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Modeling Spontaneous Volunteer Convergence using Agent-Based Simulation

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Abstract

When natural disasters occur, unaffiliated volunteers are inspired to help within their community and are known as spontaneous volunteers (SVs). Our research seeks to understand SV convergence as it relates to individual SV motivation, engagement, and decision making. We developed an agent-based model in AnyLogic to simulate the decision-making process of potential SV agents during disasters and how it affects volunteer response. Internal motivation is indicative of an agent's willingness to volunteer, which was modeled by the Theory of Planned Behavior (TPB). We alter motivational factors to assess how they impact SV participation. We examine SV engagement by exploring targeted versus random messaging from volunteer sites to agents. Agents select volunteer sites based on information sharing policies common within the social network literature. Results show that a site choice decision based on connections (friends) negatively influenced demand completion. Alternatively, having pre-existing confidence in abilities and non-targeted volunteer site to agent messaging positively influences the number of participating SVs and therefore decreases demand most significantly over a 30-day period.

Keywords
agent-based model, simulation, disaster management, spontaneous volunteer

1. Introduction
As natural disasters like hurricanes continue to occur with increasing frequency, the need for material and human resources increases. Worldwide, these disasters cost between $94 billion and $130 billion annually [1]. Disaster response, which occurs in the initial period of time after a disaster, often encourages people to help their community and, as a result, spontaneous volunteers (SVs) emerge [2]. A spontaneous volunteer is a person unaffiliated with a volunteer organization that is willing to help in disaster response. SVs provide labor and resources, often before any official organization can reach the impacted area. However, volunteer organizations cannot handle the influx of these spontaneous volunteers and many SVs get turned away [3]. The goal of this humanitarian research is to enable better integration of SVs in disaster response plans by developing a more comprehensive understanding of SV convergence. Agent-based Modeling (ABM) has shown to be a valuable tool in modeling population behaviors during disaster response. However, a majority of the research focused on ABM is used in evacuation planning. There are few models that simulate SV convergence while capturing the underlying social preferences and behaviors. Lindner, Betke, & Sackmann (2017) identify attributes for SVs in a simulation setting which include motivation, personal connections, and social networks [4]. They then attempt to construct a conceptual model for SV integration in simulation, namely a SV state-chart depicting SV behaviors [5]. Abualkhair, Lodree, and Davis simulate the movement of volunteers and beneficiaries within a disaster relief center by creating a model that contains volunteers as servers and utilizes queuing theory [6]. We developed an ABM which combines social science and operations research/management science (OR/MS) techniques to capture the salient attributes of the SV convergence process. By bridging the gap between social sciences and OR/MS, we can improve our understanding of volunteer convergence and improve policies related to disaster management.

2. Methods
2.1 Overview
We develop an ABM to evaluate the benefit SVs provide to disaster response and analyze how their response is affected by underlying behaviors and motivations. Past literature has utilized ABM in other capacities, such as evacuation planning as seen in Section 2.4. The ABM developed in this study expands on the limited research on SV convergence by applying simulation to a larger-scale population. Our ABM simulates a single geographic area

following a natural disaster. It is comprised of a population of agents (potential volunteers) and active volunteer sites. The SV state chart, as seen in Figure 1, shows the daily routine of an agent in the ABM. The agent first completes a daily check to determine their motivation to volunteer. If they are not motivated, they remain idle until the next day. If they are motivated to volunteer, they assess their volunteer site knowledge to determine if they know a site or if they need to request site information. Based on the collected information or prior site knowledge, they are ready to help, and they choose a volunteer site. The agent then travels to the volunteer site and they are either accepted or turned away based on the capacity of the volunteer reception center. At the end of the day, the agent updates their site information and the process begins once more. This research focuses on two main aspects of the agent experience: volunteer motivation and information sharing when the agent requests information.

