Modeling Human Behavioral Responses to Targeted Violence

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ABSTRACT

Securing soft targets and crowded places (ST-CPs) is a priority for law enforcement and security experts. When acts of targeted violence and terrorism occur at these locations, such as improvised explosive device (IED) attacks, they often end with mass casualties that devastate communities. One specific aspect of securing soft targets and crowded places is understanding the behavioral responses of civilians and first responders during, and immediately after, acts of terrorism and targeted violence. However, little research exists on how people behave during such violence and the implications of those behaviors on security best practices. This paper focuses on modeling human behaviors during targeted IED attacks at ST-CPs and presents findings from research conducted by RTI International and the Department of Homeland Security. Through this research, a flexible agent-based modeling framework has been developed that simulates crowd and first responder behaviors during acts of targeted violence. These ABMs simulate interactions between agents within highly customizable virtual environments that represent real world venues and events. Within these environments, researchers have modeled how changes in the physical environment, human behaviors, policies, and protective measures impact outcomes of interest like the risk of injury and death to the public and first responders. The paper details the ABM methodology and the use of the Social Force Model, the Agent-Zero Framework, and AnyLogic software to simulate and visualize the behavioral responses to IED attacks.

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INTRODUCTION

Very little research has focused exclusively on bombing events against soft targets and crowded spaces. What does exist is published most often in medical journals and examines injuries and trauma tied to improvised explosive devices (IEDs) and bombing events. Research on specific bombing types, such as suicide bombings, often examines the motives and psychology behind the offenders or target selection, not incident level characteristics captured post-event about bystanders and on-site first responders. One explanation for the lack of research on the topic may be the fact that bombings are rare outside of conflict zones, are one type of myriad weapons from which offenders and group can choose and can be difficult to collect meaningful data on. However, lacking generalized knowledge on bombings also makes it difficult to study and understand more specific questions about bombing events, such as how do individuals within the vicinity of a bombing react when the explosion occurs and how can knowledge about these reactions lead to better preventions of, and responses to, bombing events?

The purpose of this paper is to outline how researchers can use computer simulations to model behavioral reactions to bombing events when only limited amounts of real-world data exist. Understanding how people react can prepare security, staff and on-site first responders to better handle the aftermath of a bombing if one occurs. It can prepare those on the scene to make sense of the chaotic environment they have been thrust into. For those close to the blast, a quick reaction time is imperative to administering immediate care to the injured and evacuating those who are not in case of a secondary device. For those further away with limited knowledge of the particulars of the event, knowing how simulations have modeled casualties and human reactions to similar events, will allow them to initiate immediate responses using limited knowledge, such as the magnitude and number of explosions. Simulation research will also allow first responders approaching a bombing site to envision the scene they are approaching and the needs of the injured and impacted. Although after action reports and case studies have been completed on bombing events, such as the Boston Marathon bombing and the Manchester Arena bombing, these post-mortems focus on singular events and provide detailed explanations and lessons learned for those specific attacks. Computer simulations provide a framework to analyze the reactions of humans to an unlimited number of bombing events. For rare events, with possibly devastating consequences, utilizing this methodology provides those who work at soft targets and crowded spaces, and those who manage and train them, a realistic picture of what to expect if a bombing occurs.

This paper proceeds by explaining different simulation modeling techniques and which ones are most relevant to modeling a bombing at a soft target and crowded space. First, we discuss and elaborate on Pedestrian Evacuation Simulations and how bombing events research would fit within this larger body of literature. Simulation research has looked at evacuations because of fires, natural disasters, stampedes, and mass shootings, making bombing evacuation research a natural fit with the work already completed. Next, the focus turns to the combination of Pedestrian Evacuation Simulations and agent-based modeling which allows simulations to imbue specific characteristics onto agents and groups of agents. Agents could be civilians who are at a soft target, for example a transportation hub, but also staff selling tickets, law enforcement who routinely patrol the area, or private security that assist with non-criminal public safety issues. The relationship between agent-based models (ABMs) and the environment in which these models run is also discussed. How an agent acts at a transportation hub compared to a sports venue or a college campus will be impacted by the specifics of that environment. Agents evacuating narrow corridors will make different choices and have different outcomes than those evacuating a large lawn on a college campus because their environment will create restrictions, as well as restrictions to all the other agents attempting to evacuate a bombing event. In addition to providing background on agent-based modelling, the paper details the implemented decision module which lets agents select one of *n* possible behaviors. This decision module combines a movement component (Social Force Model, SFM; (Helbing & Molnar, 1995)) with a behavior module (inspired by the Agent_Zero framework; Epstein, 2014). The Social Force Model incorporates sociopsychological and physical forces into crowd behavior to model the movement of people along individual paths from their starting location to designated safe zones. The Agent_Zero component allows people to select a behavior (e.g., helping) that will disrupt their movement. In general, this decision module lets us model the way in which people respond differently to a bombing event and engage with others in the crowd during evacuations based on an individual's age, gender, and psychological aversion to risk.

