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A hybrid machine learning and microsimulation framework for simulating metro station evacuation

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ABSTRACT
Mass Rapid Transit is a globally efficient transport mode, yet its stations host large-scale pedestrian activity, leaving them vulnerable to hazards that can trigger evacuations. This study develops a pedestrian evacuation microsimulation framework capturing behavior across varying panic levels during metro station evacuations. Latin Hypercube Sampling and Random Forest modeling generate pedestrian behavior parameter combinations for calibrating the model and simulating panic conditions. Calibration uses a Genetic Algorithm, with validation via Geoffrey E. Havers statistics from CCTV data. Results show average speed fluctuates under low panic but remains stable under medium and high panic. Under low panic, most pedestrians evacuate in the later half; medium panic spreads evacuations evenly; high panic peaks in the first and last thirds. At peak hour (540 people), clearance times were 5.25–6.47 min, 5.12–5.25 min, and 4.90–5.07 min for low, medium, and high panic, respectively. These findings support countermeasures for safe, efficient MRT evacuations.

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Evacuation; panic; metro rail transit; microsimulation; Random Forest; pedestrian

1. Introduction

The Mass Rapid Transit (MRT) system has been recognized as an efficient transportation mode globally due to its large transportation capacity, high speed, eco-friendliness, and low energy consumption (Zhang et al. 2016). The continuous population growth in megacities has led to a significant and consistent increase in travel demand for metro systems, making the metro stations heavily crowded with pedestrians waiting for, boarding, and alighting from the metro transit (Lu, Deng, and Sun 2024). Metro stations are places of large-scale pedestrian activities and are consequently vulnerable to many potential risks and hazards such as fire, train failure, and terrorist attacks (Li et al. 2022). The occurrence of these events may trigger large-scale evacuation of the station. London King's Cross station fire (Moodie 1992) and the 1995 Baku Metro fire are two exemplary metro station disasters that caused the deaths of more than 300 people (Baku Metro Fire 1995). Additionally, more than 365 individuals were injured, suffering from burns,

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smoke inhalation, and other injuries sustained during the panic and evacuation (Croome and Jackson 1993). Post-accident reports of metro or subway disasters consistently revealed shortcomings in pedestrian evacuation planning and strategies. For instance, the tragic events at Daegu subway (W.-H. Hong 2004), where a fire originating in one train extended to another that was halted on the platform, resulted in a substantial loss of life and extensive damage. Given the nature of an emergency, the potential for injuries and casualties could be exceptionally severe. Thus, safe emergency evacuation in metro stations is a critical concern in the overall safety of passengers and the metro rail system (Zhong et al. 2008).

The way passengers react in emergencies, such as their speed, direction, and decision-making under panic, significantly influences the overall effectiveness of an emergency evacuation. The current body of literature accounts for panic behavior, psychological aspects, and crowd density to understand the intricacies around pedestrian evacuations during an emergency (Guo and Zhang 2022). However, these studies are deterministic in nature, which define a condition with static measures of behavioral parameters and fall short in fully elucidating the extent of panic, despite the great implications the varying levels of panic may have on the evacuation process and time (Sun and Chen 2023). Deterministic models, by their nature, assign fixed values to behavioral parameters such as walking speed and reaction time, which precludes the representation of the inherent variability in human behavior, particularly under stress (Gwynne et al. 1999). This limitation is consequential: a single parameterization cannot capture the spectrum of behavioral responses that may emerge across different individuals and panic intensities, potentially leading to an underestimation or overestimation of evacuation risk (Ronchi, Reneke, and Peacock 2013). Furthermore, deterministic approaches are ill-suited for sensitivity analysis and uncertainty quantification, both of which are essential for robust evacuation planning (Vermuyten et al. 2016). A full-scale exploration of pedestrian behavior, within and across different levels of panic, would aid in understanding evacuation dynamics, particularly for metro stations with a high presence of pedestrian traffic. Additionally, there is a clear gap in extensive calibration and validation of the pedestrian simulation model due to the lack of data availability, hindering the application of the state-of-the-art methods, including machine learning and optimization approaches for calibration purposes.

The objective of this study is to develop a pedestrian evacuation modeling framework considering wide-ranging pedestrian behavior that reveals different levels of panic during a metro station evacuation. The study develops a pedestrian simulation model that implements the Social Force Model (SFM) (Helbing and Molnár 1995) to articulate pedestrian behavior during contrasting evacuation conditions. Machine learning and advanced optimization techniques are particularly well-suited for this purpose, as they enable systematic exploration of large, multi-dimensional parameter spaces, identification of the most behaviorally influential parameters, and data-driven calibration that accounts for variability in observed pedestrian behavior (Haghani and Sarvi 2016). This research employs machine learning and advanced optimization and sampling techniques to calibrate and validate the simulation model and evaluate evacuation scenarios for a comprehensive analysis of the impacts of different extremes of panic on overall evacuation performance. Additionally, this study provides insights into evacuation dynamics in light of results on evacuation flow and time across different panic scenarios, which complements the increasing call for the analysis of pedestrian dynamics (Zhou et al. 2018).

2. Literature review

2.1. Emergency evacuation in metro stations

Past emergency events in MRT stations, such as the 2021 Manila MRT-3 fire, the 1995 Baku Metro fire, the 2000 Kaprun railroad tunnel fire, and the 2003 Daegu subway fire, highlight the importance of efficient passenger evacuation (Yu et al. 2022). Wu et al. (2022) proposed an optimization approach for passenger evacuation from multi-exit subway stations by dividing the station into four regions to ensure partitioned evacuation and implementing railings to reduce congestion. Meanwhile, Long et al. (2020) introduced a guidance scheme aimed at enhancing evacuation in metro stations through the integration of an improved empirical formula. Their approach integrated pedestrian characteristics to evaluate the influence of pedestrian behaviors on evacuation efficiency. The findings of these studies emphasize improvement strategies while they fail to articulate differences in pedestrian movement behaviors (e.g. pushing, cooperation) in various conditions, including panic. Due to the confined spaces and overcrowding in MRT stations, emergencies can easily trigger panic among the people (J. H. Wang et al. 2016), which may further influence pedestrian speed and pushing behavior and impact the overall evacuation time.

2.2. Panic behavior in evacuation simulation modeling

Studies have recently started focusing on panic behavior in evacuation simulation modeling. Hsu (2024) simulated the evacuation and sheltering processes to conduct risk assessments of crowd congestion based on factors related to seismic risk in MRT systems using a spatial evacuation risk model. This study incorporated pre-evacuation response times of 30–60 s to account for potential panic behavior, and then panic behavior was simulated in Pathfinder in steering mode. Guo and Zhang (2022) proposed a framework integrating Random Forest (RF) and Non-dominated Sorting Genetic Algorithm III (NSGA-III) for evaluating and optimizing evacuations at metro stations, considering scenarios based on passenger volume and panic level. The evaluation criteria include evacuation time, density, and cost, while inputs are passenger volume, walking speed, herding behavior rate, number of fare gates, exits, and obstacles. The average passenger walking speed and herding behavior rate were used to represent the panic level in the study. However, the abovementioned studies articulated panic in an ad-hoc fashion and/or through one-point specification of behavioral parameters. While a level of panic can be demonstrated over a range of change in criteria specifications (e.g. a speed range for low panic) (Zheng et al. 2019), such a single-point specification approach does not capture the full spectrum of panic behaviors that might emerge in real-world scenarios. Guo, Zhang, and Wu (2023) proposed a hybrid approach that integrates Building Information Modeling (BIM), AnyLogic, and machine learning to simulate evacuation events and implement proactive evacuation strategies. Panic levels are addressed in the study by correlating them with congestion. A time-period-based over-density rate rule is proposed to evaluate evacuations and determine if more congestion occurs due to existing congestion. However, defining panic based on congestion without the consideration of wide-ranging pedestrian behavior may not fully unfold their decision-making under (J. Wang et al. 2015). Similarly, L. Hong, Gao, and Zhu (2018) employed the ripple effect principle to simulate the spread and acquisition of information in a panic in metro stations. Their model integrated panic-driven information dissemination and simulated decision-making through herd behavior to predict self-evacuation. Alam et al. (2023) examined pedestrians' social and physiological behaviors during airport evacuations, particularly focusing on how these behaviors vary across panic levels, where panic was defined by a rigid set of parameter combinations.

As evident from the review above, prior studies have conceptualized and operationalized panic in markedly different ways, with varying methodological implications. Table 1 synthesizes these differences across key studies to clarify the motivation for the framework proposed in this study.

The synthesis in Table 1 reveals that most prior studies define panic through a single proxy measure or a fixed set of parameter values, which constrains the exploration of behavioral variability across a continuous panic spectrum. Furthermore, formal calibration against empirical field data is rarely reported in these studies. The present

Table 1. Comparison of panic conceptualization in prior evacuation studies.

Study	Panic Proxy/Measure	Simulation Tool	Calibration/Validation	Key Limitation
Hsu (2024)	Pre-evacuation response time (30 – 60s); steering mode	Pathfinder	Not reported	Panic is treated as a fixed time delay; behavioral variability is not modeled
Guo and Zhang (2022)	Walking speed and herding behavior rate combined	AnyLogic + RF + NSGA-III	RF meta-model validated against simulation outputs ($R^2 = 0.91$); re-validated in AnyLogic; no empirical field data validation.	Panic is represented through aggregate speed and herding rate; individual behavioral variability is not captured.
Guo, Zhang, and Wu (2023)	Passenger volume and walking speed are used as proxies; congestion is evaluated via the over-density rate rule; panic is not explicitly modeled as a behavioral construct	BIM + AnyLogic + LightGBM	Meta-model validated against simulation outputs ($R^2 = 0.91$); no empirical field data validation	Individual behavioral variation is not captured; panic is not explicitly modeled
L. Hong, Gao, and Zhu (2018)	Ripple effect for information spread; herd behavior for evacuation decision-making	Custom SFM + A-star agent-based system	Qualitative comparison with the traditional synchronous evacuation model; no empirical calibration against field data	Pedestrian speed and physical interaction forces were not varied across panic levels; behavioral heterogeneity was not captured
Zheng et al. (2019)	Panic coefficient (η) based on local pedestrian density and distance from emergency source	Custom Cellular Automata (Floor Field model)	Qualitative validation comparing four simulation cases; no empirical field data	Panic is modeled through a density/distance coefficient in a generic room setting; individual psychological variation is not accounted for
Alam et al. (2023)	Fixed SFM parameter combinations per panic level (τ, λ, G, η) identified via sensitivity analysis	PTV VISWALK	No formal calibration; sensitivity analysis used to identify influential parameters; no empirical validation	Fixed parameter sets per panic level; no systematic sampling across panic spectrum; no empirical calibration or validation

study addresses these gaps by adopting a data-driven, range-based approach in which Latin Hypercube Sampling generates a broad distribution of parameter combinations across the panic spectrum, and Random Forest feature importance identifies the parameters most sensitive to changes in pedestrian speed, the surrogate measure of panic adopted in this study, consistent with prior work (Alam et al. 2023; J. H. Wang et al. 2012; Zheng et al. 2019).

