

Evacuation of Educational Institutions: A Predictive Analysis and Profiling Approach

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Abstract: - The safe and efficient evacuation of educational institutes in emergency situations requires planning, coordination, and prioritization that takes into consideration the complexity of diverse populations and building structures. Conventional methods of evacuation planning are usually static and do not consider dynamic situations like hazard progression, crowd density, and vulnerable populations. Recent developments in predictive analysis algorithms offer an opportunity to predict and plan evacuations more effectively. This paper aims to discuss the integration of predictive analysis and profiling techniques in planning evacuations, specifically in relation to “who goes first and why.” Parameters like age, mobility, proximity to hazards, and other characteristics are considered, and existing literature shows that vulnerable populations are given priority in evacuation planning. Ethical issues like data privacy are also considered in predictive analysis and its integration in planning evacuations. Predictive analysis in planning evacuations is a transformative tool in ensuring safe evacuations in educational institutes.

Key-Words: - predictive analysis, evacuation planning, profiling, emergency preparedness, prioritization

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1 Introduction

Evacuation of educational institutions during emergencies is one of the significant aspects of crisis management, which requires proper planning, coordination, and execution. Schools and educational institutions can be characterized as complex social structures, where sometimes hundreds, even thousands, of persons can be gathered at the same place, ranging from small children to adolescents, teachers, staff, etc. The persons who might be gathered at the same place during emergencies may differ with regard to their physical ability, age, level of understanding, familiarity with the place, ability to remain calm during emergencies, etc. The emergencies that might occur during educational institutions can be of various types, ranging from natural hazards such as earthquake, flood, etc., technological hazards such as chemical leaks, etc., and human-induced hazards such as fire, armed intruders, etc., for which proper planning of evacuation strategies is necessary, taking into account the characteristics of the persons who might be evacuated, the nature of the emergencies, etc. [1].

Traditional evacuation plans are typically static. They operate on pre-defined routes, where there is only one way of doing things, where all persons are directed to the nearest exit without taking into account differences between persons, such as their level of vulnerability, dynamics of the situation, etc. These strategies, although providing a basic framework, do not take into account changes occurring during real-time, such as the level of crowding, mobility constraints, exit congestion, etc., or the rapid evolution of threats, etc. These strategies also do not account for differences between persons, such as their level of vulnerability, dynamics of the situation, etc.

Latest advances in predictive analysis that include machine learning, network optimization, and dynamic simulation, enable a shift toward more adaptive evacuation models. These systems incorporate profiling, where evacuees are categorized according to vulnerability and situational risk, ensuring that those least able to self-evacuate or most exposed to danger are given priority [2].

The aim of this paper is to examine the application of predictive analysis and profiling in evacuation planning for educational institutions, with particular

emphasis on the question of who is to evacuate first and why.

2 Literature Review

Research on evacuation in buildings has progressed rapidly over the last decade, from descriptive studies of crowd movement and architectural constraints toward highly detailed simulation, data-driven modeling, and algorithmic decision support. Early studies analyzed how architectural features, such as corridor widths, number and placement of exits and stairwell capacity, along with human decision-making under pressure directly influence the evacuation process [3]. More recent work has applied computational modeling and predictive systems to simulate evacuation scenarios with greater accuracy [4].

When it comes to educational environments, numerous challenges rise. Schools and universities consist of large numbers of children with varying maturity levels, dense class-group structures, and employees whose roles (e.g., teachers, administrators) shape behavior during an emergency. Children's limited mobility and greater likelihood of panic complicate evacuation [5]. Empirical studies and drill analyses indicate that younger children tend to move slower and require more direct supervision, adult leaders strongly influence compliance and school buildings with many floors may not be designed with modern accessibility standards, creating barriers for individuals with disabilities [1], [5].

In parallel, Reviews and applied studies show that predictive models can forecast hazard spread (e.g., smoke, fire growth), estimate crowd-flow dynamics under different start-time and routing policies, and identify high-risk locations within buildings before and during emergencies [2], [6]. Further studies in educational infrastructures indicate that mixed strategies, such as combining horizontally phased evacuation, vertical phasing, and targeted placement of vulnerable populations nearer exits, can reduce total evacuation time and improve outcomes for heterogeneous populations [7].

