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Towards Modelling Human Behaviour and Warning Message Informativity in Large-Scale Event Evacuation

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Abstract

This paper outlines a conceptual framework for an agent-based model (ABM) designed to investigate the significance of warning message informativeness in the context of large-scale event evacuations. Unlike other disaster scenarios where the detail within warning messages has been shown to impact response times and decision-making, the effectiveness of such informativeness in large-scale event settings remains underexplored. By leveraging the Protective Action Decision Model (PADM) among other psychological theories, this framework seeks to enhance evacuation simulations by incorporating a nuanced understanding of how individuals process warning messages during large public gatherings. Our approach aims to dissect the trade-offs between the conciseness and the detail of warning messages, specifically examining if and how the level of information affects evacuation behaviour in crowded scenarios. Given the study's conceptual stage, we discuss theoretical implications and propose simulation scenarios to explore this dynamic. This inquiry is foundational, setting the groundwork for subsequent empirical research to validate the framework and ascertain the relative importance of message informativeness in emergency communications during large-scale events.

Keywords: Agent-Based Simulation, Protective Action Decision Model, Warning Message Informativity

1. Introduction

In the preparation of large-scale events, simulations are often used as part of an evacuation and event planning strategy. Historical tragedies highlight the need for such strategies; The 1989 Hillsborough Disaster, resulting in 96 fatalities due to flawed crowd management and evacuation tactics, and the 2003 Station Nightclub Fire in West Warwick, Rhode Island, with 100 lives lost during a chaotic evacuation, exemplify the dire consequences of inadequate evacuation procedures. These incidents highlight that especially for large-scale events where high-density situations pose a risk of stampedes and crowd crushes, anticipating potential bottlenecks and evaluating event structures and emergency exits are crucial to ensure efficient and safe crowd control. Evacuation simulations play a pivotal role in this context, aiding in predictive analysis, enhancing safety, optimising resource allocation, and providing essential training for emergency responders. However, the complexity of human behaviour in such simulations is often simplified, with strong assumptions on crowd movements and information dissemination. Especially in emergency situations, individual and collective responses can vary significantly, creating challenges in evacuation planning. Over-simplification of human behaviour is problematic, as it can result in ineffective or hazardous evacuation strategies with optimistic estimations of evacuation times, neglecting evacuation delays. Evacuation delays can lead to preventable fatalities, often caused by individuals to waste time seeking additional information (Kuligowski and Omori, 2014). An effective warning message can reduce such delays. However, the dilemma lies in crafting such messages; they must be concise for quick comprehension, yet informative enough to prevent the delay in protective actions caused by information seeking (Kuligowski and Omori, 2014). In disaster response, the aspects of an effective warning message (Sadiq et al., 2023; Sorensen, 2000; Wood et al., 2018) have been investigated, and existing psychological models have been incorporated into evacuation simulations (e.g. Favereau et al. (2020); Ramos et al. (2022). However, in evacuation simulations for large-scale events, such models have not been included, and simplified approaches to information dissemination are employed. Furthermore, it is unclear to what extent the aspects of an effective warning message in disaster response translate to the more acute and dense setting of large-scale events. Our work addresses this gap by first investigating the current state of the art of effective warning messages and psychological disaster response models. These results are used to develop our model of warning message informativity and a behavioural model applied to the context of large-scale events. The selection of models and parameters will be guided by their applicability to large-scale event evacuations and data collection feasibility. Subsequently, we conceptualise integrating these elements into an agent-based model (ABM). The capability of the resulting ABM, namely the simulation of individual decision processes after receiving a warning message, enables researchers to observe how modifications in warning message content and delivery influence overall responsiveness and evacuation efficiency, offering valuable insights into optimising emergency communication strategies. We aim to explore the trade-offs between the informativeness and length of warning messages. We investigate whether the effectiveness of long, informative messages observed in natural disasters (Wood et al., 2018) holds in the context of dense, large-scale events.

2. State of the art

To address these challenges, we first examine warning message effectiveness and the application of psychological models in evacuation simulations.