2.3. Microsimulation and social force models

Microsimulation allows for detailed modeling of individual pedestrian movements, providing insights into people's behavior in different scenarios. These analyses employ different mathematical models, for instance, the SFM (Helbing, Farkas, and Vicsek 2000), Space-Syntax based agent simulation (Penn and Turner 2002), Cellular Automata models, or the PedGo model. Among these, the SFM was initially proposed by Helbing and Molnár (1995) and is a widely used crowd model that is applied by many simulation software packages (Ding et al. 2024). It simulates crowd behavior by considering interactions between pedestrians based on physical forces. However, as traditional SFM fails to capture the complexity of diverse crowd scenarios effectively, many studies either modified the SFM or used it in combination with other algorithms to increase efficiency. For example, Cai et al. (2022) integrated the SFM with an exit choice model to analyze the influencing factors (pedestrian density, distance from pedestrian to exits, and exit width) of different pedestrian categories in the multiple-exit scenario. Lu, Deng, and Sun (2024) combined the SFM with a fire dynamics model to find out the safe design parameters of metro stations, considering pedestrians' impatience and psychology. Qi and Qing (2023) improved the collision avoidance mechanism of the classical SFM to avoid the overlap between people or between people and walls. The combination of the SFM with deep learning models for pedestrian detection in crowd evacuation at subways demonstrated superior realism compared to traditional simulation models (Li et al. 2019).

2.4. Machine learning and optimization in evacuation studies

Similar to the study of Guo and Zhang (2022), other studies used various data and feature analysis methods along with SFM and simulation tools to eliminate redundant information from the dataset to derive an optimal subset of features (Y. Li, Li, and Liu 2017). RF is another popular feature analysis tool that involves growing multiple decision trees and combining their outputs to make predictions and optimizations in evacuation dynamics. In evacuation studies, the RF algorithm has been used to predict and identify significant factors affecting household evacuation time using demographic and behavioral variables (Rahman, Hokugo, and Ohtsu 2021) and to delineate evacuation zones (Xie et al. 2017). However, it has been used only to a limited extent to determine pedestrian panic behavior and for calibration purposes. Moreover, a tendency exists to conduct calibration and validation of the pedestrian simulation model together based only on count data, which can resemble the observed counts with or without representative values of important simulation parameters (Feliciani et al. 2020). This necessitates distinct calibration and validation processes for different criteria. The calibration of the simulation model involves a large volume of data and parameter combinations that require optimization processes to identify the best combinations of pedestrian behavior parameters to resemble pedestrian behavior within the simulation model. A detailed specification of the machine learning models employed in this study, including the RF feature importance algorithm and the Genetic Algorithm used for calibration, is provided in Section 4.

2.5. Research contribution

The contribution of this study is that it develops a methodological framework of evacuation modeling accounting for a wide range of pedestrian behavior to analyze the impacts of various panic levels on evacuation performance. A simulation model is developed, calibrated following a Genetic Algorithm (GA) and validated in terms of the Geoffrey E. Havers (GEH) statistic. The Latin hypercube sampling (LHS) method is used to generate a distribution of plausible scenarios by systematically sampling from the input variables' ranges, and then the RF algorithm is used on the gathered dataset to determine key behavioral parameters. Results from the LHS and RF are then used to simulate evacuation scenarios at different panic levels. Finally, the simulation results are analyzed to provide insight into crowd dynamics in contrasting conditions.

3. Study area

The Dhaka Metro Rail is a rapid transit system that operates in Dhaka, the capital and largest city of Bangladesh. Since its launch, ridership has been continuously increasing, growing from just over 100,000 in 2023 to 290,000 in 2024. With this rising number of passengers, the demands for crowd management within the Dhaka Metro have become critical. Thus, this research focuses on one of the busiest metro stations in Dhaka, Agargaon, to explore the evacuation scenarios. Agargaon station, as shown in Figure 1, is an elevated one, situated centrally along the line that connects Motijheel and Uttara. The station is surrounded by numerous shopping malls, bus interchanges, hospitals, and a central passport office. It also houses the central offices for metro operations. The station features two levels: the concourse on level 1 and the platforms on level 2. The station regularly experiences significant passenger volume, particularly during peak hours. This underscores the urgent need to assess and optimize the safety measures for evacuating Agargaon station during high traffic scenarios.

For the purposes of this study, evacuation is defined as the complete clearance of all passengers from both the platform level (Level 2) and the concourse level (Level 1) to the street level via the four exit stairways located near the four corners of the station on the first level. The evacuation is considered complete when the last passenger exits the station network through one of these stairways. Elevators are excluded from the evacuation routes as they are assumed to be non-operational in accordance with standard emergency procedures. This definition is consistent with the simulation model developed in this study, in which pedestrian routes were configured so that all passengers evacuate toward the nearest available exit stairway.

(a) (b)

Figure 1. (a) and (b): Agargaon metro station, Dhaka.

4. Methodology

The methodology of this study consists of three steps: (i) the development of a pedestrian microsimulation model employing SFM walking behavior parameters, (ii) the generation of behavioral parameter combinations through combined LHS and RF Regression Feature Importance techniques, and (iii) the derivation of panic evacuations and analysis. The overall framework of this study is illustrated in a flowchart showcased in Figure 2. A key methodological assumption underpinning this framework is the use of average pedestrian speed as a surrogate measure of panic behavior. It is first acknowledged that collecting empirical data during real panic events is effectively impossible for both technical and ethical reasons, a constraint that is widely recognized and consistently noted across the evacuation simulation literature (Alam et al. 2023; Sticco, Frank, and Dorso 2021). The surrogate assumption is therefore grounded not in direct panic observation, but in a convergent body of theoretical, model-based, and quasi-empirical evidence, as detailed below.

At the theoretical and mechanistic level, the foundational SFM operationalizes panic precisely through the desired velocity parameter: as perceived urgency or threat intensity increases, agents seek to move at higher speeds, generating the characteristic behavioral signatures of panic: jamming at bottlenecks, physical contact, loss of cooperative behavior, and the faster-is-slower phenomenon. Within this formulation, elevated speed is not merely a correlate of panic; it is the primary mechanism through which panic intensity is encoded and varied in the model. The present study adopts this same operationalization, which is consistent with how panic has been represented in SFM-based microsimulation research for over two decades. This assumption is further supported by prior research demonstrating that pedestrian speed systematically increases under heightened urgency and stress conditions (Alam et al. 2023; Haghani, Sarvi, and Shahhoseini 2020; J. H. Wang et al. 2012; Zheng et al. 2019). Under panic, individuals tend to accelerate toward exits, maintain higher sustained speeds, and exhibit reduced cooperative behavior, all of which manifest as an elevated average speed across the simulation network. Controlled experimental studies corroborate this: Haghani, Sarvi, and Shahhoseini (2020) found that higher urgency treatments produced faster and more immediate rushes toward exits, with evacuation times consistently shorter under high-urgency

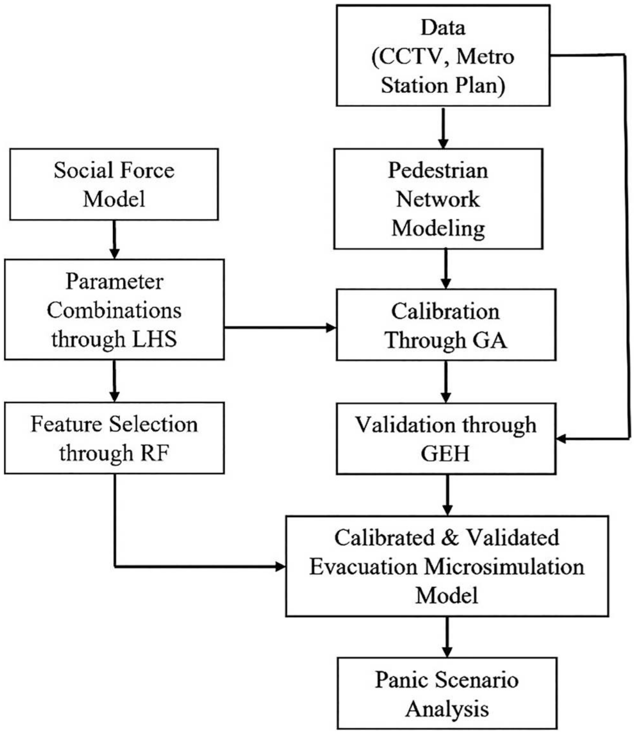

Figure 2. Methodology flowchart.

conditions, directly linking urgency level to observable speed-related outcomes in crowd behavior.

Quasi-empirical support is also available. Sticco, Frank, and Dorso (2021) analyzed a real-life high-stress stampede event (a store-opening crowd rush during Black Friday) and demonstrated that the escape-panic version of the SFM, parameterized through elevated desired speed, successfully reproduced observed pedestrian flow patterns that laboratory-calibrated, lower-speed parameters could not replicate. This provides empirical validation that elevated speed is an effective operational indicator of stress-induced movement in conditions approximating panic. Similarly, Alam et al. (2023) implemented the SFM within a microsimulation platform and conducted sensitivity analyses to identify the behavioral parameters capturing pedestrian movement under varying panic levels, operationalizing panic conditions through speed-related SFM parameters, a methodological approach directly analogous to that of the present study. Empirical studies of evacuation movement further report that pedestrian speeds during emergencies are consistently 1.4–2.0 times higher than normal walking speeds (Alam et al. 2023; Guo and Zhang 2022), providing a behavioral basis for treating speed elevation as a marker of escalating urgency.

