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# Enhancing evacuation safety in urban primary schools: an agent-based model integrating child development behaviour and health dynamics

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A R T I C L E I N F O

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A B S T R A C T

Primary schools require specific evacuation plans considering children's developmental vulnerabilities, but current models frequently overlook children's behavioural and health dynamics. Our proposed reliability-driven agent-based modelling (ABM) framework incorporates the Theory of Planned Behaviour (TPB) for decision-making and Dose-Response Model (DRM) for quantifying health hazards associated with smoke exposure, aiming to close this gap. Using real-world evacuation data from an urban primary school, we simulate risk scenarios to assess interactions between evacuation efficiency, environmental risks, and safety regulations. Results show that smoke density significantly affects system reliability, increasing evacuation time by 43.94% (±0.834) and decreasing evacuee health by 76.83% (±0.735) in the worst-case scenario. We found that more adult guides during evacuations could compensate for students' unpreparedness. However, teacher placement's efficacy and interaction vary greatly depending on smoke patterns. This outcome highlights the need for contingency-based evacuation plans customised to different environmental circumstances and acknowledges the challenges in evaluating the effectiveness of school evacuation strategies. This work contributes to schools' system safety by offering adaptive solutions for dynamic risks, emphasising the importance of child-specific reliability specifications in school emergency planning. The framework offers practical ideas for urban resilience, enabling organisations to mitigate health hazards and enhance the safety of critical infrastructures in uncertain environments.

## 1. Introduction

In the urban context, where high population density can exacerbate situations, the capacity to evacuate quickly and in an orderly manner is critical to reducing hazards and improving safety. Therefore, getting a deeper understanding of mass evacuation is of significant importance. Human reactions to emergencies can be evaluated through two stages: a) evacuation decision-making and b) the individual's evacuation movement. Evacuation decision-making is initiated from the first moment of reacting to a hazard [1] and ends once the evacuee chooses their way of escaping the hazard. This process, therefore, can be influenced by evacuees' personality features, built environment, and hazardous nature [1,2]. Afterwards, evacuees' movements and their interactions with each other, the environment, and hazards would significantly influence evacuation efficiency [3,4]. Individuals' evacuation movements are often evaluated through advanced data collection methods, such as recorded experiments, and yield rich databases of movement dynamics across various age groups [5–8] and evacuation scenarios [9–11].

In recent years, hybrid methodologies have advanced the accurate assessment of evacuation risk. *Chu* et al. *(2019)* propose an evacuation simulation system for Shanghai's residential emergency management [12]. This system linked residential complexes' indoor and outdoor components to residents' demographic and geographical attributes, improving evacuation efficiency. Other studies have combined failure model analysis with Bayesian networks for maritime evacuation simulations [13]. Scholars also merged traffic flow models with radiological dispersion simulation to better anticipate the effectiveness of emergency response [14]. An innovative study employed fire dynamics simulation alongside with active dynamic signage system to communicate real-time optimal save paths with evacuees [15]. Another study developed an urban disaster evacuation simulation model using human psychology models [16]. *Battegazzorre* et al. *(2021)* present a novel framework,

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IdeaCity, in which ABM is used in large-scale seismic evacuation simulations to model the built environment and transportation network system [17]. Tested in a town of Turin in Italy, the model could estimate the building damage and debris caused by earthquake scenarios and evaluate the interactions between the built environment, people and emergency management service capacities in the town. Later, this model was further expanded by adding a panic behavioural layer, which highlights the necessity of considering humans' psychology in massive evacuation simulations to obtain more accurate predictions of the sequences [17]. Studies also integrated building information modelling and virtual reality to simulate a fire accident on a campus, advancing this field of research by incorporating top-notch technologies and the use of computational fluid dynamics in modelling the impacts of fire emergencies on the evacuation process [18]. Nevertheless, these models prioritise adult populations and infrastructures, overlooking children's behaviour and psychological vulnerabilities. There exist some studies like *Luan* et al. *(2025)* [19] which aims to develop an enhanced Extreme Learning Machine model for rapid evacuation risk assessment in educational institutions, emphasising its importance in mitigating congestion and trampling to enhance safety and emergency response effectiveness. However, the study consisted of college students with adult-like physical and mental characteristics.

In the school setting, where children make up a significant proportion of the population, underdeveloped cognitive, physical and emotional capabilities can greatly influence evacuation behaviour. This matter is more critical in young children [6,8]. Engineers of evacuation systems still face the significant challenge of designing reliable protocols considering children's decision-making processes and health vulnerabilities. Tailored models incorporating these vulnerabilities improve evacuation safety and inform scalable measures for educational institutions during emergencies. Our research addresses this deficiency by including the Theory of Planned Behaviour (TPB) and the Dose-Response Model (DRM) within the Agent-Based Modelling (ABM) framework, thereby enhancing methodologies employed in maritime evacuation risk assessment [13], chemical plants toxic gas leakage accidents [20], and radioactive emergencies [14]. However, we highlight children's behavioural thresholds and health deterioration due to smoke exposure and use evacuation drill data to confirm the model's reliability. TPB could account for the reasons behind children's evacuation behaviour and incorporating the DRM into the modelling framework allows us to establish a scientifically grounded framework for modelling the health dynamics of evacuees during an emergency evacuation. This study then applies the modelling framework to simulate children's evacuation behaviour and safety dynamics on the first floor of a selected primary school.

The main contributions of this work are: a) introducing a new modelling framework to simulate children's evacuation under emergency, enhancing the reliability of evacuation protocols for cognitively developing population, b) including a dynamic track of smoke exposure on children's health and addressing a critical gap in evacuation studies prioritising adult population, c) providing actionable evacuation safety strategies based on hazard dynamics which can be scalable strategies to optimise school safety. The remaining sections of the paper are organised as follows: The contrasts and relevance of prior research to this work are discussed in Section 2. Next, Section 3 provides a brief background and lays the foundation for understanding the research framework. Section 4 describes the framework details, followed by simulation results in Section 5. Section 6 delves into discussions and provides strategies for future work, and the paper concludes with the study's concluding remarks in Section 7.

## 2. Related works

### 2.1. Advancements in emergency evacuation studies

Modelling human evacuation is challenging due to the complexities in representg the elements that influence human collective behaviour during emergencies [21]. Algorithms used to study human evacuation behaviour, such as Dijkstra's [22], colony optimisation [23], and Depth-First Search, have limitations in accurately depicting complex human behaviour because they ignore psychological factors and population relationships. Later, advances in computer processing capacity led to the emergence of the social-force model in 1995, one of the most well-known models for modelling pedestrian evacuation [24]. While social force models capture some aspects of human psychology and have been extended later, they often assume a homogeneous population to simulate human behaviour and are difficult to implement due to several nonlinear equations [21].

Cellular automata and ABM are the most widely employed microscopic models in evacuation research. Although cellular automata models can offer relatively suitable solutions for the complexity of human social systems, their limitations in capturing agents' free movement [25] make ABM a more compelling tool [26]. Some studies in the field of evacuation simulations expand the ABM features by defining that crowd behaviour should be considered within three levels: Individual behaviour, interactions among them, and group behaviour [27]. Another study unveiled several social interactions in the context of agent-based evacuation models, illustrating the intricate social interactions and decision-making during evacuation [28]. Studies also considered GIS-based data [29], demographic and movement dynamics of agents [30], disaster knowledge and the emotional cognition effects imposed by civilians and authority figures [31], and the effects of vehicles' presence on pedestrian decision-making [32,33] to model evacuation scenarios by ABM.

Despite the previous attempt to study human evacuation behaviour, the difficulty of considering complex factors affecting individuals' behaviour and the lack of social and behavioural theories [34] leads to ad-hoc approaches to identifying human behaviour in simulation studies [35,36]. To blend social and cognitive features with physical evacuation modelling, studies applied the Belief-Desire-Intention model in ABM and evaluated the effect of proper guidance on the efficiency of crowd evacuation [4,37–39]. Evacuation decision-making has also been explained by the Emergency Decision-Making Strategy [1]. Health Belief Model has been employed to assess disaster preparedness [40,41]. Another study applied an extended TPB to explore how risk perception influenced disaster preparedness behaviour [42]. Researchers also utilised cognitive mapping to develop wayfinding algorithms integrating ABM to simulate various levels of spatial awareness [43] and to present a more realistic approach to wayfinding [44]. The Social Identity Model has also been employed to predict pedestrian movement during emergency evacuations [45]. Crowd behaviour in poisonous gas release and fire accidents was modelled in recent studies using the OCEAN personality model and Social-Learning Theory, respectively [46,47].

### 2.2. Research on children's emergency evacuation

Due to psychological and physical differences between children and adults, scientists have employed simulation approaches to examine children's evacuation behaviour in numerous ways. The first group of studies has contributed to how individuals' characteristics and interactions impact evacuation time and speed [48,49]. Secondly, the effects of the built environment on students' evacuation behaviour have been focused on [50,51]. Simulations of recent seismic evacuations, such as those of a middle school in Sichuan province during the 2008 Wenchuan earthquake [50] and a primary school affected by the 2014 Ludian earthquake in China [51], have examined how the layout designs of these schools affect evacuation times. Thirdly, the geometric features of schools and classroom layouts have been explored in combination with individuals' characteristics and interactions [52–55]. A unique study used video drills to replicate children's evacuation, but the model failed to account for children's interactions with the built environment and the emergency [56].

Despite notable progress, prior research on evacuation simulation of children has been somewhat constrained, often focusing on specific factors such as agent types, social dynamics, and school layouts. Schools, where children spend most of their time, are often crowded places where one-by-one accompaniment by an adult during an emergency is not practical. The studies frequently focus on single-room evacuations or vertical/horizontal evacuations [57–59], overlooking the modelling of evacuations for entire building floors. On the other hand, children's evacuation is more chaotic than that of adults due to physical and psychological differences, which impose greater risks to their safety [60]. Although studies attempted to understand the movement dynamics of children considering body size, age, gender, and various built environment features [61,62], the limited availability of empirical data on the evacuation behaviour of young children constrains simulation studies. Lastly, implementing structural changes in already constructed schools can be expensive and impractical. Thus, secondary safety-enhancing measures, such as trained teachers and students, are needed to mitigate risk factors arising during emergencies and require further study [63]. Therefore, there remains significant potential to fully leverage the benefits of evacuation simulation tools, particularly ABM, to provide sufficient evacuation safety protocols designed explicitly for children's characteristics.