Being environment agnostic was one of the key functional requirements for the decision module. Environment agnostic here refers to the idea that, once developed, the decision module can be applied in a wide range of environments (indoor, outdoor, wide-open spaces, spaces with many passages such as streets or hallways). Of course, these different environment types imply different expected behaviors and to accommodate those patterns the decision module can be parameterized by the user (e.g. enabling more or less frequent helping behavior). To define the conceptual characteristics of the decision module we analyzed several case studies with the purpose of identifying generalizable behavioral patterns that can be algorithmically implemented in code.

Data Collection

This analysis employed a multi-case study methodology to identify patterns in human behavior immediately following the functioning of an improvised explosive device (IED) at a ST-CP. To this end, we used a purposive case selection strategy to meet theoretical and pragmatic considerations. To meet our theoretical goals, we limited our population to terrorist attacks in which one or more IEDs functioned at a soft target. "Soft targets and crowded places" are defined as "locations that are easily accessible to large numbers of people and that have limited security or protective measures in place making them vulnerable to attack" (DHS, 2018). We focus specifically on bombings using IEDs (i.e., "homemade" explosive devices (LaFree & Legault, 2009)) as part of a terrorist attack, which we define as ""the threatened or actual use of illegal force and violence by non-state actors to attain a political, economic, religious, or social goal through fear, coercion or intimidation" (LaFree, Dugan & Miller, 2015).

Within this set, we identified bombings that resulted in deaths and injuries, with the expectation that these bombings were more likely to result in a wider reaction by bystanders and to have open-source information available about them for analysis. To focus on responses to bombings, specifically, we excluded multimodal attacks that included additional weapon types. Like other research that examines human behaviors after targeted attacks (e.g., Bernardini & Quagliarini, 2021), we focused on Western countries, specifically European countries and the United States. We further narrowed our search to account for several pragmatic considerations. To maximize data availability, we excluded cases that did not receive in-depth media coverage. We also excluded cases that occurred before 1996, as quality video footage was unavailable.

This case selection strategy inherently excludes notable cases. For example, excluding multi-modal attacks leaves out the 2011 Norway attacks and the 2017 attacks in Paris; focusing only on Western countries excludes the 2008 Mumbai bombing attacks. These attacks, and others like them, were highly significant events with domestic and international policy implications. However, given the relative lack of research in this area, it was important to retain these strict selection criteria to build a baseline understanding of human behavioral responses to bombing attacks in these confined circumstances.

The six case studies selected include: the 1996 Centennial Olympic Park Bombing (Atlanta, USA), 2004 11M Commuter Train Bombings (Madrid, Spain), 2005 7/7 London Underground and Bus Bombings (London, England), 2013 Boston Marathon Bombings (Boston, USA), 2016 Brussels Airport and Subway Bombings (Brussels, Belgium), and the 2017 Manchester Arena Bombing (Manchester, England).

Organizing Human Behavioral Responses across Time and Space

Based on the analysis of the six case studies we developed a methodology to organize and operationalize human behavior across time and space. For this methodology we extend the work of (Bernardini & Quagliarini 2021) to narrow in on what happens during the pre-evacuation phase right after the event of an explosion. (Bernardini & Quagliarini 2021) discuss 3 post-explosion phases: 1) pre-movement phase, 2) motion phase, that constitutes the evacuation itself, and 3) a post-evacuation phase where people congregate in a safe zone. We operationalize the pre-movement and motion phases so we can model behavioral dynamics during the first few minutes after an explosion.