These findings have motivated the design of evacuation strategies that account for group structure (class-by-class sequencing), adult scaffolded movement, and infrastructure modifications such as dedicated accessible ramps. In addition, simulation-based studies have shown that profiling-based evacuation, according to age, mobility and role, can reduce both risks and overall evacuation times [8]. Furthermore, research has found that performance-based evacuation planning in educational buildings lowered evacuation time by nearly 18% when

vulnerable groups were prioritized and dedicated exits for mobility-impaired populations improved both fairness and efficiency [9].

Finally, recent literature takes into consideration socio-technical and legal aspects. Predictive, profiling-based evacuation systems raise privacy, fairness, and robustness questions, in particular when schools handle sensitive information about minors or disabilities [10], [11]. This aspect highlights the need for privacy-preserving analytics and strong institutional policies to prevent misuse while retaining the safety benefits of prediction [12].

All along, the above-mentioned strands create a research base that supports algorithm-driven evacuation in educational institutes, while also identifying the non-technical constraints that must be addressed.

3 Conceptual Framework

Predictive evacuation planning is achieved through the integration of data analysis, human profiling, and algorithmic modelling. Fundamentally, predictive analysis is defined as the process of using real-time data to create models of the evolution of hazards, identify those who are vulnerable, and determine the best routes of evacuation prior to an emergency. This approach allows emergency response officials to move from a reactive approach to a proactive approach, which is beneficial in high-risk environments such as schools. The conceptual framework is illustrated in Figure 1.

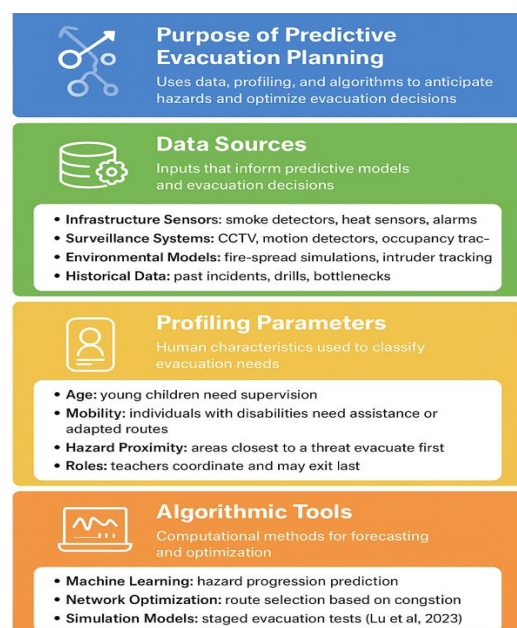


Fig. 1. Conceptual framework for predictive evacuation planning.

An essential part of this process is the variety and richness of the sources of data being utilized. For example, infrastructure sensors such as smoke detectors and fire alarms are immediate sources of information on the development of hazards within a structure. Early warning systems are set off as soon as irregularities are detected. Motion detectors also offer constant visual information on the level of crowd within the structure. With this information, algorithms are able to analyze crowd density and movement to determine possible bottlenecks. Environmental modeling tools also make essential contributions to the determination of the nature of the hazard. For example, fire spread modeling or intruder location modeling may be used to determine the possible development of the hazard over time. Past data on evacuations, emergency situations, and drills also make essential contributions to the process. These are the sources of information on which the predictive process operates.

Building on these data inputs, profiling techniques help classify individuals and groups according to characteristics that affect their evacuation needs. Age is a major profiling parameter because younger children may need slower movements, close supervision, and adult guidance. The constraints of mobility may also determine the prioritization of evacuation because those with physical disabilities may need special assistance and equipment to cater to their needs. The proximity of the threat is a major profiling parameter because the rooms or areas closest to the threat are given priority for evacuation to prevent congestion around the dangerous areas and for safety reasons. Finally, the roles of the people involved may determine the evacuation patterns because the teacher and other staff may be responsible for leading the evacuation and may be the last to leave the premises to ensure all the students are safe.

