AN AGENT-BASED MODEL OF MOBS USING THEORETICAL CONSTRUCTS OF COLLECTIVE ACTION

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ABSTRACT

Agent-based modeling (ABM) is a powerful research tool that is used in a plethora of fields. A mob is an event where a group of individuals get together online and/or offline to conduct a seemingly random act. We posit that a mob can be simulated using ABM and the constructs of the collective action theory, which is defined as all activities of common or shared interest among two or more individuals. In this research, we build an ABM using NetLogo, that can simulate a mob. Building an ABM model of the mob based on a social science theory serves as a new method to study the mob and understand the behavior of its participants. These participants form cyber-social groups on social media that act collectively (sometimes their acts lead to violence or societal conflicts). Understanding the mob phenomenon will lead to understanding similar collective action-based phenomena, e.g., organized violent protests.

Keywords: Mob, Agent-based Modeling, Collective Action Theory, NetLogo.

1 INTRODUCTION

Agent-based modeling (ABM) is a bottom-up approach for studying emerging patterns from simple interactions among agents (Duffy 2021). It is applied in a plethora of disciplines such as sociology, economics, political science (Jackson et al. 2017), and applications that are ranging from cargo routing to Artificial Intelligence (Duffy 2021). Before agents could move, ABM or Cellular Automata (CA) was used to study emerging patterns, through the use of stationary agents. Other breakthroughs such as the use of Complex Adaptive Systems (CAS) and System Dynamics allowed a more accurate study of more complex systems (Duffy 2021).

ABM is primarily used for modeling human behavior (Duffy 2021). These models can be a great choice for researchers because they allow for a high level of control on the experiment; can be run an infinite number of times (on a large scale) with all reasonable values for parameters that can allow researchers to generate all possible outputs (Mollona 2008); able to model nonlinear dynamics over time; and allow researchers to test questions that otherwise would not be possible because of ethical concerns (Jackson et al. 2017). Being able to test all parameters allows researchers to compare the model data and add or rule out variables that impact the emerging behavior (Mollona 2008).

On the negative side, ABMs have to sacrifice their realism and sometimes their validity. To fight this, it is best if ABMs are used alongside other methods of research and validated using real-world data. The two biggest concerns researchers usually have with ABMs are that ABMs are too reduced or the thought *"you get out what you put in"*. The latter can be disproved by the fact that an emerging phenomenon happens by using simple rules (Jackson et al. 2017). Models are commonly validated by comparing the ABM output to real-world data (Duffy 2021). However, this ABM validation method sometimes isn't possible because of how difficult it is to acquire a large amount of accurate real-world data. If data cannot be obtained, empirical validation or more specifically the *"Indirect Calibration Approach"*, which has been growing in popularity, can be used to validate ABMs (Duffy 2021). Smith and Conrey (2007) recommend that modelers follow the acronym KISS (*"keep it simple, stupid"*) as models are not supposed to be reality. Ormerod and Rosewell (2009) believe that the most important way a model can be validated is if it explains the phenomenon. Another way a model can be justified is if there is real-world evidence that was used for agent behavior, along with agent behavior being simple (Ormerod and Rosewell 2009). Models can slowly add complexity and researchers can find the point at which the model no longer shows the emerging phenomena (Ormerod and Rosewell 2009). Overall, it is important that models are tested for robustness and are *backed by theory* to ensure that the gap between the model and the real world is as small as possible. If these models are built carefully and are of quality, they can be a great tool to help support emerging theories (Mollona 2008).

The use of ABM in developing models for human behavior is primarily broken down into three methods: *mathematical*, *conceptual*, and *cognitive* (Duffy 2021, Kennedy 2012). The first method is the *mathematical approach* which uses simplified equations to create rules for agents (Duffy 2021), for example, Schelling's model of segregation (Schelling 1969). The benefit of this approach is it requires lower computational power than the conceptual and cognitive approaches. However, models that use this approach can be unrealistic as they lack any human cognition (Duffy 2021). The second method is the *conceptual approach* which integrates more advanced decision-making processes such as taking into account desires, goals, or beliefs (Duffy 2021), for example, the Beliefs Desire Intentions architecture (Caillou et al. 2017). The benefit of this approach is agents' behavior is more human-like without creating the computational stress of the cognitive approach (Duffy 2021). The third method is the *cognitive approach* which aims to replicate human behavior, however, it is not frequently used because it takes the most computational power and can add unnecessary complications to the model that could be done easier with a simpler model (Duffy 2021). This made the mathematical and conceptual approaches used more frequently because they are, generally, more explainable models (Duffy 2021). Our model is both mathematical as well as conceptual.