Specifically, we focus on the pre-movement phase and the very early stages of the movement phase where people still have not fully committed to a purely evacuation movement but may engage in one of the below described behaviors.

The behaviors discussed below (fleeing, observing, helping, and a neutral behavior of inactivity) are organized and reported across time, space, and agent type. This helps in understanding how behavioral response patterns change based on an individual's distance from an explosion and how much time has elapsed since the IED functioned. Five temporal phases were identified and coded for this research: 1) the initialization phase of a simulation run where, for example, agents are distributed across space according to user input; 2) micro-phase 1 that covers the behavior of agents right after an explosion and is dominated by affective decision making; 3) during micro-phase 2, lasting up to one minute, agents start to exhibit more deliberate decision making; 4) micro-phase 3 is dominated by deliberate decision making; and 5) the evacuation phase where very little decision making occurs and agents continue executing their selected behavior (e.g., helping or fleeing). Figure 1 provides additional information on each phase.

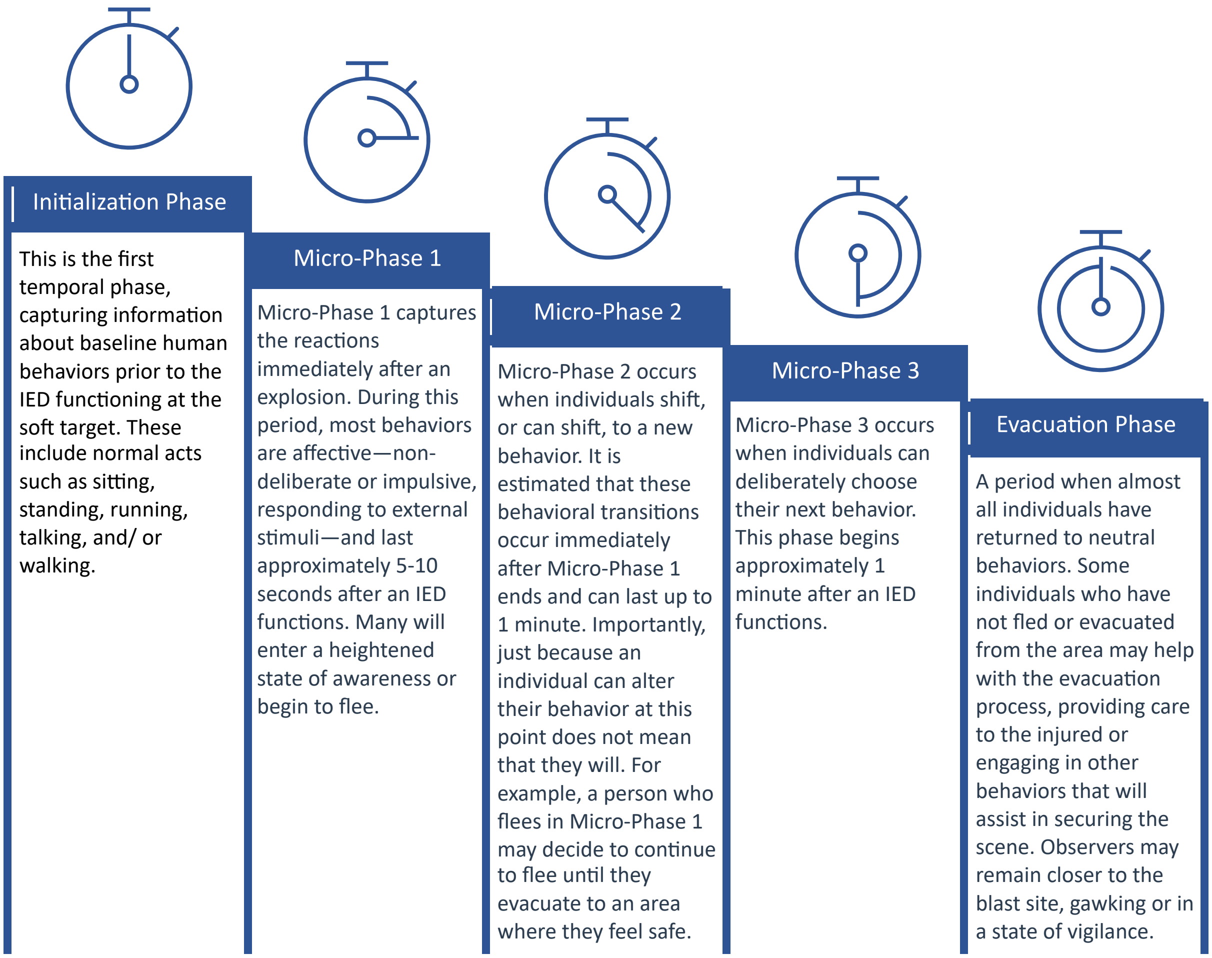
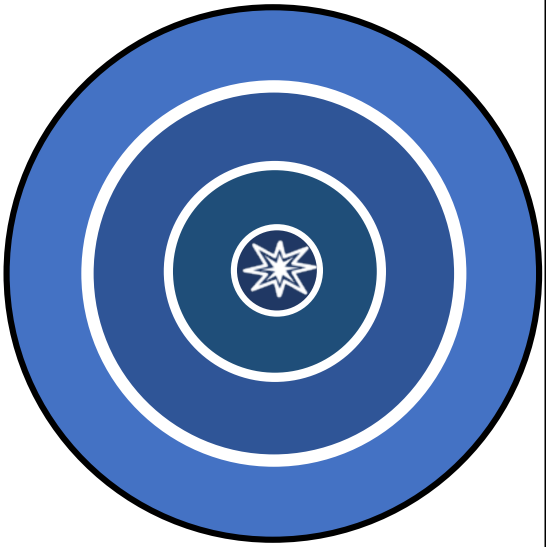