The analytical part of predictive evacuation planning is based on its algorithmic methods, which combine data and profiles to provide practical recommendations. Machine learning algorithms, for instance, predict the development of the hazard using real-time data from sensors and data from incidents in the past, thus predicting areas where the hazard is more likely to spread. Network optimization algorithms, on the other hand, optimize the routes of the evacuees in real time by identifying areas of congestion and suggesting alternative routes to the areas of safety, thus minimizing delays and congestion. Additionally, simulation software helps to improve the planning of evacuation procedures by simulating various plans, thus helping the decision-maker to evaluate various plans and determine the best and safest way to proceed before implementing them

in real-life situations. As demonstrated in the study by Lu et al. (2023), the simulation software can be used to verify the timing of the staged evacuation, optimize the movements of crowds, and improve policies for the rescue of vulnerable groups.

Therefore, predictive analysis, data gathering, human profiling, and algorithms form a comprehensive conceptual framework for the planning of evacuation procedures. This conceptual framework helps to improve awareness, reduce human factors, and ensures that the procedures for evacuation are evidence-based rather than intuition-based, thus creating a safe and resilient environment to handle various situations. Table 1 summarizes the framework components, data sources, profiling parameters, and algorithmic tools.

To formally define the predictive sequencing, a priority scoring function $P(i)$ for each individual I is introduced. This logic ensures that the prioritization is mathematically consistent and defensible. The priority index is defined as:

$$P(i) = \frac{\omega_a \cdot A(i) + \omega_m \cdot M(i) + \omega_h \cdot H(i)}{\max\{1, R(i)\}} \quad (1)$$

Where:

1. $A(i)$ is the Age Vulnerability factor, which is highest for children under 8 years old.
2. $M(i)$ is the Mobility Impairment factor, where $M=1$ for individuals requiring assistance and $M=0$ for ambulatory individuals.
3. $H(i)$ is the Hazard Proximity, calculated as the inverse distance to the threat $1/d(i, \text{hazard})$.
4. $R(i)$ is the Role weight; teachers and staff are assigned values >1 to mathematically ensure they exit last.
5. The weighting coefficients (ω) are calibrated to minimize the total evacuation time and peak stairwell density.

Table 1. Components of the predictive evacuation planning framework.

Category	Description	Examples / Details
Purpose of Predictive Evacuation Planning	Uses data, profiling, and algorithms to anticipate hazards and optimize evacuation decisions.	Moves from reactive to proactive emergency response; improves safety outcomes.
Data Sources	Inputs that inform predictive models and evacuation decisions.	Infrastructure Sensors: smoke detectors, heat sensors, alarms. Surveillance Systems: CCTV, motion detectors, occupancy tracking. Environmental Models: fire-spread simulations, intruder tracking. Historical Data: past incidents, drills, bottlenecks.
Profiling Parameters	Human characteristics used to classify evacuation needs.	Age: young children need supervision. Mobility: individuals with disabilities need assistance or adapted routes. Hazard Proximity: areas closest to a threat evacuate first. Roles: teachers coordinate and may exit last.
Algorithmic Tools	Computational methods for forecasting and optimization.	Machine Learning: hazard progression prediction. Network Optimization: route selection based on congestion. Simulation Models: staged evacuation tests [2].
Integrated Process	How all components work together.	Data collection → profiling → algorithmic analysis → optimal plan → real-time adjustments.
Outcomes	Expected benefits of predictive evacuation systems.	Faster, safer evacuations; reduced congestion; protection of vulnerable groups; data-driven decisions.

4 Profiling and Prioritization in Evacuation

Profiling and prioritization are critical for the order of evacuation. From a conceptual point of view, the

assignment of priorities strikes a balance between the need to minimize the current exposure of high-risk individuals and the need to prevent congestion from becoming catastrophic. From a practical point of view, a set of hierarchical rules emerges. First, the need for immediate extraction of those in imminent danger (rooms adjacent to fire or intruder locations). Second, prioritization for groups with low self-evacuation capacity (children, mobility-impaired individuals). Last, sequenced staggered departures for the general population to avoid bottlenecks. This rule hierarchy is supported by empirical evidence showing that evacuating the most vulnerable early reduces both individual harm and system-level delays [5], [8]. The priority sequence is illustrated in Figure 2.