## 3. Background

Modelling children's evacuation environments necessitates designing a science-based modelling framework. In this study, we integrate TBP to provide a logical decision-making mechanism. Combining a health-simulating model with evacuation time and dynamics in school evacuations offers more profound insights into unexpected events. DRM has then defined the hazard's health impacts to simulate more realistic health outcomes in emergency scenarios.

### *3.1. Evacuation decision-making mechanism and theory of planned behaviour*

TPB is a psychological framework explaining how individuals' behaviour is influenced by "individuals' attitude", "subjective norms", and "perceived behavioural control" [64]. Several studies have successfully used TPB to model intentions related to evacuation decisions and disaster preparedness behaviours [4,35]. It provides a structured framework through its core constructs—attitudes, subjective norms, and perceived behavioral control—to represent evacuation decision processes. While TPB may not fully capture the dynamic, high-stress, and heuristic-driven behaviors during real-time evacuations, it remains a valuable tool for modeling the intentional aspects of evacuation decisions. Integrating TPB enhances behavioral modeling by linking intentions to actions, and our approach incorporates these cognitive dimensions while acknowledging the need for future work to address evacuation's full complexity.

The term "attitude" describes a person's views of the results or repercussions of behaviour, which societal influence, personal values, and life experiences can influence. In the context of emergency evacuation, individuals' attitudes towards emergencies may include beliefs regarding the possible harm or danger they pose. Previous studies showed that under low visibility, pedestrians are more likely to follow neighbours, assist each other, and navigate along obstacles [65]. Another study revealed that when visibility is limited, pedestrians follow specific movement patterns, such as searching for walls and interacting differently with others, influencing their evacuation strategies and distances travelled [66]. A recent VR-based study also illustrated that individuals' risky decisions during fire evacuation are associated with their risk tolerance, smoke density, and neighbours' behaviour [67].

The second element of TPB refers to perceived social pressure or influence from others that affects individuals' intentions and behaviour. Researchers have also examined the possibility of using emotional contiguity and intimacy as predictors of evacuee decision-making [68]. *Luan* et al. *(2025)* proved that structured guidance (vs free evacuation) could reduce passengers' risky behaviour in escaping through airport terminals [19]. Given the children's inadequate psychological capacity to meet their demands during emergencies, subjective norms may influence their evacuation behaviour. The literature indicates that the relationship between adult guidance and students' evacuation choices remains inconclusive, with some studies failing to establish a significant association [69]. Meanwhile, others suggest that under emergency conditions, evacuation patterns become imbalanced when children evacuate without adult guidance [69]. However, research confirmed that children responded more immediately to adult instructions than to the warning system [70].

The third component of TPB pertains to an individual's confidence in their ability to execute an activity successfully. Evacuation training helps enhance this confidence by teaching people the necessary skills for effective evacuations [71–74]. On the other hand, behavioural rationality is crucial in children's evacuation efficiency, reflecting how they make logical decisions during evacuation [49]. Similar studies on behavioural modelling with a focus on human psychological factors in evacuation simulations integrated rationality and its influence on evacuees' decision-making [39]. Moreover, in emergencies, stable group formations may be disrupted [75], leading individuals to exhibit herd behaviour, particularly among young children [74,76]. Subsequent studies explored this phenomenon by simulating a specific group of agents known as "herders", characterized by distinct route selection behavior [77].

### *3.2. Evacuation movements and dynamics facts*

Previously, a clear and strong association between evacuation speed and the age of children has been found; as the age increases, the evacuation speed also increases [78,79]. Studies also identified evidence demonstrating the considerable influence of teachers' guidance on students' emergency response time [60,79,80]. Additionally, individuals typically form groups based on their social connections, and the characteristics of these groups directly influence walking velocity [81]. Literature evidence indicates that children evacuating in groups of two or three experience longer evacuation times. This fact is due to increased delays stemming from the larger proportion of students exhibiting group behaviour and the size of the groups [82]. Research also revealed that unobstructed corridors and suitable desk configurations in classrooms significantly enhance evacuation efficiency [83]. Reduced visibility and its impact on evacuation speeds is another crucial element, where, due to the lack of data on children's evacuation speeds during reduced visibility, we had to rely on adult speed data to understand evacuation dynamics better, specifically evacuation speed, time, and exit follow [75,81]. On the other hand, a virtual reality study proved that people would try to avoid smoke sources, potentially increasing evacuation time [84]. The experiments also demonstrated that walking speed decreases from 0.63 to 0.4 as smoke density varies [81]. Another related study showed that ideal visibility enhances rapid and confident mobility, but low visibility requires cautious navigation, possibly resulting in delays as individuals manoeuvre to circumvent obstructions [85]. Therefore, the children's evacuation movement can be influenced by factors such as age, teacher guidance, visibility, obstacles, and group size, with larger groups often causing delays.

### *3.3. Health risks associated with smoke*

Emergencies, such as fire accidents, can have an immediate impact on evacuees' health. Smoke exposure during fire accidents impacts the body by activating lung receptors, inducing oxidative stress and inflammation, and penetrating beyond the lungs, leading to systemic effects [86]. Research on firefighters subjected to extreme heat and physical exertion has shown that they may experience a higher risk of myocardial ischaemia, impaired vascular function, and increased blood clot formation [87]. On the other hand, in crowd disasters, as crowds grow, panic rises, creating an amplifying feedback loop and direct causes like crowd pressure, which causes falls, trampling, and fatalities [88]. With that, studies such as *Naili* et al. *(2019)* attempted to predict agents' health using ABM [89]. Later, scholars developed a spatiotemporal dynamic exposure model to determine the flood-related probability of injury or death. A hazard-human coupled model (HazardCM) is used to assess city dynamic exposure to rainfall-triggered natural hazards and the likelihood of injury or death [90]. *Zhang* et al. *(2023)* opted to identify the potential hazards of smoke and fire on human safety [91]. Another study utilised ABM to develop a social vulnerability index, predicting the health outcomes of populations exposed to Hurricane Harvey [92]. In a novel framework by *Golshani* et al. *(2025)* [15], Fractional Effective Dose model was embodied in ABM to address the coupled impacts of fire, heat, and toxic gas on evacuees' health and egress time.

However, there is a shortage of health theories incorporated into child evacuation simulation models to address dynamic interactions between exposure level, duration, and health outcomes. To close this gap, we incorporated the DRM in evacuation modelling. DRM is a key concept in toxicology and environmental health sciences that links environmental agent dose to health consequences. This strategy is based on the premise that the severity of a health effect is determined by both the intensity (dose) and duration of exposure [93].

## 4. Research methods and framework

### *4.1. Evacuation drills*

The empirical data used in building the modelling framework were collected through meticulous data analysis of six recorded video drills (listed in Table 1) conducted in the two classrooms of the affiliated primary school of the XXX. The school layout is illustrated in Fig. 1. To assess evacuation duration, speed, and student behaviour, this study adjusted the teachers' fixed locations and smoke emissions, reflecting that teachers remained stationary and did not escort students during both drills and simulations. Students received evacuation training from their teachers, whom the research team had previously educated. Hearing the warning, students began the experiment, which terminated when everyone reached the safe zone. Three smoke machines, with manufacturer-verified safety and health effects, altered visibility. The evacuation drills were recorded using 1080P HD CCTV cameras.

### *4.2. Children evacuation modelling framework*

Fig. 2 presents the ABM integrated framework, which uniquely integrates TPB for reasoning in decision-making and DRM for health-risk qualification. Empirical data on actual evacuation movements enhances the model's accuracy, ensuring that the simulated evacuation dynamics closely reflect real-world scenarios. Note that the study referred to available data from previous studies in each stage of creating the modelling framework, or the research team conducted evacuation drills. To ensure the transparency and reproducibility of the modelling process, the Overview, Design Concepts, and Details document protocol (ODD) has been followed [94]. Additionally, recognising many ABM models' shortcomings, the study followed comprehensive guidelines to verify the model's validity and alignment with real-world scenarios, as published by *Richiardi* et al. *(2006)* [95].

#### *4.2.1. Evacuation decision-making and behaviour rules*

In this work, the implementation of TPB was demonstrated to be efficient in improving simulation assumptions and operating guidelines. As shown in computational sociology and ABM, simpler models are purposefully used to show the complexity of evacuation dynamics rules [96]. This approach corresponds with the primary goal of ABM philosophy, which is building an abstracted system representation over real-world replication [97]. According to the introduction of the research background in Section 3.1, each element of TPB and its rationality in constructing the model framework is given below:

**Individuals' attitude:** As discussed earlier, fire can lead to specific evacuation behaviour different from what is observed during normal visibility evacuations. Through our evacuation drills, students exhibited hasty decision-making, initiating evacuation once smoke was introduced to the experiments (Fig. 3). Previous observations also revealed similar findings, as evacuation from school corridors showed that low visibility was the most significant factor affecting children's exit choices [98]. Therefore, in building the evacuation modelling framework, we assume that smoke affects children's behaviour and that they stay away from smoke sources. We further detailed the model assumption by referring to a study by *Fu* et al. *(2021)*, which suggested that smoke density is another important factor affecting evacuees' decision-making [67]. Hence, in constructing the ABM model, agents (students) are allowed unrestricted movement towards patches with a smoke density below 50 %. However, when encountering higher smoke density, agents opt for alternative patches while maintaining a minimum distance of three patches.

**Subjective norms:** Studies in the field of pre-announced classroom evacuation experiments set the pre-evacuation time from 8–20 s [99]. In our drills, we observed that the teacher's guidance greatly impacted students' first reactions. Teachers led students to evacuate within two seconds of hearing the warning, whereas, for those without teacher assistance, evacuation took up to 12 s (Fig. 4). Therefore, the model randomly assigned first reaction times to agents based on whether or not teachers were present in the classroom, with agents who lacked teacher guidance receiving longer reaction times.

Previous research on influential factors affecting children's evacuation time manifested the profound impact of adult mentors in the corridors [98]. This fact is confiremed by the curent stuudy's observations, as there is a significant difference in total evacuation time between drills with and without teachers guiding students in the corridors, as shown in Fig. 5. However, according to the mentioned study, the adult's guidance did not significantly influence the children's classroom exit choices ($p = 0.555$, Coefficient(B) = 0.697, Odds Ratio = 2.007). Therefore, the ABM model initially excludes teachers' influence on children's classroom evacuation escape options.

