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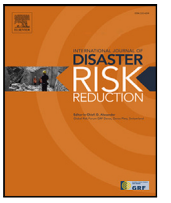

Modelling heterogeneous human mobility patterns during emergencies using archetypes

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ABSTRACT

Floods remain among the most frequent and disruptive hazards worldwide, affecting millions of people and generating substantial social and economic losses each year. Despite advances in evacuation modelling, representing heterogeneous human responses in a measurable and population-scalable manner remains challenging. Evacuation behaviour is shaped by multiple individual and contextual factors, which may result in delayed departures, non-compliance, anticipatory evacuation, or movements that deviate from official guidance. This study proposes an operational behavioural-archetypes formulation integrated within an agent-based modelling approach to simulate evacuation dynamics during flood emergencies. Three archetypes, namely, coordinated, passive, and non-coordinated, represent observable differences in whether, when, and how individuals move relative to institutional guidance. Coupled with detailed representations of buildings, road networks, and shelter infrastructure, the behavioural archetype-based framework simulates key evacuation processes, including departure timing, route selection, shelter choice, and exposure to flood hazards. The framework is demonstrated through a flash-flood evacuation scenario in Rotterdam, The Netherlands. Results highlight the importance of incorporating behavioural heterogeneity through archetypes, as it provides more realistic estimates of citizen safety during flood evacuation and avoids the underestimation of exposure inherent in homogeneous models. This approach offers valuable insights to support more adaptive and people-centred evacuation planning.

1. Introduction

Natural hazards cause severe societal impacts, with floods being among the most frequent and disruptive events worldwide. In the last two decades more than 1.6 billion people were affected by floods and resulted in global economic damages estimated at more than €600 billion [1]. In 2024, extreme weather events displaced over 824,000 people worldwide and were associated with approximately 1700 deaths, marking the highest number of climate-related displacements in the last 16 years [2]. During the first two months of 2026 alone, flood events occurred in Portugal, France, the United Kingdom, and Spain, leading to the evacuation of more than 3000 people [3,4]. The consequences of these phenomena are shaped by meteorological extremes and human-driven factors such as rapid urbanization, land-use change and the intensification of climate change [5]. This problem is expected to increase in both frequency and severity in the coming decades in the absence of effective adaptation measures [6].

Foreseeing how populations respond under critical conditions has become essential for disaster response and emergency planning [7]. Evacuation remains one of the most effective measures for minimizing injuries and casualties. However, the effectiveness of evacuation protocols is often limited by incomplete representations of real human behaviour [8,9]. In practice, this behavioural

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heterogeneity is reflected in differences in whether individuals evacuate, when they respond to warnings, and whether their movements follow official destinations and routes, including delayed departures, non-evacuation, anticipatory evacuation, and self-directed movement.

Evacuation models are commonly classified as macro-, meso- and microscopic approaches [10]. While macro- and mesoscopic models primarily represent aggregate or collective flows, microscopic approaches, can explicitly represent individual characteristics, decisions, and interactions with evolving hazard and infrastructure conditions [11–15]. More recently, agent-based models (ABMs) have gained predominance due to their flexibility to represent individual decision-making and interactions among individuals, the built environment, and evolving hazard conditions [15]. This flexibility is particularly relevant for evacuation modelling, where heterogeneous human responses can significantly influence system performance and system resilience analysis [16,17], and, in some cases, enhance adaptability by introducing diversity in response timing and movement patterns [18,19]. Contemporary evacuation ABMs incorporate behavioural heterogeneity through dimensions such as evacuation compliance, departure timing, warning response, destination and route choice, and demographic characteristics across different hazard contexts [16,20–22]. Recent applications also demonstrate the integration of behavioural responses with infrastructure disruption and evolving hazard conditions [23–26]. In flood evacuation studies, recent developments include the coupling of flash-flood processes with warning dissemination (e.g., [27]), hydrodynamic conditions with transportation and shelter allocation (e.g., [28]), and probabilistic evacuation outcomes under alternative warning scenarios (e.g., [29]). Recent literature reviews on emergency evacuation models are provided in [30–33].

These studies demonstrate important advances in representing behavioural heterogeneity. However, an important challenge remains in how multiple behavioural dimensions can be jointly structured into behavioural representations that are measurable, interpretable, and consistently operationalized within an ABM.

To address this challenge, this paper proposes an agent-based evacuation framework based on three behavioural archetypes, namely, coordinated, passive, and non-coordinated, that provide a structured representation of empirically documented evacuation responses. The formulation operationalizes behavioural heterogeneity into measurable and interpretable response types defined primarily by observable mobility behaviour. The conceptual basis and detailed definition of the archetypes are presented in Sections 2 and 3, respectively. A behavioural archetype is defined as a generalized representation of observed patterns of individual behaviour under hazard conditions, characterized by consistent decision-making responses, information use, and interaction with the built environment. The framework combines behavioural heterogeneity with detailed representations of buildings, road networks, and shelters, and flood dynamics to simulate evacuation dynamics under specific flooding conditions, including evacuation timing, route selection, shelter choice, and compliance with official guidance. This study is guided by the following research questions: (i) To what extent does modelling behavioural heterogeneity influence simulated evacuation dynamics and citizen safety compared with a homogeneous behavioural baseline? (ii) Which model parameters are most influential in shaping evacuation safety under heterogeneous behavioural assumptions?

To address these questions, the proposed framework is demonstrated through a flash flood evacuation scenario in Rotterdam, the Netherlands. The case study evaluates how behavioural variability interacts with flood dynamics and infrastructure constraints to shape evacuation outcomes, while a sensitivity analysis identifies the parameters that most strongly influence citizen safety. The contribution of the proposed formulation therefore lies in the selection and operationalization of an interpretable set of behavioural archetypes that can be operationally linked to observable evacuation responses and readily incorporated into an ABM. More detailed behavioural parameterizations can subsequently be incorporated within this structure when suitable empirical information is available.

Beyond illustrating the proposed methodology, the framework provides a practical tool for identifying vulnerable areas, assessing shelter requirements, and evaluating alternative evacuation strategies for emergency planning.

The remainder of this paper is organized as follows. Section 2 discusses the current limitations in foreseeing human mobility during emergencies, emphasizing the importance of integrating social, economic, and cultural factors, as well as the challenges associated with operationalizing heterogeneous behaviour. Section 3 introduces the definition of behavioural archetypes and presents the principles of their quantitative modelling. The capabilities of the proposed framework are illustrated through a case study in Section 4, which includes a detailed discussion of the results. Building on these findings, Section 5 explores implications for infrastructure and evacuation planning, highlighting how this tool can support both short-term operational decision-making and long-term strategic planning. Finally, Section 6 concludes the paper.

2. Human behaviour during emergencies

2.1. Conceptual domains of human mobility in emergencies

Human mobility during emergencies involves multiple domains, ranging from institutional and individual drivers to infrastructure constraints. Fig. 1 classifies the drivers of human mobility during emergencies into five conceptual domains that capture how movement decisions emerge and materialize under crisis conditions.

The institutional or governance domain is particularly important in emergency management and preparedness actions. It captures how governance structures, institutional practices, and emergency management actions shape evacuation processes. It encompasses aspects such as the timing, clarity, credibility, and dissemination of warnings and evacuation orders, as well as coordination mechanisms and resource availability. For instance, during the DANA flooding in Valencia (Spain) in October 2024 causing more than 200 casualties, the population did not receive any official warning during the first hours, therefore, they were unaware of

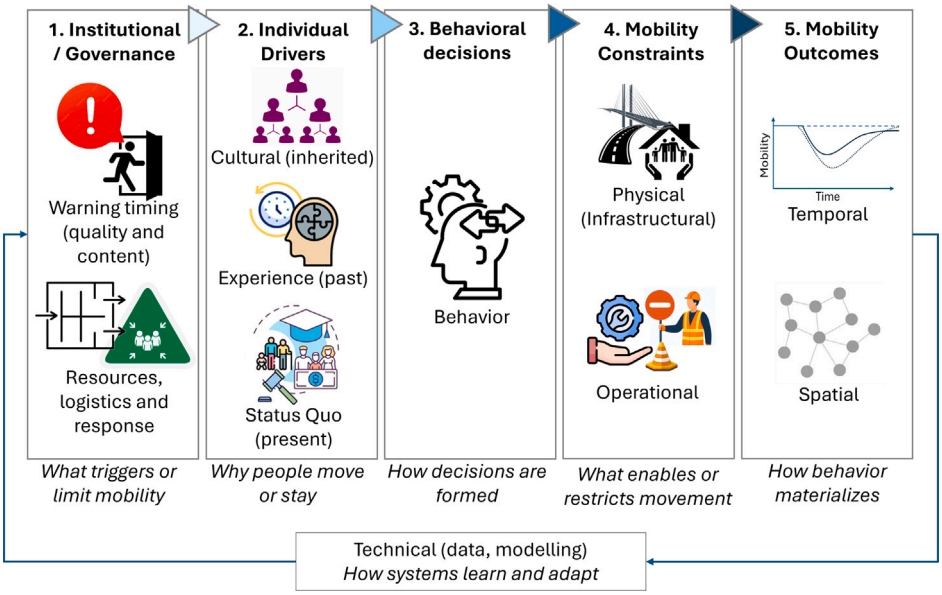


Fig. 1. Conceptual framework of human mobility dimensions during emergencies.

the potential danger and continued with daily activities. This situation significantly exacerbated societal losses [34]. In the case of Hurricane Katrina, despite forecasts warning of serious consequences 56 h before its arrival, the governor of New Orleans delayed mandatory evacuation orders and did not issue them until 19 h before, which significantly reduced the time available for a safe evacuation [35].

Within the second domain, individual drivers, we identify three key factors: (i) culture, which refers to the set of inherited norms, values, and behavioural predispositions [36,37]; (ii) past experiences with hazardous situations [38,39]; and (iii) the individual status quo, referring to the person's current socioeconomic position and immediate living conditions, including access to resources, employment stability, housing conditions, and institutional embeddedness [40,41]. Together, these three factors shape how individuals perceive and interpret risk and respond to emergency situations. In turn, they capture drivers such as place attachment, trust in institutions, perceptions of collective responsibility, and acceptable risk levels [9]. Note that the institutional/governance domain directly influences public trust in institutions. Since institutions are responsible for forecasting, coordination, response, and recovery, trust is strongly conditioned by their performance. Failures in warning dissemination, emergency response, or post-disaster recovery can generate long-term distrust, thus impeding collective responses to disasters in subsequent events. In some cultural contexts, individuals may prioritize family cohesion and delay evacuation until all household members are gathered, whereas in others, compliance with official evacuation orders may occur more rapidly. Such cultural predispositions shape both the timing and the manner in which evacuation decisions are made.

The third domain, behavioural decisions, represents how individual drivers are translated into concrete choices, such as evacuating, going to a shelter, or staying at home. This dimension captures differences in individual agency, compliance, proactivity, and response, acting as a mediating layer between individual drivers and observable behaviour. The fourth domain, mobility constraints, encompasses the physical and operational conditions that enable or restrict mobility. These include transport infrastructure, network capacity, physical damage, shelter accessibility, and emergency response measures.

The fifth domain, mobility outcomes, describes how these behavioural decisions are expressed across time and space. It reflects temporal aspects such as anticipatory actions, delays, evacuation timing, and return dynamics, as well as spatial patterns including routes, destinations, and distances travelled.

In addition to these five domains, there is a technical layer related to data acquisition and updating. Rather than constituting a standalone element of mobility, this layer supports observation, modelling, and feedback across all components. It includes data sources, analytical tools, and simulation models that allow mobility patterns to be monitored, interpreted, and fed back into institutional decision-making, thereby enabling learning and adaptive emergency response.