Recently, ABM was used to study violence in urban neighborhoods and the prospect for more ABM research in social science is on the rise as modeling software is becoming more accepted and easier to use (Duffy 2021). Retzlaff, Ziefle, and Calero Valdez (2021) stated that ABMs should make their way back into social science research as ABM has been very impactful in the past with the neighborhood segregation and Prisoner's Dilemma models.

Individuals in the mob phenomenon are purposive–those who "adjust their actions to counter variable circumstances that prevent their perceptions from matching their objective" (McPhail, Powers, and Tucker 1992)–and the mob phenomenon is an example of organized collective action (McPhail, Powers, and Tucker 1992). To an outsider, such an event may seem arbitrary, however, a sophisticated amount of coordination is involved. This phenomenon is significantly understudied due to the lack of data, theoretical underpinning, and computational resources required to process complex dynamic social processes that happen during mobs. Hence, in this research, we decided to use the ABM method to understand the mob phenomenon as it is the primary method used for modeling human behavior (Duffy 2021). It allows us to test various parameters and compare the model data to add or rule out parameters that impact the emerging behavior (Mollona 2008) and to test questions that otherwise would not be possible due to ethical concerns (Jackson et al. 2017). Understanding the mob phenomenon also provides a great opportunity to help us better understand how social media's power has been harnessed by potential adversarial state actors, paid trolls, and extremist organizations to conduct disinformation campaigns, provoke hysteria among citizens, and coordinate nefarious acts (e.g., deviant mobs).

Currently, there is a gap in communication between agent-based modelers and social scientists (Retzlaff, Ziefle, and Calero Valdez 2021). This research is one step toward bridging this gap in communication. In this work, we construct an agent-based model that serves as an implementation of our previously published theoretical model of mobs. Jackson et al., (2017) recommend reducing the complexity of the model as that increases clarity and in turn maximizes research potential. They also recommend NetLogo for beginning ABMers as it is less strenuous to learn than other programs. Hence, in this research we built a simple model and used NetLogo to seek an answer to the following research questions:

- **RQ1**: How can we use NetLogo to build an agent-based model of the mob phenomenon based on the theory of collective action?
- **RQ2**: What is the effect of the *number of invited people* on the *participation rate*? in other words, does the *number of invited people* to a mob affect the number of agents participating, hence affecting the success or failure of a mob?
- **RQ3**: How do the mob organizers affect the mob outcome?

This paper proceeds as follows. Section 2 provides a brief review of the literature related to agent-based modeling in social science. Section 3 explains the methodology followed to build the model, run the experiments, and the research findings. Section 4 highlights some of the research limitations. Section 5 concludes the study with possible future research directions.

2 LITERATURE REVIEW

ABM is used in a plethora of fields and applications, e.g., manuscripts reviewing process (Allesina 2012). Hence, in this section, we review some of the relevant work that is related to the use of agent-based modeling in social science.

Natural sciences and social sciences can benefit from being studied together as they are both needed to help grasp more complex phenomena. Research in coupled human and natural systems (CHANS) has been a growing research topic since the 1990s (An 2012). A review conducted by Li An (An 2012) set out with the goal of determining what methods are being used to model decision-making behavior, what are the strengths and weaknesses of these methods, and what changes can be made to improve how human decisions in CHANS are being modeled (An 2012). This was done by reviewing 121 publications in relation to ABM and CHANS research (An 2012). The review covered articles with many different types of models but the nine most common were microeconomic, space theory-based, psychosocial and cognitive, institution-based, experience-based, participatory agent-based, empirical or heuristic rules, evolutionary programming, and assumption-based models (An 2012). Li An concludes that there are many different CHANS ABMs but this field still lacks protocols or structures for how these models should be made (An 2012).