**Perceived behavioural control:** As discussed in Section 3.1,

**Table 1**
Evacuation drills set up and results.

| Experiments | Teacher numbers in: | | Visibility | Duration (sec.) | Participants | |
|---|---|---|---|---|---|---|
| | Classrooms | Corridor | | | Boys | Girls |
| *Exp 1–1* | 0 | 0 | Good | 74 | 46 | 31 |
| *Exp 1–2* | 2 | 2 | Good | 46 | 36 | 30 |
| *Exp 1–3* | 1 (classroom 1) | 1 | Good | 104 | 40 | 22 |
| *Exp 1–4* | 0 | 0 | Low | 82 | 47 | 37 |
| *Exp 1–5* | 2 | 2 | Low | 37 | 44 | 36 |
| *Exp 1–6* | 1 (classroom 1) | 1 | Low | 150 | 45 | 41 |

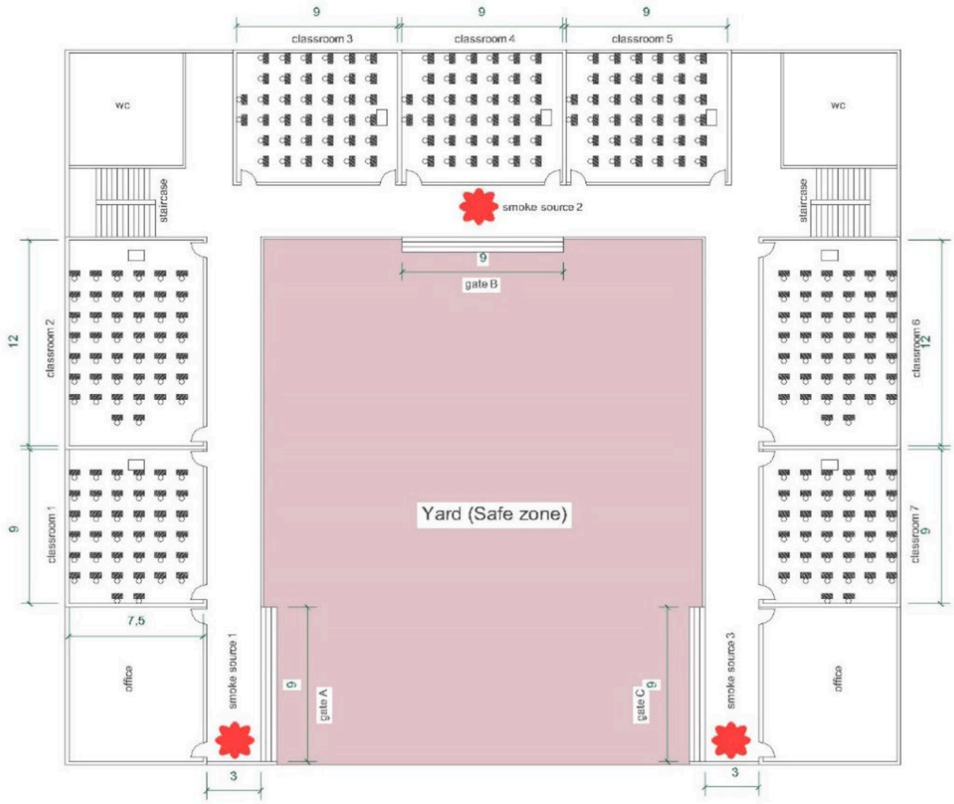


**Fig. 1.** Layout of the selected school (Dimensions are presented based on the "Meter".).

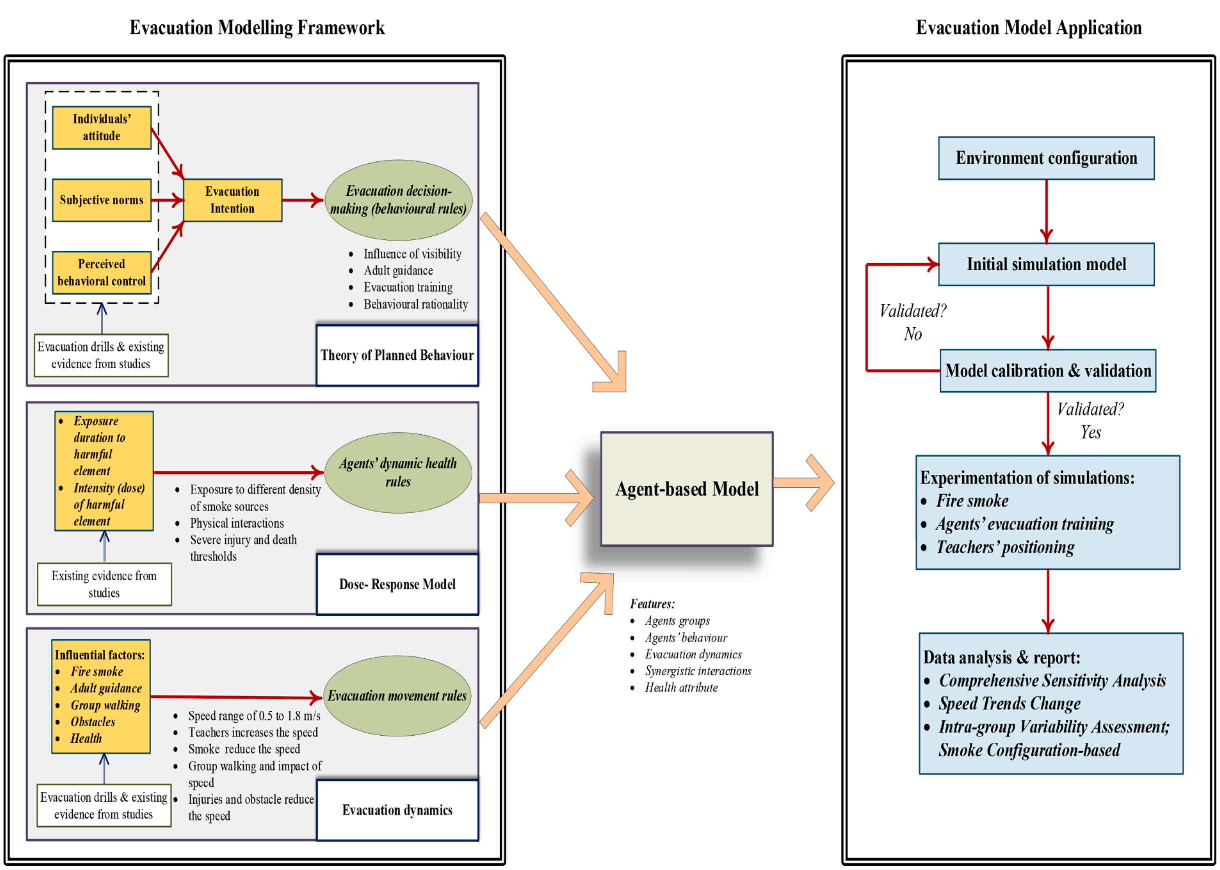


**Fig. 2.** Research framework and steps.

**Fig. 3.** Hasty decision-making in low visibility drills.

**Fig. 4.** First reaction time, Left) guided by the teacher, Right) no teacher guided.

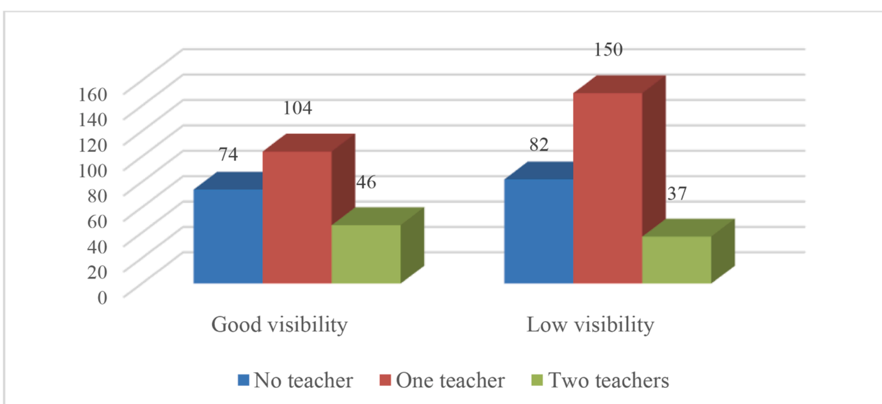


**Fig. 5.** Evacuation time categorised by adult guidance in the corridors and visibility condition.

behavioural rationality and evacuation training were considered in developing the model. Considering the influence of training on people's wayfinding and patch selection behaviour [47,100], we distinguish between two main groups of student agents: "trained" and "non-trained students". Both groups chose the nearest gate to exit, a consideration primarily found in the relevant literature [55,59,101]. While the trained students act rationally, the untrained students selfishly choose their path and movement behaviour. Trained students prioritise travel distance in their movement decisions, while untrained agents consider both the proximity to the selected gate and areas with lower population density. Given the frequent observation of peer-following behaviour through our drills, the model considered the possibility of exhibiting "herding behaviour" for both groups. However, it is essential to note that the likelihood of displaying herding behaviour is lower among trained individuals. The wayfinding behaviour of each group of agents is determined as follows:

- **Trained students** select the closest patches to the chosen gate by considering the travel distance:

$$\textit{Desired travel distance} = (D_{max} - D_i)/(D_{max} - D_{min}) \tag{1}$$

Where $D_{max}$ is the farthest distance of all patches, $D_{min}$ is the closest distance of all patches. $D_i$ is the travel distance from the target patch $_i$ to its nearest gate.

- **Non-trained students** prioritise the most appealing patch based on both the shortest distance to the selected gate and the lowest population density along the route:

$$\textit{Desired patch} = \alpha * \textit{Desired travel distance} + \beta * \textit{Desired population density}_{(min)} \tag{2}$$

Where α and β are constants that define the influence of travel distance and population density on attraction, with values α = 2 and β = 2. The "desired population density $_{(min)}$" is calculated as:

$$Desired\ population\ density_{(min)} = (P_{max} - P_i)/(P_{max} - P_{min}) \quad (3)$$

Where $P_{max}$ is the highest population density among all patches, $P_{min}$ is the lowest population density, $P_i$ is the population density of patch $_i$, computed as:

$$P_i = N_i/(2 * R + 1)^2 \quad (4)$$

Where $N_i$ is the total number of agents within the search radius, and R is the search radius.