While panic may also manifest through other behaviors such as route choice, pushing, herding, congestion patterns, and exit utilization, speed has been shown to be a reliable and practically measurable indicator of panic intensity in microsimulation environments (Alam et al. 2023; Guo and Zhang 2022). It is explicitly acknowledged that this surrogate approach introduces a degree of inferential uncertainty into the panic scenario outputs: the model does not directly observe panic but instead simulates its most tractable behavioral signature under conditions where no alternative empirical data source exists. The conclusions drawn from the panic scenarios are therefore interpreted as comparative and indicative, illustrating directional trends in evacuation performance across panic levels, rather than as precise quantitative predictions of real-world panic events. The limitations of this surrogate measure are acknowledged and discussed further in Section 7.

Initially, a pedestrian simulation model is developed utilizing multiple datasets, including CCTV footage and metro station plans. Using the SFM parameters, LHS combinations of parameters were generated, which were utilized for (i) the Genetic Algorithm (GA) in the calibration process, and (ii) the RF Regression Feature Importance Analysis. CCTV data is used, and Geoffrey E. Havers (GEH) statistics are developed to validate the simulation model. Then the evacuation scenarios are generated and simulated based on the criteria derived from the RF modeling. LHS is re-applied on the RF-identified features to generate feature combinations representing a set of evacuation scenarios for simulations. The calibrated values of the features of the base model that are not identified as influential in the RF modeling stage are retained for evacuation scenario analysis. Panic evacuations are derived from the simulations of evacuation scenarios and analyzed accordingly. An in-depth description of all the steps is given in the following sections.

4.1. Development of pedestrian microsimulation model

4.1.1. Pedestrian network coding

The Agargaon station was replicated within the VISWALK simulation platform encompassing two levels, occupying a 180×26 m area with four exit stairways located near the four corners of the station on the first level. The second level has two tracks in the middle and platforms on both sides. The first level has ticket counters, ticket vending machines, control unit, stairs, and multiple restricted portions coded as 'Blockage'. Elevators are also considered blockages, as they are assumed to be shut down in accordance with standard emergency procedures. The simulation model is showcased in Figures 3 and 4. Figure 3 presents the top view of the base model, where key spatial components are labeled, including the platform areas, ticketing area, passageways, entry/exitways, and the four corner stairways that serve as evacuation exits. Arrows indicate the primary pedestrian flow directions during normal operations. All the necessary data, including CCTV footage for pedestrian flow count and average speed, along with the station floor plan, was collected from Dhaka Mass Transit Company Limited (DMTCL). From the 12-hour video footage of a typical working day, the peak hour was identified to be from 5 PM to 6 PM, and the passenger flow in that hour was 3189. The average speed during the peak hour in different areas (Entry/Exitways, stairs, etc.) was used for base model calibration, and the total passenger flow within that time was used for validation.

From the 12-hour video footage of a typical working day, the peak hour was identified to be from 5 PM to 6 PM and the passenger flow in that hour was 3189. The selection of a single typical working day for data collection is acknowledged as a limitation of this study. Pedestrian flow patterns in metro stations can vary across days of the week,

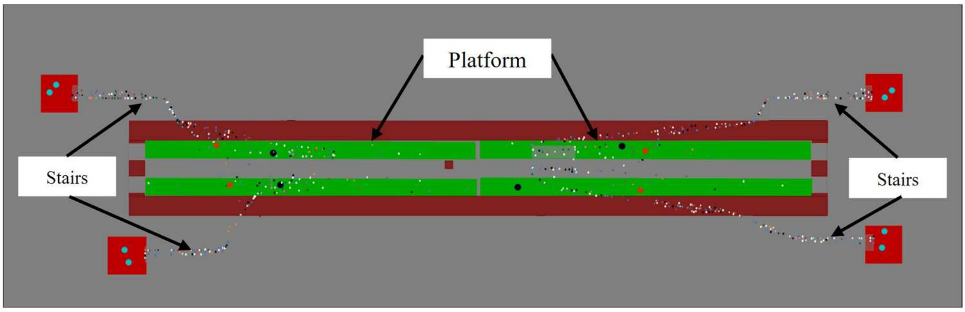

Figure 3. Base model (top view).

seasons, and special events, and a single observation day may not fully capture the range of operational conditions experienced by the station. However, the use of a single representative peak hour for simulation calibration and scenario development is consistent with established practice in pedestrian microsimulation studies, where the peak hour of the busiest typical day is commonly adopted as the design condition for evacuation modeling, as it represents the most critical scenario in terms of passenger volume and evacuation complexity. The 5 PM to 6 PM period was identified as the peak hour from a 12-hour footage covering the full operational window of the station on the selected day, providing confidence that the identified peak represents the highest demand condition within that day. Nonetheless, the calibrated model parameters and evacuation scenario results should be understood as representative of peak-hour weekday conditions at Agargaon station, and future work incorporating multiple days of observation, including weekend days, seasonal variations, and special event conditions, would strengthen the generalizability of the calibration and validation.

For the evacuation model, after calibrating the SFM walking behavior parameter values to impart panic amongst passengers, the pedestrian routes were altered with an assumption that the passengers will always choose the nearest exit during an emergency. The highest number of occupants at a single moment of the MRT station was calculated to be 540, and the pedestrian inputs for the evacuation model were adjusted accordingly.

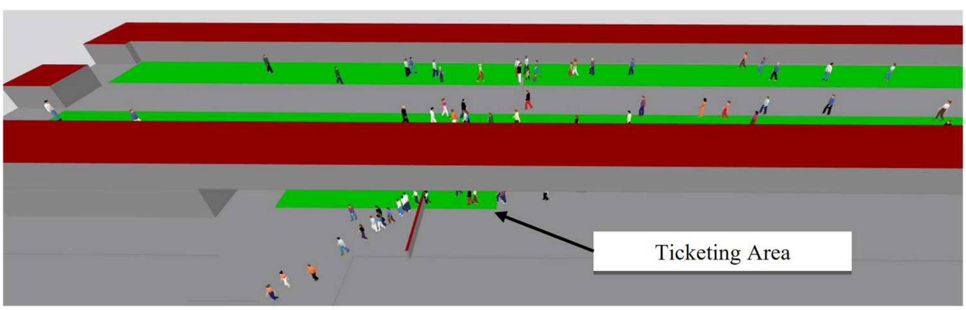

Figure 4. Base model (3D view).

4.2. Pedestrian behavior parameters: social force model

Forces in SFM consider interactions among pedestrians, involving repulsion to avoid collisions, attraction toward desired destinations, and other factors influencing personal space. According to Helbing and Molnár (1995), pedestrian motion can be conceptualized as the outcome of individuals being influenced by various forces. Physical forces account for the impact of obstacles like walls. Psychological factors, such as urgency and comfort, also influence how individuals navigate through a crowd. Pedestrians in behavioral models have specific goals, and the forces are iteratively calculated to guide their movements, ensuring collision avoidance and maintaining personal space. Force *F*, which prompts pedestrians to either decelerate or accelerate, can be calculated by Equation (1).

$$F = F_{\text{driving}} + F_{\text{social}} + F_{\text{noise}} \tag{1}$$

In the context of the SFM as applied in VISWALK, the forces influencing pedestrian behavior are directly related to the parameters described in Table 2 (Alam, Habib, and Holmes 2022). The parameter 'Side preference' was not utilized in this study as it was found to be inconsequential for the study area.

4.3. Latin hypercube sampling of SFM parameters

LHS, introduced by McKay, Beckman, and Conover (2000), is a statistical approach for creating a quasi-random sample of parameter values from a multidimensional distribution. In this method, a Latin hypercube generalizes the concept to an arbitrary number of dimensions, ensuring that each sample stands alone in each axis-aligned hyperplane containing it.

For *the X* parameter with range *[a, b]*, the range is divided into *n* intervals shown in Equation (2):

$$\Delta x = \frac{b - a}{n} \tag{2}$$

Each interval I_i for $i = 1, 2, \ldots, n$ is defined as shown in Equation (3):

$$I_i = a + (i - 1)\Delta x, a + i\Delta x \tag{3}$$

For each interval I_i, a sample point x_i is chosen uniformly at random as shown in Equation (4):

$$x_i = a + (i - 1)\Delta x + U_i\Delta x \tag{4}$$

Here, U_i is a random number drawn from the uniform distribution $U(0, 1)$.

Let k be the number of parameters. For each parameter x_i where $j = 1, 2, \ldots, k$, an $n \times k$ sample matrix S is constructed as shown in Equation (5):

$$S = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1k} \\ x_{21} & x_{22} & \cdots & x_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nk} \end{bmatrix} \tag{5}$$

Table 2. SFM parameters in pedestrian simulation.

Parameter	Description	Behavioral Interpretation	Standard Values
Tau (τ)	Represents the reaction time of pedestrians. In conjunction with the desired velocity and current velocity, Tau determines the driving force, $F_{driving}$. Reducing Tau increases both acceleration and the driving force. Consequently, decreasing Tau can shorten the throughput time in narrow passages.	A lower Tau reflects a more aggressive, urgent pedestrian who accelerates rapidly toward their destination – characteristic of high panic behavior. A higher Tau reflects a relaxed, unhurried pedestrian typical of normal conditions.	0–1
Lambda (λ)	Accounts for the reduced influence of people and events behind a pedestrian compared to those ahead. It affects the social force, F_{social}.	A lower Lambda means the pedestrian is more influenced by others behind them, reflecting heightened situational awareness. A higher Lambda reflects tunnel-vision behavior where only those ahead matter, which is common under panic.	0–1
ReactToN	Determines the maximum number of pedestrians considered when calculating the social force, F_{social}.	A lower ReactToN means the pedestrian reacts to fewer surrounding individuals, mimicking reduced situational awareness under stress. A higher value reflects more socially aware, cooperative movement.	≥0
VD	Considers the relative velocities of pedestrians and contributes to the social force, F_{social}. Increasing VD causes pedestrians to evade each other earlier when passing or meeting.	Higher VD reflects more cautious, anticipatory evasion behavior typical of calm conditions. Lower VD reflects reduced evasive awareness under panic.	≥0
ASocIso & BSocIso	They govern the direction-independent force between pedestrians.	These parameters control the strength and range of the isotropic social force. Higher values result in greater personal space maintenance, reflecting cooperative normal-condition behavior.	ASocIso = 2.72 BSocIso = 0.20
ASocMean & BSocMean	Typically associated with the repulsive forces that govern the interactions between pedestrians.	BSocMean in particular was identified as the second most influential parameter in the RF analysis. A lower BSocMean reduces the range of repulsive interaction, reflecting the compressed personal space and physical pushing behavior characteristic of high panic conditions.	ASocIso = 2.10 BSocIso = 0.30
Noise	Determines the strength of the random force term, F_{noise}. This term is added after all other forces have been calculated, but only if a pedestrian is slower than their desired speed for a certain time.	Higher Noise introduces more randomness and unpredictability in movement, which may reflect behavioral uncertainty in moderate panic. Lower Noise reflects homogeneous, directed movement typical of high panic.	0–2

Here, x_{ij} is the sample from the ith interval of the jth parameter.

