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SIMULATING EMERGENCY EVACUATIONS WITH A LEARNABLE BEHAVIOURAL MODEL

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ABSTRACT

Simulation of evacuations in emergencies is crucial in preparing authorities throughout the world to mitigate disastrous outcomes from an unforeseen crisis. In an effort to increase the effectiveness of such critical systems, several works have attempted to introduce intelligence in Multi-Agent Systems (MAS) for crisis simulation by incorporating psychological behaviours learned from the social sciences or by using data-driven machine learning models with predictive capabilities. A recently proposed Conscious Movement Model (CMM) has shown dynamic capabilities to learn and change an agent's movement patterns as conditions evolve in the environment. This research work proposes an effective framework to integrate the trained CMM into a simulation model for emergency evacuations in order to achieve realistic outcomes. The evaluation is carried out on a real-life case study of emergency evacuations in a classroom. The results show that we can produce realistic simulations similar to actual results, performing better than state-of-the-art methods.

1 INTRODUCTION

Emergency evacuation and rescue planning is non-trivial due to the unprecedented nature of human behaviour in such fast-paced situations where dangers will escalate and panic can develop (Fahy et al. 2009). Modelling and simulation techniques have been typically used to study crowded areas to devise effective evacuation plans in the event of crises such as fires, bomb threats or riots. However, the key challenge is still the simulation of human behaviour with the influence of urgency due to evolving danger. In an attempt to reproduce realistic human reactions with a computational model, we can find concepts from social sciences such as BDI (*beliefs, desires, intent*) aspects (Rao and Georgeff 1995), being integrated into Multi-Agent Systems (Sycara 1998) where each agent (people involved in the simulation) has unique characteristics and behaviour. Other works that model the human behaviour (Helbing and Molnar 1995) based on fluid dynamics, and then influencing their urgency based on observational studies (Kuligowski 2015; Lovreglio et al. 2016), have also been proposed to enhance the realism of human reactions in such emergency evacuations.

Recognizing the importance of realistic simulation of human behaviour in emergencies, we propose an architecture to integrate the Conscious Movement Model (CMM) (Othman 2021), from a prior work, into a simulation framework. Through the proposed framework, we can evaluate the emergency behaviour of the trained CMM through a real-life case study of emergency evacuation from a small classroom. With a realistic simulation for such a critical system, we can extend the proposed framework with prescriptive analytics for crisis management in future work.

Therefore, the main goal of this paper is to propose an effective design for realistic evacuation simulation with a learnable behavioural model and evaluate its level of realism through a real-life case study of a classroom evacuation. Through our proposed framework, not only can we integrate the CMM for realistic pedestrian evacuations, but also understand the level of panic at different simulation time steps that will be crucial for authorities to plan effective disaster response in times of crisis. Section 2 will cover necessary background of the Conscious Movement Model (CMM) used as the learnable behavioural model, along with some related works in emergency evacuation simulation. Section 3 will describe the design of the simulation framework and our methods. Section 4 will show our experiments and results from a real-life case study. Finally, we conclude with recommendations for further work.

2 RELATED WORK

We will first briefly discuss the fundamentals of the Conscious Movement Model (CMM) (Othman 2021) from a prior work. Next, we will explore some state-of-the-art methods for emergency evacuation simulation, including the various attempts at improving human behaviour simulation for emergencies.

2.1 The Conscious Movement Model

The proposed Conscious Movement Model (CMM) (Othman 2021) is capable of dynamic transitions between normal and evacuating states to reflect realistic behavioural reactions during emergencies. Based on promising findings (Othman and Tan 2018a; Othman and Tan 2018b) in works that introduces machine learning models to enhance realism in simulation (Othman and Tan 2019), the CMM introduces attention and memory mechanisms called the Conscious Movement Memory-Attention (CMMA) model, to capture characteristics of human behaviour from real-life video data (Wang et al. 2019). The trained CMMA can then be attached to the CMM for each agent spawned into a simulation. As such, each agent will behave realistically based on its individual experiences. Figure 1 shows the architecture of the CMM and how the CMMA functions with it.