- **Herders**, on the other hand, are attracted to areas with higher population density and are more likely to follow crowds by using:

$$Desired\ populationdensity_{(max)} = (P_i - P_{min})/(P_{max} - P_{min}) \quad (5)$$

Pushing behaviour may also emerge due to the individual's perception of a lack of control over their own movement or feeling pressed by others. Based on studies such as *Liu* et al. *(2016)* [52], this research considered identical pushing behaviour of each agent group of students. The rational behaviour of trained students will result in no-pushing behaviour, whereas a lack of evacuation training causes pushing the front neighbour among untrained students, particularly when they are waiting in a single path for more than three ticks. Herders will exhibit pushing behaviour if one of their neighbours initiates pushing. In evacuation scenarios, a brief delay often occurs as individuals cognitively process the emergency before taking action—a phase known as pre-evacuation time. This delay, which can range widely in children from 3 to 59 s [102], reflects the time needed to perceive risk and decide on appropriate responses. Observations from our drills and other studies [103] show that children typically start by following instructions and may only exhibit pushing behaviour after about a 3-second pause when movement is impeded or crowding increases. To realistically capture this, our model incorporates a fixed 3-second delay before pushing behaviour initiates, balancing empirical evidence with model simplicity. Fig. 6 provides a dynamic view showing the events' sequence that characterises the simulation experiment. Note that, apart from the previously mentioned rules, all agents are programmed to avoid collisions and obstacles.

#### 4.2.2. Evacuation movements

In this study, we adopt a speed range of 0.5 to 1.8 m/s, derived from experimental studies investigating the evacuation speeds of children aged 6 to 9 [78,79]. However, given the environmental factors, evacuees' speed can change. According to a recent study on children's evacuation speed and density, teachers' guidance in the school corridors positively and significantly impacted children's evacuation speed [104]. Low visibility is another factor with proven negative impacts on the evacuees' speed, previously discussed in Section 3.2. In total, low visibility would potentially lead to hasty evacuation due to slower human motion in search of careful navigation. Therefore, referring to the simulation study by *Ionescu* et al. *(2021)* [55], this study assumed that introducing teachers into the environment enhances the speed by eight per cent, reflecting a positive influence on the overall efficiency of the evacuation process. We also assumed that smoke in the corridors would reduce agents' speed within a five-patch radius of the smoke source by two per cent for any density level. Group walking is another element influencing evacuation speed. Furthermore, in building the ABM model, the influence of group walking on the speed of agents was assessed, as obtained from a simulation study by *Zhou* et al. *(2020)* [105]. Note that agents' health also affected their speed, where severely injured agents experienced a speed decrease (See Section 4.2.3. for more details on modelling evacuees' health attributes).

#### 4.2.3. Agents' health attributes

The immediate health impacts of emergencies on individuals can significantly influence the outcomes of evacuation processes. Large-scale seismic evacuation simulations incorporated agents' health conditions by accounting for building damage levels in indoor settings and debris accumulation in outdoor environments [106]. In our model, the agents' health ranged from 0 to 100, with 100 primarily assigned to all the student agents at the beginning of the simulations. Studies on toxic gas attacks and evacuation simulations have revealed that longer gas release durations and delayed evacuations can significantly increase the average exposure risk [19]. Similar findings have been presented in studies of radiological emergencies, where delaying the release of radiological material reduced exposure risk [14]. Incorporating DRM, the study first considered the effects of fire smoke on agents' health; the agents' health decreases as a function of both the level of exposure to harmful elements (e.g., smoke) and the duration of that exposure. Emergency medical reports indicate that immediate symptoms from exposure to heavy smoke can appear within seconds to minutes [107, 108]. Given children's smaller airways and higher breathing rates, this time span can be even shorter, and the resulting health deterioration more severe. Children are notably more susceptible to smoke exposure than adults, particularly due to carbon monoxide (CO) poisoning, and can become incapacitated at lower exposure levels. However, there is limited research on children's immediate health deterioration during fire incidents, largely due to ethical constraints preventing experimental exposure in this vulnerable population. Consequently, studies like ours must rely on adult physiological data, often derived from relatively healthy populations such as firefighters, to inform parameter settings. Therefore, due to this lack of direct pediatric data and ethical limitations, we adopted a conservative 5-second exposure threshold and tested its impact through sensitivity analysis. The cut-off point for health decline—such as a 30 % decrement—is also based on empirical adult studies and applied repeatedly as long as the agent remains exposed, consistent with DRM principles. Supporting this approach, *Purser (2002)* highlights that children are highly susceptible to smoke, exhibiting escape-impairing symptoms at carboxyhemoglobin (COHb) levels as low as 25 %. Dense smoke (≥15 g/m$^3$) can incapacitate sensitive individuals within minutes, indicating that even brief exposure to very dense smoke can cause rapid health deterioration in children. On the other hand, lower-density smoke exposure results in a lesser health impact, with a 10 % decrease for agents exposed to smoke densities below 50 %.

Second, we also incorporated agent-based rules that capture agent types and situational factors as defined in previous sections to model adverse health effects from pushing and physical contact between the agents. For example, if agents face obstacles, such as dead agents, their health is reduced by 2 %, and when others push agents into the crowd, their health is further compromised by 2.5 %. While this approach does not directly measure the magnitude of social force between agents to predict casualties [109], it captures realistic consequences of overcrowding and lack of personal space, leading to aggressive physical interactions. These rules are consistent with the DRM in that they account for additional stressors that impact agents' health over time, contributing to an overall decline in health in the simulation.

We also used thresholds for serious injury and death. Agents with health levels between 10 and 20 are seriously injured, while those below nine are dead. These criteria enable us to identify the point at which agents' health has deteriorated and survival is no longer feasible.

### 4.3. Model features and entities

The model framework was applied to the selected population, and the information for the model was collected from the chosen school administration. The school's first floor comprises seven classrooms, two offices, and two restrooms. For simulation purposes, we focused solely

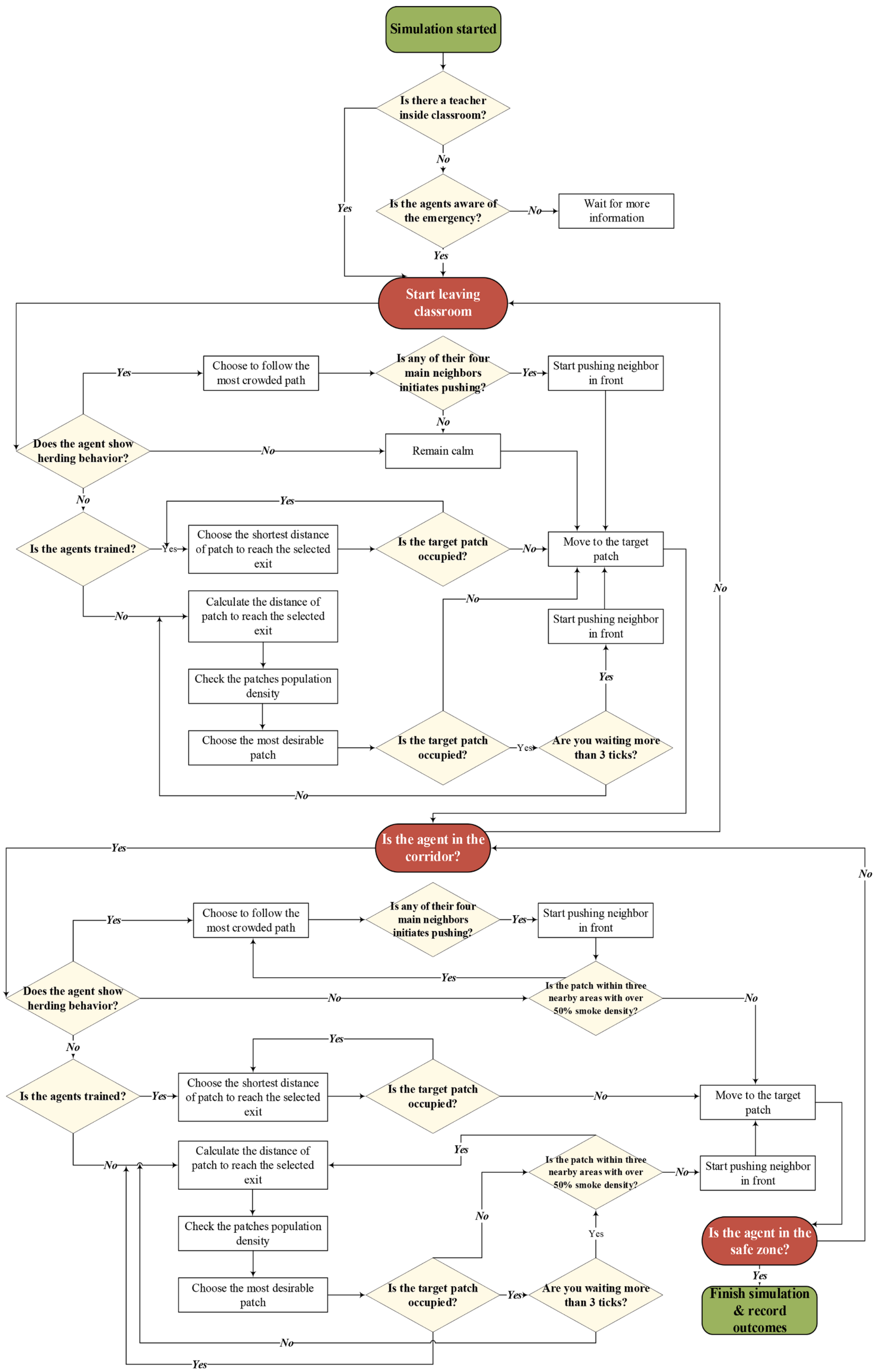


**Fig. 6.** Overview of agents' movement through the simulation environment.

on the classrooms and corridors as the available paths for escape, excluding the offices and restrooms. The first floor of the primary school has been graphically drawn in NetLogo 6.4.0 using patch agents. In general, two types of classrooms are considered: One with a length of 9 m and the other with a length of 12 m The first classroom can accommodate 44 students, while the second one has been designed to provide seats for 38 students, as shown in Fig. 7. In the model, every patch equals 0.3 × 0.3 m, and every tick equals 1 s. The students' shoulder size has also been set to 0.3 according to the available studies pointing to the shoulder size of Chinese primary school students [52,110]. Each patch can only be occupied by one agent. The size of the school furniture has been relatively adjusted to be multiples of 0.3.