For this study, LHS was utilized to generate parameter combinations. Initially, the standard values and ranges of the 9 SFM parameters were sampled using LHS to generate 100 combinations in which there was no repetition of a single value for a particular parameter to avoid clustering. Instructions were provided to not generate more than 3 decimal places due to the input restrictions in VISWALK. These 100 combinations were used firstly as inputs in the GA for base model calibration and secondly as the dataset for RF Regression Feature Importance Analysis. Another 500 combinations were generated after obtaining the results from the RF analysis, but this time only the identified important parameters were sampled. The outputs from these 500 combinations were used to divide panic levels and conduct comparative analysis.

It is acknowledged that standard LHS assumes independence between parameters, and therefore does not explicitly account for potential dependencies among the nine SFM parameters. In practice, the SFM parameters in VISWALK do not have formally documented interdependencies in the literature, and prior studies employing LHS for pedestrian simulation calibration have similarly applied it under this assumption (Alam et al. 2023; Kumar, Banerjee, and Maurya 2020). Furthermore, the primary purpose of the LHS in this study is not to capture the full joint distribution of parameters, but to systematically explore the parameter space with sufficient coverage to identify influential parameters and generate a diverse set of evacuation scenarios. Nonetheless, this represents a limitation of the current approach, and future work could consider more advanced sampling techniques such as copula-based methods that can incorporate parameter dependencies where these are known.

The speed ranges produced by the 500 LHS combinations were compared against empirical observations of pedestrian speeds under emergency and panic conditions reported in the literature. Studies have documented free-flow walking speeds of 1.2–1.6 m/s under normal conditions (Alam, Habib, and Holmes 2022), with speeds reaching up to 1.5 m/s and beyond under high-urgency evacuation scenarios (Haghani, Sarvi, and Shahhoseini 2020). The average speeds observed across the panic scenario simulations in this study ranged from 2.64 to 3.93 km/h (0.73–1.09 m/s), which fall within or marginally below the lower end of reported emergency walking speeds, reflecting the congested nature of the station environment where free-flow speeds cannot be sustained. These values are therefore considered physically plausible rather than artifacts of parameter adjustment.

4.4. Base model calibration

4.4.1. Calibration data description

The calibration of the base model relied on pedestrian speed and flow count data extracted from CCTV footage provided by DMTCL. The station is equipped with a total of 12 CCTV cameras distributed across the four key functional areas: four cameras positioned at overhead angles above each of the corner stairway entry/exit points, two cameras covering the ticketing area and fare gate zone from elevated wall-mounted positions, two cameras covering the main connecting passageways at mid-span overhead positions, and four cameras covering the platform areas from elevated positions at each end of the two platform sides. All cameras provided continuous footage across the full 12-hour operational window of the station, from which the peak hour of 5 PM to 6 PM was identified.

During the peak hour, the total observed pedestrian flow through the station was 3,189 passengers. The distribution of observed pedestrian counts across functional areas during this period was as follows: Entry/Exitways recorded a combined inflow and outflow count of 3,189 movements across the four stairways, with an average per-stairway flow of approximately 797 movements per hour; the Ticketing Area recorded 2,841 movements, reflecting that a proportion of passengers used pre-loaded smart cards bypassing the manual ticketing counters; the Passageway recorded 3,189 movements as all passengers traversed this zone; and the Platform areas recorded 3,189 boarding and alighting movements combined. The average pedestrian walking speeds observed in each area during the peak hour were extracted from the footage through manual video-tracking of individual pedestrians, and are presented as calibration targets in Table 3.

Volume-to-capacity (V/C) ratios were calculated at the primary bottleneck locations to assess the degree of constraint on pedestrian flow during the peak hour. The four corner exit stairways, each with an effective width of approximately 3.0 meters, have an estimated maximum throughput capacity of 90 persons per minute per stairway under normal conditions, giving a combined stairway capacity of 360 persons per minute. With an observed average inflow rate of approximately 53 persons per minute during the peak hour, the V/C ratio at the stairway bottlenecks was 0.15, indicating low-to-moderate utilization consistent with the observed absence of persistent congestion during normal operations. At the fare gate zone, eight operational gates each with a throughput capacity of approximately 25 persons per minute yield a combined capacity of 200 persons per minute, producing a V/C ratio of approximately 0.27 during the peak hour. These V/C values confirm that the station operates well within capacity during normal peak-hour conditions, providing the baseline against which the GA calibration targets were established.

The calibration of the simulation model is crucial for accurately simulating pedestrian dynamics and behaviors in various environments. By fine-tuning model parameters, calibration ensures that the simulation results are reliable, thereby enhancing the predictive accuracy of the model. For this study, the average speed of pedestrians across four different areas was gathered from CCTV footage and on-site analysis. To match the simulation average speeds with the observed values, a GA was utilized. GAs are search and optimization algorithms based on the principles of natural evolution, which were first introduced by Holland (1975). These implement optimization strategies by simulating evolution of species through natural selection. A GA is generally composed of two processes. The first process is the selection of individuals for the production of the next generation, and the second process is the manipulation of the selected individuals to form the next generation by crossover and mutation techniques (Razali and Geraghty 2011). A fitness function is typically used to score the accuracy of a set of provided training examples. This study utilized the Mean Absolute Percentage Error (MAPE) as the fitness function to calibrate the VISWALK model as it has proved to be reliable in similar endeavors (Kumar, Banerjee, and Maurya 2020). MAPE can be defined as shown in Equation (6).

$$f = \frac{1}{N}\sum_{i=1}^{n}\left|\frac{V_{obs} - V_{sim}}{V_{obs}}\right| \times 100 \tag{6}$$

Table 3. Observed speeds per area.

Functional Area	Mean Speed (m/s)	Std. Dev. (m/s)	Min. (m/s)	Max. (m/s)	95% CI (m/s)
Entry/Exitways	1.24	0.18	0.78	1.71	1.21–1.27
Ticketing Area	0.87	0.22	0.42	1.35	0.83–0.92
Passageway	1.38	0.15	0.91	1.82	1.36–1.40
Platforms	1.09	0.20	0.55	1.58	1.05–1.13

It is important to clarify the distinction between the calibration metric (MAPE) and the validation metric (GEH). MAPE was selected as the fitness function for the GA calibration process because it measures the percentage error between simulated and observed average pedestrian speeds – a continuous variable for which MAPE is a well-established and interpretable metric (Kumar, Banerjee, and Maurya 2020). GEH, on the other hand, is applied during the subsequent validation stage to assess how well the calibrated model reproduces observed pedestrian flow counts at the entry and exit points of the station. GEH is specifically designed for traffic and pedestrian flow count validation and accounts for both absolute and relative differences in a single statistic (Friedrich et al. 2019; Gaddam et al. 2022). These two metrics therefore serve complementary but distinct purposes – MAPE optimizes parameter values against speed observations, while GEH independently verifies that the resulting model also reproduces observed flow patterns. This two-stage approach of calibrating against one criterion and validating against another is consistent with best practice in pedestrian simulation modeling (Feliciani et al. 2020).

The fitness value of the average pedestrian speed gathered from the first 100 sets of LHS combinations was used as the initial population for the GA. As there were only 9 parameters to calibrate, with a high initial population, within 20 generations the fitness value reached a saturation point. The changes in the fitness value across generations for different areas are shown in Figure 5.

The results from the GA with fairly acceptable fitness values helped in determining the calibrated set of parameters for the different areas of the simulation model as shown in Table 4.

The calibrated parameter sets differ across the four spatial zones of the station, reflecting the genuinely distinct pedestrian behavior characteristics observed in each area. This

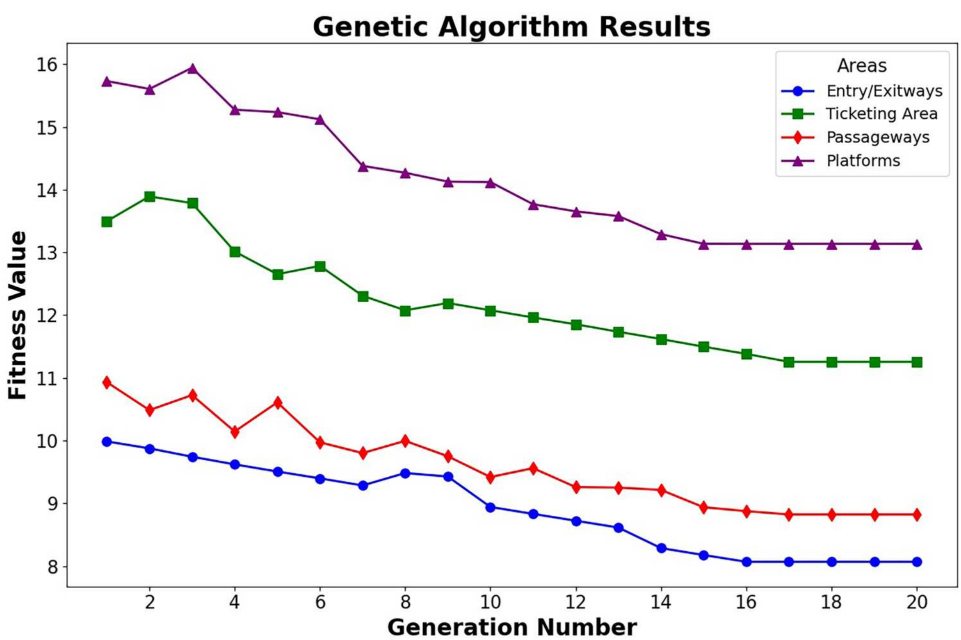

Figure 5. Fitness value vs generation number.

Table 4. Calibrated parameters.