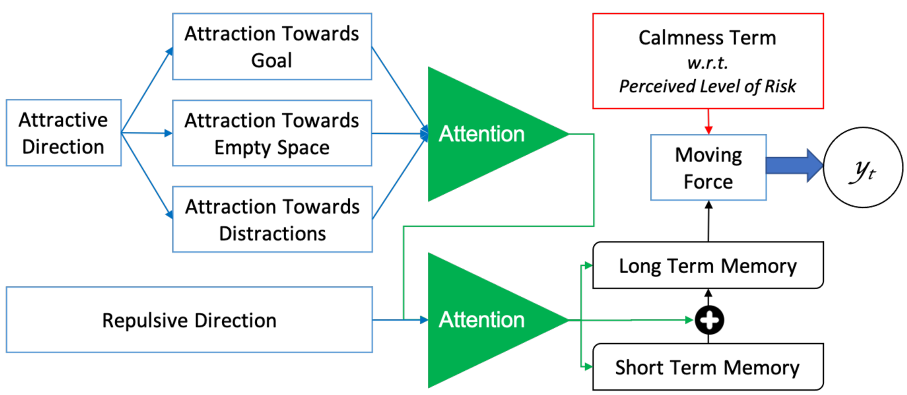


Figure 1: Overview of The Conscious Movement Model.

Three attractive directions will first go through an attention mechanism which determines the forces that have greater influences. Then, the result goes through another attention mechanism with the repulsive direction to derive the resultant force from these push-pull forces. The resultant force then goes through short-term and long-term memory mechanisms to influence the direction of motion based on prior movements. Finally, the CMM computes the moving force (acceleration) based on a pre-computed calmness term to derive the movement force for the next timestep. The proposed CMM equation to compute a pedestrian's conscious movement $\overrightarrow{CM}$ at time t is shown in Equation 1,

$$\overrightarrow{CM}(t) = f(g(\overrightarrow{A}_t, \sum \overrightarrow{R}_t), \overrightarrow{CM}_{t-1}) \times (M_t/\rho_t) \tag{1}$$

where the result of memory function, f, on the direction of motion, both attractive $\overrightarrow{A}_t$, and repulsive $\overrightarrow{R}_t$, with attention g, and the previous conscious movement $\overrightarrow{CM}_{t-1}$, is multiplied by the force of motion M_t at a rate proportional to the level of calmness ρ_t. The attractive directions, $\overrightarrow{A}_t$, include the attraction to goal $\overrightarrow{G}_t$, attraction to empty space $\overrightarrow{S}_t$, and attraction to distractions $\overrightarrow{D}_t$. For clarity, the CMMA model represents the first part of Equation 1 as shown in Equation 2.

$$\mathrm{CMMA}(\vec{G}_t,\vec{S}_t,\vec{D}_t,\vec{R}_t) = f(g(\overrightarrow{A}_t,\sum\overrightarrow{R}_t),\overrightarrow{CM}_{t-1}) \quad (2)$$

The CMMA takes in all the possible directions of motion, $\vec{G}_t,\vec{S}_t,\vec{D}_t,\vec{R}_t$, and outputs a "rational" direction of motion, $\vec{B}_t$, based on attention and memory trained from historical trajectories of real-life pedestrian movements. Figure 2 shows an overview of how each of the forces in the CMM comes into play.

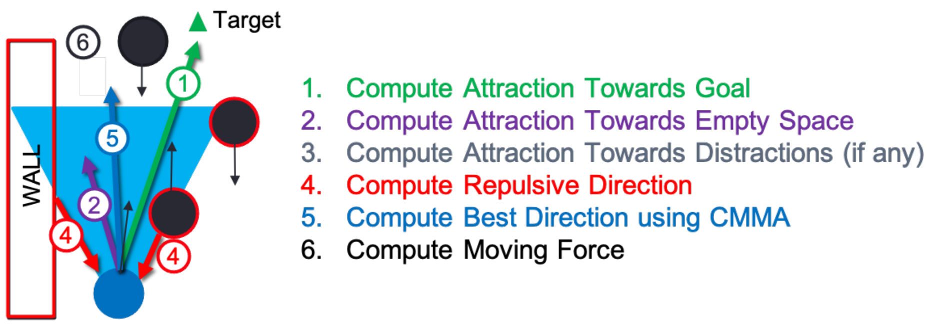


Figure 2: Forces of the CMM Model.

In Figure 2, all the possible directions of motion will present as options that an agent can take as we pass them through a memory-attention mechanism, the CMMA, as features to produce the best direction to take, instead of summing them all up like the Social Force Model and many of its variants. It differs such that an agent will reflect similar movement behaviour to pedestrian movements learned from the same scene (eg., area, space, location). With the equations proposed, the CMM can reflect movement behaviour based on as individual's level of calmness and a memory-attention mechanism (CMMA), $f(\vec{G}_t,\vec{S}_t,\vec{D}_t,\vec{R}_t)$, that will influence the direction of motion based on its surroundings and previous movements.

To this end, the CMM stands as the only behavioural model that has learning capabilities built into it so as to produce realistic behavioural reactions at every time step in a simulation. Experiments and evaluation in Othman (2021) showed superiority of the Conscious Movement Model (CMM) over existing methods for behavioural modelling in terms of realism and dynamic reactions to changing environments. Thus, the scope of this paper will only evaluate the effective integration of the CMM and the capabilities of the framework proposed.