The environmental elements used for pathfinding have been recognised by patch colour as follows: walls (black), gates (red), walkable corridors (blue), and the yard (safe zone, purple). Smoke sources, placed in three fixed locations near each exit (smoke 1, 2, and 3), allow for the evaluation of smoke's impact on evacuation efficiency, with smoke density adjustable as a percentage (0–100 %). The simulation ends when all the students reach the safe zone (yard). Each agent is represented by a coloured circle corresponding to their role: dark red for students of all types, green for classroom teachers, light red for teachers in the corridors, fire icons (with darker shades indicating higher density) for fire, and blue for deceased students. The student agents were divided into three distinct types based on their route selection and movement behaviour: trained students, untrained students, and herder students (herders), as described in Section 4.2.1, and their characteristics used in the model are given in Table X. Students are seated behind their classroom desks, with their locations randomly assigned to accommodate varying classroom capacities as needed. Teachers are fixed agents who stand behind the lectern in classes or between classroom gates in corridors every nine meters.

The Graphical User Interface (GUI) of NetLogo (presented in Fig. 8) allows users to modify several factors related to population size in each classroom, the overall proportion of trained students, the likelihood of herding behaviour for both trained and non-trained students, and the positioning of teachers. Additionally, users can adjust the configuration of smoke sources, enabling changes in smoke density for each source. Results are presented in the form of total evacuation time, variations in aggregated speed and agents' health over time, and the average distance travelled by the agents, number of herders and trained agents, and number of dead and injured agents.

When constructing a realistic model, a combination of stochastic and deterministic treatments is necessary. Stochasticity has already been applied by considering variations in agent behaviour, smoke density configurations, randomness in agents' initial reaction times, and the probability of turning (un)trained students into herders. Deterministic treatment of fate is also considered in the building layout, evacuation route choice, exit selection rules for each type of agent, initial positions of agents, movement speeds, and teachers' positions.

### 4.4. Model calibration and validation

Before initiating simulations, model parameters must be adjusted to match real-world conditions and agent behaviour during the evacuation drill. To calibrate the model, firstly, we ensured that the population of agents accurately represented a known real-world population by providing modules rooted in empirical evidence for their behaviours. Secondly, we verified that the model output could be converted into real-time units. Lastly, we acquired field data from a drill conducted at the same school for comparison with the model output [26]. Attention should be paid to the fact that the model's accuracy has been validated for the movement time and speed rules of agents, with the agents' health being excluded from the scope of calibration due to the unavailability of real-time data.

Notably, the evacuation drill for model calibration considered classrooms one and two under good visibility conditions (no smoke). Each classroom had one teacher, and two teachers were stationed in the corridors in front of each classroom. Classroom One accommodated 21 students, while Classroom Two had 15 students. The total evacuation time recorded was 31 s, and trajectory analysis revealed that students followed the rule of selecting the nearest exit gate. The behavioural rules were adjusted accordingly through multiple model runs. Recognising that achieving a 100 % match was not feasible due to stochastic elements, model outputs frequently vary between simulation runs. In alignment with the calibration method proposed by *Delcea, Cotfas, Craciun,* et al. *2020* [111], we determined the model to be successfully calibrated when the simulated results fell within the range accounting for a five per cent error margin (acceptable error of ±1.55 s) and proceeded to simulate the model under various scenarios. Additionally, model validation, which determines the degree to which the model accurately represents the simulation [32], has also been assessed by evaluating the validity of model structure, model behaviour, and program [95].

### 4.5. Model experimentation

We adopted a scenario-based simulation [112] to examine human interactions with the built environment, hazards, and safety measures. This study has developed 36 simulation scenarios to explore factors such as smoke density, placement of adult guidance, and the proportion of trained students. All seven classrooms operate at full capacity to accommodate students (each simulation had 278 agents), with agents initially starting at 100 % health. These scenarios are divided into four major categories based on smoke density, and each is further segmented into sub-scenarios to analyse the impact of different variables (guidance position and students' training) on simulation outcomes (Table 2). To

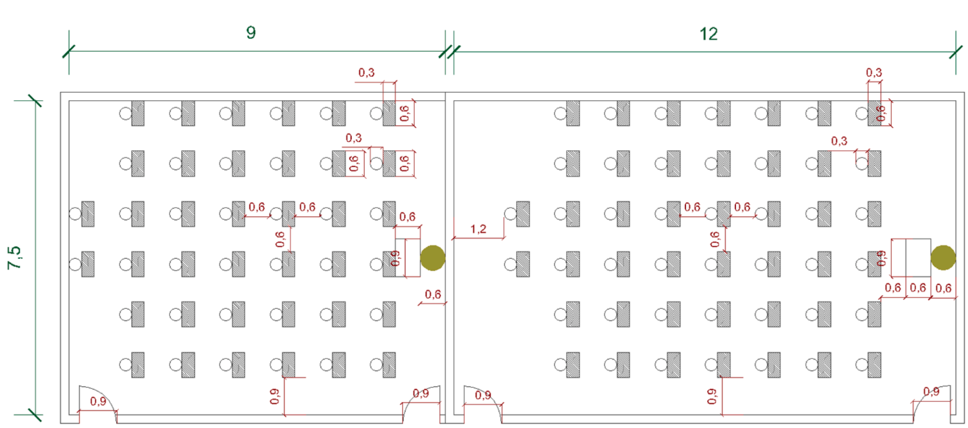


**Fig. 7.** Layout of the selected school (Dimensions are presented based on the "Meter".).

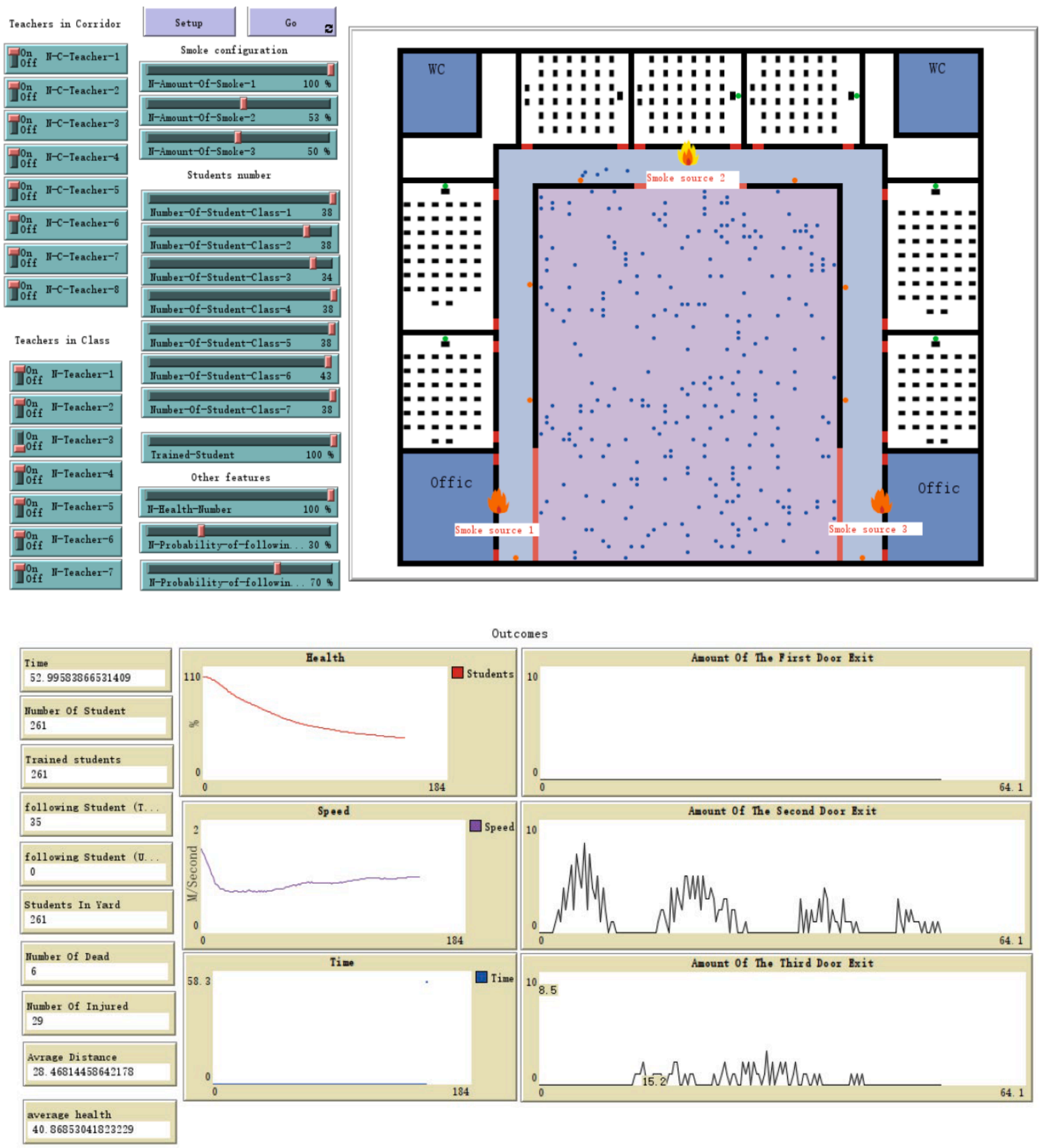


**Fig. 8.** GUI of the model.

**Table 2**
Scenarios' features.

| Scenarios characteristics | |
|---|---|
| *Smoke density (four main simulation groups)* | No smoke<br>Source 1 & 3: 100 % and source 2: 50 %<br>Source 1 & 3: 50 % and source 2: 100 %<br>Source 1: 100 % and sources 2 & 3: 100 % |
| *Positions of adult guidance* | In all classrooms<br>In all corridors<br>In all classrooms and corridors |
| *Percentage of trained students* | 0 %<br>50 %<br>100 % |

streamline the simulations, the probability of exhibiting herding behaviour for trained and non-trained students is set at 30 % and 70 %, respectively. According to the available studies and guidelines, each sub-scenario is simulated 30 times [113], and the average values are used for subsequent analysis. It is important to note that evacuation time is recorded in seconds, and health level is calculated as a percentage. For simplicity, we will use "heavy smoke source" when smoke positions are at 100 % density and avoid detailing that other smoke source(s) are simultaneously set at 50 % density.

