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INTEGRATING ACTUAL HUMAN BEHAVIOR INTO AN AGENT-BASED SCHOOL SHOOTING SIMULATION

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ABSTRACT

With the ever-growing threat of school shootings, modeling these tragedies is crucial to mitigate or reduce casualties in future events. However, agent-based models traditionally instruct agents to act based on theoretical behavior rather than actual human behavior. We present the results of 81,000 simulations of a school shooting where agent behavior is modeled after actual human behavior from a similar virtual scenario. Agents' reaction time and movement speed are drawn from probability distributions based on human data. The pathways assigned to agents are based on the human behavior exhibited in response to three social influence conditions: where the non-player characters all ran, all hid, or both ran and hid. Additionally, we manipulate law enforcement dispatch time, shooter accuracy, and magazine capacity. Results show mixed agent behavior and lower dispatch times had the largest influence on casualties. The methodology demonstrates the power of empirically defining agent behavior in ABMs.

1 INTRODUCTION

School shootings in the U.S. continue to be a rampant problem, with 2022 recording the most school shootings since 1999 (Cox et al. 2024). The Federal Bureau of Investigation (FBI) currently instructs victims of an active shooter scenario to practice the Run, Hide, Fight model (FBI 2022). This model proposes running when there is an active shooter, hiding if escape is impossible, and fighting only as a last resort. However, while individuals can be trained to follow these principles in low-consequence conditions, their behavior often changes from the stress endured in an unanticipated situation (Worthington et al. 2021; Zhu et al. 2020; Drury et al., 2009). To better understand behavior during an active shooter scenario, multi-agent crowd simulation models have increasingly been used to predict outcomes based on various factors (Sharma et al. 2020). However, the agents in these models must follow a predetermined set of behavior patterns, such as taking the shortest route to an exit without colliding with other agents (Manley et al. 2016). While these frameworks produce reliable crowd simulation behavior, the underlying framework is the same for all agents. Some systems, such as MomenTUM, allow agents based on different models, but these agents cannot interact with objects in the environment (Kielar et al. 2016). Therefore, we introduce a multi-agent simulation model where agent behavior is based on real human behavior in a similar school shooting experience. We draw data from three samples that varied in the number of non-playable characters (NPCs) who ran or hid to inform our agents' pathways, speed, and reaction time. We also manipulate additional factors in the agent-based model to evaluate their impact on the number of casualties, including shooter accuracy, magazine size, and law enforcement dispatch time. From this data, we hope to better inform training guides on how individuals should respond to a school shooting based on the variables mentioned previously.

2 BACKGROUND

2.1 Prevalence of School Shootings

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According to the K-12 School Shooting Database (2024), there were 348 incidents where a firearm was discharged on school property, resulting in the deaths of 71 individuals and injuries to a further 178 people. Furthermore, the number of annual incidents has risen dramatically since 2020. Before 2020, there was no year with more than 125 incidents; however, since 2021, the average number of incidents per year has been 257. Equally concerning is that 73.9% of school shootings ended when the shooter fled the scene, suggesting the number of casualties could be higher if shooters desired to create more victims (Haghani et al. 2023a; Haghani et al. 2023b). With the recent dramatic increase in the number of shootings occurring at schools, there is a growing need to study and understand the factors that contribute to a decrease in the lethality and duration of the events (Kerlin et al. 2021; Schildkraut and Martaindale 2023; Leija 2023).

2.2 Run, Hide, Fight

The "Run, Hide, Fight" program, devised to respond to active shooter situations, has received mixed reviews for its efficacy in minimizing casualties (Lu et al. 2023; Schildkraut and Nickerson 2020). Advocates highlight its straightforwardness, enabling quick decision-making in life-threatening scenarios by promoting running to safety, hiding, or fighting as a last resort (Lian et al. 2023; Jonson et al. 2020). Nonetheless, critics doubt its adaptability across diverse settings such as schools, workplaces, and public areas (Zhu et al. 2019; Zhu et al. 2020; Zhu et al. 2022). Concerns include the practicality of implementation, adequacy of training, and potential for panic (Awada et al. 2021; Carvalhais et al. 2024). Some argue it oversimplifies complex dynamics and fails to address the root causes of violence (Becerik-Gerber et al. 2022a; Becerik-Gerber et al. 2022b; Lin et al. 2020). Research on active shooter incidents often relies on sparse and potentially unreliable data (Bahmani et al. 2023). Our model offers a cost-effective means to simulate various scenarios, assessing how individuals respond to others running, hiding, or both. Its adaptability to different settings depends on the accuracy of behavioral data characterizing agent behavior.