Existing evacuation approaches provide complementary coverage of these domains. Survey-based behavioural studies, for example, provide evidence on institutional and individual drivers, including trust, previous experience, socioeconomic conditions, and risk-related perceptions (e.g., [35,41–48]), thereby covering Dimensions 1 and 2. Data-driven mobility studies provide direct observations of spatio-temporal movement patterns (Dimension 5) at increasingly large scales (e.g., [7,25,49,50]). While physical and hydrodynamic models primarily characterize mobility constraints associated with hazard and infrastructure conditions (Dimension 4) and their consequences for mobility outcomes (Dimension 5) (e.g., [17,18,51–53]). ABMs provide a flexible environment for combining information across these domains and have increasingly incorporated aspects of Dimensions 1 and 2 such as, warning response, demographic variability, behavioural decisions (e.g., [16,20,22–24,27,29,54]).

The challenge addressed in this research work concerns how information on underlying institutional and individual drivers (Dimensions 1 and 2) can be related to behavioural decisions (Dimension 3) and, ultimately, to observable mobility outcomes (Dimension 5), while accounting for the physical and operational constraints that condition those responses (Dimension 4). This distinction is important because the factors explaining why individuals behave differently are not necessarily the same variables through which those differences can be identified and operationalized within an evacuation model. The following subsection therefore examines the relationship between underlying behavioural drivers and their observable manifestations in evacuation mobility.

2.2. Behavioural patterns inferred from socio-economic characteristics

People's decisions during emergencies are influenced by latent mechanisms such as institutional trust, personal agency, social dependence, and risk perception. These mechanisms help explain how warnings are interpreted and whether individuals act, but they are context-dependent and difficult to measure directly. For example, the empirical relationship between individual agency and risk perception remains unclear [55]. Here, agency refers to the capacity of individuals to act independently and make decisions effectively within a given social, economic, and institutional context. Although agency itself cannot be directly observed, it can be indirectly inferred through observable behavioural actions, such as evacuation timing, route choice, or destination selection. In contrast, risk perception remains substantially more elusive, subjective, and difficult to operationalize quantitatively.

Socioeconomic, demographic, cultural, and experiential characteristics provide observable information about the conditions under which these mechanisms operate. They do not determine evacuation behaviour directly, but can influence access to resources, physical and social constraints, institutional trust, and the capacity to act. Existing sociology studies support the use of these proxies. The individual drivers identified in Fig. 1, namely cultural context, previous experience, and status quo, are interpreted through two main behavioural mechanisms, institutional trust and agency. Institutional trust influences the extent to which individuals rely on official guidance and emergency management systems, whereas agency determines their effective capacity to translate intentions into protective action. When people trust in the measures taken by authorities to ensure their safety, they tend to be less proactive than when they perceive no viable alternative but to act independently and vice versa, a dynamic often known as the risk perception paradox [55].

Regarding the cultural context, cultural background influences social expectations, trust in institutions, collective experience with hazards, and community support networks, all of which can affect whether individuals comply with official guidance, evacuate preemptively, or remain in place. Research has shown that individuals from different national or regional backgrounds may respond differently to the same emergency cues and instructions. For example, a recent cross-cultural survey of evacuation response found that participants from several European countries differed in their initial response tasks, such as information-seeking, and tendency to wait for others before evacuating [36]. Studies in coastal Bangladesh, for instance, demonstrated that patriarchal norms can restrict mobility and access to information, leading to non-evacuation or delayed response despite warnings [56]. Thus, cultural context strongly conditions institutional trust, the interpretation of risk during emergencies and agency [37].

In relation to previous experience and risk interpretation, previous disaster experience also influences how individuals perceive and respond to hazards. People without direct flood experience tend to underestimate danger, whereas those who have experienced flooding can overestimate risk or respond more proactively [57]. Experience shapes familiarity with hazards, confidence in individual agency, and expectations regarding institutional response. In some cases, prior experience increases anticipatory evacuation behaviour and autonomous decision-making; in others, repeated exposure may normalize risk and reduce responsiveness to warnings. These dynamics simultaneously influence both institutional trust and perceived agency. Both cultural context and previous experience are strongly case-study dependent, as they are shaped by local social, institutional, and hazard exposure conditions.

Socio-economic and demographic status serve as agency constraints. Structural disparities related to income, gender, age, and disability status shape both evacuation capacity and survival outcomes [25]. Among these, income plays a particularly important role because it directly affects agency, higher-income populations generally have greater flexibility to adapt their response to evolving hazards, while economically disadvantaged populations experience constrained, delayed, or forced immobility, resulting in disproportionate exposure to risk [58]. In contrast, lower-income populations may exhibit high risk awareness or trust in authorities, yet limited agency, reducing their ability to translate intention into action [41]. Consequently, economically disadvantaged populations may evacuate at lower rates and with delayed timing relative to more advantaged groups, even when provided with official warnings [27]. This pattern was evident during Hurricane Katrina, where a large proportion of low-income residents in New Orleans were unable to evacuate despite mandatory orders due to limited transportation access and insufficient financial resources [35].

Age-related factors can further reduce agency by limiting physical mobility, increasing health vulnerabilities and creating dependence on caregivers [59]. This contributes to greater mortality among the elderly population during flood disasters, while children's mobility remains largely dependent on parental decisions and household resources. During the 2024 DANA flooding event in Valencia, approximately 81% of fatalities occurred among individuals over 50 years of age [60]. Although multiple dimensions influence mobility evacuation behaviour, socio-economic status and age represent two of the most important observable proxies affecting both the capacity and timing of protective mobility.

Together, these observable proxies do not determine evacuation behaviour directly. The same observable response may arise from different combinations of institutional trust, agency, risk perception, previous experience, and contextual constraints. Their influence is ultimately manifested in whether, when, and where individuals evacuate. This distinction provides the conceptual foundation for the behavioural archetypes proposed here. Rather than requiring direct estimation of context-dependent latent mechanisms, the

framework uses observable mobility responses as the primary basis for classification, while retaining socioeconomic, demographic, and contextual characteristics as conditioning or explanatory factors.

The factors discussed in this section therefore represent potential conditioning variables rather than a set of parameters that must all be operationalized in every application. Their inclusion depends on the availability of case-specific data and empirical evidence supporting their relationship with evacuation behaviour. In the Rotterdam application, the operationalization is deliberately restricted to age and income, avoiding additional behavioural relationships that could not be supported by the available case-study information.

3. Behavioural archetype-based framework

3.1. Definition of heterogeneous archetypes

Previous research has proposed multiple theoretical and empirical classifications of human responses during emergencies, ranging from psychological response states to empirically derived evacuation typologies [23,61–65]. These studies demonstrate substantial behavioural diversity, but also illustrate that classifications may operate at different levels of abstraction and may be defined through underlying psychological mechanisms, social characteristics, or observed actions.

More recently, the use of behavioural archetypes has gained increasing attention as a way to operationalize heterogeneity in emergency modelling. Rather than focusing on underlying psychological constructs, archetypes classify populations into subgroups that reflect recurring patterns of response to disasters. Empirical studies have derived such archetypes from survey data or post-event analyses, including wildfire responses in Australia [66], with archetypes such as Threat Denier, Community Guided, or Experienced Independent households [65], and more recent classifications including social-proactive, social-protective, and social-reluctant evacuators [23]. This evidence suggests that behavioural variability during disasters tends to cluster into a limited number of functional response types, broadly corresponding to cooperative and orderly responses, inhibited or minimally reactive responses, and impulsive or weakly regulated responses.

Building on these theoretical foundations, this study proposes three behavioural archetypes: coordinated, passive, and non-coordinated, defined according to observable mobility responses to institutional guidance. Coordinated individuals act in accordance with official instructions, passive individuals remain in place or delay protective action, and non-coordinated individuals act independently of official timing, destinations, or routes. The objective of the proposed classification is not to reproduce the maximum possible number of behavioural profiles, but to provide a structured classification that remains identifiable from observable evacuation outcomes. Differences in timing, destination, route choice, and individual characteristics can subsequently introduce variation within each archetype. Table 1 defines the three behavioural archetypes in terms of their decision patterns and observable evacuation actions. For example, the passive archetype may include individuals who remain in place because of structural constraints (e.g., limited mobility, lack of transport, or caregiving responsibilities) as well as individuals who choose not to evacuate because of attitudinal or contextual factors. Both are represented as non-movers because they produce the same observable mobility response. However, demographic and socioeconomic attributes are retained at the agent level, allowing these potentially different sources of passive behaviour to be examined in post-simulation analyses and considered when interpreting policy interventions. The archetypes can also be examined in relation to trust and agency, where supported by the relevant agent attributes and contextual information; however, these factors should not be inferred from non-evacuation alone.

Note that non-coordinated behaviour should not be equated with panic. Research suggests that panic behaviour is less prevalent than commonly assumed and that individuals often retain a degree of intentionality and social orientation even under extreme stress [67]. Accordingly, non-coordinated behaviour in this framework reflects autonomous and weakly collective coordinated decision-making rather than irrational panic.

The proposed behavioural patterns are consistent with observed responses during past events, including non-evacuation despite mandatory orders as well as anticipatory evacuation. Beyond these cases, additional evidence from multiple hazard events supports the existence of heterogeneous evacuation behaviours consistent with the proposed archetypes.

During Hurricane Sandy (2012), survey-based analysis in New Jersey found that evacuation rates in mandatory evacuation zones were substantially below full compliance, with fewer than half of residents evacuating despite official orders [68]. This behaviour reflects the passive archetype. Similarly, analysis of Hurricane Irma (2017) identified distinct behavioural segments, including evacuation-reluctant individuals and those responsive to official guidance [69]. Only 58% of residents living in areas under mandatory evacuation orders complied with the directive, corresponding to the coordinated archetype, while the remaining population reflects the passive archetype. Mobile device location data during Hurricane Ian (2022) revealed multiple waves of evacuation, including anticipatory departures prior to mandatory orders, called as self-evacuation, and staggered movement patterns across affected regions [70]. Early and self-initiated departures correspond to the non-coordinated archetype, while departures aligned with official timing correspond to the coordinated archetype. This has also been observed in the European context, e.g., the 2016 and 2018 Paris floods forced 18,000 and 2500 evacuations respectively, with 750 and over 300 residents refusing to leave [70,71]. In these events, the coordinated archetype corresponds to those who followed official evacuation orders, the passive archetype represents individuals who did not evacuate.

Although explained in the context of flood emergencies, these behavioural archetypes are observed in relation to other hazards. For instance, during tornado events in the United States, evacuation rates among mobile home residents remain below 30%, even when warnings advise them to seek sturdier shelters [72]. A similar pattern has been observed in California, where a series of major wildfire events between 2017 and 2018, led to the evacuation of hundreds of thousands of people [73]. Some residents evacuated

Table 1
Heterogeneous behavioural archetypes and corresponding agent actions during emergencies.

Archetype	Decision style	Agent action
Coordinated	Guided and collective decision-making. Decisions reflect an individual with agency and institutional trust. The agent processes risk information rationally, aligns behaviour with official guidance, and coordinates actions with others, prioritizing safety and collective efficiency over individual preference.	**Evacuates:** Yes, efficiently (e.g., horizontal or vertical based on official information). **When:** In a timely manner, following warnings or evacuation orders. **Where:** To officially designated shelters and along recommended evacuation routes, with potential for orderly return once conditions stabilize.
Passive	Non-reactive decision-making characterized by remaining at the residence throughout the emergency. This behaviour can be due to either cognitive factors (e.g., low agency, fatalism, risk rejection, place attachment) or physical/financial constraints (e.g., limited mobility, caregiving duties, or lack of assistance).	**Evacuates:** No, or only as a last resort. **When:** Delayed or not at all, typically after direct impact or loss of access forces movement. **Where:** If movement occurs, it is short-range and unplanned, remaining within the immediate neighbourhood or moving to nearby familiar locations.
Non-coordinated	Autonomous and opportunistic decision-making driven by high personal agency and individual risk interpretation, often combined with low institutional trust. The agent seeks to reduce personal exposure but rejects coordinated or officially prescribed solutions, relying on personal judgement, informal information, or prior experience.	**Evacuates:** Yes, but selectively. **When:** Early or impulsively, often before official warnings or independently of evacuation orders. **Where:** To self-selected destinations perceived as safest (e.g., upper floors, relatives' homes), which may fall outside designated shelters or official routes.

early or along non-designated routes (non-coordinated archetype), others followed prescribed evacuation instructions (coordinated archetype), and some did not evacuate despite high risk (passive archetype).