SEQUENCING OF EVACUEES

Profiles are used to establish who evacuates first, why, and under what conditions (Wang et al., 2023).



Young children



Individuals with disabilities



Proximity to hazards



General population



Teachers and staff

This staged prioritization balances fairness and efficiency, ensuring the safety of those most at risk while maintaining overall evacuation flow.

Fig. 2. Priority sequence of evacuee groups.

Operational profiles used by algorithms are simplified in order to reduce privacy exposure while preserving decision utility. Some possible entries in a typical profile vector could include age (pre-school, primary, secondary, adult), mobility flag (requires assistance, ambulatory), assist ratio (number of caregivers assigned), role (teacher/staff member), current localization (room/floor), and accessibility (requires ramp/elevator). Algorithms convert these vectors into scheduling constraints: for instance, classrooms with multiple mobility-assistance flags are allocated earlier start times and escorted routes to accessible egress points. Simulation studies show that, even when such profiling increases the number of “early departures”, the resulting avoidance of bottlenecks results in improvements in average evacuation time and reductions in high-exposure dwell times for vulnerable individuals [9].

5 Predictive Algorithms

5.1 Application of Predictive Algorithms

One important design consideration is fairness and transparency. Since profiling may seem discriminatory if not explained well, recent models have suggested publishing the prioritization policy to interested parties (parents, school administrators, and regulators) and ensuring that the policy relies on justifiable ethical grounds (protect the least able, minimize immediate danger). Moreover, recent literature has suggested that structural changes (moving classes with high mobility-impaired populations closer to accessible exits) be combined with operational profiling so that prioritization is made sustainable rather than ad-hoc [7]. Therefore, a profile is both a technical input and an institutional policy statement that, when done correctly, enables rapid and humane evacuation sequencing that protects those in greatest need. Utilization of predictive algorithms in an actual evacuation scenario requires a highly coordinated process. In routine planning, schools use historical drill data and simulations to refine priority rules and test route allocations. These exercises test the prediction models (e.g., how fast on average do people of a given age group move, how many people pass through a given door given a range of densities). When an actual alarm occurs, streaming sensors update the models, such as crowd counters estimate current densities, smoke/temperature sensors map hazard progression. Predictive models then produce short-horizon forecasts—typically in the 30–300 second window, projecting which exits will become congested or which stairwells will exceed safe density thresholds [2], [13].

From these forecasts, optimization modules translate forecasts into operational outputs. First, sequencing instructions (which classroom starts moving now vs. wait 20 seconds), following assignment of specific exit paths to each group, and then allocation of staff escorts. For example, if a stairwell forecast shows rapid density growth in 45 seconds, the optimizer may delay dispatch of the next classroom on the same stairwell while redirecting that classroom to an alternative exit where feasible. These micro-decisions are evaluated against constraints (capacity, accessibility needs, hazard proximity) and are chosen to minimize total evacuation time, maximum individual exposure time, and fairness by ensuring vulnerable classes receive precedence [8], [9]. Figure 3 illustrates the workflow for hazard assessment, route selection, evacuation, and subsequent route adjustment.