2.3 Agent-Based Models in School Shooting Simulations

Agent-based models (ABMs) simulate complex systems by representing individual entities (agents) and their interactions (Aghalari et al. 2021; Arteaga and Park 2020; Lu et al. 2021; Vilar et al. 2014). In the context of school shootings, ABMs have been utilized to explore various factors contributing to such tragic events (Bott 2021; Haghani, 2020). Notable studies include Towers et al. (2015) examination of social contagion effects in school shootings, which highlighted the role of media coverage and peer influence on the likelihood of subsequent incidents. Additionally, Anklam III et al. (2015) integrated ABMs with data on school demographics and firearm access to analyze the impact of policy interventions on preventing school shootings. ABMs offer a nuanced understanding of the dynamics underlying school shootings, incorporating factors ranging from individual psychology to societal influences, thereby aiding in developing more effective preventive strategies (Scott et al. 2021).

3 METHODS

3.1 Model Overview

Our simulation was conducted in NetLogo Version 6.4. The model is based on code from Stewart (2017), which formed the basis for the variables manipulated, and the school layout from Zhu (2022). The scenario simulated a school shooting during lunchtime when students were all in the cafeteria. Each simulation begins when the shooter enters through the front entrance of the school and begins firing. The simulation ends either when all students have escaped, become casualties, or law enforcement has eliminated the shooter. Student behavior, reaction time, and running speed are based on probability distributions generated by real human behavior in a similar behavioral experience scenario. Shooter behavior follows the general path taken by the shooter in the behavioral experience but allows for deviations based on agent interactions.

Law enforcement was not included in the behavioral experience, so agent behavior is driven solely by agent interactions. Figure 1 shows the school layout along with the starting positions of the students and shooter (red). Law enforcement arrives from the east exit after a specified number of minutes.

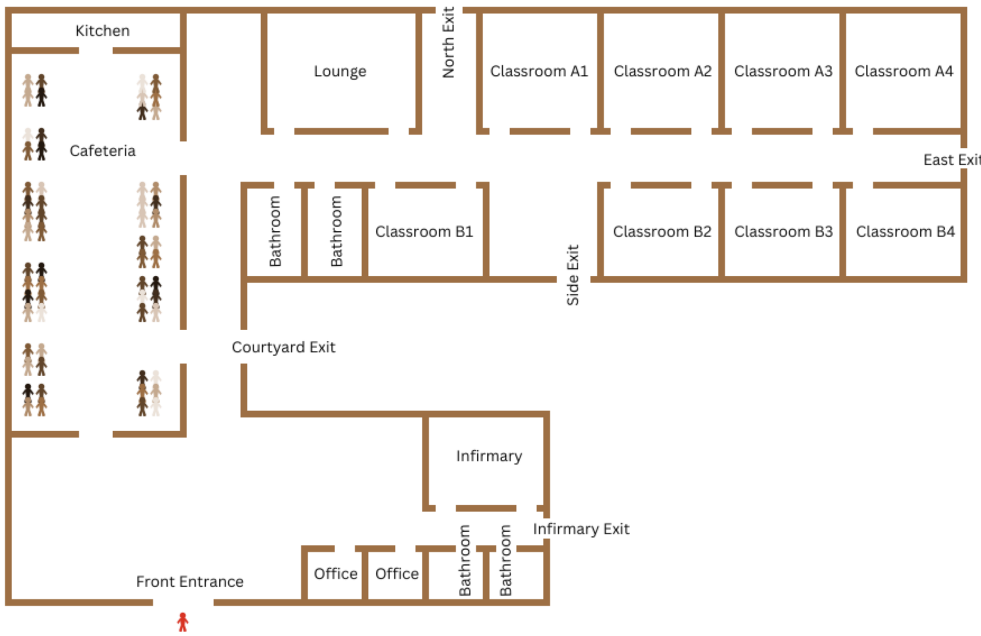

Figure 1: The school layout used in NetLogo simulations.