Compared with the seven archetypes identified by [65] in the context of wildfires, the 'threat denier', 'responsibility denier', and 'dependent evacuator' align with the passive archetype, as they rely on authorities' actions and exhibit limited individual agency. The 'considered evacuator' and 'community guided' types correspond to the coordinated archetype, reflecting more deliberate and cooperative responses. In contrast, 'worried waverers' and 'experienced independents' show similarities with the non-coordinated archetype. However, prior experience does not necessarily imply non-coordinated behaviour; rather, it may be associated with a tendency towards autonomous or less predictable responses, as individuals may rely on their own judgement instead of following official guidance. Similarly, when compared with the archetypes defined by [23], the social-proactive type aligns with the non-coordinated archetype, while social-protective and social-reluctant evacuators exhibit characteristics closer to passive behaviour. This comparison illustrates the intended level of abstraction of the proposed framework. More granular typologies remain valuable for explaining differences in motivations and decision processes, whereas the three archetypes proposed here aggregate such differences according to their observable implications for evacuation mobility. The purpose is therefore not to replace richer behavioural classifications, but to provide a structured operational layer through which their mobility consequences can be represented and compared within an ABM.

Thus, the three proposed archetypes capture fundamental variations in human mobility responses that can be observed across floods, hurricanes, wildfires, tornadoes, and other emergency contexts, providing a generalizable framework for modelling and analysis.

3.2. Modelling of heterogeneous behaviour

The proposed archetypes provide a structured representation of observed behavioural heterogeneity during emergencies. While these archetypes define the behavioural logic, their dynamic interaction and mobility patterns within urban systems require a computational modelling approach. In this case, an ABM is adopted to operationalize the archetypes, enabling the explicit representation of heterogeneous, dynamic, and non-linear evacuation processes in complex urban environments. The proposed ABM operates within a high-resolution urban environment that explicitly represents three-dimensional buildings (including habitable area and height), shelter capacity, and detailed road network topology. This spatial representation allows the model to simulate vertical and horizontal differences in exposure, as well as shelter saturation and evacuation dynamics. The model also incorporates variable evacuation warning times, enabling asynchronous responses across archetypes and capturing heterogeneous temporal dynamics.

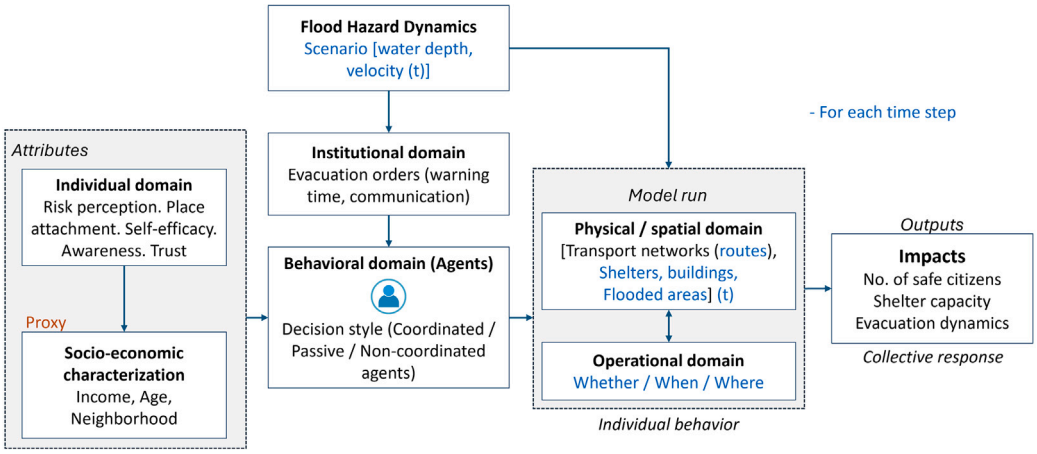


Fig. 2. Behavioural archetype-based framework applied to emergency response during flood scenarios.

The framework conceptualizes multiple interrelated domains, as explained in Section 2. Fig. 2 shows how flood hazard dynamics act as an external shock, evolving over time and space through changes in water depth, flow velocity, and infrastructure exposure. These dynamics directly shape both the institutional and behavioural domains. The institutional or governance dimension of evacuation encompasses the timing and content of warnings, evacuation orders, and coordination mechanisms.

The model operates over a predefined simulation window, discretized into time steps, which can be expressed in hours or any other relevant temporal unit. At each time step, the state of both the infrastructure and individual agents is updated dynamically, reflecting evolving flood conditions and mobility patterns. Key features of the model include:

- **Spatial infrastructure representation:** The urban environment is represented through multiple layers of geographic information, including the road network and intersections. Buildings and shelters are spatially linked to this network, allowing agents to move from their residences into the transport system. Both buildings and shelters are characterized by physical attributes such as height and area, which determine their effective capacity over time as flood levels rise and usable floors decrease. Exit nodes at the boundary of the study area represent evacuation outflows beyond the local system.
- **Dynamic flood condition:** Flood dynamics are represented through a sequence of time-indexed raster layers describing water depth and flow velocity. For each simulation step, flood intensity values are extracted from these rasters at all relevant locations, including buildings, road segments, and shelters. These values are used to compute a location-specific flood impact. The hazard directly influences both agent safety and mobility by regulating walking speed, restricting route accessibility, and inducing trapping conditions when critical thresholds are exceeded. In particular, walking speed is progressively reduced as hazard levels increase, and movement is fully inhibited under severe flood conditions. As a result, exposure and vulnerability are not treated as static attributes but evolve continuously in space and time in response to changing flood conditions.
- **Temporal triggers:** Within the simulation window, key temporal events are explicitly defined: (i) the timing and content of evacuation warnings, such as whether to evacuate the area or remain at home, as well as (ii) the flooding arrival, which subsequently evolves over time, as explained above. An important consideration is the mobilization time, defined as the interval between the reception of the evacuation warning and the evacuation initiation. This interval is not fixed but varies across agents depending on their assigned behavioural archetype, capturing differences in decision-making speed, responsiveness to warnings, and capacity to act under uncertainty.
- **Citizens (archetype agents):** Citizens are represented at the individual level as autonomous agents whose responses are shaped by individual drivers. Each agent is assigned to a behavioural archetype, namely, coordinated, passive, or non-coordinated, representing distinct observable response patterns to hazard conditions and institutional guidance. These archetypes influence how hazard information and institutional signals are interpreted and internalized. Behavioural dispositions structure operational choices such as whether to evacuate, when to initiate movement, and which destination to select. Agents may become trapped if evacuation is physically impossible, shelters are full, or hazard ratings exceed safe thresholds.
- **Decision and route choices:** Agents who decide to evacuate select routes to the nearest shelter or exit node based on building occupancy, flood depth, and hazard rating. Routes are dynamically recalculated when conditions along the path become unsafe. Evacuation is modelled as a sequential decision-making process that accounts for spatial position (x, y, z) and time (t), allowing behavioural intent to interact with evolving physical and infrastructural conditions.
- **Outputs:** The outputs of the model support quantitative assessment of safety for both people and infrastructure. They include individual outcomes, such as safe or unsafe status for each agent, as well as system-level metrics, including the percentage of safe citizens, dry floors, shelter occupancy, and road accessibility for each modelled time step. These outputs collectively capture heterogeneous mobility patterns, temporal variations in response, and the emergent dynamics of evacuation across the urban environment.

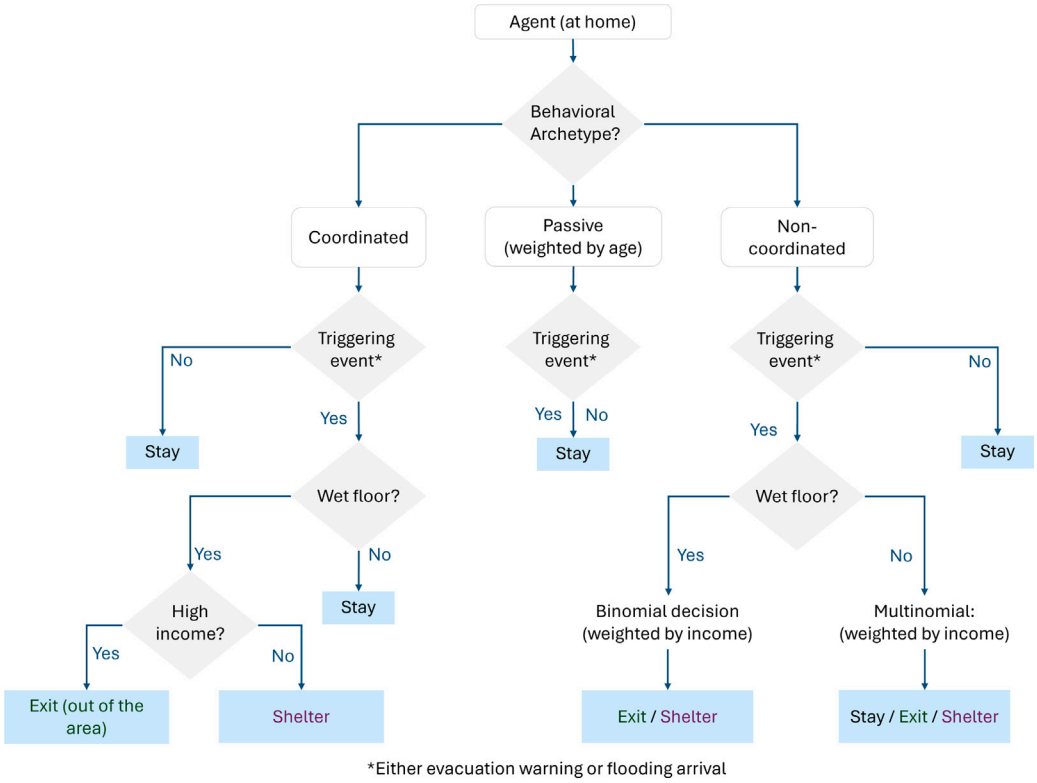


Fig. 3. Archetype-based initial actions under different exposure conditions and socio-economic characteristics.

Behavioural archetypes are assigned at the population level according to predefined reference proportions. These proportions can be derived from empirical data or surveys on evacuation behaviour and used to inform or calibrate the overall distribution such as percentages of early evacuees, compliant responders, or non-evacuees. In the absence of case-specific data, proportions from comparable events documented in the literature or other suitable proxies may be adopted, as discussed in Section 2.2.

Demographic proxies may be used to introduce structured variation within a predefined archetype distribution when suitable data are available. Age can be incorporated as a weighting factor in archetype allocation, based on the recent evidence that associates advanced age with reduced mobility, delayed response, and greater dependence on institutional guidance [74]. Accordingly, areas with higher concentrations of elderly residents receive a proportionally higher share of passive agents, while maintaining the predefined global archetype ratios. This will be further exemplified through the case study in Section 4. In the Rotterdam application, age is used to condition archetype assignment, as described in Section 4.1.

Socioeconomic and cultural attributes do not determine archetype membership directly. Instead, they modulate decision-making within each behavioural type, operating as a proxy for differential mobility capacity and access to resources. For instance, higher-income agents can be assumed to have greater access to private mobility and alternative accommodation, increasing the likelihood of evacuation outside the affected area. Accordingly, lower-income agents can be more likely to rely on public shelters or face constraints that delay evacuation. Fig. 3 summarizes how behavioural archetypes adapt their actions depending on physical exposure conditions such as dry or wet floor (i.e., floors below or above the water depth), and socioeconomic variables. Physical exposure determines the feasible decision set, while the assigned archetype structures how agents respond within that set.