Figure 1: Temporal Phases Developed to Analyze Patterns of Human Behavior across Time

Similarly, the physical distance from the explosion was segmented into four Concentric Zones: 1) the primary zone is defined by the maximum probability of dying or getting injured; 2) agents in the secondary zone have visual and auditory access to the effects of an explosion; 3) people in the tertiary zone receive only indirect information about the explosion ; 4) people in the evacuation zone will exhibit normal behaviors again. More information about each zone is provided in Figure 2.



Primary Concentric Zone
The blast radius – the area around the explosion with a high probability of injury or death. Most people in the Primary Zone can see, hear, and feel the direct effects of the explosion. The size of this zone is primarily dependent on the magnitude of the explosion and the environment.
Secondary Concentric Zone
The area immediately outside of the blast radius where there is a low likelihood of being injured. People can hear the explosion and more readily see its effects on those within the Primary Zone. This zone's size depends on the environment and, to a lesser degree, the explosion's magnitude.
Tertiary Concentric Zone
The area where most people have no clear view of the explosion or its casualties. People can hear the explosion and see its effects on people in the Secondary Zone; they may also see fire or smoke. The size of this zone is primarily dependent on the environment.
Evacuated Zone
People will have a limited understanding of what has occurred. Most of their knowledge of the explosion will be based on observations of those in other zones moving away from the blast and secondary information about the explosion. In this zone, most people will feel safe enough to return to normal behaviors.

Figure 2: Geographic Concentric Zones Developed to Analyze Patterns of Human Behavior across Place

SIMULATION METHODS

One of the most published approaches to simulating evacuation scenarios is the Social Force model (SFM; Helbing & Molnar 1995). The SFM assumes that the movement of a crowd through an environment is influenced by a mixture of sociopsychological and physical forces. In this vein, evacuation scenarios generally implement optimal-path-finding algorithms that move a crowd of people from a starting location to a safe location along the shortest path. This research typically ignores the fact that people have a variety of behaviors to choose from during an evacuation and provides agents with no decision-making capabilities other than to head to the nearest exit along the most expedient pathway. This research uses an agent-based modeling approach that combines traditional evacuation modeling approaches (implemented using the SFM) with explicit agent decision making (using an Agent_Zero Framework inspired approach; Epstein, 2014). The rest of this section further details the components of this approach. In combination, they provide a much more realistic depiction of the unfolding dynamics after an IED functions.