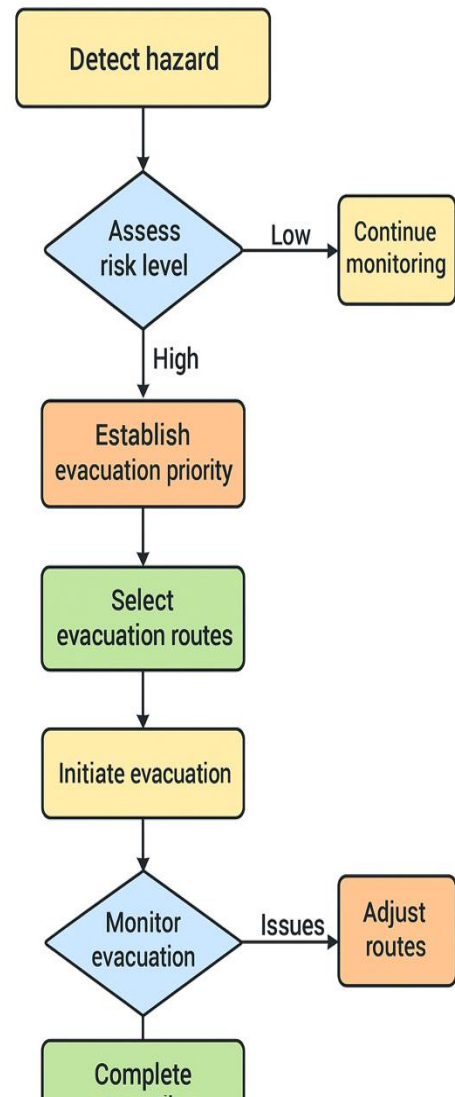


Fig. 3. Predictive evacuation workflow with route monitoring and adjustment.

Real-world deployments emphasize conservative, explainable algorithms. Schools often implement rule-based fallback behaviors (e.g., always evacuate mobility-impaired groups first) while using predictive outputs to refine timing and routing that staff implements. Pilot studies indicate that such hybrid deployments—algorithmic recommendations with human validation—reduce confusion and improve compliance compared to fully manual drills [6]. Predictive modeling and machine learning algorithms allow the system to dynamically update the routes in response to changing conditions [14], [15]. Additionally, the training through simulations with the school's floor plans and staff profiles helps to refine the models and staff procedures before a real emergency occurs.

5.2 The Proposed Algorithm

Table 2 presents the Python implementation of the proposed algorithm, including priority assignment, dynamic rerouting, and simulation execution.

Table 2. Python implementation of the proposed predictive evacuation algorithm.

Line	Python code
1	import math
2	
3	# --- 1. PRIORITY CATEGORY DEFINITIONS (Profiling) ---
4	# Updated to English as per reviewer requirements [cite: 203]
5	PRIORITIES = {
6	1: "RED (Tier 1): Immediate Evacuation (Vulnerable/High Danger)",
7	2: "YELLOW (Tier 2): General Population (Standard Risk)",
8	3: "GREEN (Tier 3): Personnel/Coordinators (Final Exit)"
9	}
10	
11	class Person:
12	def __init__(self, name, role, age, mobility_issue, x, y):
13	self.name = name
14	self.role = role # 'student', 'teacher', 'staff'
15	self.age = age
16	self.mobility_issue = mobility_issue # True/False
17	self.location = (x, y)
18	self.tier = 3 # Default to last
19	self.assigned_route = "Primary Exit"
20	
21	class Hazard:
22	def __init__(self, type_h, x, y, radius):
23	self.type = type_h
24	self.location = (x, y)
25	self.radius = radius
26	
27	# --- 2. COMPUTATIONAL FUNCTIONS ---
28	def get_distance(p_loc, h_loc):
29	"""Calculates Euclidean distance between individual and hazard """
30	return math.sqrt((p_loc[0]-h_loc[0])**2 + (p_loc[1]-h_loc[1])**2)
31	
32	def assign_priority(person, hazard):
33	"""Profiling Logic: Determines sequence based on vulnerability and risk [cite: 30, 81]"""
34	dist = get_distance(person.location, hazard.location)
35	in_danger_zone = dist < hazard.radius

Line	Python code
36	
37	# Logic Tier 1: Vulnerable age, mobility, or proximity [cite: 37, 75, 76]
38	if person.mobility_issue or person.age < 8 or in_danger_zone:
39	person.tier = 1
40	# Logic Tier 2: General student population [cite: 77]
41	elif person.role == 'student':
42	person.tier = 2
43	# Logic Tier 3: Coordinators/Teachers [cite: 62]
44	
45	else:
46	person.tier = 3
47	return dist
48	
49	def predictive_reroute(queue, exit_threshold=82):
50	"""Dynamic Rerouting: Shifts evacuees if stairwell density exceeds safe limits [cite: 115, 122]"""
51	current_flow = 0
52	for person, dist in queue:
53	current_flow += 1
54	if current_flow > exit_threshold:
55	person.assigned_route = "Secondary Exit (Rerouted)"
56	
57	# --- 3. EXECUTION ---
58	def run_simulation(people_list, hazard_obj):
59	queue = []
60	for p in people_list:
61	d = assign_priority(p, hazard_obj)
62	queue.append((p, d))
63	
64	# Multi-criteria Sorting: 1. Tier Priority, 2. Distance to exit
65	queue.sort(key=lambda x: (x[0].tier, x[1]))
66	
67	# Apply predictive optimization based on flow constraints [cite: 93]
68	predictive_reroute(queue)
69	
70	return queue