Macro-scale social behavior phenomena, such as the bystander effect, frequently developed from multiple interactions between individuals. These interactions can be modeled using agent-based models. Agents, refer to a self-contained entity that can be affected by other agents or its environment. ABM has been used in social science to look at how segregation can form in neighborhoods without any centralized plan for segregation. When using ABM to study theories and emerging phenomena, these phenomena can be studied from the ground up by social scientists. For that reason, ABM might be preferred by social scientists because it can help them find an explanation for why the phenomenon is happening where other modeling methods might struggle (Smith and Conrey 2007).

Cerdá, Tracy, and Keyes (2018) created an ABM of New York City to research different violence prevention strategies using Repast which was implemented with the use of Eclipse- a popular integrated development environment (IDE) for Java development. This model was created using public health data, to make equations that accurately represent the New York City environment and agent characteristics such as age, sex, race/ethnicity, education, household income, probability of natural death, probability of moving, probability of homicide, and probability of non-fatal violence. The model had four different strategies, do nothing (control), hot-spot policing, cure violence (implementing social workers to work in troubled neighborhoods), and a strategy that combined both cure violence and hot-spot policing. The model was then calibrated and tweaks to the model were made such that the model's data matched the real-world data of New York City. Next, they tested the robustness of the model's data by running eight groups of data collection and for each one testing a range of values for a specified variable such as varying the range a police officer could stop a violent act. The combination of both cure violence and increased hot-spot police patrol strategies was the most cost-effective strategy tested at lowering violence. They also found that the racial inequalities of violence in the real world persisted in the model. To counteract these real-world inequalities, Cerdá, Tracy, and Keyes (2018) believe that policies are necessary because just the use of cure violence or hot-spot police patrol was not enough to solve the inequality of violence in the model.

Group social conflict is a phenomenon that is closely related to the mob phenomenon. It has been studied using ABM. The group social conflict situations can vary and can be impacted by many different factors. Hence, this phenomenon has been researched by a large portion of professions such as psychology, sociology, history, political science, and police studies. Currently, it is looked at by the level of intensity of the event, e.g., a civil war would be of high intensity while peaceful protests would be of low intensity. It has been found that high levels of grievance in a population lead to social conflicts to happen such as protests. Social conflicts grow/shrink in size based on a contagion process similar to how information or diseases spread. ABM has successfully been used to help model these social conflicts using threshold-based rules. Threshold-based rules may lead to chain reactions leading to a quick change in behavior from agents. Epstein's models of civil violence showed how mobs of people avoid getting in trouble, bursts of violent action can happen, and how policing or authorities impact the mobbers' behavior. Epstein's model lacked the use of any empirical data for validation, along with having unrealistic agent movement, unrealistic cop interactions, and a static environment (Lemos et al. 2013). Lemos et al. (2013) compared ABM models that represented ranges of different social conflict events, such as worker protests, guerrilla warfare, and riots. For example, Davies et al., (2013) model of the London Riots from 2011 used real-world data to help accurately model the probability of an agent joining or leaving a riot (Lemos et al. 2013). Davies et al., study suggested that phone signal could be shut off in specific areas to slow down rioters' ability to coordinate plans, but after more research, results have been mixed on if this would be beneficial (Lemos et al. 2013). The use of social media or the use of communication methods is still a topic in social conflicts that needs more research. An ABM following Epstein's model was used to understand how the amount of police affects the number of violence in urban cities (Lemos et al. 2013). Fonoverova et al., (2012) created this model and compared simulated data results with that of data collected by the FBI in 5,560 cities in America (Lemos et al. 2013). They found that there is a nonlinear correlation between the amount of police agents needed to keep crime levels constant as the size of the city increase. They also found that larger cities showed spread-out outbursts of violence, while smaller cities showed single outbursts at a time (Lemos et al. 2013).