3.2 Behavioral Experience

The behavioral experience was conducted to characterize the range of actual human behaviors in reaction to an immersive virtual active school shooting scenario. A 3D model of the school with the same layout as Figure 1 was constructed in the Unity game engine. A total of 545 Participants were recruited from Prolific.com, a well-validated source of online participants for behavioral research (Douglas et al. 2023). Participants were randomly assigned to one of nine conditions capturing all combinations of the gunman's closeness to the participant located in the cafeteria (front entrance, east exit, and cafeteria) and the behavior of 37 non-player 3D characters (NPCs) (all run from the shooter, all hide from the shooter, half run, and a 50-50 mix of running and hiding). In the 50-50 mixed condition, the same 18 NPCs are assigned to hide and the same 19 are assigned to run. Participants began the experience by practicing moving using their mouse/trackpad and keyboard. After they passed this stage, participants were given 7 locations to navigate to help familiarize them with the school's layout. Only if participants completed both training sessions in 15 minutes did they participate in the actual school shooting experience. The experience lasted a maximum of 70 seconds but could end early if participants escaped beyond the boundaries of the school and were marked safe. The experience had a maximum of 70 seconds because, beyond that time, participants' behavior often changed from their initial reaction (for example, to hide in the kitchen) to exploring the school. Participants were free to go where they wanted but could not pass through boundaries or NPCs and were not targeted by the shooter, avoiding data censoring resulting from the incapacitation of the agent. Data from the behavioral experience from each social influence condition in our study (NPCs run, hide, or a mix of running and hiding) is used to inform agents' movement speed, latency to begin movement, and the probability of a student's behavior.

3.3 Student Running Speed and Reaction Time

Using data from the behavioral experience, students' speed of movement and latency to begin movement following the first shot are stochastic parameters assigned to each student and vary with each trial. For speed, a total of 43,952 observations of speed sampled at half-second intervals were used to estimate a probability distribution in the three conditions in which NPCs run (N=12,163), hide (N=18,024), or a combination of running and hiding (N=13,765). The data suggest that observed speeds follow a mostly discrete distribution with probabilities concentrated at three speed values (0, 2, and 3.5 yards per second), with some probability distributed between these speed values. The discrete values suggest that the simulation hardware and software artificially constrained movement in the behavioral experience. Given that human movement is continuous and not constrained by mouse hardware, we fitted more realistic Exponential distributions for each social influence condition. We used @RISK, an add-in for Excel, to fit the speed data for each of the three social influence conditions from the behavioral experience, resulting in Exponential distributions defined by bias-corrected maximum likelihood estimates. Exponential distributions provided suitable fits based on minimum (best) values of the Bayesian Information Criterion (BIC) for all three conditions. Complementary Cumulative distributions (CCDs) for speed are plotted for all three conditions in Figure 2 for both the observed data (blue) and fitted Exponential distributions (red). Since the estimated shift parameter = 0 for all three distributions, the Exponential lambda parameters equal the indicated means.

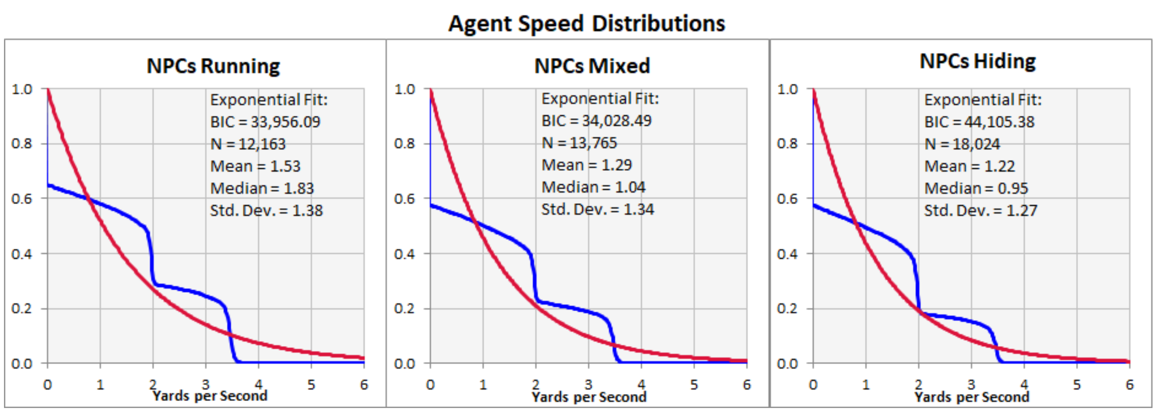

Figure 2: Complementary Cumulative probability distributions, i.e., probability (Y) human agent speed exceeds X. Blue represents the observed data, and the red curve is the fitted Exponential distribution.