2.1. Warning Message Effectiveness

The protective action decision process following a warning message about a hazardous event is iterative. It involves four key phases as stated in Wickens et al. (2015): comprehending the message, assessing its believability, verifying the information, and personalising the risk. This process, particularly during the verification phase, often includes additional steps of seeking and sharing information, collectively termed 'milling'. These stages are not sequential; individuals may cycle through them repeatedly in no fixed order. Ultimately, this process culminates in the individual's decision on which protective measures to adopt, based on their feasibility. This process, especially 'milling' behaviour, contributes to evacuation delays. In this study, we define an effective warning message as a message that minimises possible evacuation action delay. In this context, an effective warning message has been studied in different kinds of emergencies. For natural disasters, an effective message should contain information on the nature of the warning message, location, guidance, time and source of the hazard risk (Sorensen, 2000). Wood et al. (2018) further summarized the findings of recent research on these criteria, which can be found in Table 1. They further investigated what constitutes an effective warning message in the context of wireless emergency alerts for mobile devices during natural disasters. They found that longer, more informative warning messages reduced warning response delay. This contrasts findings from other studies, which identified brief messages as sufficient (Sadiq et al., 2023). The impact of the amount of information provided on motivating protective action for different hazards and the point at which additional information is no longer beneficial is still unknown (Wood et al., 2018). To our knowledge, there is no study investigating the warning effectiveness for evacuating large-scale events, a scenario which is often acute.

Table 1. Specification of criteria contained in an informative warning message according to Wood et al. (2018)

Criteria	Specific Aspects
Hazard	Consequences of the hazard's impact
	Threat posed
	How protective action can reduce consequences
Guidance	How to take protective action to maximize health and safety
	Linking of the protective action to basic human values (e.g., evacuate to keep your family safe)
Location	Location of the event
	Areas affected and unaffected
Time	By when protective action should be taken
	How long the action should continue
Source	Who the message is from

2.2. Psychological Models on Human Response in Crisis Situations

This decision-making mechanism is influenced by various psychological factors, as explored in several psychological models. Numerous psychological models on human response in crisis situations exist, but to our knowledge, only four of these are directly related to disaster scenarios. Namely, the extended parallel processing model (EPPM) (Witte, 1992), the person-relative-to-event theory (PrE) (Duval and Mulilis, 1999), the protection motivation theory (PMT)(Maddux and Rogers, 1983) and the protective action decision model (PADM) (Lindell and Perry, 2012). EPPM looks at how people respond to fear appeals in messages and balances between perceived threat and efficacy. PrE theory suggests that protective action, for example, evacuations, is taken based on an individual's perception of an event's proximity relative to themselves, considering both situational and intrapersonal factors. PMT proposes that the attitude towards health behaviour (e.g. quitting smoking) depends on the perception of threat (severity and likelihood of consequences, e.g. lung cancer) and perception of response- and self-efficacy. It is usually applied when a disease endangers an individual's health. Recurring factors in these models are situational and personal characteristics, perception of risk and protective action efficacy. The PADM includes all of these – except for self-efficacy- and is further extended with different types of cues, channels used to obtain information and perceptions of information sources and stakeholders to explain how people decide to take a specific protective action such as evacuating.