Finally, the spread of rumors has been a problem in workplaces for a long time as they affect workers' attitudes along with lowering work production (Tseng and Son Nguyen 2020). Tseng and Son, (2020) furthered research on this topic by creating an ABM using NetLogo. They chose ABM as it was important to have heterogeneity in the model to study social interactions. One advantage of research in ABM is that researchers don't always need advanced math or statistics skills to perform effective research. Their goal was to find the factors that affect the spread of rumors, along with finding methods to counteract the spread of rumors. In their model, they wanted to have rumors spread over social networks in addition to in person.

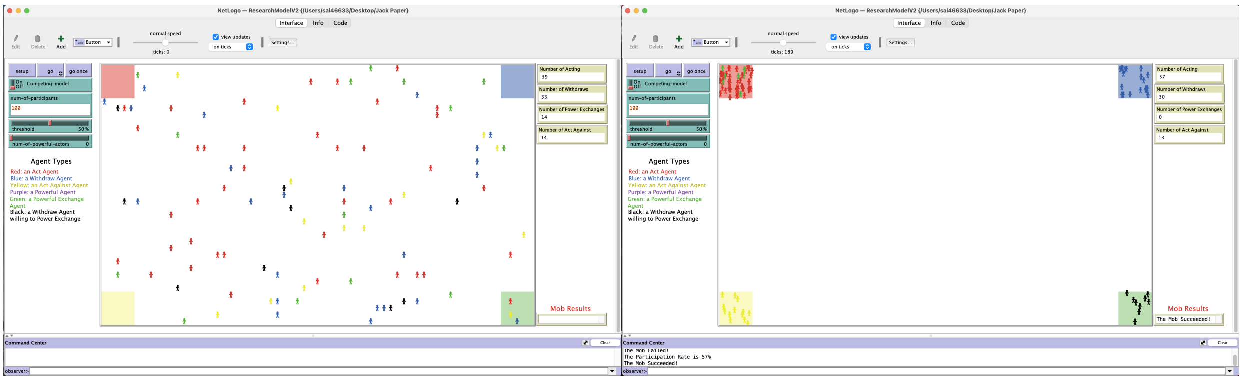

Figure 1: shows the model. The left figure shows the model once the user clicks the setup button, while the figure on the right shows the model once the simulation ends.

They did this by adding SITSIM model which uses Social Impact Theory (SIT). Factors such as *persuasive-constant*, *environmental bias*, *counseling of leader*, *social network usage*, *power of influencer*, and *distance between agents* were used to determine if the rumor would be spread. This ABM represented a contagion model where three different agent types (susceptible, infected, or recovered) exist. The model would run for 75 ticks each tick would add 20 new agents, and in the end, there would be a total of 1,500 agents. Then they took data from the model and calculated the Expected Integrated Mean Squared Error (EIMSE). This data showed that "environmental bias" and "counseling of leader" had the largest impact on rumors spreading. To counteract the spread of rumors in the workplace, Tseng and Son Nguyen (2020) recommend that leaders address rumors with employees right away, and build connections with all team members. They also found that rumors were spread faster over social media than through face-to-face interactions, but overall more rumors were spread face-to-face than over social media.

Compared to existing studies, this research provides a new way (i.e., using Agent-based modeling) to study the formation of the mob phenomenon based on factors extracted from the theory of collective action. To the best of our knowledge, this has not been done before.

3 METHODOLOGY

In this section, we explain the method we used to conduct this research. This includes a brief explanation of the theoretical model as this has been published in (Al-khateeb and Agarwal 2014b, Al-khateeb and Agarwal 2015b, Al-khateeb and Agarwal 2014a, Al-khateeb and Agarwal 2015a) and a detailed explanation of the ABM as it's the main contribution of this paper.