2.2 Emergency Evacuation Simulation

Modelling crowd dynamics for simulating emergency evacuations has produced several notable works to date. Almeida et al. (2011) proposed flow-based modelling and cellular automata to simulate evacuation in crowded spaces using a Multi-Agent System (MAS) model. Their MAS model integrates BDI techniques (Beliefs, Desires, Intentions) from social sciences, where agents are driven by Desires (goals), according to certain Beliefs (knowledge of the world) and Intentions (actions) to fulfil the Desires. Zhong et al. (2017) proposed an automatic model construction of human crowd dynamics. The automated model is capable of describing the crowd dynamics in different and unseen scenarios, based on a set of behavioural rules.

The problem was formulated as a symbolic regression problem and solved by using self-learning gene expression programming. However, modelling crowd dynamics only allows for an abstract study from a macroscopic view. A common flaw of such models is dismissing the likelihood of collective individual behaviour affecting the overall crowd dynamics. Hence, several works have also studied the behavioural dynamics of individual evacuees in emergencies. Lovreglio et al. (2016) introduced an Evacuation Decision Model (EDM) that allows predicting the pre-evacuation state of an evacuee among three possible states: Normal, Investigating, Evacuating. Considering the perceived risk for an evacuation scenario, a person may transition from normal to investigating the situation, to finally transitioning into evacuating state where they will search for the nearest exits. Gelenbe and Wu (2012) attempted to enhance the human outcome of emergency situations by means of symbiotic simulation and other tools. In order to tackle large-scale human evacuation, the assembly of physical sensors, communication with evacuees and emergency personnel, path-finding algorithms for a safe evacuation, simulation and prediction, and decision tools were proposed.

With the current state-of-the-art, we identified the human behavioural modelling aspect to be of the highest importance yet with very few advancements in the past years. Simulating emergency evacuations in enclosed spaces is of high importance due to the probability of undesirable outcomes when an emergency strikes. The motive of such simulations is always to improve evacuation time and reduce casualties in the event of such disasters. Hence, even up till today, research is ongoing to improve these methods so as to save more lives in times of crisis.

3 METHODS

We will now describe the integration of the trained Conscious Movement Model (CMM), as described in Othman (2021), to inject realistic human behaviour into a simulation framework for simulating emergency evacuations. With a more realistic simulation, we can achieve accurate outputs for effective analysis. As such, this work can extend to automated strategy generation and prescription through multi-objective optimization. However, the latter is not within the scope of this paper. Based on the overview shown in Figure 3, this paper will focus our evaluations up to the realism of the output measures from our proposed framework.

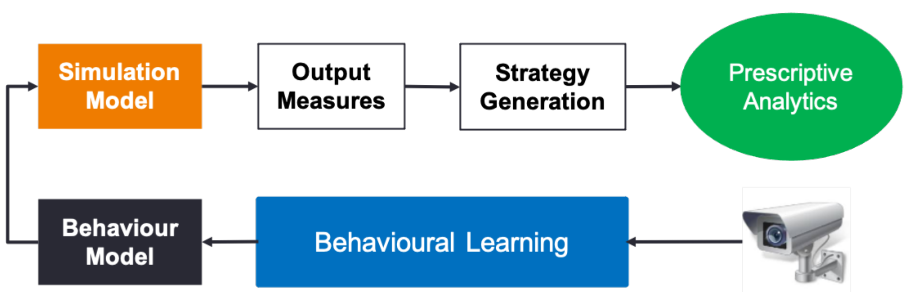


Figure 3: Overview of Simulation Framework with Prescriptive Analytics.

We integrate the CMM's behavioural learning architecture into our simulation framework that can run simulations with realistic behavioural characteristics based on the specific scene under study. The novelty of this contribution can be attributed to the integration of a realistic behavioural model learned from real-life CCTV footage of pedestrian movements in a specific scene so as to produce more realistic outcomes for effective prescription of strategies. In a typical simulation model for emergency evacuation of a particular area, we have static and dynamic data where we can observe how dynamic data changes in different scenarios with respect to static data.

In this Multi-Agent System that we are proposing, each agent will be equipped with the ability to process anything they see or encounter in the simulation environment and react accordingly based on forces acting around them, their prior knowledge (memory), and their attention to the surroundings. At the start of the simulation, these evacuees will need to transition from a normal state to evacuating state. This is handled by the CMM's computation of calmness that assesses each agent's perceived level of risk and dynamically transition the state for each of them accordingly.