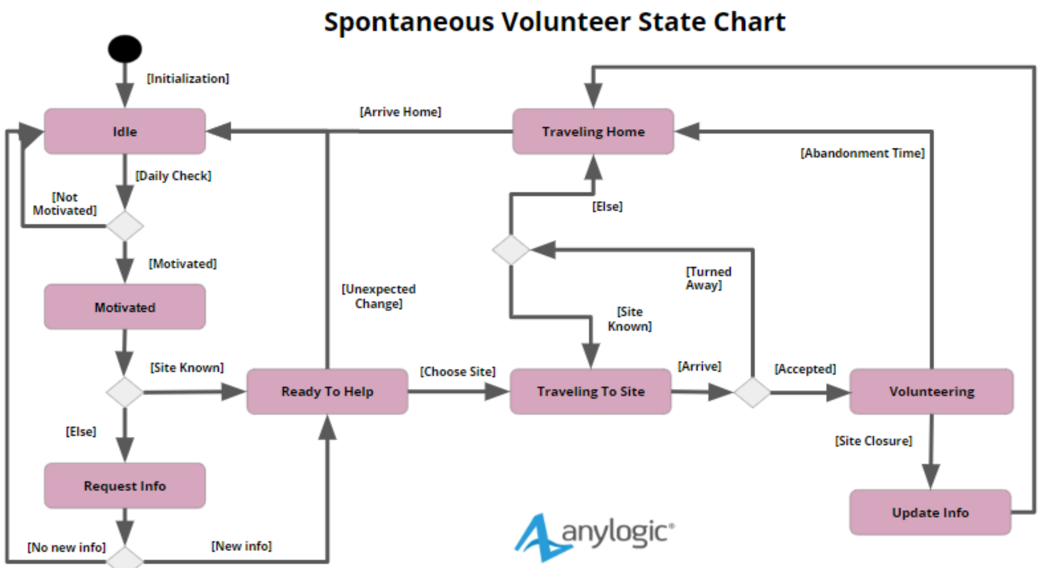

Figure 1. Spontaneous volunteer state chart showing the daily process of an agent in the ABM

2.2 Spontaneous Volunteer Motivation

We examine how motivation influences SV participation within the context of spontaneous volunteerism through the Theory of Planned Behavior (TPB) framework. TPB postulates that intention is a precursor for acting upon a behavior, where "intention follows reasonably from specific beliefs that people have about the behavior" [7]. These beliefs are based on three things: attitude (A), subjective norm (SN), and perceived behavioral control (PBC). Attitude considers people's general sense of favorability toward performing a behavior. The subjective norm is the social pressure felt by an individual. Meanwhile, perceived behavioral control is one's confidence in themselves to perform the behavior. The relationship between behavioral intention (BI), attitude, subjective norm, and perceived behavioral control can be represented mathematically by Equation (1) (where w_A , w_{SN} , w_{PBC} are weights for each factor and sum to 1) [8]. These weights are based on existing literature [9, 10, 11] and chosen specifically to test a robust and varied set of cases. The translation of BI to behavior (B), are converted using a function, such that the probability of behavior is represented by *f* (BI), as shown in Equation (2). Experiments were also conducted using both linear and Sigmoid functions for *f*(BI). How these are measured and quantified is discussed in Section 3.1.

$$BI = w_A A + w_{SN} SN + w_{PBC} PBC \tag{1}$$

$$P(B = 1) = f(BI) \tag{2}$$

In the context of an SV's attitude, an exponential function reflecting news coverage of a disaster is used [12]. The function assumes that as less coverage is delivered about the disaster, the less positive an agent's attitude will be. Subjective Norm, which looks at how different sources of social influence could affect an SV, was broken into two pieces. These social influences are the percentage of neighbors volunteering and those on social media who are volunteering. PBC is a value based on past experience as an SV or experience/skills-set in an equivalent task. Agents with prior training or relevant experience start with a higher initial PBC value compared to those agents with no prior training or relevant experience.

2.3 Information Sharing and Site Choice

To simulate decision making, specific weights can be given to each factor associated with a group decision making process [13]. In our ABM, agents can interact with each other through their social network to gain site information and make a decision on their volunteer location. An agent requests information from their social network. A receiving agent makes a decision to respond to the request for information, known as the probability of response. Information sharing during disaster response can be related to distance, with the probability of information sharing being higher if agents are closer to each other [14]. If the receiving agent chooses to respond, then the requesting agent updates their information about volunteer sites including volunteer site opinion, a value ranging from 0 to 1. From the collected information, the requesting agent can then make a decision on which volunteer site to attend.