Ground-floor agents face immediate exposure (wet floor), while for upper-floor agents that remain unaffected no evacuation is considered depending on their archetype. For ground-floor agents, coordinated individuals may evacuate following official guidance; high-income agents are more likely to leave the affected area, reflecting access to private transportation and alternative accommodation, whereas lower-income agents are more likely to use public shelters. Passive agents predominantly remain in place regardless of guidance. Non-coordinated agents make binary decisions between available options (e.g., exit or go to shelter), with probabilities weighted by income, capturing autonomous and weakly coordinated behaviour.

For upper-floor (dry floors), coordinated agents remain at home and evacuate only if instructed; while non-coordinated agents select among three alternatives, stay at home, evacuate outside the area, or relocate to a shelter, using a weighted probability conditioned on income. All evacuation decisions for non-coordinated agents are implemented probabilistically to avoid deterministic behaviour. Binary choices are modelled as Bernoulli trials, and multinomial choices use normalized probabilities to sample a single action. This approach ensures behavioural diversity while maintaining transparency and interpretability.

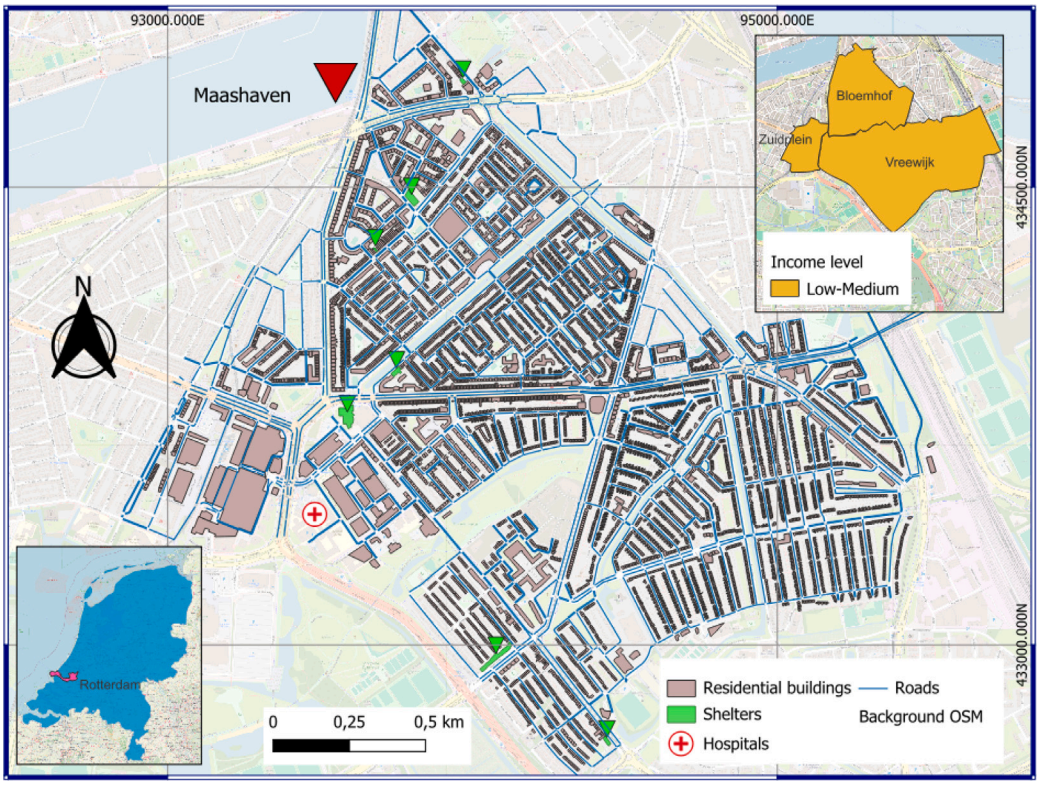


Fig. 4. Rotterdam case study: dike failure at Maashaven.

In addition to action selection, each archetype also modulates evacuation timing relative to the warning. Coordinated agents tend to react promptly upon receiving evacuation instructions, non-coordinated agents may initiate evacuation spontaneously, even prior to official warnings, and passive agents often delay evacuation or may not evacuate at all. This temporal heterogeneity reflects the combined influence of individual behaviour and contextual constraints on evacuation dynamics.

4. Flash-flood emergency response in Rotterdam

4.1. Case study description

The proposed flood evacuation model is applied to the urban context of Rotterdam, a critical economic and logistical hub in the Netherlands. The city is a densely populated, low-lying urban area characterized by an extensive network of rivers, canals, and port infrastructure. Rotterdam is located in the Rhine-Meuse delta, where coastal storm surges, high river discharge, and intense precipitation may interact, creating a complex multi-hazard flood environment [75]. However, the city is protected by an integrated system of flood protections, such as dikes, storm surge barriers, and pumping stations. The probability of large-scale flooding is low, but residual risk remains due to extreme hydrological conditions or potential failures of flood defenses. Dike failures may result from structural weaknesses, prolonged hydraulic loading, or compound hydro-meteorological conditions such as heavy rainfall combined with elevated river discharge and coastal water levels.

Within this context, this study considers the dike-breach scenario at Maashaven, which may lead to flash flooding of surrounding urban districts. The scenario assumes a complete failure of the local flood defense segment (dike km 36.1) and simulates the resulting flood propagation and evacuation behaviour across the affected urban area. The Maashaven branch represents a potential impact to the southern port area of Rotterdam, directly affecting densely populated riverfront neighbourhoods, including Zuidplein, Bloemhof, and Vreewijk. This area is predominantly residential with low-medium income and contains key infrastructure such as several shelters and a hospital, as illustrated in Fig. 4.

The considered infrastructure includes 1231 road network segments, 9059 residential buildings, and 7 shelters. Road networks and shelter locations are extracted from Open Street Maps (OSM), while building geometries, including area and height, are obtained from national open data sources [76]. Building height is used to estimate vertical population distribution.

Agents select shelters according to network distance and may redirect to an alternative shelter when the initial destination is unavailable. Shelter availability varies dynamically with flooding and occupancy. The corresponding capacity, closure, and admission rules are detailed in Appendix A.

The flood hazard scenario considered corresponds to scenario 19,626 from the national flood risk datasets provided by Rijkswaterstaat [77]. This scenario represents a potential dike-breach event with an exceedance frequency of approximately 1 in 400,000 years. The available flood rasters provide spatially explicit information on water depth, flow velocity, arrival time, and flood extent. This return period is adopted based on the availability of open-source data on dike failure probabilities in the Dutch context; however, the modelling framework is applicable to other return periods or hazard scenarios. To enable dynamic simulation within the proposed ABM, the flood evolution is discretized into four consecutive time steps of one hour each. This temporal resolution is based on the layer of arrival time, where four hours corresponds to the maximum flood impact in the study areas. Thus the water-depth provided in [77] represents the final flood state, which corresponds in the model to the fourth hour after the flooding started. Intermediate flood conditions are represented by progressive increases in flooding over the preceding time intervals, allowing the model to capture the temporal interaction between hazard propagation and evacuation behaviour.

Nighttime is considered as the critical scenario, as citizens are generally less aware and less connected to information channels, and authorities may face greater challenges in disseminating warnings effectively. This assumption is also adopted for the sake of model simplification. However, it does not reduce the general applicability of the approach, since the analysis could be extended to other times of the day or different temporal configurations. Therefore, it is assumed that citizens are at home at the beginning of the scenario. Regarding the first time trigger, (i) the warning phase, the event considered is a dike failure, which occurs suddenly and therefore provides limited reaction time. For this reason, the warning is issued two hours before the expected flood arrival (Hour 2). The warning message advises residents to remain at home if possible; however, residents located on the ground floor are required to evacuate due to their higher exposure to flood. It is assumed that warning information is reliable and effectively reaches all residents in the affected area. For instance, municipalities constitute a trusted communication channel in the Netherlands and were widely used to disseminate information during the 2021 flood events [48]. The second time trigger corresponds to the (ii) arrival of the flood, which begins two hours after the warning is issued (Hour 4). That is, The warning is issued at Hour 2 and flooding begins at Hour 4, providing a 2-h evacuation window. Flood intensity increases until Hour 8, and the simulation continues until Hour 10 to capture late-stage mobility. Ground-floor residents are instructed to evacuate, while residents on safe upper floors are advised to remain in place. The first two hours (Hour 0 to Hour 2) represent baseline conditions, prior to the emergency phase.

Population data are available at the postal-code level from CBS PDOK [78] and are allocated to buildings proportionally to their volume, with residents subsequently distributed across floors. The study area contains 34,319 residents. Income data are obtained from StatLine dataset [79] and classified according to the Zuid-Holland energy-poverty framework [80]. The three neighbourhoods are predominantly in the low–medium income category; the complete income thresholds used in the behavioural rules are reported in Appendix A.

Agent archetype assignment is informed by previous flood evacuation evidence. During the 2021 Limburg floods, 24.3% of residents did not evacuate despite receiving evacuation notifications [48], consistent with earlier estimates indicating that approximately 20% of residents may remain behind following preventive evacuation instructions [81]. Accordingly, 20% of agents are assigned to the passive archetype. Because no direct empirical estimate is available for the non-coordinated archetype, a 20% share is adopted as a modelling assumption and subsequently examined in the sensitivity analysis; the remaining 60% are coordinated.

The baseline archetype distribution is then applied within each postal code, with agents randomly assigned to buildings and floors. Socioeconomic attributes, including income and age, are also available at the postal-code level. To reflect evidence linking advanced age with delayed evacuation [74], postal codes with higher shares of residents aged 65 and above are assigned proportionally more passive agents, while ensuring that passive agents still comprise 20% of the total population. Archetypes for younger residents are assigned according to the baseline proportions.

As the population in this context is predominantly low-medium income, it is assumed that coordinated and non-coordinated agents have limited capacity to evacuate outside the affected area, increasing their reliance on local shelters, while passive agents are more likely to remain in place regardless of the flood hazard.

Agents act individually, with behavioural decisions conditioned by archetype, residential-floor exposure, and socioeconomic attributes as described in Fig. 3. Archetypes also determine reaction timing relative to the warning. Coordinated agents respond at warning time, non-coordinated agents may act before the warning, and passive agents respond after a delay. The exact reaction-time ranges and decision probabilities are reported in Appendix A.

Agents are assumed to travel on foot, as flash floods generally preclude vehicle evacuation, and route choices are made along the shortest available paths. Pedestrian walking speed varies dynamically with local flood conditions using a flood Hazard Rating (HR) metric combining water depth and flow velocity [82,83]. Age-related mobility differences are represented through reduced walking speed and lower HR tolerance for elderly agents [84]. The corresponding thresholds and mobility parameters are summarized in Appendix A.

Routes are dynamically re-evaluated when local flood conditions exceed pedestrian-safety thresholds. Agents unable to complete a viable route are classified as trapped; similarly, residents whose occupied floor becomes inundated are classified as unsafe. Here, *unsafe* denotes conditions in which personal safety can no longer be guaranteed, rather than fatality.

Agents select the nearest suitable shelter and may redirect when capacity or flood conditions make the preferred destination unavailable. Detailed routing, re-routing, shelter-capacity, closure, and admission rules are provided in Appendix A. The ABM is implemented in Python using the Mesa library.

4.2. Evacuation emergency results

To account for stochastic variability in agent behaviour, the baseline scenario was simulated using 100 independent replications with integer random seeds ranging from 1 to 100. The random seed initializes the model's pseudo-random number generators and

Table 2
Summary statistics across 100 stochastic simulation replications ($N = 34,319$ agents per replication).