The goal for each evacuee will simply be to reach an exit. To this end, the CMM can directly be used for regular evacuees navigating a scene and evacuating to the nearest or safest exit when a threat is encountered, or emergency evacuation procedure commences. As for staff or security personnel tasked to usher evacuees to safety, we can also think of them as regular pedestrians with fear of danger but with a different goal. While ensuring their safety by keeping a safe distance from the threat, the goal of these ushers will be to reach as many people as they can and guide them to safety. For rescuers coming into a place of crisis, they also need to portray realistic human behaviour as well. The main difference for rescuers is the calmness threshold since they need to have a higher threshold to handle threats. Therefore, we can adopt the CMM for all three different typical roles by setting the appropriate goals for each of them as follows:

1. Evacuees
   - Goal: To reach the nearest/safest exit as quickly as possible.
2. Staff/Security Ushers
   - Goal: To get to as many people as possible, pointing to the best evacuation route while maintaining personal safety.
3. Rescuers
   - Goal: To reduce threat and guide evacuees to safety.

In a realistic evacuation setting, each evacuee may also consider changing their goals to avoid getting hurt and evacuate quickly, either by rushing to the nearest exit or by searching for the safest exit. This decision-making process can considered a game of weighing the risks and rewards. Hence, we developed a Panic Game to help each evacuee decide whether they should update their goal or not. We illustrate the algorithm for the Panic Game as a flowchart in Figure 4.

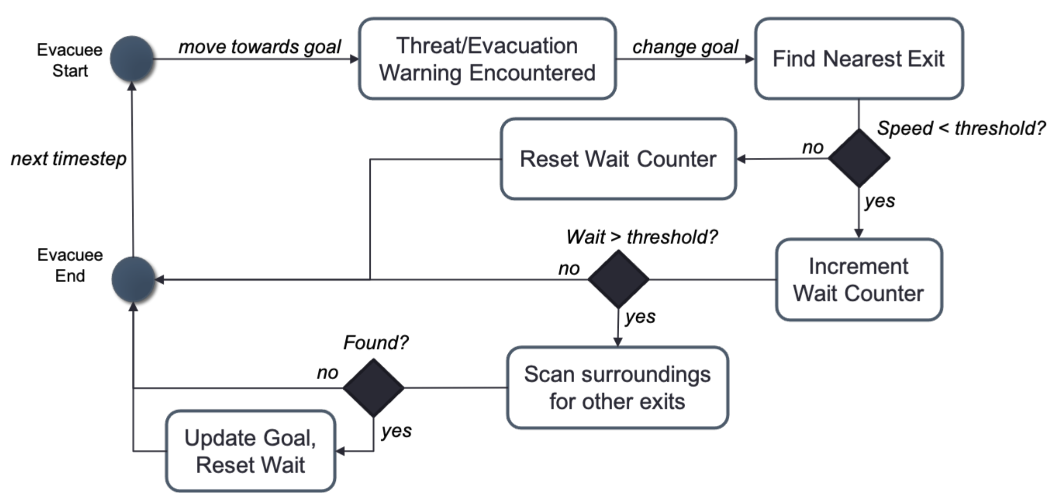


Figure 4: Panic Game Flowchart.

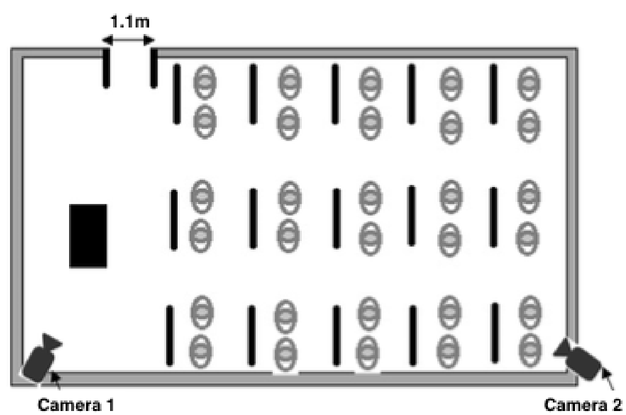
For each evacuee, the Panic Game will go on as long as they are still in the scene and have yet to reach any exit. Through the Panic Game, the evacuees may also encounter ushers or rescuers to point or help them to safety. Hence, the implementation of the Panic Game will allow for no further changes to the CMM or the respective goals for the different roles in the simulation. The Panic Game is designed to reflect the realistic nature of humans to update their goals based on what they think is most beneficial to achieve their desired outcome. In the case of evacuation, the desired outcome is to evacuate safely and as quickly as possible. Hence, an agent will search for the nearest exit when they encounter a threat or evacuation warnings such as directions from ushers/rescuers or exit signs. In approaching their exit, an agent may also change their goal if they are having difficulty getting through their current exit and find another nearby exit that may be faster to get through. The threshold for speed and wait are predetermined values set at the start of the simulation. All agents will follow through this Panic game and eventually get to the best exit with respect to their own experiences. The simulation will then end once all evacuees are cleared from the scene.