Areas	Tau	ReacToN	ASocIso	BSocIso	Lambda	ASocMean	BSocMean	VD	Noise
Entry/Exitways	0.5	3	2.467	0.20	0.042	1.723	1.851	3	1.2
Ticketing Area	0.9	6	2.281	0.28	0.055	1.539	2.190	2	1.5
Passageway	0.4	3	2.605	0.18	0.037	1.812	1.754	3	1.0
Platforms	0.8	4	2.300	0.25	0.048	1.636	1.980	2	1.3

spatial heterogeneity is not a symptom of overfitting but rather a physically motivated modeling choice. In the Entry/Exitways, pedestrians move with moderate urgency in directional flows, justifying intermediate Tau values. In the Ticketing Area, the presence of queuing and slower, more deliberate movement is reflected in a higher Tau and ReactToN. In the Passageway, unobstructed directional flow results in the lowest Tau, reflecting faster movement. On the Platforms, the combination of waiting behavior and sudden movement toward trains is captured through intermediate parameter values. Each calibrated set was validated independently against observed GEH values for its respective zone, and all zones achieved acceptable GEH scores as shown in Figures 6 and 7. Area-specific calibration is consistent with established practice in microsimulation modeling, where spatially heterogeneous parameter sets are used to reflect genuine behavioral differences across distinct functional zones (Alam et al. 2023; Alam, Habib, and Holmes 2022).

4.5. Base model validation

In assessing the simulation model's validity, GEH is a valuable tool. GEH is able to provide a numerical score that quantifies model performance and is a reliable goodness-of-fit check in validating simulation models (Gaddam et al. 2022). A lower GEH

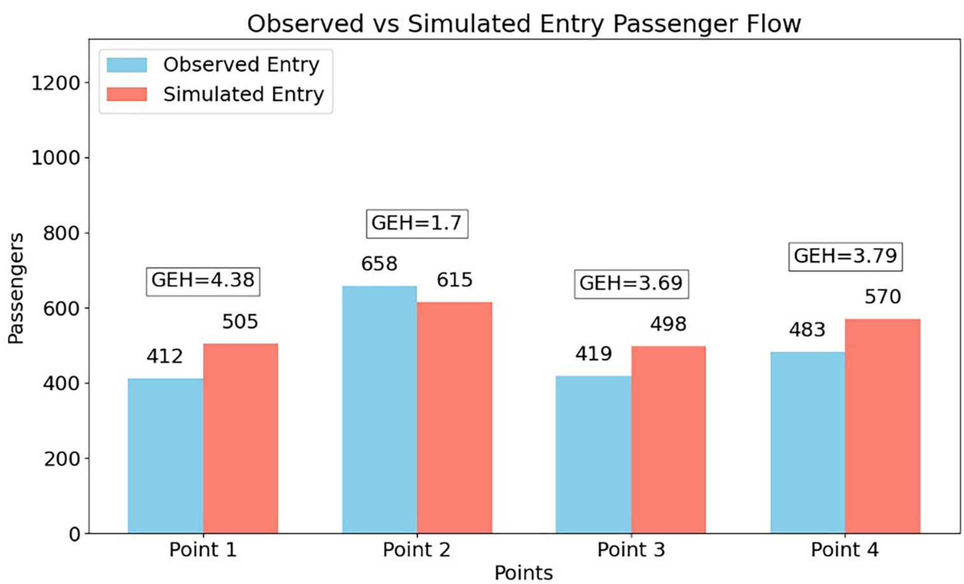

Figure 6. Base model validation (entry points).

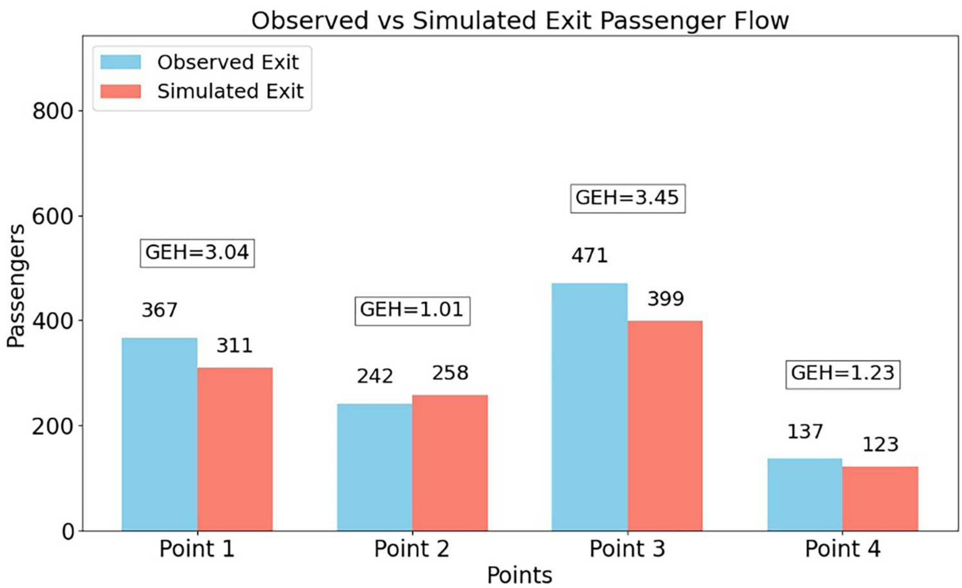

Figure 7. Base model validation (exit points).

value indicates a better match between the simulated data and the observed data, while a higher value suggests a larger discrepancy. GEH can be defined according to Equation (7) (Feldman 2012).

$$\mathrm{GEH} = \sqrt{\frac{2(x-y)^2}{x+y}} \tag{7}$$

Here, x is observed flow and y is simulated flow.

In this study, the GEH values are calculated in all four entry/exit points. The entry pedestrians are considered to be the ones that entered the station and reached the platform to enter the trains, and the exit pedestrians are the ones that started from the trains and reached the exit. For the calibrated parameters, the GEH values for the entry passenger flow are given in Figure 6 and for the exit passenger flow in Figure 7.

This rigorous validation ensures the accuracy and reliability of the simulation model in replicating actual pedestrian behavior.

4.6. Machine learning model specification

This section provides a formal specification of the two machine learning and optimization methods employed in this study: the RF Regression Feature Importance algorithm and the GA.

4.6.1. Random forest feature importance

The RF algorithm is an ensemble learning method that constructs multiple decision trees during training and outputs the mean prediction of the individual trees. In this study, RF Regression is employed, as the target variable, average pedestrian speed, is continuous.

The feature importance is determined by measuring the total reduction in Mean Squared Error (MSE) contributed by each parameter across all trees in the forest, as given in Equation (8).

$$\text{Variance}(t) = \frac{1}{N_i} \sum (y_i - \bar{y})^2 \tag{8}$$

Here, N_i is the number of samples in node t, y_i is the value of the ith sample, and $\bar{y}$ is the mean value of samples in node t. Features that contribute the greatest reduction in MSE across all splits are ranked as most important. In this study, the 100 LHS-generated parameter combinations and their corresponding average simulation speeds constitute the training dataset. The nine SFM parameters serve as independent variables and the average pedestrian speed is the dependent variable. The RF model was implemented using standard scikit-learn settings with 100 estimators.

4.6.2. Genetic algorithm

The GA used for base model calibration follows a standard evolutionary optimization procedure. An initial population of candidate parameter sets is drawn from the 100 LHS combinations. The MAPE fitness function (Equation (6)) evaluates each candidate against observed pedestrian speeds across the four spatial zones. Selection, crossover, and mutation operations are iteratively applied over successive generations until the fitness value reaches a saturation point, which in this study occurred within 20 generations. The GA parameters used in this study are consistent with those reported in comparable pedestrian simulation calibration studies (Kumar, Banerjee, and Maurya 2020).

5. Evacuation scenario generation and simulation

As not all SFM parameters are associated with panic behavior, sampling all nine parameters would not provide the level of exploration aimed in this study. To identify the key parameters affecting the average speed of pedestrians, the surrogate measure of panic behavior adopted in this study, as justified in Section 4, the RF Feature Importance technique was utilized. Existing research has shown feature selection using RF to be reliable (Jaiswal and Samikannu 2017). A full specification of the RF Regression algorithm, including the MSE-based impurity criterion and the variance calculation method (Equation (8)), is provided in Section 4.6.

In this study, the initially generated LHS combinations were used as the dataset for feature importance analysis, where the nine SFM parameters are the independent variables, and the average speed of pedestrians is the dependent variable. The RF model identifies which parameters contribute most to explaining variance in pedestrian speed across the 100 LHS-generated simulation runs. The influential parameters identified by the RF modeling are then used in the generation of evacuation scenarios through a second application of the LHS process, this time sampling only across the identified influential parameters. The calibrated values of the non-influential parameters from the base model are retained unchanged across all evacuation scenario simulations. All the combinations of key features representing a set of evacuation scenarios are simulated, and panic levels are explored accordingly.

6. Results & Analysis

6.1. Analysis of feature selection results

The Feature Importance analysis on SFM parameters suggested 'Tau' to be the most sensitive parameter in altering the average speed of pedestrians, with an importance factor of 0.4506. Among the other parameters, BSocMean, ReacToN, ASocMean, and Lambda exert the most substantial influence on pedestrian behavior, with importance factors of 0.1624, 0.0893, 0.0872, and 0.0701, respectively. The importance ranking of all these parameters, according to their importance factor, is shown in Figure 8. In contrast, the remaining four parameters exhibit comparatively lower significance in shaping the observed behavioral patterns. These findings are consistent with the behavioral interpretations outlined in Table 1. Tau, as the parameter governing pedestrian reaction time and acceleration, is expected to be the dominant driver of average speed; lower Tau values produce more aggressive acceleration toward exits, directly elevating the network-wide average speed, consistent with observations that under high-urgency conditions, pedestrians exhibit shorter reaction times and more rapid initial acceleration (Haghani, Sarvi, and Shahhoseini 2020). BSocMean governs the range of repulsive social interaction between pedestrians; lower values compress personal space and increase pushing behavior characteristic of higher panic intensities, which aligns with experimental findings that under panic, inter-personal distances reduce substantially as the urgency to reach exits overrides normal social spacing norms (Moussaïd, Helbing, and Theraulaz 2011). ReacToN and ASocMean jointly regulate how pedestrians respond to their immediate neighbors, and their combined influence on speed reflects the role of crowd density effects in shaping evacuation dynamics (Ding et al. 2024).