## 5. Results

This section presents three analyses: a sensitivity study on parameters' effects, speed trends under smoke conditions, and intra-group variability in evacuation influenced by smoke, training, and teacher positions.

### 5.1. Comprehensive sensitivity analysis

Sensitivity analysis enables researchers to systematically examine the effect of parameters' variations across a spectrum of plausible scenarios rather than relying on fixed parameter configurations for accurate assessments [26]. This section employed sensitivity analysis, a robust method to investigate the impact of smoke configuration partially, teachers' position and numbers, trained students and response in evacuation total time and agents' health. Fig. 9 shows multiple bar charts, each of which is a dual-level chart depicting the fraction of untrained agents and the placements of teachers. On the next level, it marks four smoke spots. Separate bars show evacuation time, death toll, and injuries.

The optimal safety strategy was thought to involve the presence of teachers in both classrooms and corridors. However, based on simulation results presented in Fig. 9, its effect on evacuation time cannot be universally generalised, as students' training is another important factor influencing total evacuation time. For example, in scenarios where the agents are entirely untrained, the importance of teachers' positioning and number becomes evident as smoke severity increases. In most simulations conducted with heavy smoke, the multiple use of adults' guidance can reduce evacuation time. However, for scenarios where the proportion of trained students increased, altering teachers' locations or utilising them in multiple locations did not positively impact the evacuation time of reducing agents when faced with smoke. This finding suggests that students may encounter challenges in low-visibility conditions when provided with numerous adult guidance and evacuation instructions.

By comparing scenarios divided by teachers' positioning, we observed that when teachers are only available in classrooms and a severe smoke source is present in the horizontal corridor, the increase in the proportion of trained students may have a detrimental effect on the death toll. However, in similar scenarios without smoke, the positive impact of students' training on reducing injuries was evident. Contrarily, when teachers were solely present in the passage during heavy smoke in a single vertical corridor, students' training positively impacted evacuation time. Nevertheless, this factor demonstrated conflicting effects on the evacuation time of students guided by teachers in the classrooms, particularly in scenarios where heavy smoke simultaneously affected either the horizontal or two vertical corridors. Therefore, in most cases, positioning teachers in classrooms increases potential health hazards for students.

Through all iterations, when severe smoke sources were present in the horizontal corridor, having teachers in both corridors and classrooms or exclusively in corridors demonstrated superior performance in reducing the death toll compared to relying solely on adults' guidance within classrooms. This conclusion was consistent across all simulation sets involving various proportions of trained students. However, employing multiple teachers' guidance slightly increased total evacuation time in most scenarios.

The comparison within the inner graphs revealed a significant change in evacuation time and the number of deaths associated with smoke configurations. This increase was consistently highest in scenarios where the horizontal corridor was heavily affected by dense smoke, regardless of the proportion of trained students or teachers' location. In such conditions, students from three classrooms in a horizontal corridor were unable to exit through the nearest gate (exit B) and were forced to choose alternative exits for escape. Apart from scenarios with heavy smoke in the horizontal corridor, a steady linear increase in death toll was observed, starting from smoke-free observations to scenarios with one or two heavy smoke sources in the vertical corridor(s). However, no similar pattern for total evacuation time was observed. Despite anticipating longer evacuation times in scenarios with two simultaneous smoke sources, considering two additional factors and the

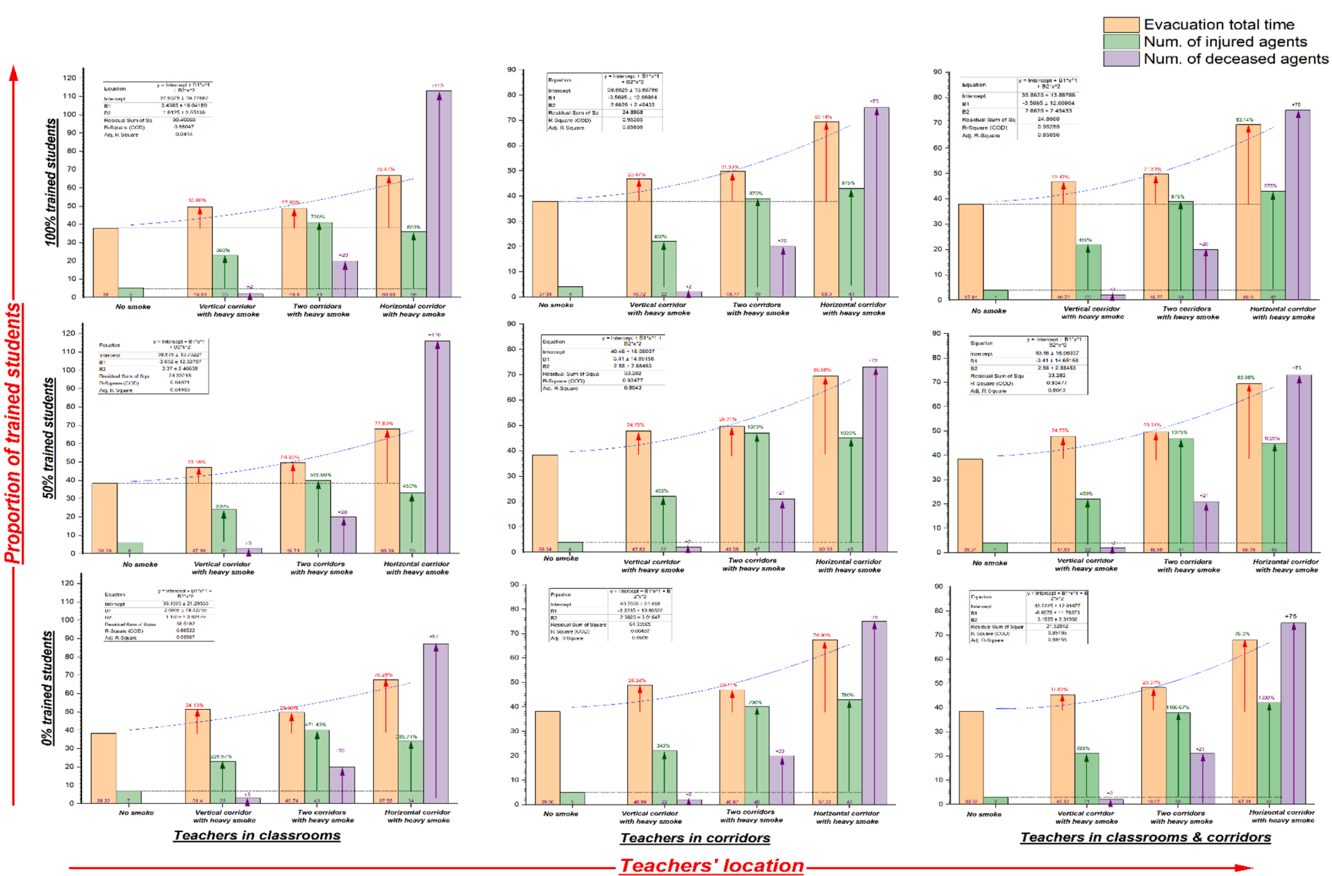


**Fig. 9.** Charts for sensitivity analysis.

randomness of parameters in simulations contradicted this initial expectation.

### 5.2. Speed trends change

The initial noteworthy observation regarding the impact of smoke on children's movement behaviour was the noticeable change in their average speed. Similar trends have been observed for the simulations in each smoke configuration category. To illustrate this trend while maintaining simplicity in the data presentation, Fig. 10 exclusively depicts the speed change over ticks for smoke configurations where the proportion of trained students was set to 50 %, and teachers were positioned in both corridors and classrooms. The average speed initially decreases across three smoke configurations—smoke-free, smoke source in one vertical corridor, and smoke sources in two vertical corridors. Subsequently, the average speed increases upon reaching a certain level, which is associated with decreased density near exits. This increase is particularly pronounced when agents escape through environments with two heavily dense smoke sources in the vertical corridors. The likely reason for this sharp increase is the placement of smoke sources at the corridors' endpoints, prompting agents to choose alternate exits. As a result, agents spend less time in these locations and move quickly towards exit B. Despite agents having two exits to select from, the slope of the speed increase is less in scenarios with one heavy smoke source in the left corridor. One possible explanation is that agents' exposure to low-density smoke in the right corridor affects their speed and health, as they still opt to exit through Gate C. Interestingly, despite the significant change in average speed, evacuation times remain nearly identical for these two smoke configurations. In the smoke-free scenario, the speed also exhibits a decrease followed by an increase; however, after a while, a steady speed is observed until the end of the evacuation, which lasts for a shorter duration than the evacuations above. Notably, setting a single heavy smoke source in the horizontal corridor and two weak smoke sources in other corridors results in a continual decrease in average speed.

### 5.3. Intra-group variability assessment: smoke configuration-based

The sensitivity analysis findings showed that the smoke configuration significantly impacted the total evacuation time and agents' health status. Thus, MANOVA analysis was employed to investigate the influence of students' training and teachers' positions on total evacuation time and average final health across four different smoke density combinations. Before conducting MANOVAs, the study meticulously assessed the test's assumptions. We checked the existence of outliers in each subset of the dataset using Mahalanobis distance and examined the linear relationships between each pair of dependent variables within each independent variable group. Next, multivariate normality was assessed using the Shapiro-Wilk test, and multicollinearity among the dependent variables was examined. MANOVA analysis was then performed using SPSS 24, and the assumption of equality of covariance matrices was also verified. The agents' average final health and evacuation total time for each scenario is given in Table 3.

- No-smoke scenarios (baseline scenarios)

The fewest fatalities and injuries occurred during the smoke-free evacuation simulations, indicating that the school layout can provide a safe evacuation plan free from significant fire incidents. All exits exhibited a constant flow rate, as students distributed themselves equally among the closest exits, with Gate B showing the highest flow rate per second. However, despite examining the impacts of students' training and the positioning of adults' guidance on total evacuation time and average agents' health statuses, MANOVA test revealed no statistically significant differences across the levels of the proportion of trained agents and teachers' locations in a linear combination of both dependent variables (all $p > 0.05$). Additionally, there was no statistically significant interaction effect between teachers' position and the proportion of trained students on the combined dependent variables, with $F(8, 512) = 0.812$, $p = 0.593$, and Pillai's Trace $= 0.025$. Therefore, evacuation time and agents' health did not exhibit significant differences among the four smoke-free scenarios, encompassing different combinations of students' training and adults' guidance positioning.