2.3. Modelling and Simulation of Evacuation Process

Many kinds of evacuation simulations exist, and some of them are based on parameters that can be found in the psychological models of human crisis response. ABMs are commonly used as their unique characteristic of a bottom-up structure, the ability to model heterogenous agents, and their actions leading to emergent behaviour make them especially suitable to meet the needs of evacuation simulation.Chen et al. (2023) for instance, present an interdisciplinary ABM that integrates empirical decision data from surveys and drills into simulations for tsunami evacuation. Their model uniquely considers natural and built environment impacts and social system dynamics, highlighting the non-linear effects of milling time and evacuation participation on mortality estimates. Ramos et al. (2022) used PADM as a basis of their behavioural ABM for wildfire evacuation, where they modelled an agent's decision to evacuate as a function of their risk perception and risk threshold. Risk perception is modelled as a function of internal (socio-demographic data) and external factors (fire model, observing others leaving, evacuation order). They did not consider all parameters of the PADM such as stakeholder perception or protective action perception. The reception of an initial evacuation order was dependent on a failure probability set by the user.Roy et al. (2022) developed an ABM exploring how multiple information sources influence flood risk perception and evacuation decisions. The model further incorporates factors such as hazard risk, household socio-demographics, and social network influences, using data from Miami-Dade County. It found that higher trust in hazard forecasts and social network recommendations increases evacuation compliance, highlighting the interplay of trust in information sources on evacuation behaviours. (Favereau et al., 2020) introduce a multi-method simulation approach integrating Risk Homeostasis Theory (RH) Wilde (1982) for evacuation decision-making during volcanic eruptions. RH suggests that individuals have a target level of risk they are willing to accept, and their behaviour adjusts in response to perceived changes in risk. For example, if people feel safer due to precautionary measures, they may take more risks, maintaining their personal risk threshold. The model combines system dynamics (SD) and ABM to simulate individual risk perception and acceptance levels influenced by vulnerability, trust, knowledge, and community sense. The research, focused on the 2008 Chaitén eruption in Chile, reveals how psychosocial factors and individual decision-making processes impact evacuation outcomes. In terms of warning strategy, Van Der Wal et al. (2021) explored evacuee responses to different emergency communication strategies using ABM. They tested the impact of dynamic emergency exit floor lighting, staff guidance at exits, and public announcements in English on evacuation efficiency in transport terminals with diverse crowd compositions. The findings suggest that dynamic lighting and staff guidance improve evacuation times in high-density situations and for individuals unfamiliar with the environment. At the same time, English announcements had mixed effects depending on the crowd's language proficiency. Their research highlights the importance of tailoring emergency communications to crowd characteristics for better evacuation outcomes. Many simulations for crowd evacuation scenarios exist. However, to our knowledge only Lovreglio et al. (2016) include pre-evacuation behaviour in their model. They simulate cinema theatre evacuations by applying behaviour theories to predict actions across three states—normal, investigation, and evacuation—factoring in perceived risk within evacuation scenarios. Their model incorporates the influences of environmental- and social cues, demographics, personal characteristics, and behavioural uncertainty. However, agents were moving during the evacuation decision process. Unlike disaster simulations that often incorporate some aspects of psychological models for disaster response, crowd evacuation simulations have typically not utilised these frameworks. This oversight highlights a significant research gap in understanding the protective action decision process for large-scale events, which could differ markedly from more commonly studied scenarios such as hurricanes, tsunamis, and building evacuations. As highlighted, ABMs have been instrumental in this domain, offering a 'laboratory environment' for testing various parameters, creating hypothetical scenarios, and determining the level of detail necessary to predict crowd behaviour accurately. This research aims to explore the trade-off between the informativeness and length of warning messages within the context of crowd evacuations, acknowledging that findings from other disaster scenarios may not directly apply due to the unique dynamics of large-scale event movements. Identifying gaps in current models, particularly in the context of large-scale events, guides our methodological approach to developing a more nuanced ABM that integrates key aspects of effective warning messages and psychological behaviour models.