Response latencies for the first movement following the first shot were fitted for six different distributions, conditional on the NPCs in the behavioral experience (Running, Hiding, or Mixed) and whether the human in the behavioral experience escapes outside the building or remains in the building. Sample sizes for the six conditions ranged from 46 to 140. Parameters were estimated for Exponential distributions using the same software and procedure described above for speed distributions. In all six cases, the Exponential distribution had the lowest or very nearly the lowest BIC compared to other distributions. We chose to use Exponential distributions for all cases given ease of implementation in the NETLOGO software. Complementary Cumulative distributions CCDs for latency are plotted for all six conditions in Figure 3 for both the observed data (blue) and fitted Exponential distributions (red). The estimated shift parameter is positive in all six cases and the displayed mean for each case is the sum of the Exponential lambda parameter and the shift parameter. Consistent with the BICs and nearly coincidental CCDs in Figure 3, the Exponential distributions are a good approximation to the empirically observed latency data.

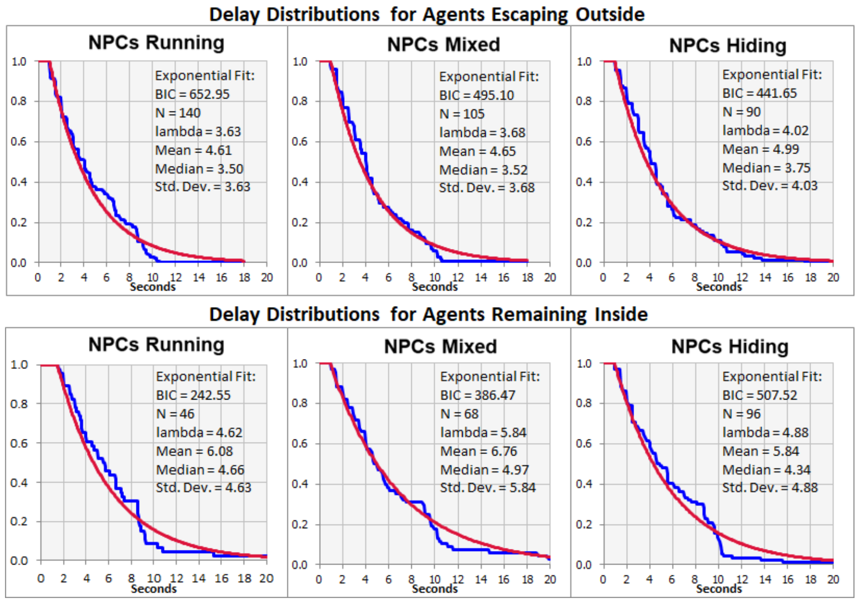

Figure 3: Complementary cumulative probability distributions, i.e., probability (Y) human agent movement delay exceeds X. Blue represents the observed data, and the red curve is the fitted Exponential distribution.

3.4 Agent Characteristics

Unlike other models that define agent characteristics based on theory, our model assigns agent characteristics to students based on probability distributions from real humans. Sixty students in this model had their behavior (whether the student runs or hides and to where), speed (yards per second), and reaction latency (seconds) to the shooting drawn from each of the social influence conditions from the behavioral experience described earlier. The variation in agent characteristics is represented by probability distributions summarized in Table 1, conditional on both manipulated NPC behavior and measured human behavior (escaped or remained in the building). The starting location of each of the 60 students was arranged as students would sit in a cafeteria during lunchtime, similar to the behavioral experience. Each student was assigned a behavior pathway based on a discrete probability distribution using the probabilities in Table 1 and depicted by the green lines in Figure 4. Students would follow their assigned behavior as closely as possible but could not run into other students. The discrete probability distribution of behavior pathways is generated from the percentage of participants in the behavioral experience who engaged in each of the following behaviors. Each student was assigned a constant running speed from the Exponential distribution described in Table 1. Students' response latency following the first shot was assigned from one of the Exponential distributions defined in Table 1, conditional on their assigned behavior (running or hiding). If students were shot by the shooter, they were marked as casualties and the shooter would no longer target them. We do not distinguish between students injured and those who die from being shot as this often depends on external factors (location of wounds, emergency medical response time, size of the victim, etc.) that are outside the scope of this simulation. If students managed to reach the outer boundaries of the school or enter a classroom, they were marked as safe from the shooter. Students were marked as safe when entering classrooms, as many classrooms have bulletproof doors preventing the shooter from entering, which is not true of other rooms such as the kitchen or office rooms. Furthermore, the classrooms in our simulation had no internal windows. Finally, any student who did not reach safety or become a casualty was considered at risk when the simulation ended. .