4 EXPERIMENTS & EVALUATION

To evaluate our proposed framework, we will look at a small enclosed space where a fire breakout may occur. Schools and classrooms normally hold regular fire drills to prepare students for when a fire breaks out. Vanumu et al. (2020) evaluated emergency evacuation of classrooms for different age profiles and reported their findings. In order to verify and validate that our proposed methods can realistically reflect real-life situations, we built a similar model and compared the input-output transformation between them. Since the experiments conducted by Vanumu et al. (2020) are based on real-life evacuations, achieving similar transformation and output results will prove that our model can reflect real-world behaviour accurately. Hence, we built our model to scale based on the experiments in the case study. The model simulated 43 students evacuating an 8.1m x 5.8m classroom through a single door. Figure 5 shows a snapshot of the classroom, and Figure 6 shows the schematic representation of the classroom.

Source: Image from Vanumu et al. (2020).

Figure 5: Classroom Snapshot.



Source: Image from Vanumu et al. (2020).

Figure 6: Classroom Schematic.

The individual speeds of the students follow a normal distribution, as specified in the work by Vanumu et al. (2020). Following the inputs set in the experiments, we simulated the evacuation over four scenarios with different door widths and desired speeds (normal distribution with different mean (μ) and standard deviation (σ)). We then evaluated if our model can achieve similar output results in each scenario as shown in Table 1.

Table 1: Details of Classroom Evacuation Experiments.

Scenario	**Door Width** (m)	**Speed Distribution**	**Total Evacuation Time** (s)
1	0.8	$\mu = 0.93$, $\sigma = 0.29$	15.70
2	1.1	$\mu = 1.01$, $\sigma = 0.27$	17.76
3	0.3	$\mu = 0.36$, $\sigma = 0.26$	47.60
4	0.8	$\mu = 0.50$, $\sigma = 0.15$	26.47

4.1 Verification & Validation

We built our proposed framework with Unity 3D. Unity also provides a bridge to use Machine Learning models developed in Python. Hence, the CMMA model was written and trained in Python, while the CMM was written in C# within Unity. To verify that the model was built correctly, we designed the space in Unity 3D to a proportional scale, as shown in Figure 7. The walls are static objects that cannot move, while the tables are represented by movable static objects. The logic of our model simply defines the goal of each agent to cross the exit as quickly as possible. We then recorded the total evacuation time from the start of the simulation until the last agent exits the room. Figure 8 shows a snapshot of an evacuation being carried out.

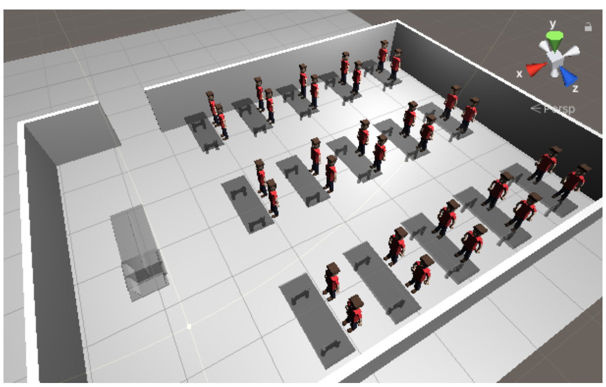


Figure 7: Classroom Model 3D.

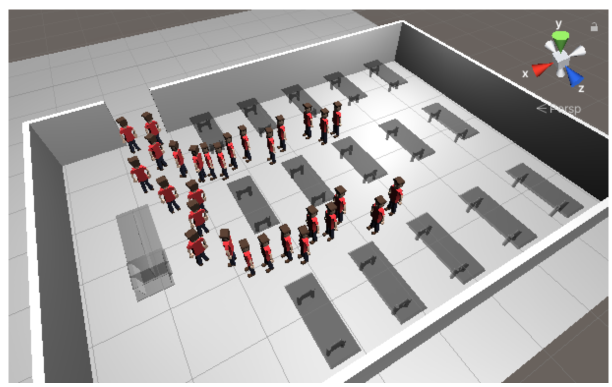


Figure 8: Classroom Evacuation 3D.