Outcome	Mean (%)	Mean (No. citizens)	95% CI (%)	Range (No. citizens)
Unsafe/trapped citizens	50.36	17,285	50.34–50.39	17,173–17,379
Citizens reaching shelters	9.87	3388	9.86–9.89	3312–3447
Citizens outside the area	1.49	512	1.48–1.50	461–559

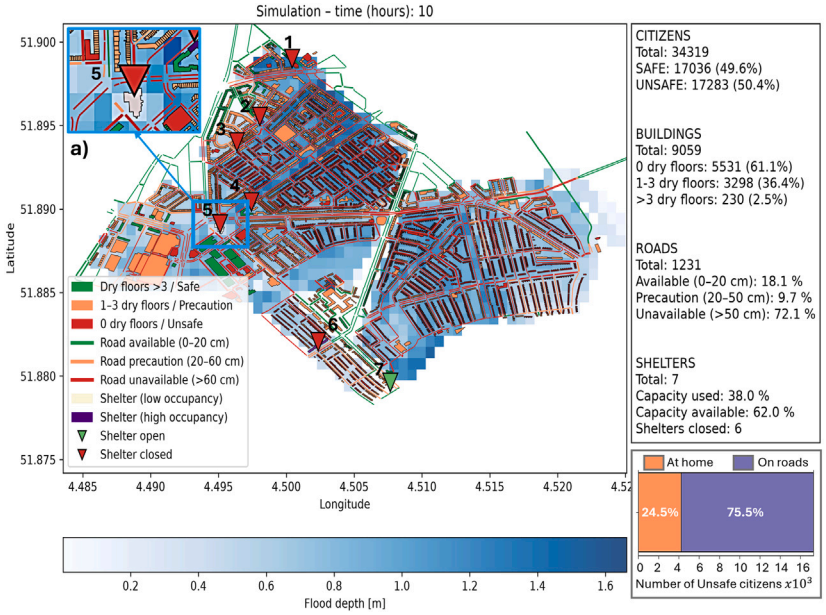


Fig. 5. Flood impact assessment in case of Maashaven dike failure at simulation Hour 10.

therefore defines a reproducible stochastic realization of the simulation. Specifically, the seed affects the individual assignment of behavioural archetypes, behaviour-specific reaction times, stochastic decisions of non-coordinated agents, and the within-timestep order in which agents are updated. All spatial inputs, population attributes, flood conditions, network characteristics, shelter capacities, and behavioural parameter values are not influenced by the seed across replications. Aggregate evacuation outcomes are reported as means across these replications, together with 95% confidence intervals and the observed range, see Table 2.

Across 100 stochastic replications, aggregate outcomes show limited variability (Table 2), with approximately half of the population classified as unsafe or trapped. This low variability is consistent with the model formulation, as once the scenario conditions and agent attributes are specified, most hazard, infrastructure, mobility, and behavioural rules are deterministic, while randomness is confined to a limited number of agent-level assignments and decisions. The consistency across replications therefore demonstrates that the aggregate results are not strongly dependent on the selected random seed. Subsequent analyses are conducted using Seed 3 as a representative seed, selected by proximity to the mean results.

The study area is highly exposed to flooding, as illustrated in Fig. 5. Of the 34,319 residents considered in the simulation, approximately 50.4% experience unsafe conditions during the event. Although the maximum water depth reaches up to 1.6 m, flooding affects the entire area. This is particularly relevant because most buildings consist of one or two story houses, leaving 61.1% of structures with no dry floors. As a result, residents are often forced to evacuate horizontally rather than seeking vertical refuge. This situation is further aggravated by the short warning time and the rapid inundation of the central zone, specially affecting the road network connecting the neighbourhoods. As water depth increases, key routes become impassable, making evacuation efforts difficult, particularly towards Shelter 5, which becomes isolated, leading to unused shelter capacity, see detail in Fig. 5 (a). In addition, water ingress compromises shelter accessibility and leads to several shelter closures after Hour 6, further increasing citizen exposure to hazardous conditions. Among the agents classified as unsafe, nearly 24.5% remain trapped inside their homes, including residents who remained at home despite receiving the warning. However, most unsafe cases occur when individuals become trapped on roads while attempting to reach a safe location.

Fig. 6 provides both aggregate and archetype-disaggregated evacuation dynamics over time. At the population level, less than 40% of the citizens remain safe at home, while trapping increases markedly after Hours 6–7 as flood depths increase and road availability decreases. The archetype-disaggregated results show the contribution of coordinated, passive, and non-coordinated citizens to each evacuation state over time, together with their final safe/unsafe outcomes. Consistent with the prescribed

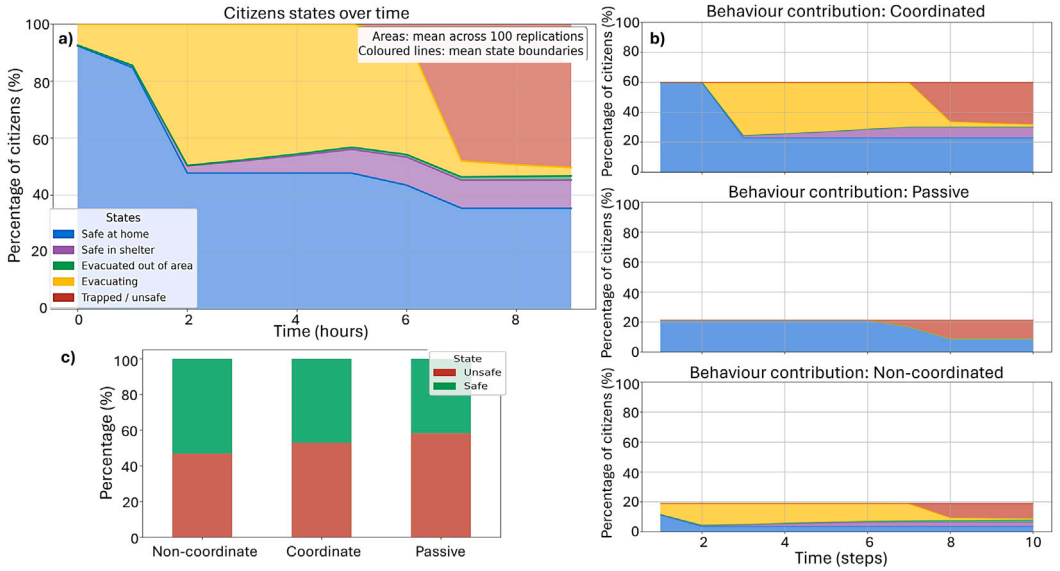


Fig. 6. Evacuation dynamics under heterogeneous behaviour for the Maashaven dike-failure scenario. (a) Citizens-level evolution of evacuation states; (b) Contribution of coordinated, passive, and non-coordinated archetypes to each evacuation state over time; and (c) final safe/unsafe outcome disaggregated by behavioural archetype.

behavioural rules, non-coordinated agents initiate evacuation before the official warning, whereas passive agents delay evacuation or remain in place. This disaggregation also shows how these behavioural differences combine with the evolving flood conditions to produce different final safety outcomes across archetypes.

4.3. Impact of archetype-based heterogeneity relative to a homogeneous behaviour

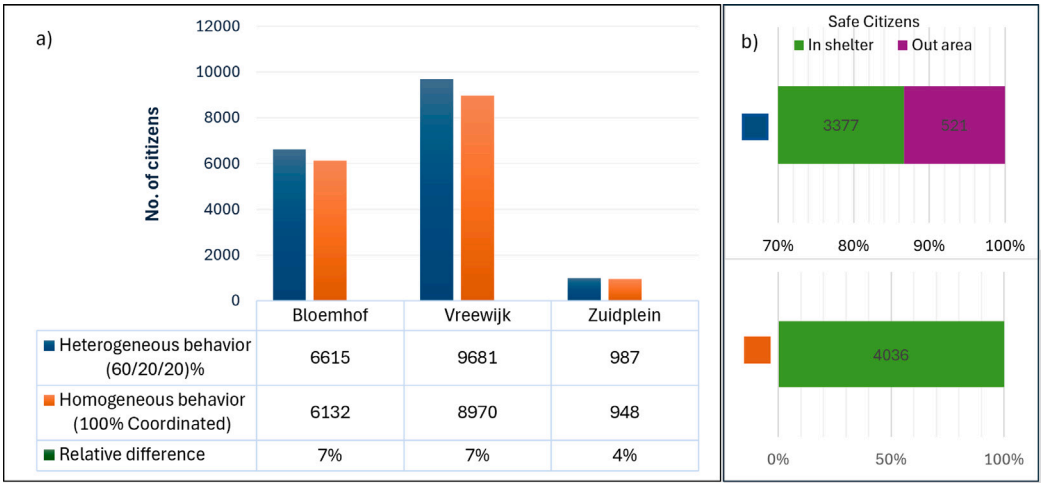
To assess the influence of behavioural heterogeneity, the baseline scenario (60% coordinated, 20% non-coordinated, and 20% passive) is compared with a homogeneous scenario in which all citizens follow coordinated behaviour (100%). Thus, the homogeneous assumption represents a particular case of the proposed archetype-based formulation rather than a separate modelling approach. Flood and infrastructure conditions are identical in both simulations. As shown in Fig. 7(a), considering a heterogeneous behavioural distribution leads to a higher number of affected individuals. The largest difference is observed in Bloemhof and Vreewijk (7%). These percentages represent the underestimation of the safety conditions of thousands of residents, specifically 1233 people, when homogeneous behaviour is assumed. It is noted that this value is subject to uncertainty related to the assumptions adopted in this model, particularly the proportion of non-coordinated agents. Variations in this parameter could further increase the number of citizens in unsafe conditions. This aspect will be further discussed in Section 5.

Another notable difference concerns evacuation choices. In the fully coordinated scenario, individuals follow official guidance and evacuate towards designated shelters. In contrast, under heterogeneous behaviour some individuals may also leave the affected area entirely, a pattern mainly associated with the non-coordinated archetype (Fig. 7b). In this sense, non-coordinated behaviour does not necessarily imply poorer individual evacuation outcomes, as these agents may evacuate before the official warning and can leave the affected area rather than relying on local shelters.

The differences become even more evident when comparing the evacuation dynamics over time as shown in Fig. 8. In the heterogeneous scenario, evacuation begins earlier, but it also introduces behaviours that deviate from the assumptions embedded in evacuation planning. For instance, some individuals move in directions not anticipated by the plan, such as leaving the area instead of evacuating to the nearest shelter (Fig. 8b), while others remain at home despite evacuation warnings. This behaviour becomes particularly evident between Hours 5 and 7 (Figs. 8a and b), when passive individuals in the heterogeneous scenario become trapped earlier than in the homogeneous case, as expected from their prescribed delayed-response behaviour. Consequently, assuming homogeneous behaviour may lead to an overly optimistic assessment of evacuation performance under the conditions examined here, as it does not capture the system-level effects associated with behavioural diversity.

4.4. System-level effects of behavioural interactions

The preceding comparison includes differences that are partly expected from the prescribed archetype rules. To examine whether the model also generates system-level effects beyond these direct assumptions, the baseline scenario (60% coordinated, 20% non-coordinated, and 20% passive) is compared with an idealized scenario in which non-coordinated agents are reassigned to coordinated behaviour (80% coordinated, 0% non-coordinated, and 20% passive). The original coordinated population (i.e., focal coordinated agents) is kept unchanged, enabling direct comparison of the same 20,560 agents across both scenarios.



	Bloemhof	Vreewijk	Zuidplein
Heterogeneous behavior (60/20/20)%	6615	9681	987
Homogeneous behavior (100% Coordinated)	6132	8970	948
Relative difference	7%	7%	4%

Fig. 7. For the case of Maashaven dike failure, comparison of (a) unsafe citizens in the neighbourhoods of Bloemhof, Vreewijk and Zuidplein for heterogeneous (blue bars) and homogeneous behaviour (orange bars); (b) Safe citizens disaggregated by evacuation choices in the case of heterogeneous (upper bar) and homogeneous behaviour (lower bar).