Table 1: Student behavior probability distributions from behavioral experiences. The first Exponential parameter is the distribution mean and the 2nd is the shift parameter, which is the minimum value with non-zero density.

		Run Condition	Mixed Condition	Hide Condition
Reaction Time (number of seconds)	Assigned Probability Distribution for Runners	Exponential (3.63) + 0.98	Exponential (3.68) + 0.97	Exponential (4.02) + 0.96
	Assigned Probability Distribution for Hiders	Exponential (4.62) + 1.45	Exponential (5.84) + 0.92	Exponential (4.88) + 0.96
Running Speed (yards per second)	Assigned Probability Distribution	Exponential (1.53)	Exponential (1.29)	Exponential (1.21)
Percent of Participants Assigned to Pathway	Run to North Exit	55.36%	57.41%	38.71%
	Run to East Exit	16.07%	9.26%	0.00%
	Run to Courtyard Exit	16.07%	3.70%	6.45%
	Hide in Kitchen	5.36%	14.81%	12.90%
	Hide inside Cafeteria	5.36%	9.26%	24.19%
	Hide outside Cafeteria and Kitchen	1.79%	5.56%	17.74%

The shooter's behavior in the simulation is modeled after the shooter's behavior in the behavioral experience. The shooter moves at a constant speed of 0.25 yards per second as the shooter in the behavioral experience moves slowly, keeping his weapon ready at all times. The shooter will follow a default path depicted by the red path in Figure 4, where he gains entrance to the school building through the front entrance, enters the cafeteria, exits into the top hallway, and walks toward the east exit. It should be noted the shooter in this simulation never reaches the east exit before law enforcement arrives. This was done intentionally to keep the simulation within the bounds of the school. If any other agent is within 30 yards and 180 degrees of the direction the shooter is facing, the shooter will target that agent until the agent becomes a casualty, the agent escapes, or the shooter dies. The shooter will target the closest agent if multiple agents are within this range. If no agents are within this range, the shooter will follow the default path previously described until all agents are marked safe or the shooter dies. The shooter targets an agent by first orienting in the direction of the agent and then firing one round per second until the agent becomes a casualty, a closer agent is identified, or the shooter dies. The shooter can move while shooting at an agent. The shooter's accuracy varies between a 25%, 50%, and 75% chance of creating a casualty. Each time the shooter fires a round, the remaining rounds in his magazine decrease by one. Magazine capacity is varied between 10, 20, and 30 rounds. When the shooter's magazine reaches zero, he will pause for three seconds to reload, during which he will not move or target any other agents. The shooter has unlimited ammo as the number of rounds the shooter carries and switching to a secondary weapon were outside the scope of this simulation.

There was no law enforcement in the behavioral experience, so the law enforcement officers arrived at the east exit after either 1 minute, 3 minutes, or 5 minutes. Dispatch times are low because in this scenario we assume the two officers responding are school resource officers (SROs) already on school grounds when the shooting begins. After arriving, law enforcement walks in the opposite direction students are running, which corresponds to the blue path in Figure 4. Law enforcement officers move at a speed of 0.75 yards per second and avoid running into students. When the shooter is within 30 yards and 180 degrees of the direction law enforcement is facing, the officers will fire at the shooter, always turning the shooter into a casualty. Specifics regarding law enforcement training, equipment, willingness to confront the shooter, and other contextual variables are outside the scope of this study.

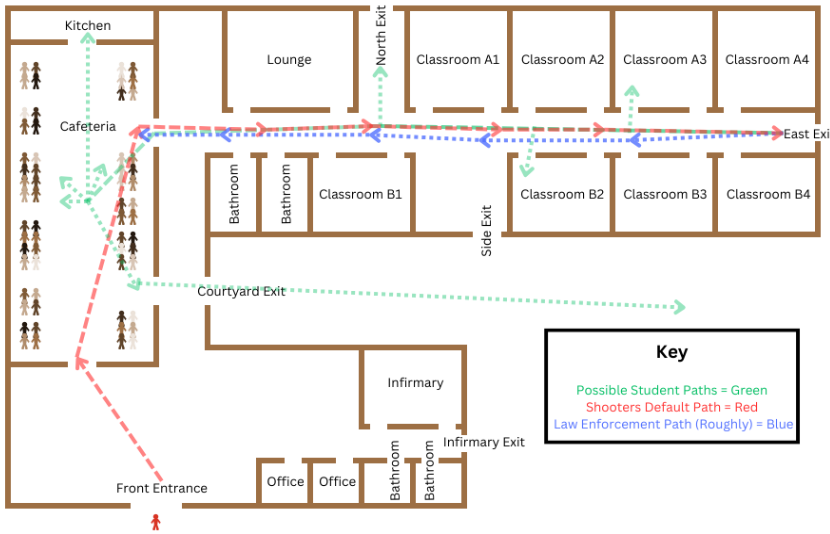

Figure 4: Student, shooter, and police default pathways.