We verified that the events and agent behaviours are represented correctly. Based on social science theories of evacuation behaviour, we also observed typical behaviours reflected by the agents throughout the simulation. Next, we statistically validated our model to evaluate its ability to reproduce results similar to real-life scenarios of this scene. At face value, we observed an accurate representation of real-world expectations based on the speeds and behaviour of agents in getting towards an exit upon evacuation instructions. In order to evaluate whether the total evacuation time, given by function E, between the simulation Y and the real system Z are the same, we conducted a hypothesis test with an accuracy of ± 0.5 seconds, $\varepsilon = 0.5$, and a high probability of 95%, $\alpha = 0.05$. We first computed the required number of replications from the inequality equation in (3).

$$R \geq \frac{Z^2_{\alpha/2,R-1} S^2_0}{\varepsilon^2} \tag{3}$$

The population variance S^2_0 was retrieved from an initial sample for each scenario. We derived that no less than six replications are required. Therefore, we conclude that it is sufficient to execute six replications (runs) for each scenario, s. The total evacuation times for each scenario are presented in Table 2.

Based on the average of 6 independent replications for each scenario, a t-test with a level of significance $\alpha = 0.05$ and replication size $n = 6$ was conducted. We derived the null hypothesis H_0 and the alternate hypothesis H_1 for the simulation result Y_i and the true value Z_i as follows:

Hypothesis $\mathbf{H_0}$. : $E(Y_i) = E(Z_i)$ *seconds.*
Hypothesis $\mathbf{H_1}$. : $E(Y_i) \neq E(Z_i)$ *seconds.*

Table 2: Experiments for Classroom Evacuation Time (seconds).

Scenario	1^{st} Run	2^{nd} Run	3^{rd} Run	4^{th} Run	5^{th} Run	6^{th} Run
1	17.02	15.18	16.16	16.02	15.21	15.04
2	18.10	17.11	18.19	18.02	17.15	17.25
3	46.02	48.44	48.20	47.05	48.32	46.98
4	26.22	27.57	26.18	27.38	26.13	26.19

We then computed the t-score, t_0, for each scenario, s, with the mean (μ_y^s) of the $n = 6$ replications and its standard deviation σ_y^s against the true value $E(Z_i)$, as shown in Equation 4.

$$t_0^s = \left| \frac{\mu_y^s - E(Z_i)}{\sigma_y^s / \sqrt{n}} \right| \tag{4}$$

With critical value $t_{critical} = 2.571$ for a 2-sided test, Table 3 presents the corresponding t-score for each of the scenarios. Since it shows that all the t-values (t_0) are lower than the critical value, we have no reason to reject the null hypothesis H_0.

Table 3: Classroom Hypothesis Test t-score.

Scenario	$E(Z_i)$	Mean (μ)	Standard Deviation (σ)	t_0	Accept/Reject
1	15.70	15.77	0.77	0.223	Accept
2	17.76	17.64	0.52	0.565	Accept
3	47.60	47.51	0.97	0.227	Accept
4	26.47	26.61	0.67	0.512	Accept

From the results, we can safely state that the average total evacuation time for each scenario is the same as the output from a real-life simulation. As such, we confirmed the model's ability to predict the future behaviour of the real system when the model input data matches the real inputs from Vanumu et al. (2020). Further experiments with different input parameters (eg., number of people) produced correspondingly correct changes in the output. Hence, we can conclude that this simulation model is indeed an accurate representation of the real system.

4.2 Simulation Experiments & Discussion

In order to evaluate the accuracy in movement behaviours of the CMM used in our proposed framework, we compare the trajectories generated against some of the state-of-the-art behavioural models. The Headed Social Force Model (HSFM) (Farina et al. 2017) is a revised version of the traditional Social Force Model (SFM) (Helbing and Molnar 1995) to include pedestrian's heading along with more complex equations to account for group behaviour and cohesion.

The Social Force Model with Tolerance (SFM-T) (Wang et al. 2019) is another revision that introduces a tolerance coefficient to encourage directional change in the SFM equations. This revision aim to address deadlock issues that exists within the HSFM. The simpler equations for SFM-T allows the integration of panic behaviour introduced by Helbing et al. (2000) to simulate emergency evacuations. The degree of panic is introduced such that pedestrians will portray individualistic behaviour if panic is low, but herding behaviour if panic is high. As such, we will call this model SFM-T+P, short for Social Force Model with Tolerance and Panic. Based on the experiments done by Helbing et al. (2000), we will set the panic level $\rho = 0.4$ to reflect appropriate urgency behaviour.

To make experiments fair, we simulate all three models on our proposed simulation framework over six replications and report the average results. With these models, the trajectories in our experiments show that they can all avoid collisions accordingly to evolving situations. However, looking at the changes in speed shown in Figure 9, we can still observe significant differences.