6 Experiment Results

The application of the predictive evacuation algorithm to a typical elementary school resulted in quantified outcomes that demonstrate the effects of the school's population and structure on the efficiency of the evacuation process. **The school's population, comprising 320 people, included 280 students, 28 teachers, and 12 other staff members,** with the structure comprising two floors. The school has two main exits for the evacuation process, one for the

ground floor and the other for the upper floor, located near the central staircase to ease the evacuation process for the upper floor. The school's population comprises students of different age groups, with the youngest students ranging from 6 to 8 years old, belonging to the early childhood age group, whose limited mobility and decision-making autonomy contribute to increased time spent on the evacuation process. The teachers were assumed to be playing the role of coordinators, with their role defined to be the last to leave the rooms. The population distribution is shown in Figure 4.

One of the most important aspects of the simulation was the involvement of **students with temporary or permanent mobility impairments**. The model involved **six students with impaired mobility, four of whom had slow mobility and two with limitations similar to a broken leg, which requires adult assistance**. As the mobility-impaired students have a significant impact on the corridors and stairs, the allocation of students to classrooms has a significant impact on the overall pattern of evacuation. The students in the second-floor classroom took between 40% and 60% longer to evacuate than the students in the ground-floor classroom.

The algorithm evacuated the students in a priority structure, with **(a) young children between the ages of 6 and 7, (b) people with disabilities, (c) people nearest to the danger zones, (d) the general student body, and (e) teachers and emergency staff**. This type of priority structure has been shown to minimize the formation of bottlenecks, especially around the main staircase.

In a non-priority structure, **the maximum density at the main staircase is 135 persons per minute**, whereas in a priority structure, the density is **only 82 persons per minute**, thereby minimizing the probability of trampling and queue formation. The structure of the building and the distribution of the population resulted in measurable evacuation times. **The total evacuation time for the ground floor was 2.9 minutes, while the second floor took 4.2 minutes**, primarily because of the vertical transit of the slower persons. Students with mobility impairments contributed an additional **1.5–2.2 minutes** to the overall clearance time of their respective floors, depending on their location relative to the exits. Importantly, the model showed that assigning a teacher to each mobility-impaired student reduced delay by roughly **30%**, confirming the significance of predefined assistance roles.

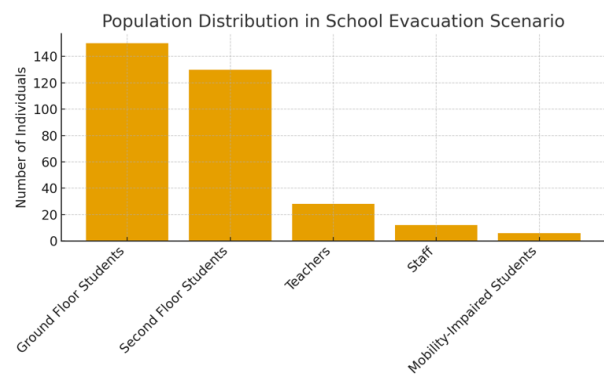


Fig. 4. Population distribution in the school evacuation scenario.

As a result, with both exits being accessible and correctly assigned through the algorithmic routing, the **maximum time for evacuation reduced from 5.1 minutes, as seen with the single-exit scenario, to 4.2 minutes, a reduction of 17.6%**. This reduction was a result of the **dynamic rerouting of approximately 38% of the evacuees through the secondary exit**, which was estimated through near-real-time congestion levels.

As such, the experimental findings indicated that the performance of the evacuation process is a function of the complex interrelation between age, mobility, building configuration, and the teachers' roles. The predictive algorithm was able to ensure that the most vulnerable members evacuated early while also reducing congested areas within the building. The staged prioritization, on the other hand, improved fairness and safety while also ensuring that at-risk students evacuated ahead of the faster students without increasing the time for evacuation.