3.5 Simulation Procedure

Data for this study was collected in the following manner. Each of the three social influence conditions (run, hide, mixed) received its own model. In each model, the magazine capacity (10, 20, 30), shooter accuracy (25%, 50%, 75%), and dispatch time (1 minute, 3 minutes, 5 minutes) were crossed to create a total of 27 combinations. 1000 trials were conducted for each combination, resulting in 27,000 trials per model and 81,000 trials overall. The primary dependent variable was the average number of casualties per trial. Figure 5 summarizes the agent-based model study design, showing which variables were included in each model.

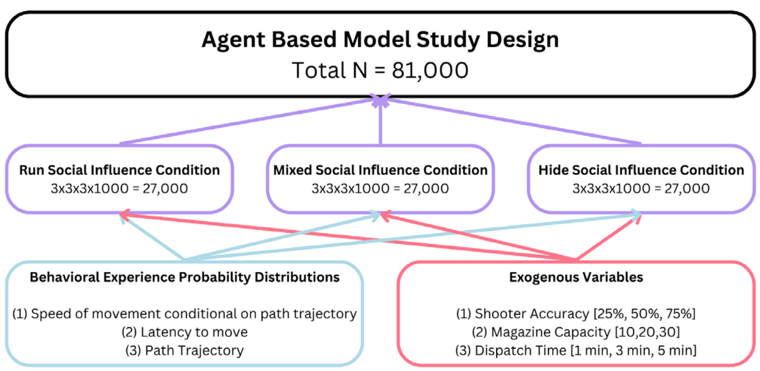

Figure 5: Agent-based model study design.

4 RESULTS

4.1 Number of Casualties

The following ANOVA model includes only the main effects and two-way interactions between the condition and the other variables to account for differences in student characteristics between each condition. A 3 (condition) x 3 (dispatch time) x 3 (shooter accuracy) x 3 (magazine capacity) ANOVA for the number of casualties found a significant main effect for condition ($F(2,80977)=37578.98$, partial $\eta^2=.28$), a significant main effect for dispatch time ($F(2,80977)=41736.64$, partial $\eta^2=.31$), a significant main effect for shooter accuracy (F(2,80977)=12930.07, partial η^2=.10), a significant main effect for magazine capacity (F(2,80977)=30.68, partial η^2=.00), a significant interaction between condition and dispatch time (F(4,80975)=1248.54, partial η^2=.02), a significant interaction between condition and shooter accuracy (F(4,80975)=381.45, partial η^2=.01), and no significant interaction between condition and magazine capacity (F(4,80975)=1.50, partial η^2=.00). Table 2 summarizes the follow up pairwise t-tests using Holm's correction (α = 0.05).

Table 3: Follow up pairwise t tests predicting number of casualties.

Factor Variable	Level 1	Level 2	Mean 1	SD 1	Mean 2	SD 2	η^2
Condition	Hide	Mixed	10.79	3.86	5.76	2.52	1.54
Condition	Hide	Run	10.79	3.86	9.18	3.65	0.43
Condition	Run	Mixed	9.18	3.65	5.76	2.52	1.09
Dispatch Time	5 min	3 min	11.28	3.83	8.59	3.43	0.74
Dispatch Time	5 min	1 min	11.28	3.83	5.87	2.59	1.66
Dispatch Time	3 min	1 min	8.59	3.43	5.87	2.59	0.90
Shooter Accuracy	75%	50%	9.91	4.19	8.89	3.95	0.25
Shooter Accuracy	75%	25%	9.91	4.19	6.94	3.17	0.80
Shooter Accuracy	50%	25%	8.89	3.95	6.94	3.17	0.54
Magazine Capacity	30	20	8.65	4.03	8.58	3.98	0.02
Magazine Capacity	30	10	8.65	4.03	8.50	3.96	0.04
Magazine Capacity	20	10	8.58	3.98	8.50	3.96	0.02