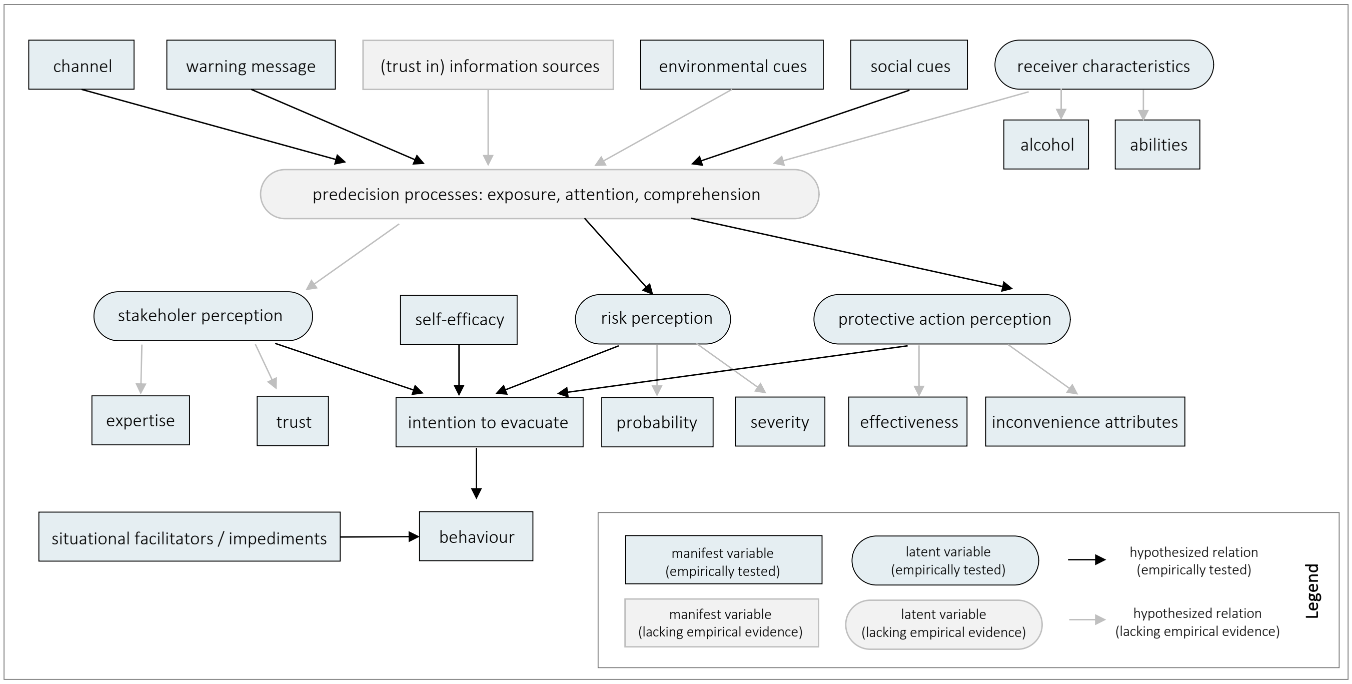

Figure 1. Extended PADM Model The model by Lindell & Perry (2012) contains factors influencing the choice of behavioral response to threats. Self-efficacy is added from the PMT (Maddux and Rogers, 1983). In this graph, boxes represent variables and circles latent variables (constructs). Arrows represent (hypothesized) relations. Boxes, circles and lines in blue are variables based on the model with empirical evidence, whereas boxes, circles and lines in grey are lacking empirical evidence.

3. Materials and Methods

Building on the insights gained from our literature review, we outline our methodological framework designed to refine evacuation simulations by integrating the processing of warning message strategies and a disaster response-related behavioural model.

The selection process for the underlying theoretical model that guides our ABM development was conducted in the following way. Given the complexity of evacuation behaviour during large-scale events, we prioritised models that account for individual and collective dynamics. After conducting a systematic literature review using keywords such as 'Event evacuation,' 'Protective action decision,' and 'Evacuation behaviour' in Google Scholar and assessing the psychological models in the first 10 results, we determined the Protective Action Decision Model (PADM) to be most fitting. This choice was because the PADM was the most frequently mentioned model and had empirical support for the parameters involved. Unlike PrE, which focuses narrowly on individual perceptions of event proximity, PADM considers factors influencing the evacuation decision.

Despite EPPM appearing in relevant literature (Heath et al., 2018), its limited mention suggested a narrower applicability for our purposes. Additionally, many of its factors also appear in PADM, missing only fear and self-efficacy. RH theory, while prominent in studies of driving behaviour (Wilde, 1982), is rarely applied in disaster contexts, though its concept of risk tolerance has been used in some simulations of evacuation behaviour (Favereau et al., 2020) . PMT might also be valid in the context of acute disasters (Chenoweth et al., 2009), but many variables are already part of the PADM. Thus, our ABM is mainly based on the PADM, enhanced by elements of RH and PMT, to accurately simulate evacuation decisions. We extend the PADM to include self-efficacy (PMT and EPPM) and risk tolerance (RH) as additional agent properties. The remaining properties related to the PADM are social- and environmental cues, warning message, receiver characteristics (alcohol and hearing/ seeing ability), pre-decision processes (exposure, attention, and comprehension), risk perception and trust in information sources. In this first version of our simulation, channel is omitted since for now we only have one information channel, namely screens as warning devices. A graphical representation of our extension of the PADM is depicted in figure 1 and an explanation of the variables is provided in table 2. In the ABM, we further simplified the model by excluding protective action perception under the assumption that all participants agree that an evacuation is necessary. Stakeholder perception was also not included, as we could not find any supporting empirical evidence in the literature. Situational facilitators are implicitly modelled through motive-based action selection.

3.1. Warning Representation

Since we aim to quantify the effects of warning messages, we require a numerical representation of their informative-