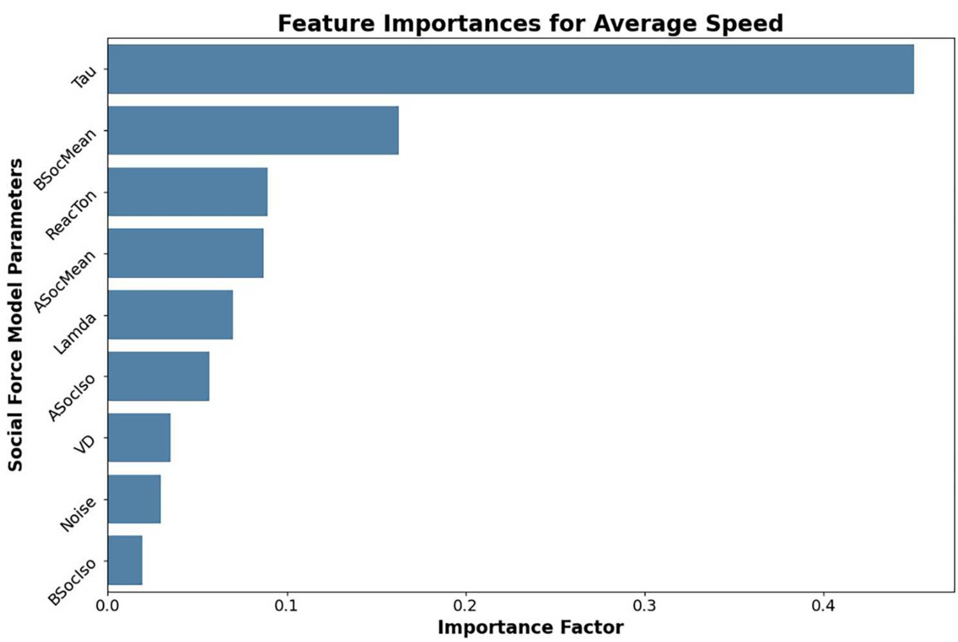

Figure 8. Feature importance ranking.

6.2. Exploration of panic evacuations

The evacuation environment is categorized into three distinct levels: Low Panic, Medium Panic, and High Panic. The differentiation is based on the velocity of pedestrians, assuming a correlation between panic intensity and speed (Alam et al. 2023; J. H. Wang et al. 2012). This assumption is further supported by studies demonstrating that pedestrians under heightened urgency exhibit systematically elevated walking speeds, reduced cooperative behavior, and shorter reaction times (Haghani, Sarvi, and Shahhoseini 2020; Zheng et al. 2019). While panic may also manifest through other behaviors such as herding, route choice, and pushing, speed represents a practically observable and simulation-tractable indicator of panic intensity consistent with prior metro and airport evacuation modeling work (Alam et al. 2023; Guo and Zhang 2022). In this case, an ascending order of simulation numbers was orchestrated based on the average pedestrian speeds in each of the 500 simulations to form a graphical representation illustrated in Figure 9.

This plot facilitated an assessment to finally depict three different panic levels through examination of the gradual increase of average speed. The initial sharp increase of the average speed until the start of a slight decline in the curve slope was determined to be Low Panic, which consisted of the first 180 simulations and the highest average speed of 3.60 km/h. The range where the decline of the slope continued up until a sudden jump in average speed from 3.74 km/h in the 291st simulation was declared Medium Panic, and the rest of the increasing average speed simulations were considered to be High Panic, with an average speed range of 3.79 km/h to 3.93 km/h.

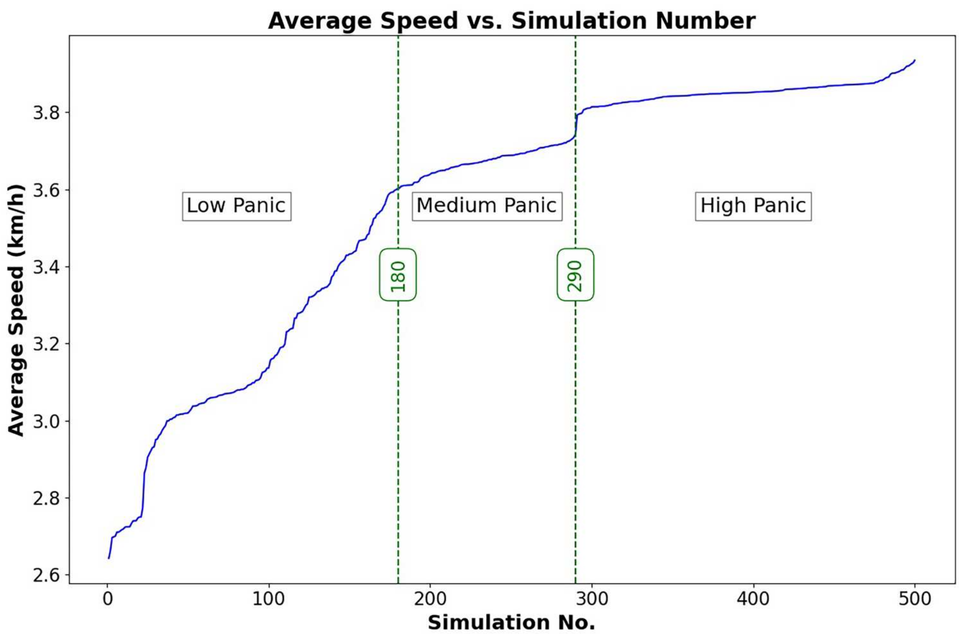

Figure 9. Panic evacuation exploration.

6.3. Analysis of evacuation performance

The overall evacuation performance of all the simulations under three levels of panic conditions is presented in Table 5. The total clearance time is recorded from the start of the evacuation procedure to the time of the last pedestrian leaving the MRT station. The average individual evacuation time is the average travel time of all the pedestrians in the simulation network. From Table 5, it is apparent that the total clearance time is the longest, with significant variation between lowest and highest times. The clearance times are shorter in Medium Panic conditions and the shortest in High Panic, as supported by previous studies (J. H. Wang et al. 2016). In Low Panic, across the simulations, the variation between the lowest and highest values suggests non-uniform behavior amongst pedestrians, as typically in less-urgency situations, pedestrians experience comparatively relaxed environments and have the freedom to choose their paths. However, in Medium Panic and High Panic, the pedestrians exhibit a homogeneous response to the urgency of the situation and that leads to uniform behavior. A similar observation can be made from the variation of average individual evacuation times in different levels of panic. The average speed in Low Panic situations also varies across simulations, as the SFM parameters are set to reflect stronger individual preferences and interactions. In Medium and High Panic, these parameters might be adjusted to reflect stronger forces towards evacuation, reducing variability.

Across the simulations, under different levels of panic, the Interquartile range (IQR) was found to be 0.3292 for Low Panic, 0.0500 for Medium Panic, and 0.0296 for High Panic. It is evident that the variability in pedestrian speeds significantly decreases as panic levels increase. In the Low Panic scenario, the wide IQR indicates substantial variability in walking speeds whereas the much smaller IQRs for Medium and High Panic scenarios signify a marked reduction in speed variability. The decreasing IQR values highlight how increased stress and urgency lead to more uniform pedestrian responses, with less variation in speed as individuals prioritize urgent evacuation. While it may appear counterintuitive that higher panic produces less rather than more speed variation, this can be explained by the behavioral homogenization that occurs under extreme urgency. Under Low Panic, the wide range of LHS parameter combinations reflects diverse individual behavioral tendencies, producing a high IQR. Under High Panic, the parameter combinations converge toward configurations that impose strong, uniform driving forces on all pedestrians simultaneously, suppressing individual differences. This behavioral homogenization under extreme urgency has been documented in experimental crowd studies, where high stress causes individuals to abandon

Table 5. Pedestrian network performance.

Panic Levels	Measures	Total Clearance Time (s)	Average Individual Evacuation Time (s)	Average Speed (km/h)
Low Panic	Lowest	315	86.35	2.6429
	Average	342	100.20	3.1714
	Highest	388	116.63	3.6023
Medium Panic	Lowest	307	82.38	3.6033
	Average	312	84.19	3.6686
	Highest	315	86.27	3.7439
High Panic	Lowest	294	78.16	3.7928
	Average	298	79.94	3.8592
	Highest	304	81.41	3.9348

independent decision-making and conform to dominant crowd movement patterns, and is consistent with the finding that simple behavioral rules dominate individual variation under high-urgency, leading to more uniform collective movement (Moussaïd, Helbing, and Theraulaz 2011). Related box plots of the average speed among all the segmented simulations are shown in Figure 10.

Now, to understand the variability of the average speed across the evacuation time in a single evacuation simulation, Figure 11 was plotted to compare the different levels of panic as distinct patterns emerge in average speeds over time. In this case, for each panic level, the simulation that represented the average of all the average speeds across simulations was selected to be analyzed. In the Low Panic scenario, average speeds initially rise significantly as pedestrians react to the situation, but then gradually decrease, indicating a lack of sustained urgency and emergence of bottlenecks in critical points. The initial sharp rise of average speed in Low Panic demonstrates high variation, which may be due to cooperation amidst evacuees and the significant differences in their rushed behavior across individuals (Alam et al. 2023). In the Medium Panic scenario, speeds rise and then stabilize, reflecting a moderate, consistent pace as pedestrians maintain a manageable and efficient speed throughout the evacuation. In contrast, the High Panic scenario shows a sharp initial increase in speed to over 4 km/h, driven by high-urgency (Haghani, Sarvi, and Shahhoseini 2020), followed by a decrease to 3.85 km/h as the initial rapid pace becomes unsustainable. The peak speeds briefly exceeding 4 km/h occur transiently during the initial surge phase before congestion builds at exit points. The standard free-flow walking speed has been empirically established at approximately 1.34 m/s (4.82 km/h) under unobstructed conditions

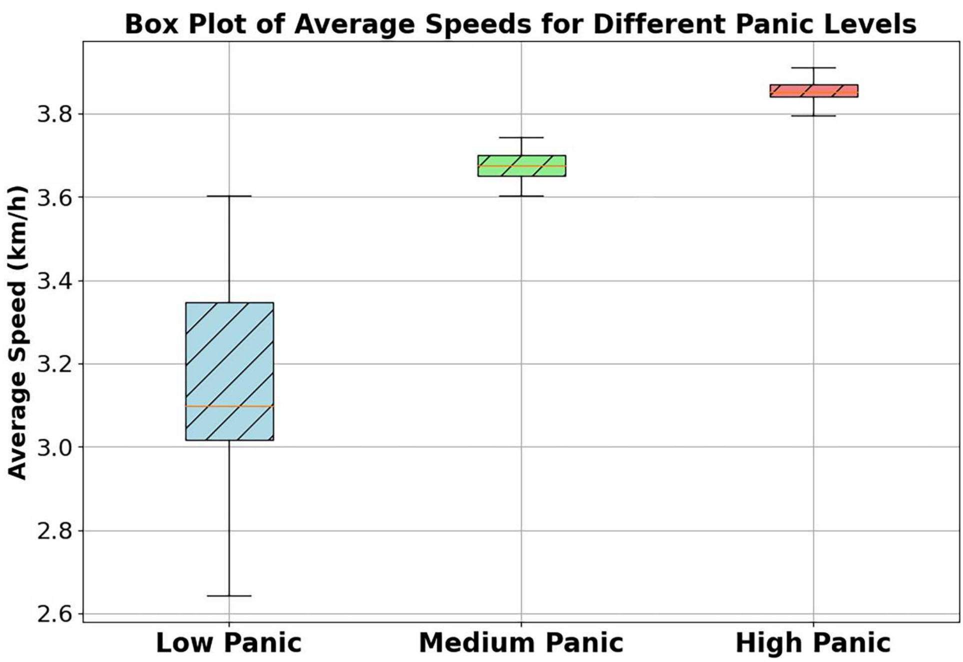

Figure 10. Box plots of average speeds for different panic levels.