Figure 6 summarizes the student status at the end of each simulation by the percentage of casualties, percentage of students who did not reach safety (risk), and percentage of students who reached safety for each of the main effects included in the preceding ANOVA model. The difference in the percentage of casualties for each main effect is the same as described by the pairwise t-tests above. For all main effects except dispatch time, the percentage of students at risk is relatively the same. As dispatch time increases, the percentage of students at risk decreases. Figure 7 summarizes the same student status categories for the two significant interactions between condition and dispatch time and between condition and shooter accuracy. As dispatch time increases, the percentage of casualties increases faster in the hide condition compared to the run and mixed conditions. Similarly, as shooter accuracy increases, the percentage of casualties increases at a higher rate in the hide condition compared to the other two and at a higher rate in the run compared to the mixed.

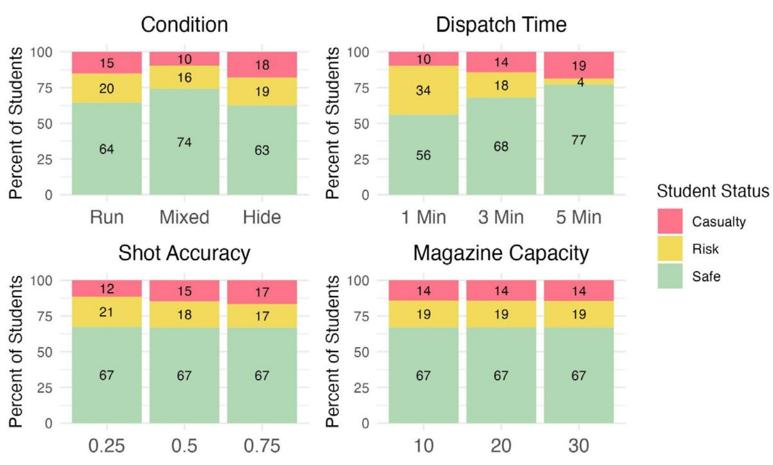

Figure 6: Student status by social influence condition, dispatch time, shot accuracy, and magazine capacity.

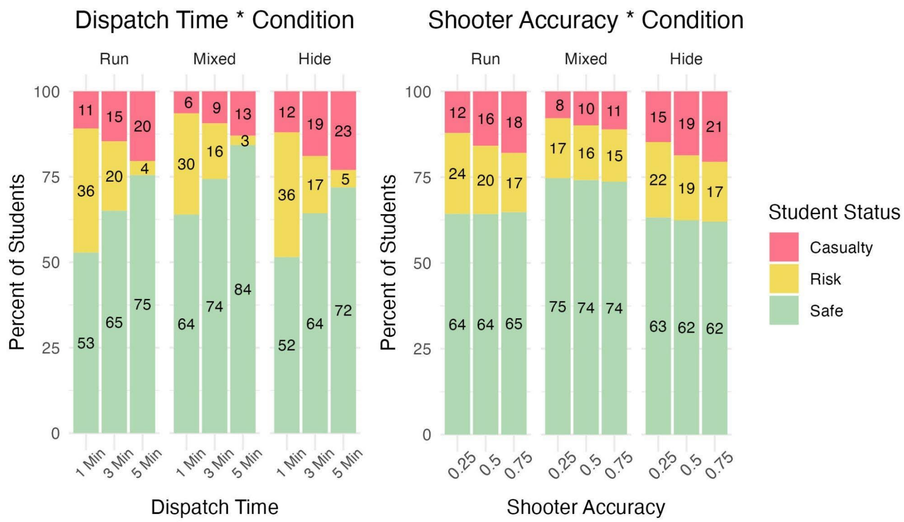

Figure 7: Student status by dispatch time by social influence condition and by shooter accuracy by social influence condition.

4.2 Shooter and Law Enforcement Casualties

In Table 4, we report the percentage of trials in which the shooter or a law enforcement officer became a casualty for each of the three dispatch times in our simulation. Only dispatch time was reported because this was the only variable of interest with significant results. A chi-square test of association found a significant relationship between the percentage of trials law enforcement became a casualty and dispatch time ($X^2(2, N = 81000) = 6155.50$, $p < 0.001$, $V = 0.28$). Similarly, a chi-square test of association found a significant relationship between the percentage of trials in which the shooter became a casualty and dispatch time ($X^2(2, N = 81000) = 80.33$, $p < 0.001$, $V = 0.03$). The correlation between dispatch time and duration of the simulation was 0.96. There was a strong association between shooter casualty rates and dispatch time, with higher dispatch times resulting in a lower shooter casualty rate. In contrast, there was only a weak association between law enforcement casualty rates and dispatch time. The high correlation between dispatch time and simulation duration suggests law enforcement arrival plays an important role in bringing active shooter scenarios to an end.