3.1 The Theoretical Model

Al-khateeb et al., (Al-khateeb and Agarwal 2014b, Al-khateeb and Agarwal 2015b, Al-khateeb and Agarwal 2014a, Al-khateeb and Agarwal 2015a) examined the sociological theory of collective action and extracted the factors that lead to the formation of a mob and its success (or failure) in cyberspace and physical space. Collective action can be defined as an activity of common or shared interest among two or more individuals (Olson 2009). From the logic of collective action by Mancur Olson (Olson 2009), we found that one factor that encourages mobbers to participate in a mob is the amount of utility (benefits) they will gain by participating. This is also supported by James Coleman's argument in his 1973 book "there is a single action principle which governs the actions of the actors in the system: Each actor chooses those actions which maximize his utility given environmental context created by the events..." (Coleman 2017). Also, the utility difference which is defined as the amount of utility (benefit) gained by an actor (a mobber) from the pair of possible outcomes (success or failure) of the same event (e.g., the mob) will determine his/her interest in participating in that mob. As the amount of gained utility increases the interest in participating in the mob also increases and vice versa. Another factor that Coleman mentioned in his book that can affect mobbers' decision to participate is control, i.e., to what extent an individual could affect the outcome of the event (Coleman 2017). If the mobber has an interest in participating in a mob and has control over the outcome of the mob, the mobber is considered powerful (e.g., a mob organizer). By summing the power of all mobbers, we can determine the importance of a mob. If the importance of a mob exceeds a certain (predetermined) threshold value, then we can hypothesize the mob will more likely succeed. Otherwise, the mob is more likely to fail. Here, we named the sum of the power of all mobbers as the *participation rate*. We calculate the participation rate using two formulas shown in equations 1 and 2 below. Equation 1 takes into consideration the effect of people who act against the mob, while Equation 2 does not take into consideration the effect of people who act against the mob.

$$ParticipationRate = \frac{(a+b-c)}{d} \tag{1}$$

$$ParticipationRate = \frac{a+b}{d} \tag{2}$$

where a is the number of acting agents, b is the number of powerful agents, c is the number of act against agents, and d is the number of invited agents. The reason we used these two equations is to study the effect of the people who oppose the mob goal (and act against it) on the mob outcome. In the second equation, we ignore the effect of those people. So, the first case is analogous to viewing what happens during a mob as two competing events where some people act while others act against them. However, in equation 2, the mob can be viewed as one event represented by only those who act. In both cases, the number of acts against agents will be there however, in equation 1 we count for it, while in equation 2, we do not count for it. Also, in both cases, the *participation rate* will be used to determine if the mob succeeded or not, i.e., if the *participation rate* exceeds the provided threshold value that means the event was important enough to attract enough people to participate, so it will be marked as a successful mob, otherwise, it will be marked as an unsuccessful (fail) mob. The threshold value can be estimated using various methods, e.g., based on empirical observations of known mobs or shared knowledge from law enforcement agencies, etc.

3.2 The Agent-based Model

Our choice of using NetLogo to build an Agent-based model of the mob phenomenon relies upon the recommendations from the literature (Jackson et al. 2017, Groff et al. 2019, Smith and Conrey 2007) that highlighted its simplicity and greater community support.

Figure 1 shows the model. The screen is divided into three areas: the left side represents the model input parameters, the middle is a rectangle grid that varies in dimensions and shows the progress of the model and the movement of the agents, and the right side represents the model output. Our grid size changes dynamically depending on the number of participants inserted with no agent overlapping, so the number of agents do not exceed 4% of the total space available to them as followed by Clark Mcphail et al., (1992) when they modeled the agent locomotion (i.e., agents movements in a crowd). For the model inputs, users can click on the *Competing-model* switch, if "On" the participation rate will be calculated using equation 1 otherwise, it will be calculated using equation 2. The users can choose the number of agents they would like (i.e., how many people were invited to participate in the mob). This is done by entering a number in the *num-of-participants* input on the top-left side of the NetLogo screen. Below that, the *threshold* slider can be adjusted from 0 to 100. Below that, the *num-of-powerful-actors* slider can be adjusted ranging from 0 to the *num-of-participants*, to represent the number of powerful agents (e.g., mob organizers) that will be participating in the mob.