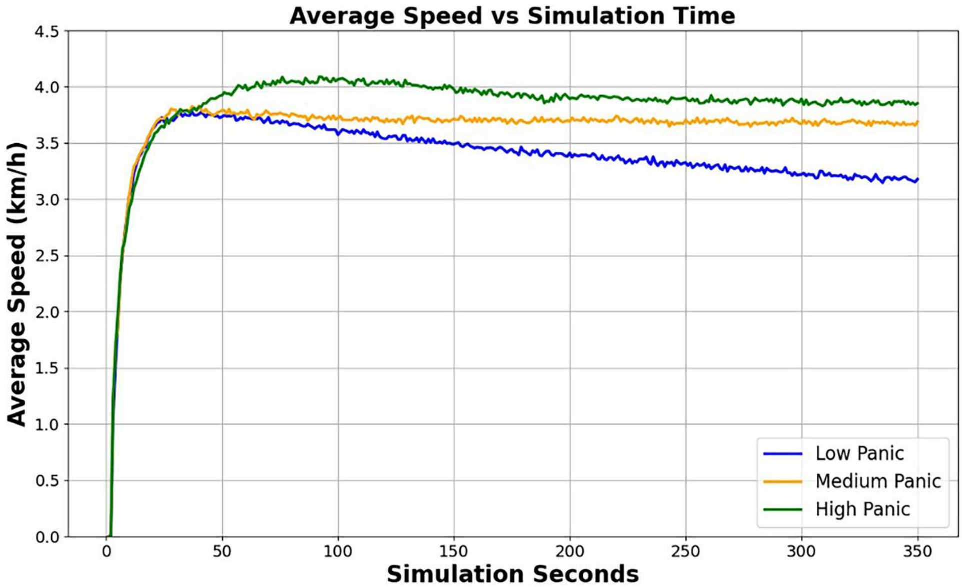

Figure 11. Average speed variation across simulations.

(Weidmann 1993), with speeds in the range of 1.0–1.5 m/s commonly reported in emergency evacuation contexts before density effects constrain movement (Haghani, Sarvi, and Shahhoseini 2020). The average speeds across all panic scenario simulations in this study ranged from 2.64 to 3.93 km/h (0.73–1.09 m/s), which falls within the lower end of this empirical range, reflecting the congested nature of the station environment. The brief initial exceedance of 4 km/h under High Panic is, therefore, considered physically plausible rather than an artifact of parameter adjustment, as it is consistent with transient acceleration behavior documented at the onset of emergency evacuations before crowd density effects take hold (Haghani, Sarvi, and Shahhoseini 2020).

To understand the rate of consolidation of exited passengers over simulation time in the same single simulations for each panic level, frequency distribution graphs were generated as shown in Figures 12–14.

For this plot, in each panic level, three bar graphs are generated for the simulations in which the average speed of pedestrians was lowest, average, and highest. Figure 12 shows that in the Low Panic scenario, the number of evacuees starts small and increases steadily over time. As time progresses, the evacuation rate picks up significantly, reaching a peak around 200–220 s, indicating a buildup in the number of evacuees. The examination of this graph reveals that in low panic, the larger share of evacuees is likely to exit the MRT station during the latter half of the evacuation time. For the Medium Panic in Figure 13, the bar graph shows a more consistent increase in evacuees over time compared to the Low Panic scenario. The number of evacuees rises steadily with less fluctuation between 'Lowest,' 'Average,' and 'Highest' values. The minimal change in bars suggests that people evacuate at a relatively uniform rate once the panic level increases, with fewer variations in individual evacuation times. For the High Panic scenario, Figure 14 shows a sharp initial rise in the number of evacuees, reflecting a high level of urgency

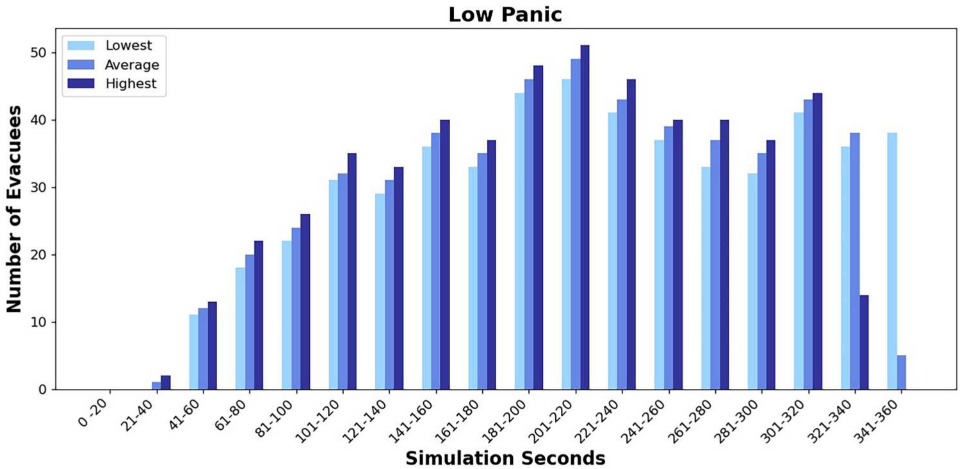

Figure 12. Distribution of low panic evacuation completion.

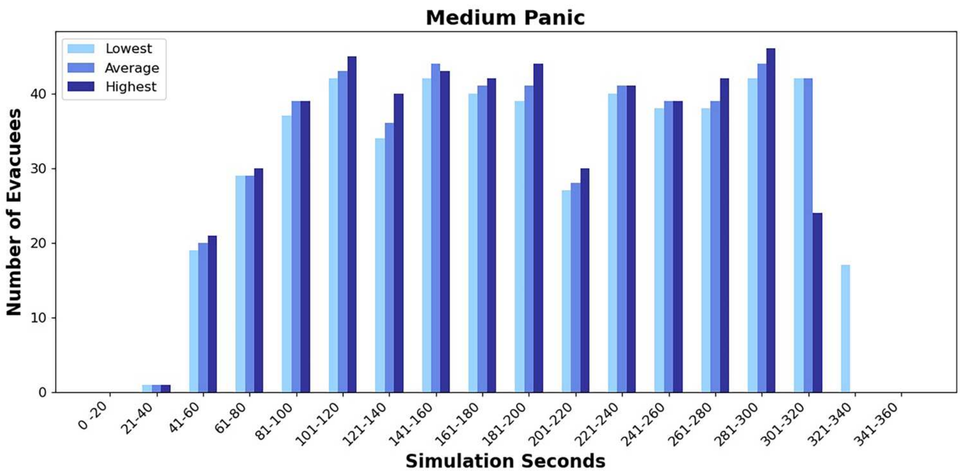

Figure 13. Distribution of medium panic evacuation completion.

that drives rapid movement toward the exit. The number of evacuees quickly increases, peaking early in the time frame, and then gradually declines. This decline is due to a large crowd reaching the exit points from all over the MRT at a very fast pace creating congestion and bottlenecks, which is also understandable from Figure 11. This decline is followed by another rise in evacuees as congestion cleared up in the exit points allowing the rest of the passengers to evacuate swiftly. The resulting bimodal distribution pattern, particularly visible in Figure 14 under High Panic, reflects a well-documented physical phenomenon at constrained exit points. The first peak represents the initial wave of evacuees reaching the exit stairways rapidly under high-urgency. The subsequent trough occurs as this rapid convergence creates temporary clogging at the limited exit points, intermittently reducing the outflow rate. Once this congestion clears, remaining passengers exit swiftly, producing the second peak. This intermittent clogging and

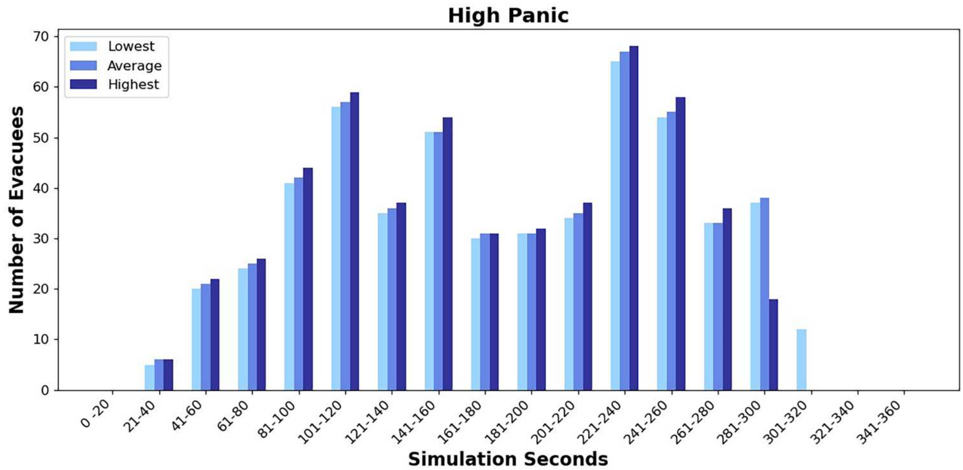

Figure 14. Distribution of high panic evacuation completion.

clearance pattern at bottlenecks has been documented in studies of pedestrian and granular flow, where alternating phases of arch formation and collapse produce characteristic bimodal outflow distributions (Zuriguel et al. 2014). The pattern has also been reproduced in pedestrian evacuation simulations where the exit width is constrained relative to the incoming pedestrian flow (Helbing, Farkas, and Vicsek 2000). The pattern is less pronounced under Low and Medium Panic because lower urgency produces a more temporally spread-out evacuation flow that does not simultaneously overwhelm exit capacity, resulting in smoother unimodal outflow distributions (J. H. Wang et al. 2016; L. Wang et al. 2016).