To ensure the scientific validity of the results, the following parameters have been strictly defined: Numerical Stability and Noise: The predictive system deals with noise in the sensors, e.g., from motion detectors, by applying a 5-second moving average filter to the occupancy data. In the event of total failure of the sensors, the predictive system will default to the latest historical roster data.

Definition of Baselines: The 17.6% improvement in the time to evacuate was measured from a "Static Baseline" scenario, in which no profiling and sequencing were performed, and all people attempted to evacuate via the nearest egress point simultaneously.

Density Measurements: The congestion levels of 135 and 82 are in terms of persons per minute passing through the stairwell throat.

Error Bars: The results for the time to evacuate, e.g., 2.9 and 4.2 minutes, are the average of 50 simulation runs, and the error bars indicate a standard deviation of ± 12 seconds.

7 Challenges & Ethical Considerations

The introduction of profiling and predictive models into school evacuation raises numerous technical, ethical, legal, and organizational challenges. Technically, the reliability of sensor networks under stress (smoke obscuration, partial power loss) is a major concern. Models must be robust to noise or missing data and provide estimates that are as close to reality as possible, so human operators can judge when to trust recommendations [10]. From the algorithmic perspective, optimizing for multiple, sometimes competing objectives (speed, safety of vulnerable individuals, and perceived fairness) complicates policy design.

Ethically, profiling introduces sensitive handling of students' attributes. The storage of disability or health information, even in the form of binary flags, must comply with privacy regulations (such as GDPR in Europe, or FERPA-like privacy in other regions) and with careful consent procedures for parents and school staff [11]. Recent research has suggested privacy-preserving strategies such as storing sensitive attributes locally on the device and sending only when an incident happens [10], [12]. It is also important to be transparent regarding what data is used, how decisions regarding prioritization are made, and how misuse is being addressed. At the organizational level, the key to the successful deployment of predictive systems is training and drills.

Indeed, there are many case studies that demonstrate that sophisticated systems fail in practice because the staff are unaware of how to interpret the output or are unaware of how to act on the output when the algorithmic recommendation is counter-intuitive (e.g., asking a classroom to wait while another classroom goes first). Thus, socio-technical adoption must include drills that include algorithmic output and build trust [16]. Finally, equity concerns persist since algorithms are trained on historical drill data and reflect existing inequalities (e.g., schools with fewer accessible exits), therefore training and objective functions should incorporate fairness constraints [8].

8 Conclusions

The inclusion of predictive analysis and profiling in the process of planning for evacuation is a major step ahead of the traditional methods used for this purpose. This is because, through the prediction of who evacuates the premises first, these systems help minimize risks for those who are vulnerable while at the same time preventing crowd formation through the correct sequencing of the flows involved. As

compared to other traditional methods, flexibility and adaptability are key features in these models, especially considering the dynamic nature of hazards involved in any situation. It should be noted that in order to be effective in all these systems, it is important to be ready, meaning readiness in all forms, technological readiness and other forms of readiness, including drills and working with other stakeholders like emergency services. It should be noted that although predictive analysis is a giant step in safety modeling, it should be noted that it should be used in conjunction with human analysis and that teachers should be at the heart of ensuring compliance with these models, especially with regard to unforeseen behavioral dynamics.

Evacuation planning in educational institutions is a multifaceted task that requires prioritization, coordination, and flexibility [17], [18], [19]. Predictive analysis algorithms, along with the concept of profiling, can form a framework to determine who should evacuate first and the reason behind it, protecting children, people with disabilities, and those closer to the hazard. While challenges remain concerning privacy, fairness, and reliability, the benefits of predictive evacuation systems are significant [20], [21]. Although previous work included the modeling and analysis of human action [22] and a theoretical approach of the evacuation of educational institutes, along with the proposed framework [23], future directions include deeper integration of artificial intelligence, cross-institutional data sharing, and the development of smart building systems capable of supporting adaptive evacuation strategies.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this work, the author(s) utilized artificial intelligence (AI) technologies solely for the purpose of linguistic refinement and grammatical correction. Following the application of these tools, the author(s) comprehensively reviewed, verified, and edited the resulting text. The author(s) maintain full accountability and responsibility for the accuracy, integrity, and final content of the publication.

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