)	General	General	SC, FC, Demog
Muttarak and Lutz (2014)	General	General	Econ, FC, Demog.
Naeimi et al. (2019)	Iran	Earthquake	Econ., Demog.

Table B.1 continued from previous page

Author	Country	Disaster type	Human behavior
Islam et al. (2023)	General	Hurricane	Demog.
Zhang and Chang (2014)	General	General	Demog.
Abdelgawad and Abdulhai (2010)	General	General	Demog.
Grajdura et al. (2021)	USA	Wildfire	Econ, Demog, PE, IR
Cheng et al. (2013)	USA	Hurricane	Demog, EC, WM
Grajdura and Rowangould (2025)	USA	Wildfire	PPC, Demog, EC
Hasan et al. (2012)	USA	Hurricane	Demog, Econ, FC, PE, PPC
Nadimi et al. (2025)	Iran	Earthquake	FC, PE, Demog, IC, EC
Troncoso Parady and Hato (2016)	Japan	Tsunami	EC
Ling et al. (2021)	USA	Hurricane	Demog, PE, PPC, SC, IR, IC, WM
Bian et al. (2022a)	USA	Hurricane	PPC, IR
Anyidoho et al. (2022)	USA	Hurricane	Econ, Demog
Huang et al. (2017)	China	General	PPC, IR, IC, WM
De Maio (2013)	General	General	PPC, EC
Sadri et al. (2014a)	USA	Hurricane	Econ, Demog, PE, FC
Lambert et al. (2013)	USA	General	EC
Muthohar et al. (2020)	Indonesia	Volcanic	PE, IC, SC
D'Amico et al. (2024)	General	General	PPC, EC
Chen et al. (2024)	USA	Hurricane	PPC, Demog, WM
Dixit et al. (2012)	USA	Hurricane	PPC, FC, PE, WM, EC
Intini et al. (2019)	General	Wildfire	Demog, EC, SC
Iwai (2025)	Japan	Tsunami	Demog, EC
Zhang et al. (2024b)	USA	Earthquake	PPC, EC, SC
Mahittikul et al. (2024)	Thailand	Tsunami	Demog, PE, PPC, IR, IC, WM
Robinson and Khattak (2010)	USA	Hurricane	Demog, Econ, FC, PE, EC, IR, IC, WM
Xu et al. (2016)	USA	Hurricane	Econ, Demog, EC
Bian et al. (2019)	USA	Hurricane	Econ, FC, PE, Demog, EC, SC
Bian et al. (2023)	USA	Hurricane	PPC, WM
Rambha et al. (2021)	USA	Hurricane	Demog, Econ, FC, PE, EC, WM, IR
Raei et al. (2025)	Canada	Wildfire	Demog
Wong et al. (2020b)	USA	Wildfire	PPC, PE, WM
Morooka and Yamada (2017)	Japan	Flood	PPC, EC
Jin et al. (2025)	China	Flood	Demog, Econ, IR, SC
Jiang et al. (2021)	USA	Hurricane	SC
Li et al. (2022b)	USA	Tornado	PPC, Demog, IR, EC
Lim et al. (2019)	Philippines	Flood	Demog, Econ, FC, EC
Hasan et al. (2011)	USA	Hurricane	Demog, Econ, FC, PE, PPC, EC, IR, IC, WM
Sadri et al. (2017a)	USA	Hurricane	FC, PPC, SC
Kuligowski et al. (2022)	USA	Wildfire	Demog, Econ, FC, PE, PPC, EC, IR, IC, WM
Mapa et al. (2026)	USA	Wildfire	PE, EC
Urata and Hato (2021)	Japan	No-notice	Demog, PPC, EC, SC, WM
Ahmed et al. (2020)	USA	Hurricane	Demog, Econ, SC, IR, IC
An et al. (2015)	General	General	PPC, IR
Makinoshima and Imamura (2024)	Japan	Tsunami	EC, WM
Diaz et al. (2023)	USA	Hurricane	Demog, Econ, FC, PPC, EC, SC
Wong et al. (2020a)	USA	Wildfire	FC, Econ, SC
Ma and Lee (2025)	USA	Wildfire	PPC, Demog, EC
Anyidoho et al. (2023)	USA	Hurricane	EC