Table 2. Factors Influencing Emergency Response

Parameter	Description	Sources
Channel access and preferences	Where do people get their information from during an emergency? (staff, family and friends, strangers, news)	Lindell and Perry (2012); Fujimoto et al. (2020); Strahan and Watson (2019); Zeng et al. (2019)
Warning message	Did people perceive the warning message?	Lindell and Perry (2012); Fujimoto et al. (2020); Strahan and Watson (2019)
Information sources	Perception of person/group/institution disseminating the warning message (trustworthiness)	Lindell and Perry (2012); Fujimoto et al. (2020)
Environmental cues	Sights, smells, or sounds that signal threat	Lindell and Perry (2012); Fujimoto et al. (2020); Strahan and Watson (2019)
Social cues	Observations of other people’s behavior (e.g., evacuation, milling)	Lindell and Perry (2012); Fujimoto et al. (2020); Mileti and Fitzpatrick (1992)
Receiver characteristics	Abilities (hearing and seeing), intoxication level	Lindell and Perry (2012); Beckmann et al. (2021); Zeng et al. (2019)
Predecision processes	Exposure and attention to and comprehension of cues and messages	Lindell and Perry (2012); Fujimoto et al. (2020)
Risk perception	Perceived likelihood of being personally harmed by threat and perceived severity of threat for personal health and finances	Lindell and Perry (2012); Fujimoto et al. (2020); Heath et al. (2018); Strahan and Watson (2019); Chenoweth et al. (2009)
Stakeholder perception	Trustworthiness and perceived knowledge of stakeholders (event organizer, staff, emergency service, family/friends...)	Lindell and Perry (2012); Fujimoto et al. (2020); Liu et al. (2019)
Protective action perception	Perceived effectiveness of possible behavioral responses and their inconvenience attributes (costs, required knowledge, skills, time, effort, and cooperation)	Lindell and Perry (2012); Fujimoto et al. (2020); Strahan and Watson (2019); Terpstra and Lindell (2013); Liu et al. (2019); Chenoweth et al. (2009)
Situational facilitators/impediments	Factors influencing situational factors (action before warning, group)	Lindell and Perry (2012); Fujimoto et al. (2020); Rasmussen and Wikström (2022)
Intention	Intention to engage in protective action	Lindell and Perry (2012); Fujimoto et al. (2020); Albarracín et al. (2001); Becker et al. (1995)
Self-efficacy	Confidence in own abilities	Maddux and Rogers (1983); Beckmann et al. (2021); Chenoweth et al. (2009)
Risk tolerance	Level of risk the individual is willing to accept	Wilde (1982)

ness. Drawing from Wood et al. (2018), we identify 10 key attributes that constitute an effective warning message. To automate the scoring of warning messages, we are compiling a database of KatWarn messages, each annotated for content based on these attributes using ChatGPT’s assistance. Firs ChatGPT was provided with thre examples of how a warning messages should be annotated and then for each attribute ChatGPT was asked wheter the given information is present in the warning messages. This database is used to fine-tune a pre-trained transformer model, such as BERT (Devlin et al., 2019), creating a ’warning message encoder’ that evaluates message informativeness, as depicted in figure 2.

3.2. Agent-Based Model of Large-Scale Events

As aforementioned, ABMs are well-suited for simulating protective action decision-making during crowd evacuations at large-scale events because they can account for the complex interactions and heterogeneity among individuals. ABMs allow for the modelling of individual behaviours based on specific rules, simulating how different factors (e.g., risk perception and social influence) affect each agent’s decisions. This approach is particularly effective in capturing the dynamic nature of crowds, where individual decisions and interactions can lead to emergent behaviours not predictable from the aggregate. Our model delineates two primary states for agents: "normal" and "emergency." In the normal state, agent behaviour adheres to the specifications outlined by Meyer et al. (2024), with actions driven by individual characteristics such as age, gender, or fitness level, and immediate needs (e.g., thirst) dictating movement towards specific goals (e.g., the nearest drinks stall). This framework is expanded to encompass "sense of safety" and "information" as additional motives in the emergency state, prompting evacuation or information-seeking actions, respectively. Transition to the emergency state is triggered by the perception of a warning message or exposure to environmental or social cues, with these newly introduced motives diminishing based on PADM-derived principles.

3.2.1. Information Processing

Before information can be processed, a warning message needs to be perceived first. The perception probability is computed using a physical model which calculates how well a warning message can be seen depending on an agent’s relative location to the warning source. Each message w is represented as a 10-dimensional vector (i.e. n = 10) derived from the attributes listed in 1 with values ranging from 0 to 1 indicating the presence and extent of