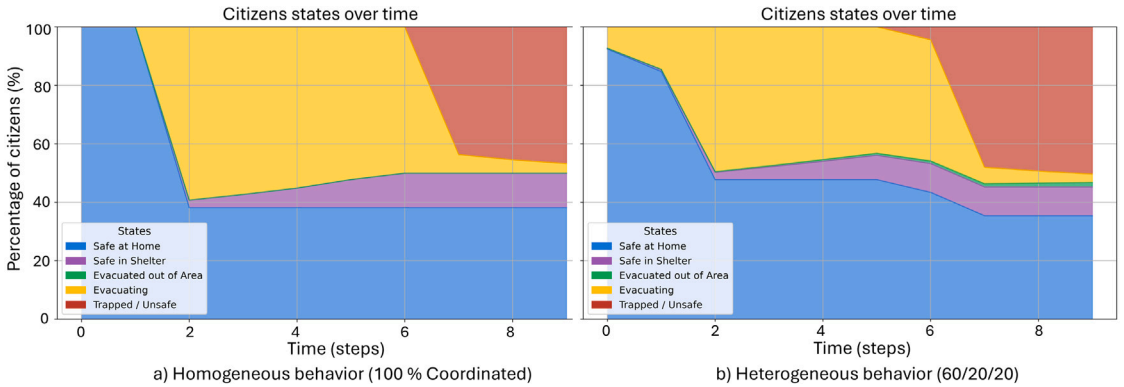


Fig. 8. Comparison of evacuation dynamics for the case of Maashaven dike failure. (a) homogeneous and (b) heterogeneous behaviours.

The analysis shows that behavioural heterogeneity can affect agents whose own behavioural rules remain unchanged. Among the 20,560 focal coordinated agents, the proportion classified as unsafe or trapped decreased from 48.4% in the baseline scenario to 46.8% in the idealized scenario, while shelter arrivals increased from 45.2% to 46.4%, correspondingly. At the individual level, 559 coordinated agents who were trapped on the road in the baseline scenario successfully reached shelters in the idealized scenario, whereas no coordinated agent experienced the opposite transition. These results show that behavioural differences can propagate through the shared evacuation network and affect the safety of other agents beyond the outcomes directly prescribed by the archetype definitions.

5. Decision making under limit data and uncertainty

5.1. Sensitivity analysis to behavioural and temporal assumptions

Multiple factors can significantly influence evacuation outcomes, including hazard intensity, the effectiveness of early warning systems, and infrastructure availability. While these factors are defined by the scenario, this section focuses specifically on two assumptions embedded within the model itself and how they may influence evacuation outcomes: (i) the safe evacuation time and (ii) the behavioural archetype assignment to the population. To assess the influence of the first parameter, defined as the period between the issuance of the evacuation warning and the arrival of the flood event, scenarios ranging from 1 to 6 h were considered, representing different levels of warning anticipation under flash flood conditions. For the second, the ratio between non-coordinated and coordinated agents is analysed, with the proportion of passive individuals, i.e., 20%, kept constant based on evidence from previous studies. Six behavioural compositions are evaluated, ranging from no non-coordinated agents (0% non-coordinated and 80% coordinated) to 50% non-coordinated and 30% coordinated agents.

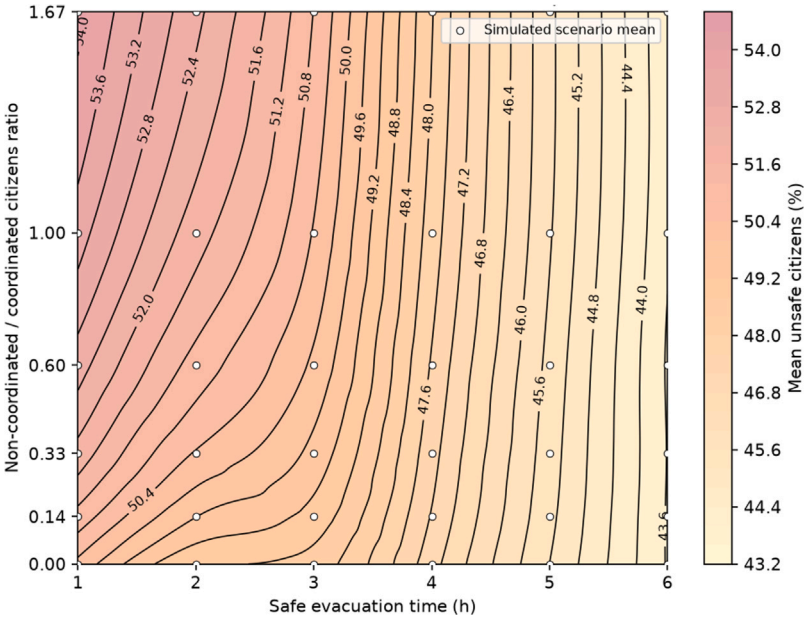


Fig. 9. For the case of Maashaven dike failure in Rotterdam, unsafe citizens' contour map as a function of safe evacuation time and behavioural composition.

Fig. 9 summarizes the combined influence of safe evacuation time and behavioural composition on the mean percentage of unsafe citizens. Across the parameter space, safe evacuation time has the strongest influence on the safety outcome, increasing the available evacuation time consistently reduces the unsafe population for all behavioural compositions. Behavioural composition nevertheless has a systematic effect. For a given evacuation time, increasing the proportion of non-coordinated relative to coordinated agents generally increases the mean percentage of unsafe citizens. This effect is more pronounced at shorter evacuation times and can be explained by the unpredictable nature of non-coordinated behaviour, which, given the lack of anticipation, can lead to congestion or suboptimal decision-making during the evacuation.

As the safe evacuation time increases from 1 to 6 h, the proportion of citizens in unsafe conditions decreases across all behavioural distributions. For example, in a scenario without non-coordinated agents (ratio 0.0), varying the safe evacuation time results in a decrease of unsafe citizens from 50.4% to 43.6%, corresponding to approximately 2334 fewer individuals in the final outcome.

The progressive reduction in the vertical variation of the contour lines towards longer evacuation times indicates that the influence of behavioural composition becomes comparatively smaller as more time is available for evacuation. A wider contour spacing is also observed around 2 to 3 h and ratios of 0 to 1. This central zone is a plateau of relatively low sensitivity, where moderate changes in either time or ratio produce only small changes in the safety outcome. At the same time, the contour spacing suggests that the safety gains obtained from additional evacuation time are not uniform across the analysed range, with the strongest reductions occurring approximately between 3 and 5 h. Beyond approximately 5 h, additional evacuation time continues to improve safety, but the magnitude of this improvement becomes smaller. Notably, even with 6 h of evacuation time and the most favourable behavioural composition considered, with no non-coordinated agents, around 44% of citizens remain unsafe, a residual fraction mainly attributable to passive behaviour and lack of accessible shelters. This is an important policy insight: extending warning lead time is highly valuable but when evacuation time is limited improving evacuation strategy and adherence to evacuation orders is as important as gaining more time.

The contour curves vary depending on the study case, particularly according to infrastructure characteristics and available evacuation options. Comparing the current case study with an alternative scenario of the Parksluizen dike failure affecting the western port districts of Rotterdam shows significant differences in the contour curves (see Fig. 10). Parksluizen dike-failure case study and flood impacts are shown in Figs. B.1 and B.2, respectively, and described in Appendix B. In the Parksluizen case, the ratio between non-coordinated and coordinated agents becomes more influential, especially when the safe evacuation time is limited. Also, the residual floor is much lower (6 h and no non-coordinated behaviour), the unsafe fraction drops to around 26%, compared with about 46% in the previous case.

This difference can be explained by exposure to the built environment. In the case of Maashaven dike failure, the population is highly exposed because most buildings consist of one- or two story-buildings, forcing a large number of residents to rely on horizontal evacuation. As a result, variations in safe evacuation time have a pronounced impact on the proportion of unsafe citizens. In contrast, in the alternative scenario associated with a different dike failure, a larger share of buildings has multiple dry floors, providing opportunities for vertical refuge and reducing the immediate need for evacuation. In that context, while safe evacuation time still influences safety outcomes, its effect is less pronounced than in the current scenario, where rapid and widespread evacuation is required.

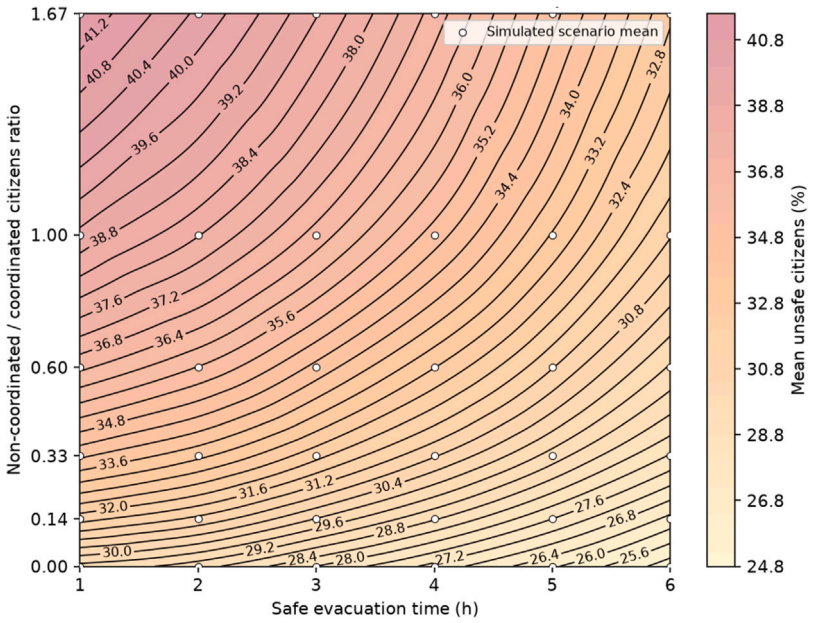


Fig. 10. Unsafe citizens' contour map as a function of safe evacuation time and behavioural composition. Parksluizen dike failure in Rotterdam.

5.2. Model calibration and validation needs

Empirical calibration and validation of the evacuation framework are not performed in the present study. The Rotterdam case study represents a hypothetical dike-breach scenario rather than a reconstruction of an observed flood evacuation; consequently, event-specific evacuation trajectories and behavioural observations are not available for direct comparison with the simulated population response. The results should therefore be interpreted as evidence of model behaviour and of how behavioural heterogeneity and modelling assumptions influence simulated evacuation outcomes.

The formulation nevertheless provides a basis for future calibration because the behavioural archetypes are defined primarily through observable mobility responses. Calibration would require observations of warning reception, evacuation decisions, departure timing, routes, destinations, and shelter use. Whereas validation would require observations against which the resulting evacuation dynamics and final outcomes could be evaluated. Mobility datasets such as aggregated mobile-phone records, GPS trajectories, and other digital traces can provide information on departure timing, trajectories, destinations, and return dynamics [85–87], complemented by surveys and operational records describing warning reception, evacuation decisions, shelter use, and emergency outcomes. Because the archetypes are classified from observable mobility responses, their proportions and behavioural parameters can in principle be estimated from such data without requiring direct observation of latent psychological mechanisms.

Table 3 summarizes the main model quantities requiring empirical calibration or validation, the corresponding observations, and potential data sources.

Several modelling assumptions should be considered when interpreting the results. The current implementation represents pedestrians individually, however, it does not include household-level coordination, social influence, imitation, or explicit pedestrian interactions. The road network does not impose edge-capacity constraints or congestion; network effects instead arise from route availability, evolving flood exposure, re-routing, and destination accessibility. Shelter closure thresholds, age-related mobility modifiers, and selected behavioural probabilities are literature-informed or operational assumptions rather than case-specific calibrated values.

The case-study configuration further assumes that residents are initially at home, successfully receive the official warning, and evacuate on foot. These assumptions define the nighttime flash-flood scenario examined here and would need to be adapted for other emergency contexts.

Future work should therefore focus on empirical calibration and validation against observed evacuation data, explicit representation of household and social interactions, and extension to additional transport modes and capacity-dependent network dynamics. The model assumptions and parameterization choices in Appendix A are intended to facilitate such extensions and case-specific calibration.

5.3. Support decision making under uncertainty

The proposed framework can offer substantial value as a decision-support tool, even in the presence of the uncertainties discussed in previous sections. By explicitly accounting for behavioural variability, it supports more robust infrastructure planning and evacuation management strategies in both the short and long term.

Table 3
Data requirements for future calibration and validation of the evacuation model.