Table B.1 continued from previous page

Author	Country	Disaster type	Human behavior
Guan and Chen (2021)	USA	Hurricane	PPC, EC
Bian et al. (2022b)	USA	Hurricane	IR
Sarwar et al. (2018)	USA	Hurricane	Econ, Demog, WM
Golshani et al. (2020)	USA	General	FC, EC, Demog, Econ
Chang et al. (2021)	USA	Hurricane	Econ, Demog, EC
Urata and Pel (2018)	Japan	Tsunami	PPC, EC, Demog
Sun et al. (2024)	USA	Hurricane	Demog, Econ, FC, PE, PPC, EC, IC, WM
Hall et al. (2017)	Indonesia	Tsunami	PPC, PE, EC, IC
Bernardini et al. (2016)	General	Earthquake	PPC, EC
Mozumder et al. (2008)	USA	Wildfire	Econ, Demog, EC
Wambura and Wong (2025)	Canada	Wildfire	Demog, SC, PE, PPC
Tsekeni et al. (2025)	USA	Hurricane	EC, IR
Elhami-Khorasani et al. (2023)	General	Fire	Demog, Econ, FC, PPC, PE, EC, SC, IR, IC, WM
Alawadi et al. (2022)	USA	Hurricane	PPC, PE, WM
Cheng et al. (2011)	USA	Hurricane	Demog, EC
Chen et al. (2021a)	USA	Tsunami	PPC, Econ, WM, SC, PE
Toledo et al. (2018)	Israel	Wildfire	Demog, Econ, FC, PE, EC, SC
Koshute (2013)	USA	Hurricane	WM
Wang et al. (2020)	General	General	PPC, EC
Wang et al. (2021)	General	General	Demog, Econ, PE, PPC, FC, EC, SC, IR, IC, WM
Chen and Cheng (2020)	China	Earthquake	Demog, EC, PE
Xu et al. (2022b)	USA	Wildfire	EC, WM
Han et al. (2023)	Japan	Tsunami	IC
Chen et al. (2022)	USA	Tsunami	Demog, PE, EC, IR, IC, WM
Demiroluk et al. (2016)	USA	Multi-Hazard	PPC, PE, Demog., WM
Elejalde et al. (2025)	Chile	Wildfire	WM, IC, SC
Wolshon et al. (2005)	USA	Hurricane	FC, PE, Demog., PPC
Roy and Hasan (2021)	USA	Hurricane	IC, WM, SC, PPC
Syamsidik and Istiyanto (2013)	Indonesia	Tsunami	PE, SC, PPC
Sadri et al. (2017b)	USA	Hurricane	IC, IR, SC
Greer et al. (2023)	USA	Hurricane + COVID-19	FC, PPC, PE, Demog.
Reyes-Norambuena et al. (2025)	General	General	Demog., PPC, SC
Hou et al. (2020)	China	Chemical	WM, IC, PPC
McLennan et al. (2019)	Australia	Wildfire	PE, PPC, WM, SC
Alawadi et al. (2020)	USA	Hurricane	FC, Demog., SC, PE
Rashid et al. (2025)	USA	Hurricane	IC, WM, SC
Ricchetti-Masterson and Horney (2013)	USA	Hurricane	SC, Demog, Econ
Wu et al. (2024)	USA	Hurricane	PPC, EC, SC
Adjei et al. (2022)	USA	Hurricane	PPC, WM, IR
Bernardini et al. (2016)	Italy/General	Earthquake	PPC, Demog., PE

Notes: SC: Social Concerns, IR: Information Resource, IC: Information Channels, FC: Family Context, PE: Past Experience, Demog.: Demographic, WM: Warning Message, PPC: Physical and Psychological Context, Econ.: Economic Condition, EC: Environmental Concern

C Agent-based simulation working

This Fig C.1 illustrates the logic of agent-based simulation, where individual characteristics (e.g., speed, demographics, risk perception, psychology, and social factors) interact with environmental factors (e.g., location, disaster type, familiarity, time, and weather) to influence the behavior and interactions of agents during evacuation.

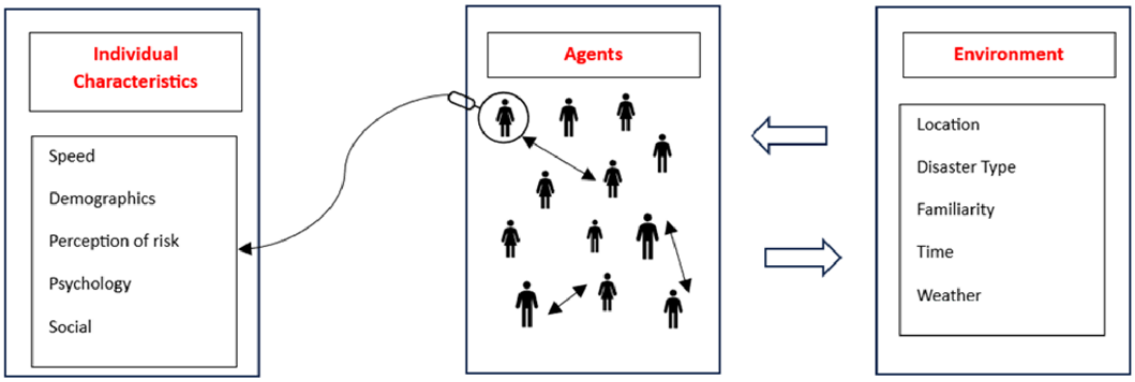


Fig. C.1. Agent-based simulation working logic adapted from Metcalf (2007).