The evacuation behavior can also be examined in typical simulations showcased in Figures 15–17.

Research has showcased that in panic situations, pedestrians crowd together and the evacuation efficiency becomes lower (J. H. Wang et al. 2016). That resonates in this study as shown in Figure 15 for low panic conditions. But Figures 16 and 17 demonstrate that as the panic level goes higher, the increased average speed prevents the model from creating congestion throughout the evacuation. In Medium Panic, the low variance in average speed causes no consistently significant congestion to form at the exit points throughout the evacuation period. In High Panic, despite the propensity to form congestion around the middle of the evacuation period, evacuees exit swiftly with high speed through the shortest path. The finding that High Panic produces shorter total clearance times than Low Panic warrants discussion in the context of the well-known 'faster-is-slower' effect, which describes how higher pedestrian urgency can paradoxically increase evacuation time through persistent clogging at exit bottlenecks (Helbing, Farkas, and Vicsek 2000). It is important to note that the faster-is-slower effect has been shown to be most pronounced when pedestrian density at exits reaches levels sufficient to cause persistent arch formation and sustained clogging (Zuriguel et al. 2014). In the present study, the maximum occupancy of the station at any one time is 540 passengers distributed across a 180×26-meter two-level station with four exit stairways, producing a relatively low density per exit. Under these conditions, even under High Panic, exit bottlenecks are

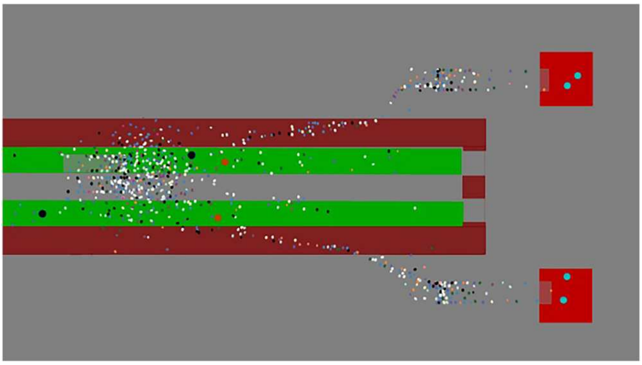

Figure 15. Low panic evacuation.

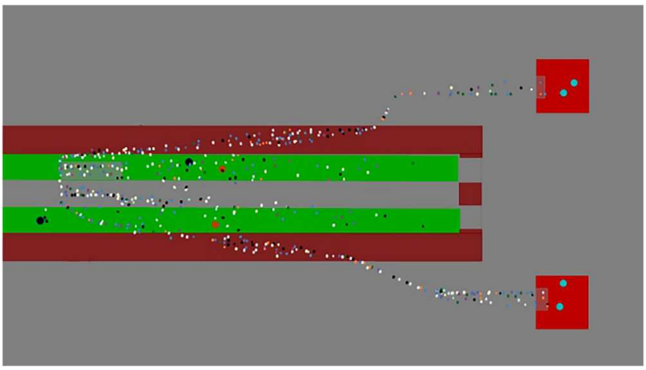

Figure 16. Medium panic evacuation.

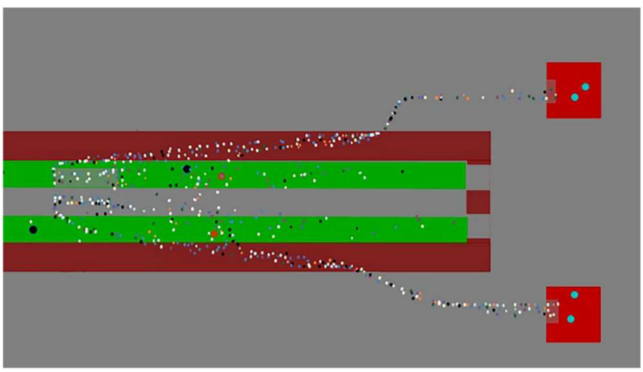

Figure 17. High panic evacuation.

transient rather than persistent – as evidenced by the bimodal pattern in Figure 14 where the congestion phase is followed by rapid clearance. Under Low Panic, pedestrians move slowly and spread their exit timing over a longer period, producing a longer total clearance time despite minimal congestion. This is consistent with studies demonstrating that the faster-is-slower effect emerges only above a critical density threshold, and that at lower densities higher urgency can reduce clearance times by driving pedestrians more efficiently toward exits (Haghani, Sarvi, and Shahhoseini 2020; Moussaïd, Helbing, and Theraulaz 2011). The present findings are therefore not inconsistent with the faster-is-slower literature but represent a density regime in which the persistent clogging mechanism does not dominate. Future studies with higher passenger occupancy levels would be valuable to explore whether the faster-is-slower effect emerges at greater station densities.

7. Conclusions

This study has outlined a framework to impart panic conditions in a pedestrian simulation platform and explore the crowd dynamics in an evacuation scenario. Behavioral parameters that influence pedestrian movement have been examined and, key parameters have been identified. The categorization of panic levels into Low, Medium, and High, based on pedestrian speed, effectively illustrated how different levels of urgency influence evacuation patterns. The results show that in Low Panic scenarios, pedestrian speeds exhibit considerable variability due to relaxed behavior and individual preferences, leading to less uniform evacuation. In contrast, Medium and High Panic conditions result in more uniform speeds and quicker evacuation times, as increased urgency compels pedestrians to move more consistently and swiftly. The analysis of evacuation dynamics revealed that total clearance times are longer under Low Panic conditions due to variability in pedestrian behavior, while Medium and High Panic scenarios demonstrate more efficient and rapid evacuations. Box plots of average speeds and frequency distribution graphs further illustrate the decreased variability in pedestrian speeds as panic levels increase. The High Panic scenario, despite initially creating congestion, ultimately leads to a more rapid evacuation as congestion is cleared quickly. This outcome is specific to the low-to-moderate density conditions of the study station, where exit bottlenecks are transient rather than persistent, and should not be interpreted as a universal finding. At higher passenger densities, the faster-is-slower effect may emerge, and the relationship between panic level and clearance time may reverse. The Medium Panic scenario showcases such behavior that does not compel any significant congestion to form during the evacuation. Conversely, Low Panic conditions show a slower buildup and peak of evacuees, reflecting the less urgent nature of the evacuation.

The findings of this study carry several practical implications for evacuation planning, crowd management, and infrastructure design. The identification of Tau and BSocMean as the most influential behavioral parameters suggests that evacuation planning strategies should account for the behavioral shift in reaction time and personal space dynamics that occurs as panic intensifies. Specifically, the results indicate that under Medium and High Panic conditions, pedestrians self-organize rapidly toward exits without requiring extensive guidance, whereas Low Panic conditions, where behavioral variability is highest, represent the scenario in which active crowd management interventions such as staff guidance, signage, and exit assignment strategies are most likely to improve evacuation efficiency. For infrastructure design, the bimodal outflow pattern observed under High Panic highlights the importance of exit capacity relative to peak inflow demand. Stations with a low ratio of exit width to peak occupancy are more susceptible to transient bottleneck formation even at moderate occupancy levels. The results suggest that widening exit stairways or increasing the number of accessible exits would be the most impactful structural intervention for improving High Panic evacuation performance at stations of this typology. These insights are directly applicable to the ongoing expansion of the Dhaka Metro Rail network, where new stations are currently being designed and existing stations are being evaluated for safety compliance.

This study also indicates some limitations to be addressed in future research. For example, reaction delay to emergencies amongst pedestrians has not been introduced in this study. The exclusion of reaction delays is particularly relevant under High Panic conditions, where the initial surge of movement is driven by an immediate response to the emergency stimulus. In practice, reaction delays vary across individuals and are influenced by proximity to the emergency, crowd density, and awareness of emergency cues. The inclusion of stochastic reaction delays in future work would be expected to moderate the initial speed peak observed under High Panic and potentially reduce the severity of the transient bottleneck phase, thereby affecting both the bimodal outflow pattern and the total clearance time. Furthermore, evacuation modeling for persons with mobility needs was not integrated as a part of this study. The exclusion of mobility-impaired pedestrians is a further limitation, as this group moves at lower speeds and may create localized bottlenecks, particularly under High Panic conditions, where faster-moving pedestrians have reduced tolerance for slower individuals ahead of them. Future work should incorporate heterogeneous pedestrian populations to capture these interaction effects. Density analysis of the study areas could also identify critical points posing a risk of impeding evacuation. It would also be interesting to explore the movement of people on the curbside, interaction with vehicles, as well as accident and stampede events. Additionally, the current study is based on a maximum occupancy of 540 passengers at Agargaon station at a single moment in time, which is below the passenger volumes recommended by standards such as the National Fire Protection Association for full-platform and train evacuation scenarios. Future studies should explore higher occupancy scenarios to examine whether the faster-is-slower effect emerges at greater densities in this station configuration. The methodology developed in this study is applicable to other elevated metro station configurations with similar spatial layouts and exit arrangements. However, the specific findings regarding panic level and clearance time relationships are influenced by the station geometry, exit capacity, and occupancy level of the Agargaon station. Application to stations with substantially different geometries, higher occupancy levels, underground configurations, or different exit arrangements may produce different relationships between panic intensity and evacuation performance; direct transferability of the quantitative findings should not be assumed without recalibration. Furthermore, the calibration and validation of the base model rely on CCTV footage from a single typical working day and one identified peak hour. While this represents the most critical design condition for evacuation modeling, daily and seasonal variability in passenger flow patterns was not captured, and future work incorporating multi-day observation data would strengthen the robustness of the calibration.

Nevertheless, this study advances the pedestrian evacuation modeling framework by integrating both social-physiological behaviors and varying levels of panic into the assessment of MRT station evacuations, as well as identifying key influential behavioral parameters and showcasing complex crowd dynamics. The results of this study can be utilized in optimizing MRT station design, as well as other similar public infrastructure, as the methodology is adaptable, flexible, and applicable in other scenarios.

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Disclosure statement

No potential conflict of interest was reported by the author(s).

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