Agent-Based Modeling

One simulation modeling method used to study human behaviors after an IED functions is agent-based modeling. Agent-based modeling is a bottom-up simulation approach to study complex social systems with explicit agent-agent and agent-environment interactions (Railsback & Grimm, 2019). Bottom-up refers to the concept that system-level behavior of an ABM is the product of explicit agent-agent and agent-environment interactions over time. An agent-based model is populated with agents that represent entities in real life (e.g., individual people, vehicles). An important feature of agent-based modeling is the explicit decision-making process individual agents engage in, which is encoded as a decision-making module. This decision-making process may be as simple as a probability drawn from a distribution (to change from one state to another, e.g., alive -> dead) or as complicated as a state chart with multiple external inputs received from other agents or the environment that are used to determine how an agent moves through behaviors. The implementation of individual agents and their respective interactions with explicit decision making allows for a high degree of behavioral heterogeneity during a simulation run of the model. For the present research, we have implemented a decision-making module that combines a movement component (Social Force Model, SFM) and a behavior selection module (inspired by the Agent_Zero famework; Epstein, 2014) that allows individuals to engage in affective or deliberate behaviors. This module determines individuals' movements based on the selection of a path to a specific safe zone in the environment. Movement may be disrupted by the selection of a specific behavior from a set of possible behaviors using the Agent_Zero approach.

For this project we have selected AnyLogic (2024) to model human behavioral responses to targeted violence. AnyLogic is a comprehensive modeling platform that not only has a rich editor to build constrained environments it also has the capability to automatically build these environments based on CAD files. AnyLogic also comes with a tested pedestrian flow model with which the basic movement of agents through constrained environments can be modelled. In addition to the flow model, agent movement can also be augmented with individual decision making by agents using state-chart based behavior processes.

Agent Types & Behaviors

In our model, agents can be assigned to one of two groups: civilians or first responders. Different groups have different behavioral profiles. For example, law enforcement agents are specifically calibrated to help the injured and dead and not engage in other behaviors. In the current version of the simulation, civilian agents can engage in several behaviors once an IED functions. These behaviors include fleeing, observing, helping, and a neutral behavior of inactivity. *Fleeing* can be either an impulsive or deliberate behavior. Individuals who flee are actively attempting to exit the venue and reach safety. *Observing* manifests in the models as agents who remain in place and are in a heightened state of awareness of the danger around them. In the real world, this could include people who are frozen in shock, gawking, or vigilant. Helping occurs when an individual is within a specific distance of a casualty and approaches the injured or dead. *Neutral* behaviors entail moving around the environment or standing in place. After an IED functions, agents that return to their pre-event behavior are coded as engaging in neutral behaviors. Casualties of the IED functioning include individuals who are killed or injured. Casualties will remain in the location where they were injured or killed for the duration of the simulation.

Social Force Model

The Social Force model (SFM) is a simulation modeling technique to capture pedestrian movement (Helbing & Molnar 1995). The technique was later adapted to the escape panic domain (Helbing, Farkas, & Vicsek, 2000) with a much reduced set of parameters compared to the original model. The original formulation of the SFM is based on the insight that the movement of individuals in a crowd can be modeled as the interaction of repelling and attracting forces. The SFM thus determines how agents can optimally move through a complex environment with a variety of environmental features, such as walls and doors, and how they physically interact with other agents. The additive forces of this technique determine the directions in which agents will move and the speeds at which they move. The SFM also determines the distances agents will keep from each other and features of their environment. Taken together, these forces are used to calculate movements through simulated environments that mirror the movements of individuals and crowds in the real world. The SFM determines how the individuals in these models, such as spectators and law enforcement, can evacuate from the environment if they choose.

Agent_Zero Framework

To model the real-world behavior of individuals after an IED attack at a soft target and crowded place, this research applies the Agent_Zero (Epstein, 2014) decision making framework. This framework can be used to simulate an agent's ability to choose between competing behaviors like those already described – fleeing, observing, helping – when placed in an emergency. Those behaviors were identified through the multi-case study analysis (see Data Collection section above). By collecting data on real-world behavioral reactions to targeted IED attacks, we created an empirical grounding for implementing the Agent_Zero framework. As an example, once an IED functions in the model, agents receive an affective stimulus from the blast, the strength of which varies based on their distance from the blast site. The agent must then choose between several behaviors such as fleeing, observing, helping, or not reacting at all. If agents cannot initially choose, they remain in a frozen state until they can choose. This behavioral element allows for the simulations to be calibrated to mirror what has previously been observed at actual IED attacks, such as those at the Boston Marathon and Centennial Olympic Park.