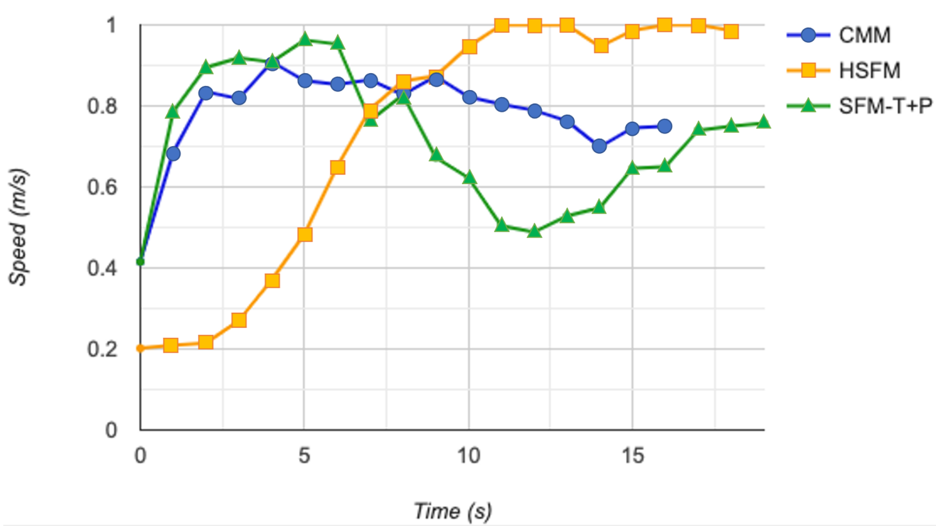


Figure 9: Classroom: Speed Changes of Behavioural Models.

The HSFM reflected no urgency behaviour at all as it gradually increased its speed towards the exit. As a result, there were barely any clogs at the exit and the total evacuation time was much higher due to the lack of urgency. The SFM-T+P, on the other hand, does not evolve its level of panic that affects urgency throughout the simulation. As a result, the speed shot up very quickly at the start and dramatically dropped towards the bottleneck as pushing and incoordination developed. This caused a drop in the frequency of exit per second as well, leading to higher evacuation time on average. As for the CMM, we can observe a realistic increase in speed as urgency rises at the start and a stable decrease when approaching the bottleneck.

As a result, the CMM achieves a much lower total evacuation time on average. As a comparison to the average evacuation time from the real-life case study, we showed that the CMM can produce similar evacuation times in Section 4.1. However, the HSFM and SFM-T+P reported much longer evacuation times on average in this experiment. This suggests that the output measures from the other two behavioural models are not sufficiently realistic. Now that we have shown the superiority of the CMM against existing methods, we can next evaluate its emergency behaviour by looking at the development of calmness over time against the average speed, as shown in Figure 10.

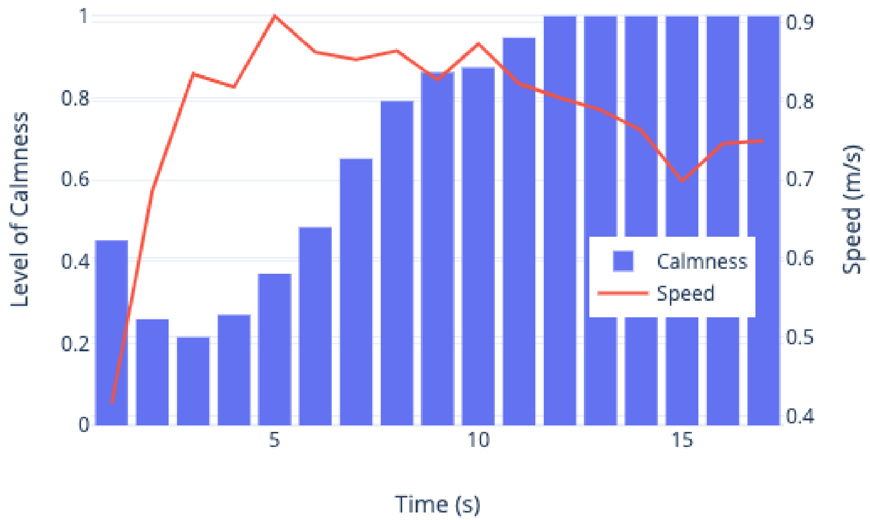


Figure 10: Classroom: Development of Calmness vs Average Speed over Time (CMM).

In a small setting such as a classroom, the spread of emergency is much faster as everyone is much closer to each other. Hence, we can see the average speed spikes as the level of calmness drops. As evacuees start to leave the area of evacuation (getting past the exit), the calmness level starts returning to normal, and speed becomes more regulated. With a behavioural model that can reflect emergency behaviour realistically, the simulation framework we have proposed can be used to perform analysis on output metrics in order to understand the system under study and seek improvements to optimize the overall average evacuation time. In any evacuation system, the goal is to minimize the evacuation time with minimal injuries. Moving too fast and disorderly can cause unnecessary injuries such as tripping, falling, or hard collisions. Therefore, we can conduct experiments on different independent variables to monitor how different speeds can affect the total evacuation time. Table 4 shows the different categories of moving speed for an average human.