Model component	Model quantities to calibrate/validate	Required empirical data	Potential data sources
Evacuation decision	Archetype shares; probability of staying, sheltering, or leaving the affected area.	Proportion of residents who evacuated, remained at home, used shelters, or left the affected area.	Post-event surveys; interviews; municipal and emergency-management records.
Warning dissemination	Warning coverage, reception probability, and effective warning time.	Time, spatial coverage, and proportion of residents receiving and acknowledging official warnings.	Cell Broadcast/SMS logs; municipal warning records; surveys; emergency communication systems.
Reaction time	Archetype-specific departure delays and anticipatory departure times.	Warning-reception and actual departure times at individual or population level.	Surveys; warning logs combined with aggregated mobility data; evacuation-drill observations.
Socio-demographic effects	Income-dependent decision weights; age-related archetype and mobility modifiers.	Evacuation decisions, departure times, and destinations by age, income, disability, and household characteristics.	Stratified surveys; census and municipal statistics; anonymized or aggregated population data.
Pedestrian mobility	Base walking speed and age-related speed modifier.	Walking speeds under dry and flooded conditions for different population groups.	Controlled experiments; evacuation drills; anonymized video or voluntary GPS observations; empirical literature.
Flood-hazard response	HR tolerance; debris factor; maximum walkable depth; road hazard thresholds.	Flood depth and velocity associated with reduced mobility, route abandonment, rescue, or inability to continue evacuation.	Controlled experiments; emergency-service and road-management records; drill observations; empirical literature.
Route choice and re-routing	Shortest-path preference; alternative-route selection; re-routing response and maximum attempts.	Observed trajectories, route changes, avoided or blocked streets, travel times, and detours.	Aggregated GPS/mobile data; traffic or pedestrian counts; video observations; road-incident logs; surveys.
Shelter operation	Effective capacity; closure threshold; admission and redirection rules.	Opening and closure times, local flood conditions, arrivals, occupancy, rejected arrivals, and redirections.	Shelter operational records; emergency plans; municipal and civil-protection records.
Population and building allocation	Population per building and floor; age distribution; residential-floor allocation.	Household composition, residential location, building use, height, and occupied floor.	Census and municipal registers; cadastral/building data; housing providers; anonymized or aggregated records.
Flood-hazard representation	Flood arrival time, depth, velocity, spatial extent, and temporal evolution.	Observed flood extent, water levels, flow conditions, and timing.	Gauges; high-water marks; field surveys; georeferenced images; satellite/drone observations; hydraulic-model comparison.
Evacuation outcomes	Predicted safe, trapped, sheltered, evacuated, and rescue outcomes.	Number and location of trapped or rescued residents, shelter arrivals, outward evacuations, travel times, and final population distribution.	Emergency-service records; emergency calls; civil-protection and municipal records; shelter operators; aggregated mobility data.

In the long term, the framework allows the assessment of evacuation performance across multiple levels, including infrastructure systems, institutional evacuation management, and citizen behavioural responses. From an infrastructure and evacuation performance perspective, the results highlight several structural limitations in the study area. Most buildings consist of one or two story houses, which leaves residents highly exposed to flood impacts and offers limited opportunities for vertical evacuation. An exception is the Zuidplein neighbourhood, which includes several taller building that results in multiple dry floors. Regarding horizontal evacuation, although several shelters are available within the area, their capacity is insufficient to accommodate the potentially affected population. Even if all the shelters operated at full capacity, approximately 9900 people, they would cover only about half of the estimated demand, considering the 18,141 unsafe citizens in this scenario (see Fig. 5). In addition, the spatial distribution of shelters could be more strategic, as they are currently concentrated in Bloemhof and Vreewijk in a single portion of the study area. A more distributed placement could improve evacuation efficiency and accessibility.

Despite the neighbourhoods being well connected through the road network, the rapid evolution of the flood event can quickly compromise key routes, increasing the number of citizens exposed to unsafe conditions. Complementary evacuation measures, such as the deployment of boats by emergency response teams, could therefore play an important role in improving evacuation effectiveness. More broadly, the framework allows the identification of socially vulnerable groups that may face greater barriers to evacuation, helping decision-makers incorporate equity considerations into evacuation planning.

By explicitly representing infrastructure and behavioural archetypes, the model enables the evaluation of both hard and soft adaptation measures within a unified modelling framework. In this context, hard adaptation measures refer to interventions

that modify either flood hazard (e.g., levees, dikes, flood barriers, and engineered drainage systems) or the built environment (e.g., housing flood adaptations or permeable pavements). In contrast, soft adaptation measures aim to strengthen institutional and societal capacity to anticipate, respond to, and recover from flood events through regulatory, organizational, educational, and behavioural strategies. Each of these aspects is discussed below.

Soft adaptation measures can be analysed, as the framework explicitly incorporates behavioural archetypes and their socio-cultural and socioeconomic drivers. These measures influence how individuals and institutions perceive and respond to floods. They include improvements in early warning systems allowing evacuation alerts to be issued earlier, evacuation planning and zoning policies that influence route selection, shelter availability, and destination choices. For instance, assigning residents to predefined shelters in advance could significantly improve evacuation performance. Currently, there is no widely accessible system that provides residents with clear information about available shelters and their occupancy capacity, which may lead to inefficient shelter allocation and increased congestion during evacuation. Educational and awareness programs may also influence the distribution of behavioural archetypes over time by increasing the proportion of coordinated agents. Finally, evaluation and learning mechanisms that enable iterative updates to model parameters as new knowledge becomes available, reflecting institutional learning processes. These mechanisms can also incorporate strategies to counteract risk memory decay, a phenomenon where awareness and preparedness decline over time due to fading memories of past events or generational turnover [88]. For example, regular drills, public education campaigns can reinforce knowledge and reduce the loss of risk awareness.

In the short term, the framework can also support real-time evacuation management. Even without live monitoring, it can serve as a baseline to identify areas with higher exposure, enabling authorities to prioritize evacuation efforts and allocate resources more efficiently. For example, by anticipating which roads are likely to become impassable, traffic management measures such as preemptive road closures or rerouting can be planned to ensure safer evacuation routes. When combined with tracking or monitoring capabilities, the system could additionally observe evacuation dynamics as they unfold, identifying who evacuates, who remains at home, and where individuals move within the network. Such information would allow emergency managers to assess exposure levels, population displacement, and shelter occupancy in near real time. behavioural responses could also be inferred from observed movement patterns, such as departure timing, destination choices, and reactions to official warnings or evolving hazard conditions, further supporting dynamic adjustments to evacuation strategies during rapidly developing flood events.

Importantly, non-evacuation patterns should be interpreted cautiously, as similar observed outcomes may reflect different underlying needs and therefore require different policy responses, ranging from logistical support to risk communication. The framework enables this distinction by linking behavioural outcomes with relevant demographic and behavioural attributes.

6. Conclusions

This study proposed an operational archetype-based framework for representing behavioural heterogeneity in flood evacuation models through observable differences in whether, when, and where individuals move relative to institutional guidance. The framework organizes empirically documented evacuation responses into three measurable and interpretable archetypes, namely, coordinated, passive, and non-coordinated. Based on the scenarios examined, the homogeneous behaviour assumption can underestimate population exposure compared to the heterogeneous representation. The framework also provides a structured way to relate observable evacuation responses to socioeconomic, demographic, and contextual characteristics without requiring direct estimation of the underlying behavioural mechanisms. By integrating behavioural responses with institutional guidance, individual characteristics, mobility constraints, and spatial evacuation outcomes, the framework provides a common structure for examining the interaction between human behaviour, hazard evolution, and evacuation infrastructure.

The sensitivity analysis showed that evacuation outcomes are jointly influenced by the available evacuation time, behavioural composition, and infrastructure conditions. Increasing evacuation time from one to six hours significantly reduces the number of unsafe citizens, with differences of up to approximately 2334 people, highlighting the critical role of timely early warnings and risk communication. The influence of the archetype distribution increases depending on infrastructure conditions, with higher proportions of non-coordinated relative to coordinated agents generally increasing the unsafe population, particularly when evacuation time is limited. In areas dominated by low-rise buildings, limited vertical evacuation forces reliance on road networks, making evacuation time the dominant factor. In scenarios with taller buildings and available dry floors, vertical evacuation reduces time dependency, and behavioural composition, especially the balance between non-coordinated and coordinated responses, becomes more influential.

The idealized scenario analysis further showed that behavioural composition can generate system-level effects through the shared evacuation network beyond the outcomes directly prescribed by individual archetype rules.

The proposed framework can serve as a decision-support tool for both infrastructure and evacuation planning in the short and long term. In the short term, it can support operational evacuation management by identifying areas with higher expected exposure, allowing authorities to prioritize evacuation efforts and improve traffic management during emergencies, for example by anticipating which roads may need to be closed earlier to ensure safer evacuation routes. This potential becomes even more relevant if combined with mobility data or real-time monitoring systems. In the long term, the framework can support preparedness and planning by evaluating how different policies affect both physical risk and built environment, as well as human behaviour.

Although this study focuses on flood evacuation, the proposed framework is transferable to other case studies and hazard types. By adapting the hazard representation and exposure conditions, the approach could be applied to scenarios such as wildfires, earthquakes, or other rapid-onset disasters. This flexibility highlights the potential of the framework as a general tool for evacuation planning and disaster risk assessment across different contexts.

The main limitations concern the absence of empirical calibration and validation against an observed evacuation event, the simplified representation of social interactions and transport dynamics, and the use of several literature-informed or operational assumptions that remain case-specific. Future work should therefore prioritize calibration and independent validation using observed evacuation data, including warning reception, departure timing, trajectories, destinations, shelter use, and final outcomes. Extensions to household and social interactions, additional transport modes, and capacity-dependent network dynamics would further increase the framework's applicability.

CRediT authorship contribution statement

Erica Arango: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Maria Nogal:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

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

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Appendix A. Complete model specification

See Table A.1.

Table A.1
Complete model specification, parameter values, and modelling assumptions adopted for the Rotterdam case study.

Parameter/ Component	Model implementation	Rotterdam case-study specification	Parameterization basis
Temporal and flood-hazard representation			
Temporal resolution	User-defined temporal resolution controlling model updates and hazard-state changes.	1 h per model step.	Case-study specification.
Warning and evacuation window	Warning and flood-onset times are user-defined and determine the available pre-impact evacuation time.	Warning at Hour 2; flood onset at Hour 4; 2-h evacuation window.	Case-study specification; evacuation window examined in sensitivity analysis.
Flood evolution and simulation duration	Flood conditions are updated from sequential depth and velocity states over the simulation period.	Four 1-h flood intervals; maximum flood state at Hour 8; simulation ends at Hour 10.	Flood-data discretization/case-study specification.
Hazard rating and classification	Pedestrian flood exposure is represented using $HR = d(v + 0.5\,DF)$; HR classes determine mobility conditions.	Low: $HR < 0.75$; Medium: $0.75 \leq HR \leq 1.5$; High: $1.5 < HR \leq 2.5$; Severe: $HR > 2.5$.	Literature-derived formulation and thresholds [82,89]; $DF = 0.5$ case-study assumption.
Pedestrian mobility and age-related vulnerability			
Flood-dependent walking speed	Walking speed decreases as HR increases and becomes zero under severe hazard conditions.	1.8 m/s for $HR \leq 1.5$; 1.0 m/s for $1.5 < HR \leq 2.5$; 0 m/s for $HR > 2.5$, before age modification.	Literature-derived [82].
Age-related mobility	Walking speed and HR tolerance can be modified according to demographic vulnerability.	Elderly speed multiplier = 0.6; HR tolerance = 0.75 for elderly and 1.5 for other agents.	Literature-informed modelling assumption [82,84].

(*continued on next page*)

Table A.1 (*continued*).