Table 4: Percent of trials shooter or either law enforcement officer became a casualty.

Dispatch Time	Percent of Trials Shooter Became Casualty	Percent of Trials Either Law Enforcement Became Casualty	Average Simulation Duration (Seconds)
1 Minute	98.15%	43.44%	201.76
3 Minutes	96.64%	46.70%	296.15
5 Minutes	81.76%	43.24%	387.29

5 DISCUSSION

5.1 Relationship Between Condition and Casualties

Agents based on the mixed condition were significantly less likely to become casualties compared to the run and hide conditions. Despite a similar percentage of agents running to the North Exit as the run condition, agents in the run condition running to other exits likely contribute to clogging in the top hallway near the lounge and bathrooms, similar to a chokepoint in a real building. Agents in the hide condition were the most likely to become casualties because they tried to hide in the cafeteria or kitchen and did not have enough time to escape from the shooter. Even when the dispatch time was 1 minute, approximately 12% of agents became casualties in the hide condition. While no one simulation can be used to inform policy, based on the performance from each of our social influence conditions, victims of shooting should aim to run away as quickly as possible with a preference for routes with fewer people, even if they are a longer distance. Furthermore, our simulation provides evidence for building planners ensuring that high-capacity rooms such as cafeterias and auditoriums, have sufficient exit locations and wide enough egress lanes to prevent bottlenecks.

5.2 Relationship Between Model Parameters and Casualties

In our simulation, we varied the dispatch time, shooter accuracy, and magazine capacity. Dispatch time had by far the largest effect, with twice as many casualties in 5-minute dispatch time conditions compared to 1 minute on average. While the dispatch times in the study were short, any dispatch time over 6 minutes meant the simulation ended before law enforcement showed up. This result is consistent with previous research showing approximately one-third of shootings end within 2 minutes and more than two-thirds within 5 minutes FBI (2022). The presence of school resource officers (SROs) or armed staff can help dramatically reduce the time it takes to confront a shooter and reduce casualties. Shooter accuracy had a linear impact on the number of casualties. We do not provide any broad policy recommendations, as this variable was primarily intended to verify our simulation results. Finally, magazine capacity had no meaningful effect on the number of casualties.

5.3 Shooter and Law Enforcement Casualties

In the majority of trials in our simulation, the shooter became a casualty. A shooter casualty was particularly likely when the dispatch time was 3 minutes or less. In contrast, the percentage of trials in which a law enforcement officer became a casualty was consistently around 45% for all dispatch times. It should be noted that this means the officer was struck somewhere on the body, including body armor, where little or no injury may have occurred. In our model, law enforcement had the upper hand in targeting the shooter as the shooter was typically targeting students who were closer, allowing law enforcement to fire the first shot. Law enforcement casualty rates were so high in our model because both shooter agents and law enforcement agents had the same firing range, accuracy, and tactical skills. In actual active shooter situations, law enforcement casualty rates will depend on law enforcement training and available equipment, as well as exogenous factors related to shooter tactical skills and weaponry.

5.4 Limitations

While our agent-based simulation is the first to model agent behavior on observations from a behavioral experience of a school shooting, several improvements could be made to enhance the realism. Real-life outcomes will depend on many exogenous variables that are not modeled in our simulation. Additionally, we do not know the extent to which contextual variables embedded in the agent assumptions would moderate the outcomes. While these limitations prevent us from believing the exact number of casualties reported, we can still observe the relative effects of the manipulated factors. Our model serves as a methodological demonstration that can be expanded to make accurate predictions in particular situations.

5.5 Conclusions

Our agent-based model used observed human behavior to inform agent decision-making latency to act, how to respond, and how quickly to respond. Results indicate that agent behavior and law enforcement dispatch time were the most important factors in reducing the number of casualties in a school shooting. Using behavioral data from a virtual simulation to inform agents' behavior provides an empirical basis for defining agent behavior in response to a stressful event such as a school shooting. This methodology can be applied and tailored to better inform policymakers' decisions related to planning, mitigation, training, training guides, and design choices to minimize vulnerability and the severity of an attempted school shooting.

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