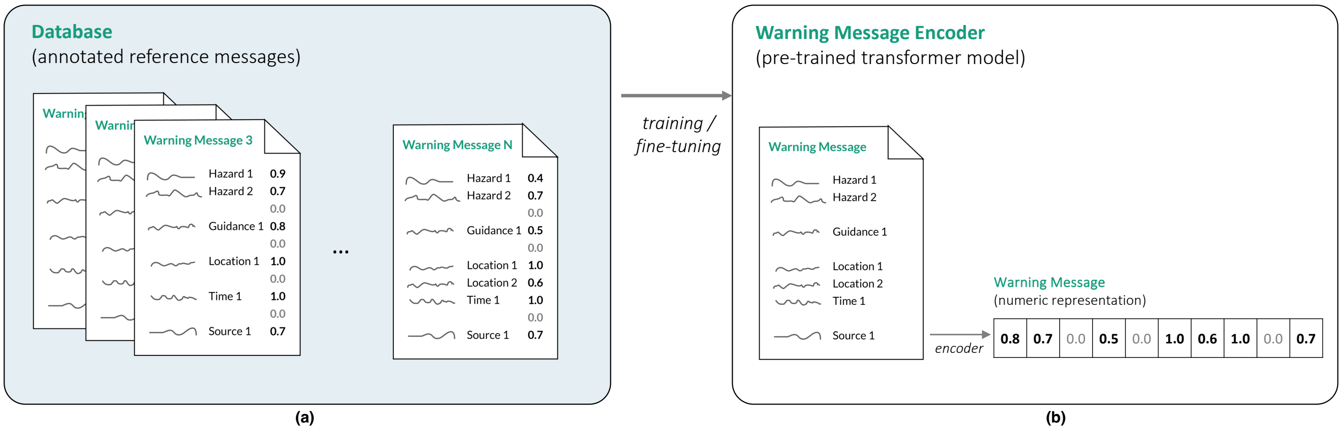

Figure 2. **(a)**: Conceptual depiction of annotated warning message database **(b)**: Visualization of warning message encoder input and output

these attributes, where 1 signifies maximum informativeness.

$$w = (w_1, w_2, \dots, w_n), w \in \mathbb{R}^n \text{ where } w_i \in [0,1] \tag{1}$$

Each agent A has an attention capacity, denoted by λ, which ranges between 0 and the length of the warning message l. This value is drawn from a beta distribution on the assumption that most participants have a similar attention capacity, processeing most of the information. This will later be adapted after obtaining further experimental values. The attention will be modeled differently depending on whether the source of the warning message is audio or visual. Attention for an audio warning message is modeled by a window which represents the length of the warning message received, where the starting point i is randomly sampled:

$$w_A = (w_i, \dots, w_{(i+\lambda)}) \tag{2}$$

This is based on the hypothesis that once an audio warning message is received, attention is sustained for a specific length of time as shown in figure 3. For visual warning message information parts are randomly sampled with the protective action recommendation having a higher probability of being selected, reflecting the ability to selectively process written information. This exact representation of a warning message allows us to simulate in detail what information agents can exchange when they enter the milling process. Furthermore, we derive an informativity score defined as:

$$\text{Informativity} = \frac{\sum_i^{(i+\lambda)} w_A}{l_{\text{ideal}}} \tag{3}$$

Where l_{ideal} is the length of an ideal warning message i.e. 10. In the case of a repeated perception of the warning message ($n_{\text{perceived}} > 0$), unreceived parts of the warning messages are sampled as a starting point (stp) with higher probability, depending on the information motif M_{info}:

$$P(stp = i) = \begin{cases} 0.5 & \text{if } n_{\text{perceived}} = 0 \\ 1 - (w_i + M_{info})/2 & \end{cases} \tag{4}$$

Furthermore, an agent shares his knowledge of the warning message with other agents in their proximity with a certain probability depending on how "extroverted" they are.

3.2.2. *Decision Process*

We simulate different reactions after the first reception by incorporating the perceived warning message with other factors relevant to the PADM. For now, the functional relationships between influencing parameters are assumed to be in a weighted linear relationship but can be replaced with different functions after further empirical evidence has been retrieved or to test alternative theories. For readability reasons, we omitted the weights in all the equations hereafter. We model the parameters by equipping each agent with the corresponding properties. Environmental and social cues, denoted cue_{env} and cue_{social} respectively, are both represented as binary variables where 0 and 1 signal the absence or presence of the corresponding cue, respectively. If an agent is in the receptive proximity of either of these cues then the variable is set according to a specific probability:

$$p(\text{cue} = 1) = 1 - \frac{d_{ij}}{(d_{\max} + 1)} \tag{5}$$

Where d_{ij} is the distance of an Agent i to a cue j and $d_{\max}$ is the maximum distance, a cue is considered to be perceptive from. All the other properties are represented on a continuous scale ranging from 0 to 1. While some properties are dynamically changing (i.e. environmental cues, social cues, alcohol), depending on how the agent interacts with their environment, others are static and are initialized according to distributions derived from survey data