Once the user clicks the ***setup*** button (see Figure 1-left), the model will randomly place all the agents in the grid which is shown in the center of the Graphical User Interface (GUI) of Figure 1. Each agent will randomly receive control/no control and interest/no interest assignments. Based on the control (i.e., the control of an agent on the mob outcome, which could be 0 or 1) and interest (i.e., the interest of an agent in participating in a mob, which could be 0 or 1) assignments, they will respond differently such that:

1. If an agent **has interest and control**, then the likelihood of the agent's participation is the highest, i.e., the agent will **act**.
2. If an agent **has interest** but **doesn't have control** then the agent **may act** (i.e., has 50/50 chance of acting or withdraw). So, the likelihood of agent participation is lower than in the previous case.
3. If an agent **does not have interest** but **has control** then the agent has two choices – either will **withdraw**, i.e., will not act, or execute **power exchange** (i.e., relinquish power to possibly gain control over other events (mobs) or to simply gain social capital–as stated by Pierre Bourdieu, is "*the value that one gain from personal connections such as membership in a family, an ethnic association, elite clubs, or other solidarity groups*" (Biggart 2008)). These agents can perfectly exchange power with agents of the second case above.
4. If an agent has **no interest** and **no control**, then the agent will have two choices – either will **withdraw** or **act against** the group.

Powerful agents/actors inserted by the user will always have interest and control, so they will always **act** in the mob.

Once, the user clicks the ***go*** button, in the upper left corner of the GUI, agents will move into their assigned groups in the GUI based on their type, i.e., act (red), withdraw (blue), power exchange (green), act against (yellow), withdraw agents willing to power exchange, i.e., from point 2 above (black), and the powerful agents/actors inserted by the user (purple). Once all the agents are grouped up, a power exchange will occur between the withdrawing agents that are willing to power exchange (black) and the power exchange agents (green). This will make the withdraw agents that were willing to power exchange (i.e., the black agents) move near the withdraw (blue) and near the power exchange (green), then the green agents move near the red agents (i.e., they will act). Once all agents have grouped together again, the simulation will output the *number of acting agents*, *number of withdraw agents*, *number of power exchange agents* left, and the *number of act against agents* at the right side of the GUI. Then the outcome of the mob will be determined and displayed in the bottom-right of the screen and in the command center.

To determine if a mob has succeeded or failed, the model calculates the *participation rate*. This is done in two different ways depending on if the *Competing-model* switch is set to 'On' or 'Off'. Once the participation rate is calculated, it will be printed in the command center, then compared to the threshold selected. If the *participation rate* is less than the *threshold*, then the mob fails. If the *participation rate* is equal to or greater than the *threshold*, then the mob succeeds.

3.3 Experiment-1 Setup

Using the model explained above, we ran an experiment to answer the second research question, i.e., *does the number of invited people to a mob affect the number of agents participating, hence affecting the success or failure of a mob?* We simulated a total of 80 mobs, 40 with the competing-model switch set to 'On' and the other 40 mobs with the switch set to 'Off' using the BehaviorSearch component in NetLogo. The 40 mobs with each switch case (On and Off) resulted from simulating 4 sets of 10 mobs each. The *num-of-participants* in each set was equal to 10, 100, 1000, and 10,000 invited mobbers/agents. In all the simulated mobs, we set the number of powerful actors to zero so we can calculate the participation rate without the effects of the powerful actors, i.e., to simulate the case when we do not know the number of mob organizers. The findings of this experiment are explained in 3.5.

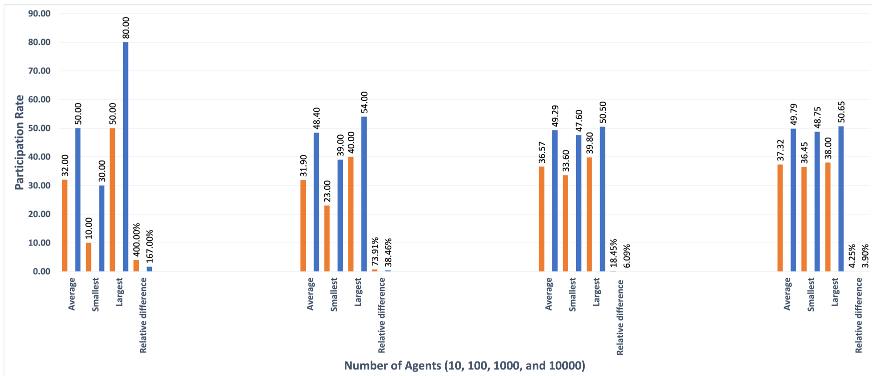

Figure 2: shows the participation rate consistency as the number of agents increased from 10 to 10,000. Orange bars represent the experiment results when we have competing mobs (i.e., the competing-model switch is set to On) while blue bars show the mob when we do not count for the act against agents, i.e., the competing-model switch is set to Off.