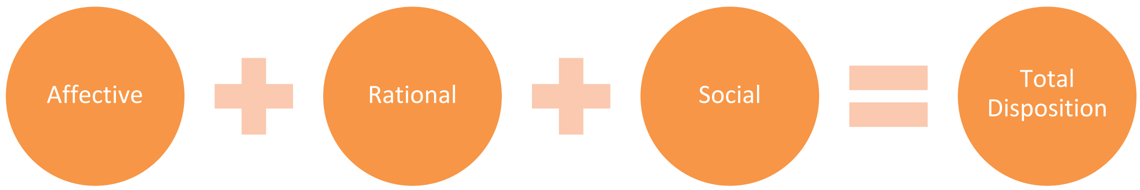


Figure 3: Visual representation for an agent's disposition towards any given behavior

Following along with the Agent_Zero framework, an agent can have an overall disposition (a tendency) towards committing or acting out a behavior. This overall total disposition is comprised of three (3) factors:

- **Affective Disposition:** The affective disposition representing the individual agent's emotional response to an event. It is expected that this dominates initial reactions to an event but becomes less dominant over time.
- **Rational Disposition:** The rational disposition represents the agent's conscious decision response to an event. While initially expected to be less impactful, over time post-bomb in this is expected to dominate an agent's response and overall disposition.
- **Social Disposition:** The social impact represents the effect other agents' dispositions have on a given agent's disposition towards a behavior. This dimension allows for behaviors (e.g., mob panic) to exist and spread within an agent population.

An agent's overall total disposition is an aggregation of its affective, rational, and social dispositions. Each of these elements independently change over time and collectively impact an agent's behavior. A visual representation for an agent's disposition towards any given behavior is depicted in 3.

Validation of the Model

Multiple iterations of simulations are commonly run to quantify the between-run variability inherent in ABMs. The number of times the scenarios must be run to produce meaningful averages varies from model to model. For example, Bienzeisler et al. (2021) found that 36 simulation runs were sufficient for their transportation models. In addition, ABMs with explicit decision-making modules, such as the ones developed for this research, take a lot of time and computing power to complete. For this reason, researchers will run only the minimal number of iterations necessary to produce a robust average. To collect data for our initial analysis we have performed 10 simulation runs of the two IED scenarios. We have observed a low variability between runs in the outcome variables (e.g., number of people in safe zones). This points to a robust average and indicates that we can stay within the iteration limit reported by Bienzeisler et al. (2021). For future scenarios of different location and venues we will run the same type of analysis to establish the robustness of our overall modeling approach.

CONCLUSION

This research introduces an innovative methodology that incorporates human behavioral responses into traditional agent-based evacuation modeling. For the Boston Marathon scenario, four behaviors were developed as responses to an explosion and subsequent crowd reactions—fleeing, observing, helping, and a neutral behavior. Observing currently represents a combination of behaviors that are driven by a reaction to the IED and a heightened awareness of the environment (e.g., gawking, freezing, vigilance). Additional behaviors will be added to future models deployed in other environments (e.g., hiding). Another model enhancement for future simulations includes the introduction of small-group behaviors. Depending on the ST-CPs and event, small groups within the environment (e.g., families, couples, friends) could have a significant impact on the flow of individuals and crowds.

New agent types will also be included in future environments. Currently, spectators and law enforcement officers represent the individuals moving through the Boston environment. Future environments will also include agents representing security, event staff, the elderly, and children. Similar to this model, each of these agent types will have different behavioral profiles that are based on theory and the prior case study research.

Finally, future environments will also provide evidence as to whether the preliminary behavioral patterns identified for the Boston scenario will also occur in other types of ST-CPs (e.g., outside a sports arena, inside a transportation hub, and at a medical facility). As the model is further developed, it is expected that the simulation results will improve.

ACKNOWLEDGEMENTS

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