D Glossary of acronyms

This appendix lists all acronyms used in the paper, grouped by category. Acronyms are also defined at first use in the text and, where they appear in tables, in the corresponding table notes.

Table D.1. Glossary of acronyms and definitions used in this study.

Acronym	Definition
Optimization approaches and equilibrium concepts	
SO	System optimal
CSO	Constrained system optimal
NA	Nearest allocation
UE	User equilibrium
DUE	Dynamic user equilibrium
SUE	Stochastic user equilibrium
ESUE	Expanded stochastic user equilibrium
BRUE	Bounded rational user equilibrium
ISE	Integrated scenario-based evacuation
Optimization formulations and modeling components	
LP	Linear programming
MILP	Mixed-integer linear programming
MINLP	Mixed-integer nonlinear program
MIP	Mixed-integer programming
MISOCP	Mixed-integer second-order cone programming
NLP	Nonlinear programming
CTM	Cell transmission model
BPR	Bureau of Public Roads (travel time function)
SAA	Sample average approximation
CVaR	Conditional value-at-risk
PSL	Path-size logit
RRM	Random regret minimization
SIR	Susceptible–infective–removed
Solution algorithms	
CG	Column generation
GA	Genetic algorithm
PSO	Particle swarm optimization
SA	Simulated annealing
TS	Tabu search
Simulation methods	
ABM	Agent-based modeling
GIS-ABM	Geographic information system-integrated agent-based model
S-ABM	Spatial agent-based model

Acronym	Definition
CFD-ABM	Computational fluid dynamics-coupled agent-based model
MAS	Multi-agent system
TMS	Traffic microsimulation
PMS	Pedestrian microsimulation
PMS+FH	Pedestrian microsimulation with flood hydrodynamics
DES	Discrete event simulation
SD	System dynamics
MCS	Monte Carlo simulation
DTA	Dynamic traffic assignment
S-DTA	Stochastic dynamic traffic assignment
DNL	Dynamic network loading
DSQ	Dynamic spatial queuing
LTM	Link transmission model
LWR	Lighthill–Whitham–Richards traffic flow model
SPCTM	Stochastic pedestrian cell transmission model
QBM	Queue-based model
MFM	Mean-field model
Simulation–optimization coupling frameworks	
S–O	Simulation–optimization
IOS	Iterative optimization-based simulation
ISO	Iterative simulation-based optimization
SSO	Sequential simulation–optimization
ASO	Alternating simulation–optimization
Classification codes used in Tables 5 and 7	
H	Human-centric structural type (no movement simulation)
I1	One-way integrated structural type
I2	Two-way integrated structural type
C1	Empirical/statistical behavioral representation
C2	Cognitive/process-based behavioral representation
C3	Rule/assumption-based behavioral representation
PA	Protective action
DT	Departure time
DS	Destination selection
MC	Mode choice
RC	Route choice
PD	Pre-evacuation decisions
RSD	Road-segment designation
RP	Risk perception
OW	Official warnings/orders
RTI	Real-time traffic information

Acronym	Definition
SNS	Social media/social networking service
SNI	Social network influence
TCA	Threat and coping appraisal
ID	Information diffusion
TEM	Traffic efficiency metrics
BO	Behavioral outcomes
LSO	Life-safety outcomes
EOC	Evacuation order compliance
DTC	Departure-time compliance
DC	Destination compliance
P	Parameter-based integration
B	Behavior-oriented integration
Technologies, frameworks, and organizations	
AI	Artificial intelligence
ITS	Intelligent transportation systems
IoT	Internet of Things
GPS	Global positioning system
ATIS	Advanced traveler information system
MCDM	Multi-criteria decision-making
NBC	Nuclear, biological, and chemical
WUI	Wildland–urban interface
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
AFAD	Disaster and Emergency Management Presidency (Turkey)
DHS	US Department of Homeland Security
EM-DAT	Emergency Events Database
FEMA	Federal Emergency Management Agency
FHWA	Federal Highway Administration
IFRC	International Federation of Red Cross and Red Crescent Societies
NWS	National Weather Service
PETS	Pet Evacuation and Transportation Standards Act
SDGs	Sustainable Development Goals
SFDRR	Sendai Framework for Disaster Risk Reduction
UNDRR	United Nations Office for Disaster Risk Reduction