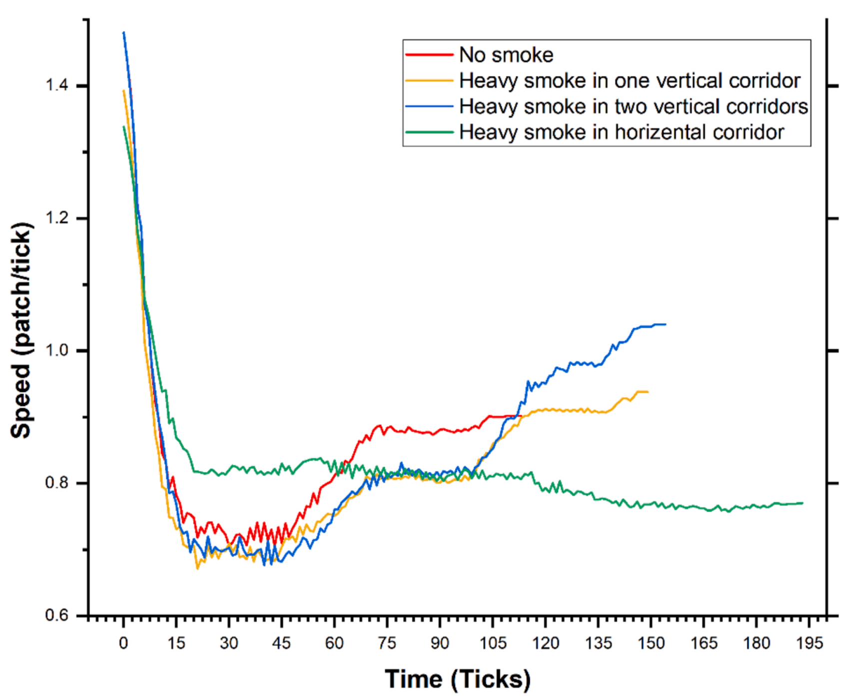


**Fig. 10.** Speed change for different smoke configurations (for scenarios where 50 % of agents were trained and teachers were positioned in both classrooms and corridors).

**Table 3**
Simulation results.

| Smoke configuration | Trained students' proportion | Teachers in: | Average final health status | | Evacuation total time | |
|---|---|---|---|---|---|---|
| | | | *Mean* | *Std.* | *Mean* | *Std.* |
| No smoke | 0 % trained students | *Classrooms* | 53.81 | 1.15 | 38.32 | 1.28 |
| | | *Corridors* | 53.55 | 1.50 | 38.06 | 0.79 |
| | | *Both classrooms & corridors* | 54.14 | 1.40 | 38.52 | 1.69 |
| | 50 % trained students | *Classrooms* | 54.06 | 1.32 | 38.29 | 1.26 |
| | | *Corridors* | 53.76 | 1.43 | 38.34 | 0.86 |
| | | *Both classrooms & corridors* | 54.08 | 1.12 | 38.55 | 1.45 |
| | 100 % trained students | *Classrooms* | 54.56 | 1.59 | 38.00 | 0.61 |
| | | *Corridors* | 53.98 | 1.37 | 37.84 | 0.75 |
| | | *Both classrooms & corridors* | 53.81 | 1.15 | 38.22 | 1.15 |
| Heavy smoke in one vertical corridor | 0 % trained students | *Classrooms* | 52.41 | 0.97 | 51.40 | 4.28 |
| | | *Corridors* | 52.58 | 0.72 | 48.89 | 4.87 |
| | | *Both classrooms & corridors* | 52.40 | 0.76 | 45.39 | 4.17 |
| | 50 % trained students | *Classrooms* | 52.38 | 0.55 | 47.16 | 5.56 |
| | | *Corridors* | 52.55 | 0.61 | 47.83 | 5.68 |
| | | *Both classrooms & corridors* | 52.55 | 0.61 | 48.28 | 4.99 |
| | 100 % trained students | *Classrooms* | 52.79 | 0.90 | 49.63 | 5.98 |
| | | *Corridors* | 52.61 | 1.13 | 46.72 | 5.43 |
| | | *Both classrooms & corridors* | 53.03 | 1.03 | 47.87 | 5.45 |
| Heavy smoke in two vertical corridors | 0 % trained students | *Classrooms* | 53.74 | 0.74 | 49.74 | 4.78 |
| | | *Corridors* | 46.88 | 0.72 | 46.97 | 6.04 |
| | | *Both classrooms & corridors* | 46.72 | 0.87 | 48.27 | 6.75 |
| | 50 % trained students | *Classrooms* | 47.00 | 0.87 | 49.25 | 4.48 |
| | | *Corridors* | 46.78 | 0.73 | 49.58 | 5.33 |
| | | *Both classrooms & corridors* | 46.76 | 0.84 | 48.11 | 4.69 |
| | 100 % trained students | *Classrooms* | 47.20 | 0.71 | 48.60 | 7.41 |
| | | *Corridors* | 46.59 | 0.73 | 49.77 | 6.14 |
| | | *Both classrooms & corridors* | 46.76 | 1.17 | 48.25 | 4.52 |
| Heavy smoke in horizontal corridor | 0 % trained students | *Classrooms* | 30.49 | 1.08 | 67.55 | 3.04 |
| | | *Corridors* | 30.23 | 1.08 | 67.33 | 2.42 |
| | | *Both classrooms & corridors* | 30.47 | 0.94 | 67.91 | 3.35 |
| | 50 % trained students | *Classrooms* | 30.74 | 1.04 | 68.09 | 4.42 |
| | | *Corridors* | 30.42 | 1.20 | 69.39 | 5.70 |
| | | *Both classrooms & corridors* | 30.42 | 1.20 | 68.20 | 3.77 |
| | 100 % trained students | *Classrooms* | 30.70 | 0.98 | 66.68 | 8.33 |
| | | *Corridors* | 30.69 | 0.98 | 69.30 | 5.51 |
| | | *Both classrooms & corridors* | 30.54 | 0.97 | 69.58 | 5.09 |

- Scenarios with heavy smoke in one vertical corridor

In the second smoke configuration, the smoke with the highest density was positioned in the left corridor, while two additional smoke sources with 50 % power were placed in the horizontal and right corridors. Consequently, the agents had only two exits to escape through: gates B and C. This group of simulations experienced the second-highest number of injuries and the lowest number of deaths (except in smoke-free scenarios). Using MANOVA analysis, we observed a significant impact of students' training on the amalgamation of dependent variables, as evidenced by a significant Pillai's Trace, $F(4, 520) = 2.988$, $p = 0.019$, Pillai's Trace = 0.045. Further scrutiny revealed that the training of students significantly influenced the average final health of the students ($F(2, 260) = 5.541$, $p = 0.004$, partial $\eta^2 = 0.041$). Post hoc pairwise comparisons using the Scheffé test were conducted to investigate disparities between groups, ensuring a robust control over the Type I error rate across all comparisons. These post hoc examinations revealed significant disparities in the final health statuses of scenarios with 100 % trained students compared to those with no training (Mean difference = 0.3877, SE = 0.12259, $p = 0.007$). Additionally, the position of teachers significantly impacted the total evacuation time ($F(2, 260) = 4.295$, $p = 0.015$, partial $\eta^2 = 0.032$). Post hoc analyses revealed significant disparities in evacuation time between scenarios in which teachers concurrently directed students in both classrooms and corridors vs those in which teachers exclusively managed students in classrooms (Mean difference = −2.2155, SE = 0.76980, $p = 0.017$). The interaction between the proportion of trained pupils and teachers' positions was significant, indicating that these factors collectively affect total evacuation time ($F(4, 260) = 4.129$, $p = 0.003$, partial $\eta^2 = 0.06$).

- Scenarios with two heavy smoke in both vertical corridors

In evacuation scenarios involving two smoke sources in vertical corridors operating at full capacity and one smoke source with lower density in the horizontal passage, the agents had only one exit available to go through exit B. For the first time, we observed a high number of deceased agents and significantly increased injuries compared to the last smoke configuration. However, the evacuation time did not show a significant change. MANOVA tests provided further insights into the agents' health and total evacuation time differences in the simulation data. The multivariate tests did not demonstrate a significant effect of any independent variables on the combination of dependent variables. Further analysis revealed that the training of students significantly influenced their average final health ($F(2, 260) = 3.945$, $p = 0.021$, partial $\eta 2 = 0.029$), where those simulations run by 100 % trained students have a significant difference in terms of agents' average health with the simulations conducted by all non-trained students (Mean difference = 0.5304, SE = 0.19220, $p = 0.023$).

- Scenarios with heavy smoke in horizontal corridor

In the fourth smoke configuration, the horizontal corridor experienced heavy smoke, while two other vertical corridors were affected by 50 % smoke sources. Consequently, evacuation was only feasible through gates A and C. These simulations reported the highest number of deaths (indicating the lowest health statuses) and total evacuation time. However, the MANOVA tests revealed that there emerged no statistically significant distinctions among the varying levels of the proportion of trained agents and teachers' locations in a linear combination of both dependent variables (all $p > 0.05$). Likewise, neither teachers' positions nor the proportion of trained students exhibited any discernible impact on the evacuation total time and agents' average health statuses.

## 6. Discussions

Schools function as critical micro-systems within the broader emergency response framework. Limited data on children's perceptions and behaviours during emergencies restricts the reliability of school evacuation simulations, leading most studies to rely on movement patterns and adult psychology to model their behaviour. This study addressed this need by understanding children's evacuation behaviour and interactions with hazards, built environments, and safety measures during emergencies. Consistent with existing studies in system safety during evacuations and hazard dynamics [14,19], smoke density emerged as a dominant risk factor causing delayed evacuation time and deteriorated health levels. Introducing smoke into the school environment could negatively affect evacuation time by up to 76.83 % (±0.735) in the worst-case scenario. Smoke also negatively impacted health by reducing agents' average health by up to 43.94 % (±0.834) when we modelled having a smoke source in the horizontal corridor. Notably, the lowest negative impact of smoke on evacuees' health was observed when heavy smoke was present only in a vertical corridor, resulting in a 2.68 % (±0.621) deterioration in the average health.