3.4 Experiment-2 Setup

Clark Mcphail et al., (1992) stated that purposive actors/agents in the same gathering can generate similar reference signals that result in varying forms of collective action of varying complexity:

1. Independently: no communication between agents when they decide to act or not.
2. Interdependently: agents communicate with other agents to figure out what to do.
3. Voluntarily or Obediently: agents communicate with their bosses (e.g., powerful agents) and do what they are asked to do, i.e., to act the same way as the powerful agents.

Our *first experiment* is analogous to the first two forms mentioned above, i.e., *Independently*: after agents are invited to participate in the mob, they decide what to do based on their interest and control and *Interdependently*: agents in the second and third case communicate to do the power exchange so some of them decide to act while others decide to withdraw.

Using the model explained above, we ran a second experiment to answer the third research question, i.e., *how do the mob organizers affect the mob outcome?*. In this experiment, for each powerful agent if the agent has two or more neighbors within 1.5 patches, then these agents will follow what the powerful agent does, i.e., they will act. Using this setting, we simulated an additional 180 mobs, 90 mobs with the competing-model switch set to 'On' while the other 90 mobs with the switch set to 'Off' using the BehaviorSearch component in NetLogo. In all mobs, we set the *num-of-participants* to 10,000 while the number *num-of-powerful-actors* to be 1000 (i.e., 10% of the number of invited people), 2000 (i.e., 20%), 3000 (i.e., 30%), 4000 (i.e., 40%), 5000 (i.e., 50%), 6000 (i.e., 60%), 7000 (i.e., 70%), 8000 (i.e., 80%), and 9000 (i.e., 90%). This experiment is analogous to the third form mentioned by Clark Mcphail et al., i.e., *Voluntarily* *or Obediently*. As they stated, “Two or more persons might adopt the reference signals of a third party because they do not otherwise know what to do, or because they willingly do whatever their third-party peer proposes, or because they are dependent upon that third party for resources which the latter might withhold if they declined” (McPhail, Powers, and Tucker 1992). The findings of this experiment are explained in 3.5.

3.5 Results/Findings

By running experiment-1 explained above and simulating 80 mobs, we found that *the number of invited people does not affect the rate of participation, however as the number of invited people increases, the participation rate consistency* (measured using the relative difference which is the $[largest - lowest]/lowest$) *increases*. This is due to the law of large numbers, i.e., the more samples (agents) we have, the better the result (more consistency) see figure 2. We also found, *on average, the participation rate is higher (49.37% vs. 34.45%) when we do not have agents acting against the mob*. We posit that this may be due to the fact that, in reality when there are no agents acting against a mob, the risk of mob participation will be lower, hence more agents/mobbers will be encouraged to participate.

By running experiment-2 explained above and simulating 180 mobs, we found that *the mob organizers affect the mob outcome linearly, i.e., the more organizers (powerful actors) the higher the participation rate, hence the higher the chance of a mob being successful* (see figure 3). We also found that as the number of powerful actors increases, the difference between the participation rate when the competing-model switch is set to On or Off decreases, which might be explained by the “bandwagon effect” (Kelly 2022) (see figure 3).

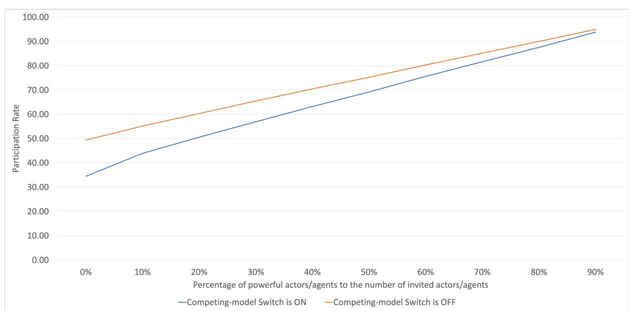

Figure 3: shows the participation rate increases linearly as the number of powerful actors/agents are added to the mob. The orange line shows the average participation rate when the competing-model switch is set to On, while the blue line shows the average participation rate when the competing-model switch is set to Off.