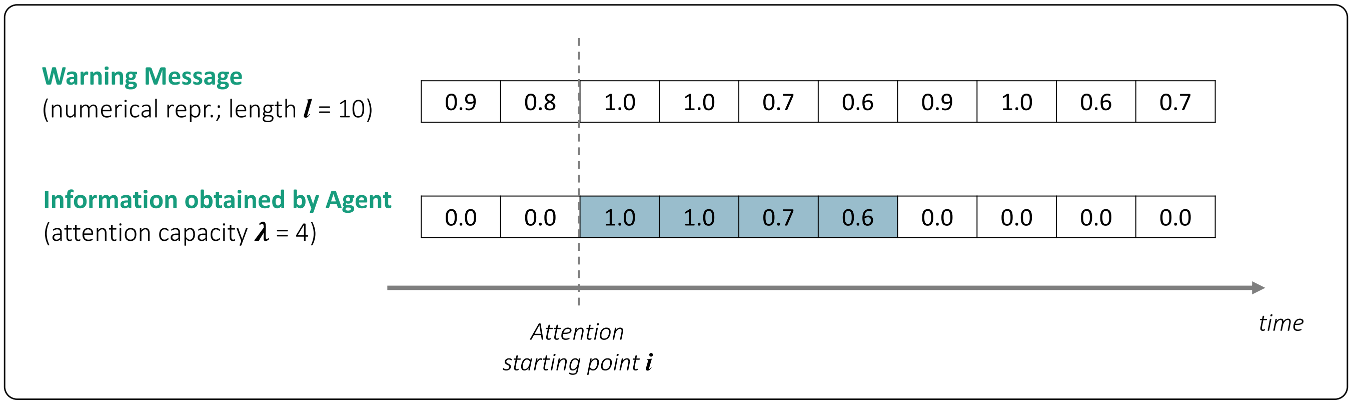

Figure 3. Example of information obtained by an Agent with attention span 4

(i.e. trust in information source, abilities) which will be collected in the future. Based on the hypothesis that if an environmental cue or social cue is present an agent has heightened attention and that alcohol consumption inhibits attention abilities, attention for an Agent A is calculated the following way:

$$\lambda_{At} = \lambda_{A_{t-1}} + cue_{env} + cue_{soc} - (1 - sober) \times \lambda_{A_{t-1}} \tag{6}$$

Furthermore, it is assumed that if environmental cues are present (i.e. $cue_{env} = 1$), then an agent is aware of the hazard type, and the corresponding value in the warning message array is set to 1. Receiver characteristics such as language fluency ($lang$) are considered by multiplying the representation of the received warning message with the corresponding value. Trust in the source ($trust_{source}$) is taken into account in the same manner. The received warning message then becomes a function of the original warning message, attention and the other agent attributes:

$$w_A = trust_{source} \times lang \times (w_i, \dots, w_{(i+\lambda)}) \tag{7}$$

One main aspect of the warning message is the protective action recommendation w_{pa}, if an agent has been able to retrieve this information, then the agent is informed and the value for the information motif $M_{info} \in (-1;1)$ is computed as follows:

$$M_{info} = \begin{cases} score_{info} - (cue_{soc} + RP)/2 & \text{if } w_{\mathrm{pa}} > 0 \\ -1 & \text{if } w_{\mathrm{pa}} = 0 \; \& \; cue_{soc} = 1 \end{cases} \tag{8}$$

Representing an increased need for information when perceiving social cues. This is in accordance with Mileti and Fitzpatrick (1992). Similarly, the higher the perceived risk of an agent the stronger the need to gather additional information, in accordance with findings in (Mileti and Fitzpatrick, 1992; Fujimoto et al., 2020). If an agent is subjected to social cues and has not learned about the protective action w_{pa}, then the information motif is -1, thus causing the agent to pick the action "information seeking". Furthermore, M_{info} is normalised such that $M_{info} \in (0;1)$. Risk perception is computed as a result of the prediction process in the following way:

$$RP = (score_{info} + cue_{env})/2 + \left(1 - \frac{1}{n_{soc} + 1}\right)cue_{soc} \tag{9}$$

Where n_{soc} represents the number of times a social cue has been perceived. Finally the decision to evacuate is made when the risk perception is above an individuals risk threshold, similarly to Ramos et al. (2022). Equation 9 implies that frequent exposure to a social cue will eventually lead to an evacuation decision.

4. Simulating the Hamburg Harbour Festival

As an example of a large-scale event, we modelled the annual Harbour Festival in Hamburg, Germany. The festival takes place in the area surrounding the port, including the waterfront and various venues along the Elbe River. It features various activities such as ship parades, live music performances, fireworks, food and drink stalls, and cultural events. The Hamburg Harbour Festival attracts many visitors each year and is considered one of the biggest port festivals in the world. For the model, we represented only a section of the whole area around the public transport station "Landungsbrücken" (upper right in figure 4). This area contains several attractions for visitors, including a stage (green rectangle in figure 4) and access to the waterfront via several footbridges (bottom of figure 4). To model evacuation communication, we position several warning devices across the modelled area and compute their perceptibility range, indicated by the regions coloured in shades of blue. Agents within this range can perceive the warning message issued by the device. Agents enter the area from several entry/exit points at the area's borders. They then move towards targets such as food stalls, the stage, or a different exit point utilising physics-based pedestrian movement and a needs-based action selection mechanism. Similarly, after an evacuation warning message is emitted,