Contrary to the widespread assumption that teachers are the most critical facilitators influencing school evacuations' efficiency, our investigation reveals a more nuanced picture. We confirmed that increased adult guides during evacuations, especially during affected visibility, can supplement the students' lack of preparedness. However, the practicality of such an approach is challenging since not all school staff are available during emergencies, and covering everyone becomes impossible. Therefore, as an alternative, empowering students with basic evacuation knowledge emerges as a more sustainable solution. However, its effectiveness and interaction with teachers' positioning vary significantly based on the smoke configuration. For instance, in scenarios where heavy smoke encumbers exit in the left corridor, students' evacuation preparedness could significantly improve evacuees' average health by 1.2 % (±0.463), decreasing the number of casualties and injuries. In such a scenario, strategic teachers' positioning throughout all classrooms and passageways could compensate for the lack of self-preparedness, effectively reducing evacuation time by 10.475 % (±2.764). On the contrary, assuming having 100 % well-prepared students, a similar teacher positioning strategy could shorten evacuation time by 6 % (±3.63). For a single smoke source in a vertical corridor, a balanced combination of teacher placement and students' preparedness could lead to more efficient evacuation. Yet, this approach loses efficacy when smoke dynamics change, particularly when the horizontal corridor is affected. Interestingly, the findings revealed that although various safety strategies did not significantly reduce evacuation time in this specific case, they were still effective in saving lives—a conclusion that aligns with those drawn by [114] . Contrary to *Wang* et al. *(2023)* [13], our model revealed that the strategic positioning of guides in passways rather than classrooms could significantly reduce deaths and injuries. This result underscores the necessity for contingency-based evacuation plans tailored to diverse environmental conditions and recognises the difficulties in assessing the efficacy of school evacuation procedures.

We also noted that although all three exits had similar widths, agents in a hurry tended to choose the closest area of the gate, even if other areas of the gate were less congested. In exits A and C, agents primarily utilised the corners of the gates, leaving much of the area unused. On the other hand, agents arrived at exit B from opposite directions, resulting in a simultaneous and rapid outflow of agents from both sides of the gate. Our results are consistent with those of earlier studies published in the literature [115,116], suggesting that the width of the exit should be carefully considered during its construction. Increasing the width beyond a certain level may not effectively alleviate congestion and smooth the flow during emergencies. Consistent with prior research, we found that most casualty instances occurred near corridor exits due to congestion [109].

The practical implications of these findings are profound for school administrators, urban planners, and emergency managers tasked with ensuring safety during evacuations. Institutions can adopt more comprehensive and adaptive evacuation strategies by recognising the limitations of solely relying on teacher guidance and the challenges posed by students' lack of emergency training. Equipping students with basic evacuation knowledge is crucial, offering a practical solution to complement teacher-led initiatives. These pre-evacuation trainings, as discussed by *Haghani* et al. *(2024)* [117], may focus on behavioural modifications to improve the evacuation system's efficiency from within rather than seeking outside solutions. This observation highlights the need for adaptable response strategies that account for fluctuations in environmental variables. Integrating these insights into school emergency preparedness protocols and urban safety planning enables institutions and municipalities to improve their capacity to minimise risks and safeguard the safety and well-being of individuals during emergencies. Moreover, additional hazard mitigation strategies, such as smoke ventilation, can be considered to mitigate the health impacts of smoke [118].

This study, despite its contributions, exhibits some shortcomings that warrant attention in future research. The simulation initially concentrated on a single-story school configuration, as the school administration prohibited full-building evacuation drills owing to safety apprehensions. Therefore, lack of empirical data on vertical mobility during exercises constrained our capacity to develop and validate a multi-story evacuation model. Toilets and office areas were omitted from the simulated workplace. This choice was based on the observation that students rarely use offices during class hours and that restrooms are generally used briefly and by a limited number of students at any given time. Subsequent research should seek to integrate vertical circulation and stairwell dynamics once relevant data is accessible.

Second, while agents were allocated uniform physical attributes (e.g., movement velocity and body dimensions), we incorporated behavioural diversity by differentiating between "trained" and "untrained" pupils. These groups demonstrated distinct decision-making techniques, path selection behaviours, and social interactions (e.g., herding and pushing). Nevertheless, further individual-level variability, such as variations in ambulation velocity, situational awareness, and decision-making latency, was not included and should be addressed in future models to improve realism and generalizability. We also acknowledge the simplifying assumption of treating teachers as stationary 'guide posts' in the current model, which does not capture their active role in escorting students observed during drills. Future work will aim to incorporate mobile teachers to reflect realistic evacuation behaviours better and improve model fidelity. Future studies may also investigate the model's scalability for urban-scale disasters, integrating mixed-age and disabled populations, as well as various infrastructure types.

Third, the model utilised a dose-response framework derived from adult toxicological data owing to the absence of child-specific empirical evidence. Although DRM concepts were utilised to estimate the potential decline in children's health during evacuation, physiological disparities, such as reduced airway dimensions, elevated respiratory rates, and immature organ systems, likely render children more susceptible to smoke exposure than adults. The absence of pediatric-specific dose-response characteristics limited our ability to compare simulated health outcomes with actual pediatric data directly. Future research must emphasise the collection of such data to facilitate enhanced, child-specific health models.

Fourth, the simulation assumed static and homogeneous smoke dispersion, neglecting the complex fluid dynamics that govern smoke movement, visibility, and exposure in actual fire situations. Modelling dynamic smoke behaviour requires the integration of computational fluid dynamics (CFD) techniques, which are resource-intensive and exceed the scope of this study. Similarly, fire-structure interactions, such as flame propagation over materials or smoke generation from non-structural components, were omitted; however, they can considerably influence evacuation safety. Future studies must integrate these dynamic environmental processes to depict temporal fluctuations in hazard conditions more precisely.

These enhancements would certainly expand the model's applicability and facilitate more thorough disaster management and urban resilience initiatives. Nonetheless, such expansions necessitate considerable computational resources, significant data, and interdisciplinary collaboration—elements that surpass the scope and aims of the current work. As outlined in Section 4.2.1, ABM deliberately utilises simplified and abstract representations to encapsulate the fundamental dynamics of evacuation behaviour, rather than striving for comprehensive real-world replication. This methodology is well-documented in the literature and facilitates concentrated insights into essential behavioural mechanisms.

## 7. Conclusions

This study advanced our understanding of children's evacuation safety by developing an adaptive and reliable system for addressing dynamic hazards in primary schools. By integrating TPB and health-risk qualification (DRM), we extended the existing methodologies in this field to the children's population. Our findings on the smoke threshold and teachers' positioning offer actionable insights for education settings, emphasising the role of evacuation preparedness and infrastructure design in system safety. In conclusion, the following key findings encapsulate the principal insights derived from this study:

- Recommendations for school evacuation plans derived from the simulation results emphasise prioritising the provision of essential emergency knowledge to pupils as a crucial element of evacuation preparedness. This understanding empowers pupils to respond effectively when teachers or staff are absent or when environmental conditions alter unexpectedly.
- Contingency-based evacuation strategies for various smoke and hazard scenarios must be developed. Teacher deployment must be revised in response to environmental conditions, such as intense smoke, to improve evacuation efficiency and safety by strategically placing teachers along corridors.
- Improving exit design is critical. Exits must be engineered to reduce congestion, considering exit width, flow dynamics, and possible bottlenecks, particularly at corridor exits. The simulations suggest that increasing exit widths above a particular threshold may not substantially reduce congestion.
- The use of adult guides in specific areas should be emphasised, particularly in the case of fire emergencies. Strategically positioning teachers or adult guides in areas where they can assist students most effectively, such as near exits and in high-density student areas, can reduce fatalities, especially when students are less prepared.

## Ethical approval

This ethical investigation was authorised by Chengdu University of Technology's institutional review board. The school management provided ethical approval before the evacuation drills, assuring that all processes followed human participant research ethics.

## Informed consent

All participants who participated in the investigation provided informed assent. Students' parents were informed about the evacuation drills and gave their written agreement before participating.

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## CRediT authorship contribution statement

**Homa Bahmani:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Yibin Ao:** Writing – review & editing, Supervision, Resources, Project administration. **Dujuan Yang:** Writing – review & editing, Supervision, Conceptualization. **Qiang Xu:** Resources, Funding acquisition. **Jianjun Zhao:** Resources, Funding acquisition.

## 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

**Table X**
Student agents' characteristics in the agent-based model.

| Name of value | Range/value | Short description |
|---|---|---|
| *ID* | 1 to $N^{th}$ student in the model | Each agent will be presented with a unique ID to be recognised in the model. |
| *Simulation-Location* | Pxcor Pycor | Retains the agents' location as the agents's position will constantly change. |
| *Class-Location* | Classroom 1,…, 7 | The primary sitting place of the agent. |
| *Speed* | [0.5,…, 1.8] | The study considers the minimum and maximum speeds of 0.5 and 1.8 m/s, respectively, which are subject to be affected by numerous factors such as smoke, group size, and injury. In each step, the agent will first collect information from neighbours nearby, such as smoke presence and health level, to set the speed. |
| *Health* | [0,…, 100] | The health level of all the student agents' will be primarily 100, and it will be affected by smoke, crowd-induced force, and obstacles encountered. |
| *Trained-Student?* | 0–100 % | The proportion of trained students among the total population. |
| *Probability-of-herding-behavior?* | 0–100 % | Due to the agents' age and uncertainty in human behaviour, both trained and untrained agents can exhibit herding behaviour, and training can prevent the frequent occurrence of herding behaviour. |
| *Test-injured?* | 10 < health <20 | To determine whether an agent has previously been injured, ensuring avoidance of double counting. |
| *Injured?* | Yes/ no | To see if the agent is injured (to adjust the speed further). |
| *Test-smoke?* | Yes/ no | To see if the agents are in the proximity of 5 patches near the smoke source. |
| *Test-smoke-health?* | Depending on the smoke density | To see if the impact of smoke density on health has been determined. |

(*continued on next page*)

**Table X** (*continued*)

| Name of value | Range/value | Short description |
|---|---|---|
| *Distance-Turtle* | Variable | To calculate the distance from the current patch to the selected gate. |
| *Distance-Turtle*-Max | Variable | To calculate the maximum distance of all the patches to the selected gate. |
| *Path-Taken* | Variable | The path taken to exit |
| *Time-Student* | Variable | The agents' evacuation time |
| *Fixed* | Yes/ No | To verify whether the agent is stuck in congestion for a specific duration or not. |
| *Push* | Yes/ No | Depending on the agent type, they exhibit different pushing behaviours. |
| *Category* | Gate 1 / 2 | Exit choice between gates in the classrooms |

## Data availability

Data will be made available on request.

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