4 LIMITATION

The findings of this model may not be generalized to real-world mobs yet because the model is not validated using ground truth data (due to a lack of data that can be used for mob model validation, however, we are currently working on finding a way to collect such data). However, this theoretically supported model should give us a good estimation.

5 CONCLUSION & FUTURE RESEARCH DIRECTIONS

In this study, we simulated a total of 260 mobs using an agent-based model of the mob phenomenon built based on factors extracted from the theory of collective action. We built this model using NetLogo, a widely used agent-based modeling tool, and the experiments were run using the BehaviorSearch component in NetLogo which can be used to simulate many mobs with different parameters value. Understanding the mob phenomenon can greatly help in explaining other mob-like events that are becoming widespread globally due to the affordability of social media, ease of use, the effectiveness of individuals or groups in conducting coordinated acts, the anonymity of the internet, and various other factors. In recent years, mobs "have taken a darker twist as criminals exploit the anonymity of crowds, using social networking to coordinate everything from robberies to fights to general chaos" (Tucker and Watkins 2011, Steinblatt 2011). Recently, the term "mob" has been increasingly used to mark electronically orchestrated violence, such as January 6, 2021, attack on the U.S. Capital in Washington, D.C., by a group of angry protesters that lead to property damages, government disruption, and injuries or death for some of the protesters (Staff 2021, Barry, McIntire, and Rosenberg 2021). In another incident, an army of small investors from all over the world used Reddit to coordinate "flashmob investing" (Pratley 2021) to create a stock market frenzy, causing GameStop's stock value to rise from $20 to $483 in less than a month (Brignall 2021). These events show that our systems (security, financial, etc.) are not equipped to handle such highly coordinated and flash events, underscoring the importance of systematically studying such behaviors. This work serves as a proof of concept that an agent-based model to understand real-world mobs can be constructed based on factors extracted from social science theories (e.g., collective action theory). This model can be added to the extensive collection of social science models that can be found in the NetLogo "Models Library". Most of the factors used here have been studied in the literature, but have never been used computationally to simulate and study mobs. The model still needs to consider other factors such as the time of the event, the existence of social ties between the mobbers, the location of the events, etc. as all these factors can significantly affect the mobber's decision to act/participate in a mob (or to act against the mob), so this is one of the future research directions. Another future research direction could be to compare the results obtained from the model to ground truth data (real-world mobs) as it would serve as a great model validation method. Of course, building a more accurate model requires interdisciplinary knowledge and collaboration between psychologists, sociologists, and computer scientists. This work is one step toward bridging this gap in communication.

ACKNOWLEDGMENTS

This material is based upon work supported in part by the Office of the Under Secretary of Defense for Research and Engineering under award number FA9550-22-1-0332, U.S. Office of Naval Research (N00014-10-1-0091, N00014-14-1-0489, N00014-15-P-1187, N00014-16-1-2016, N00014-16-1-2412, N00014-17-1-2675, N00014-17-1-2605, N68335-19-C-0359, N00014-19-1-2336, N68335-20-C-0540, N00014-21-1-2121, N00014-21-1-2765, N00014-22-1-2318), U.S. Air Force Research Laboratory, U.S. Army Research Office (W911NF-20-1-0262, W911NF-16-1-0189), U.S. Defense Advanced Research Projects Agency (W31P4Q-17-C-0059), the U.S. National Science Foundation (OIA-1946391, OIA-1920920, IIS-1636933, ACI-1429160, and IIS-1110868), Arkansas Research Alliance, the Jerry L. Maulden/Entergy Endowment at the University of Arkansas at Little Rock, and the Australian Department of Defense Strategic Policy Grants Program (SPGP) (award number: 2020-106-094). Any opinions, findings, conclusions, or recommendations expressed in this material are those of the author(s) and do not necessarily reflect the views of the U.S. Department of Defense. The researcher(s) gratefully acknowledges the generous support.

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