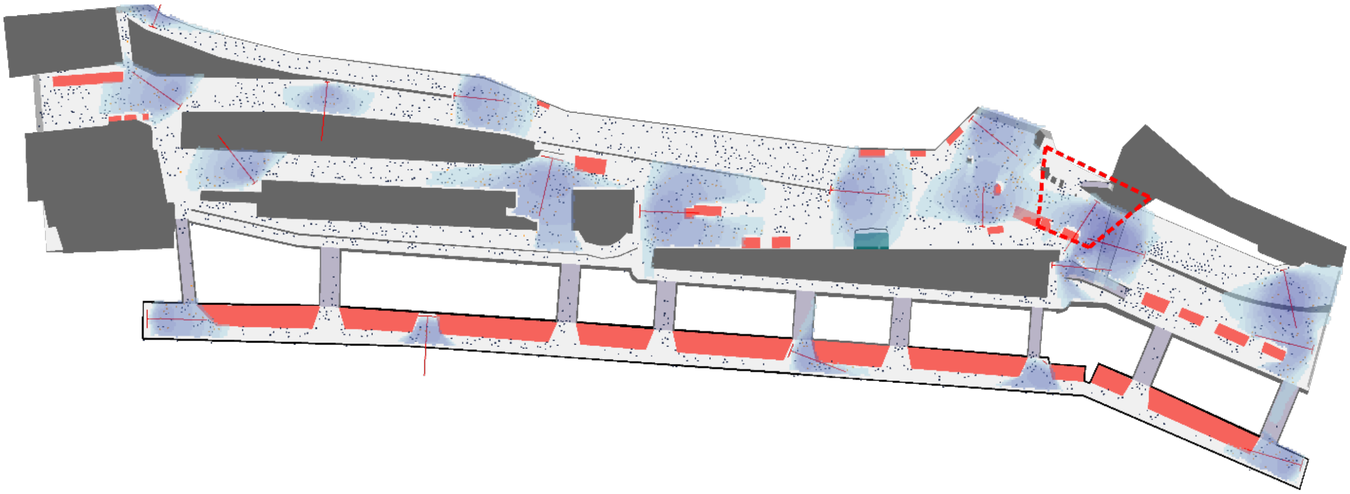

Figure 4. Snapshot of the ABM of the Hamburg Harbour Festival with agents (persons) depicted as little dots. The area comprises buildings (dark grey), stalls (red) and a stage (green). Visibility of information displays is rendered in shades of blue.

agents begin to evacuate or seek additional information. This implementation is the first simplified version of the introduced framework, including a binary warning message perception, information seeking and -sharing, displays as warning devices, hunger, thirst, entertainment and rest as needs. We hypothesise that

1. unlike in the scenario of a natural disaster, the message informativeness is less important for reducing evacuation delay, and short and concise messages are more effective;
2. The location and quantity of warning devices are most impactful in reducing evacuation delays;
3. Including an information and decision process leads to more accurate evacuation times than employing a simple multiplier effect.

5. Conclusion and Future Work

Our work has established a foundational framework for integrating warning message informativeness and disaster response models into agent-based modelling (ABM). With the aim of investigating to what extent warning message informativeness plays a result in evacuation outcome in a dense and interactive environment where both environmental- and social cues are frequently encountered. Recognising the current model's limitations, especially its reliance on theoretical assumptions over empirical evidence, we outline several directions for future enhancement: We will use the model to explore scenarios under varied assumptions about the functional relationships between variables. This will help us understand the model's dynamics under different conditions and demonstrate its adaptability to various emergencies. Sensitivity analyses are crucial to identify which parameters significantly affect the model's outcomes. This step will direct our empirical research efforts to refine these parameters and inform the required complexity of the model. To move beyond simple linear assumptions, we plan to collect data through surveys and virtual reality (VR) experiments. This data will help us refine the parameters' mathematical representation and validate the model's realism. Qualitative feedback from experts experienced in event evacuations will externally validate the model's utility and realism. While our model presents an approach to simulating evacuation scenarios, it has limitations. One significant challenge is accurately capturing and validating individuals' risk perception, particularly in experimental settings such as VR, which can feel artificial to participants. Furthermore, the opportunity to validate our model against large-scale events involving real emergencies is rare, complicating efforts to test and refine our simulations against actual outcomes. Currently, our model's assumptions, especially concerning the functional relationships between parameters, are largely theoretical. The lack of empirical evidence for these relationships underscores the necessity of our planned future work, emphasising the importance of grounding these assumptions in solid empirical research.

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