Parameter/ Component	Model implementation	Rotterdam case-study specification	Parameterization basis
Buildings, population, and vertical exposure			
Building floors and inundation	Building height is converted into floor count, and inundation depth determines the number of affected floors.	Floors = $\max(\lfloor H/3 \rfloor, 1)$; flooded floors = $\lceil d/3 \rceil$.	Literature-informed geometric approximation [90].
Population and floor allocation	Postal-code population is allocated to buildings and subsequently distributed across floors.	Allocation proportional to building volume; residents distributed approximately uniformly across floors.	Case-study data/modelling procedure.
Initial location and home safety	Agents start at their residential building and are evaluated dynamically against vertical inundation and local hazard.	Home is safe while the occupied floor remains non-inundated and hazard remains below the applicable threshold.	Spatial-data input/operational model definition.
Behavioural archetype assignment			
Archetype distribution and spatial assignment	Archetype shares are user-defined and assigned probabilistically within the population.	60% coordinated, 20% non-coordinated, 20% passive; distribution applied within postal-code areas.	Passive share empirically informed [48,81]; non-coordinated share is a modelling assumption and sensitivity parameter.
Age-conditioned archetype assignment	Demographic attributes may modify relative archetype-assignment probabilities while preserving the target aggregate distribution.	Elderly relative weights: coordinated = 0.30; non-coordinated = 0.00; passive = 0.70.	Literature-informed modelling assumption [74].
Reaction times	Archetypes determine response timing relative to the official warning.	Coordinated: 0 h; non-coordinated: −1 or −2 h; passive: [insert final implemented range].	Archetype definition/modelling assumption.
Decision activation	Behavioural decisions are evaluated when the archetype-specific response time is reached; hazard evaluation also begins with flood onset.	$t_{current} \geq t_{warning} + t_{reaction}$ or $t_{current} \geq t_{flood}$.	Model implementation.
Behavioural decision rules			
Coordinated decision rule	Protective action depends on residential-floor exposure and income.	Ground floor: medium-high/high income → exit; low/medium-low income → shelter. Safe upper-floor residents remain at home.	Framework-defined modelling rule.
Non-coordinated decision rule	Feasible actions are selected probabilistically according to floor exposure and income.	Ground floor: binary exit/shelter choice. Upper floors: baseline stay = 0.50, exit = 0.25, shelter = 0.25, adjusted by income.	Framework-defined modelling rule/modelling assumption.
Income-dependent destination choice	Income modifies evacuation-outside-area probabilities for non-coordinated agents.	Ground-floor exit probability: low = 0.20; low-medium = 0.40; medium-high = 0.60; high = 0.85. Upper-floor exit probability is adjusted and normalized.	Case-study socioeconomic classification [80]; probabilities are modelling assumptions.
Passive decision rule	Passive agents do not actively select an evacuation destination unless subsequent hazard conditions make their location unsafe.	Remain at home under the baseline behavioural rule.	Archetype definition.
Road network, destinations, and routing			
Road-network representation	Pedestrian movement is represented over an undirected graph using road-segment length as route cost.	1231 road segments; edge weight = `length`.	OpenStreetMap/model implementation.
Origin and destination connection	Buildings and shelters are linked to the evacuation network through their nearest road-network node.	Nearest-node connection.	Model implementation.
Exit and shelter selection	Exit- and shelter-bound agents select the nearest reachable suitable destination based on network distance.	Boundary road nodes define exits; shelter alternatives are considered when the preferred shelter is unavailable.	Model implementation/case-study modelling assumption.
Route selection	Initial paths are computed using weighted shortest-path routing.	Weighted shortest path; edge weight corresponds to road-segment length.	Model implementation.

(*continued on next page*)

Table A.1 (*continued*).

Parameter/ Component	Model implementation	Rotterdam case-study specification	Parameterization basis
Flooded-network response and re-routing			
Road hazard and re-routing trigger	Agents re-evaluate their current route when local flood conditions exceed the adopted pedestrian-mobility thresholds.	Water depth ≥ 0.50 m or $HR > HR_{\text{tolerance}}$, where $HR_{\text{tolerance}} = 1.50$ for non-elderly agents and 0.75 for elderly agents.	Literature-informed thresholds [82,89].
Re-routing rule and limit	Replanning begins from the current network position and preserves the intended evacuation objective unless an alternative shelter is required.	Maximum of 10 re-routing attempts.	Model implementation/computational assumption.
Flooded-road and capacity treatment	Hazardous roads remain represented in the graph and no explicit pedestrian congestion model is imposed.	No flood-dependent edge penalty, edge-capacity constraint, queueing mechanism, or density-dependent speed function.	Model design/scope assumption.
Route failure and trapping	Agents are classified as trapped when no viable continuation to a safe destination can be completed.	No viable route/destination or maximum re-routing attempts exhausted.	Operational model definition.
Shelter representation and operation			
Shelter capacity and floors	Capacity is determined from usable area and the number of available floors.	4 m^2/person; floors $= \max(1, \lfloor H/3 \rfloor)$.	Standards-informed capacity assumption [91]; geometric approximation [90].
Shelter closure and dry-floor availability	Flooding reduces usable shelter space and may prevent new admissions.	Closed to new arrivals when local depth > 0.20 m; at least one dry floor must remain.	Conservative modelling assumption.
Admission and occupancy	Agents are admitted only when the shelter is open, reachable, has a dry floor, and has remaining capacity.	Occupancy increases only after successful admission; existing occupants remain safe while usable dry space remains.	Model implementation.
Safety and outcome classification			
Safe outcomes	Agents may be classified as safe at home, in shelter, or outside the study area.	Home: occupied floor remains non-inundated; shelter: successful admission to usable capacity; outside: designated exit reached.	Operational model definition.
Unsafe/trapped outcomes	Agents are classified as unsafe when flood exposure or unavailable evacuation options prevent continued safety.	Home: occupied floor inundated; road: no viable safe continuation; shelter-bound: no accessible shelter with usable capacity.	Hazard-informed operational definition.
Stochasticity and reproducibility			
Stochastic implementation	A user-defined random seed controls stochastic archetype assignment, reaction times, behavioural choices, and randomized model operations.	Seed passed to the Mesa model.	Computational implementation.
Replication and representative-run analysis	Stochastic variability is assessed using independent replications; one representative realization is used for detailed spatial and agent-level outputs.	100 baseline replications; seed 3 selected as the realization closest to the median final unsafe population.	Robustness and representative-run protocol.

Appendix B. Flash-flood emergency response in Rotterdam: Parksluizen dike failure

This alternative scenario considers the dike-breach at Parksluizen, affecting the western port districts of Rotterdam, specifically Spangen, Nieuwe Westen, Middelland, Oude Westen, and Dijkzigt. Among these neighbourhoods, Spangen and Nieuwe Westen are classified as low–medium income, while Middelland, Oude Westen, and Dijkzigt are categorized as medium–high income. This area is characterized by relatively limited shelter capacity, as illustrated in Fig. B.1.

The considered infrastructure includes 1130 road network segments, 6103 residential buildings, and 3 shelters.

The flood hazard scenario 19,545 is adopted from the national flood risk datasets provided by 'Rijkswaterstaat' [77]. This scenario represents a potential dike-breach event with an exceedance probability of approximately 1 in 1,000,000 years.

Regarding population, a total of 48,649 residents are considered within the study area based on the StatLine dataset [79]. All other modelling assumptions and methodological steps remain consistent with those described in Section 4.1.

The breach of the Parksluizen dike represents a critical flooding situation, as the impact extends throughout the entire area, with water depths of up to 4 m, as shown in Fig. B.2. In this context, the road network can be severely affected, with 78.6% of roads either inoperable or unsafe, reducing the effectiveness of horizontal evacuation. Approximately 36% of the 48,649 citizens

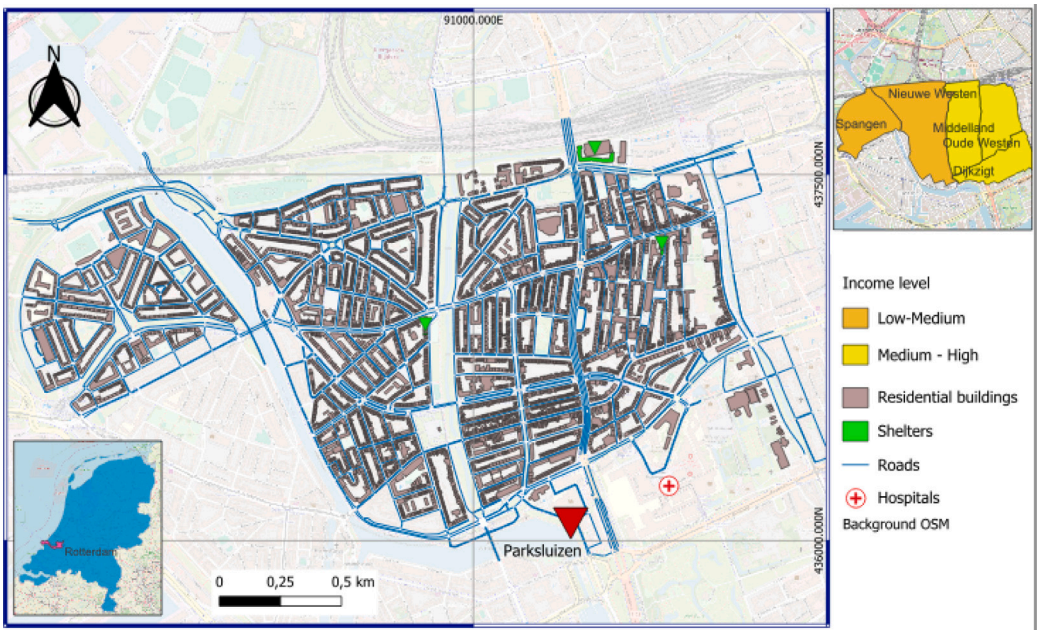

Fig. B.1. Rotterdam case study: dike failure at Parksluizen.

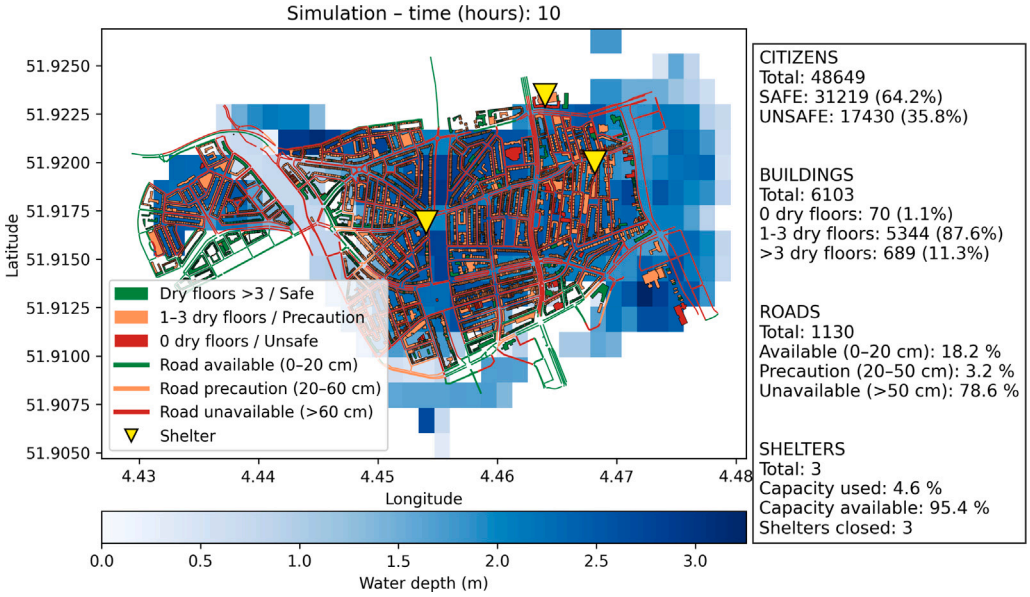

Fig. B.2. Flood impact assessment in case of Parksluizen dike failure at simulation hour 10.

considered are exposed to unsafe flood conditions. However, this scenario includes the highest number of tall buildings, with 98.9% retaining at least one dry floor. This allows vertical evacuation to account for a significant portion of the evacuation dynamics, which is particularly important given the limited shelter capacity in the area.

Data availability

Data will be made available on request.

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