Table 4: Categories of Moving Speed.

Category	Slow Walk	Fast Walk	Jogging	Running
Speed Range (m/s)	1.21 - 1.75	1.76 - 2.21	2.22 - 2.68	2.69 - 2.97

For a small classroom, the ideal size for an exit should be able to produce a good average evacuation time that is proportional to the number of people evacuating from the classroom. Hence, we conducted experiments to compare different door sizes for different speed categories and their corresponding effects when the number of evacuees increases. Figure 11 shows the effects of different door sizes on the average evacuation time for 25 evacuees, and Figure 12 shows the effects on evacuation time for different numbers of evacuees with a fixed door size of 0.8 metres.

The different categories of moving speed show that high speed will only make it worse on the resulting evacuation time when the exit is too small. With wider doorways, faster speed can allow for shorter evacuation time. However, fast walking and jogging speed can also achieve almost the same average with lower possibilities of hard collisions and injuries. In Figure 12, the results showed that the evacuation time increases proportionally with more people evacuating. Although the fastest speed can achieve the lowest average evacuation time throughout different numbers of evacuees, we can see that jogging speed can also achieve low evacuation times, but with much lesser pushing and collisions resulting from unnecessarily high speed.

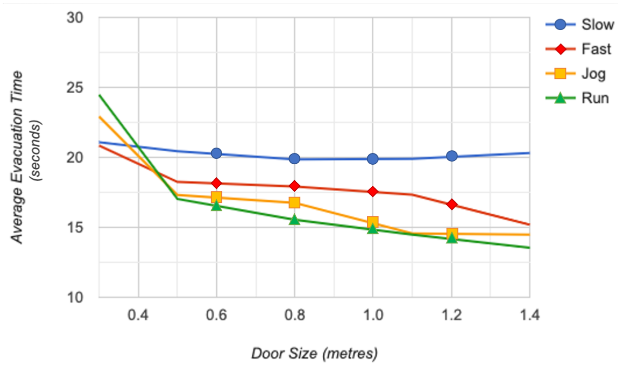


Figure 11: Effects of Door Size.

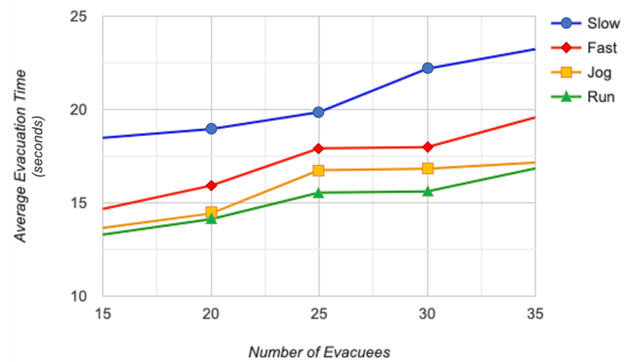


Figure 12: Effects of Evacuees Size.

Hence, the experiments showed that it is most ideal for a classroom with a typical size of 30–35 people to have a door no smaller than 0.8m and preferably a regulator (teacher or student leader) to ensure the speeds of evacuees are within the fast-walking to jogging speed range.

5 CONCLUSIONS

We proposed a simulation framework to integrate intelligent agents trained from real-life video, reacting to emergencies realistically. The results showed improvement over state-of-the-art methods in related areas in terms of realistic behaviours based on the social sciences of human behaviour. Due to the plethora of possible crisis events in the world, we focused on emergency evacuations to enable a rigorous study of an important real-world problem. Any influences coming from different types of crises (eg. fire, riots, bomb threats) will require careful research to integrate with our proposed framework.

We have shown how we can use the Conscious Movement Model to simulate evacuation in a small classroom. From the results, we were able to analyse the development of calmness throughout the evacuation and how the number of evacuees or door size can affect total evacuation times. This framework can be extended to much larger crowds with problems such as overcrowding, etc. Due to space constraints, we believe it is more important to fully evaluate one type of constrained space, as presented for the experiments. Further work will include experiments in larger settings and analysis of various factors contributing to the total evacuation time. Furthermore, we will attempt to tackle some shortcomings such as the latency of using CMMA through a bridge in Unity.

To this end, we have achieved our aims and objectives to improve the level of realism in simulating emergency evacuations through high-accuracy behavioural modelling. Injecting a higher sense of realism into critical simulations, such as crisis management, will be highly beneficial to the world at large. Therefore, it is imperative to continue pushing this research forward. We hope to extend this framework with prescriptive analytics through multi-objective optimizations so that authorities can get optimal plans for evacuation without much tedious work. We will also need to consider introducing distributed parallel architectures for faster speed performance, critical in times of emergency.

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