Once an agent has decided to volunteer, they can choose a volunteer site. Policies related to volunteer site choice decisions were created based on volunteer interviews [15]. The first policy is a decision based on proximity, with an agent choosing the closest site. Second, an agent can choose a site based on a site score comprised of a site's opinion and distance from the agent, as shown in Equation (3). This idea was developed given that a volunteer would want to give back to the community while feeling that they are completing meaningful work. The weights were derived from literature related to social networks-based decision support models, which examined decision making for which restaurant to visit [16]. The site policies are generalizable, and the weights can be varied in future sensitivity analysis.

$$Score_i = 0.2(Site\ Opinion_i) + 0.8\left(\frac{1-Distance_i}{Max\ Distance}\right) \tag{3}$$

Third, given that the volunteer site has messaged the population regarding the amount of work left to completed at their location (total work remaining), the agent will go to the site that has the most total work remaining. This information is delayed by three days to represent more realistic conditions following a disaster. Fourth, the agent can refer to their social network to determine where their connections (friends) have had the best experiences and choose their volunteer site accordingly.

2.4 Volunteer Engagement

The research also seeks to understand one-to-many information sharing, an aspect that involves more than just the SV state chart. Information dissemination and subsequent volunteer engagement was investigated in literature. Various network types were explored both generally and as related to disaster response. When examining flood warning information dissemination and evacuation planning, both one-to-one and one-to-many information sharing strategies were utilized as information sources. These information sources were categorized as global broadcasting, neighbor observations, and social interactions [12]. Scale-free and small world networks were explored more generally. In a small world network, "a friend of a friend is likely to be my friend" and in a scale free network, certain agents had a higher number of connections, but most had few connections [17].

Site to agent messaging techniques were examined, either targeted or random. Targeted messaging was defined as an initial message that was sent to fewer agents with more connections. Random messaging involved an initial message sent to more agents, without specific screening for number of connections. All experiments were run in the ABM by varying the parameter associated with this experiment.

3. Results and Discussion

3.1 Experimental Design

The ABM was created in Anylogic Personal Learning Edition version 8.5.1 and ran on an Intel(R) Xeon(R) CPU E5-2680 v2 with 128 GB of RAM. The initial model parameters were standardized with a population of 200 agents and 3 volunteer sites with a 30-day timeframe. A set of cases and their baseline parameters were developed to test parameters related to motivation, site choice selection, and volunteer engagement experiments (Table 1). For each case of the experiments, 100 replications were completed, and the data was output to Microsoft Excel. The data of interest involved plotting the total work remaining and volunteer attendance over the 30-day period. Ideal circumstances would show plots of total work remaining declining, with elimination by day 30. Additionally, a higher number of total participating SVs on a given day would be a preferable policy.

Table 1: Table listing parameters used for experimentation.

	Variable	Baseline	Levels Tested	Explanation
Motivation	weightA	0.3	0.3, 0.19	Weight of parameter A in TPB model
	weightSN	0.35	0.35, 0.405, 0.54, 0.27	Weight of parameter SN in TPB model
	weightPBC	0.35	0.35, 0.405, 0.54, 0.27	Weight of parameter PBC in TPB model
	pbc%	0	0, 0.4	Percent of population with an initial PBC of 1
	useSigmoid	1	0, 1	Binary value, 1 if Sigmoid function is used in Equation (2), 0 if linear function is used
Volunteer Engagement	maxInitialMessage	10	10, 40	Messages were either sent to 10 or 40 agents
Site Choice	siteChoiceSelection	1	1, 2, 3, 4	1 = Distance, 2 = Site Score, 3 = Total Work Remaining, 4 = Friends

Three separate motivational experiments were developed and evaluated in an effort to validate the ABM. By adjusting the weights for A, SN, and PBC, we can evaluate the effects of various possible population demographics in order to better understand SV response. For example, it has been found PBC is the "strongest predictor of intention" in older adults [9]. Therefore, an experiment is conducted to mirror older adults through a high weightPBC, moderate weightSN, and low weightA. We also investigated the effects of an experienced and inexperienced volunteer population through pbc%, assuming that experienced volunteers would have a higher confidence in their abilities and therefore a PBC of 1. The last experiment examines the effect of changing the function that translates behavioral intent of volunteering to the behavior of volunteering itself by utilizing a linear or sigmoid function to do so.

Eight cases were developed to test information sharing, site choice, and volunteer engagement. The ABM was set to a scale free network, ensuring that volunteer engagement could be accurately assessed with targeted and random messaging.

3.2 Motivation Results and Discussion

When comparing experiments with a high weightSN or a high weightPBC, we find that agents more affected by social norms will become motivated sooner and in greater force (Figure 2a). The case where agents are more influenced by PBC could be reflective of SVs who wait longer for roads to be deemed safe or those who wait to evaluate how great the need is for SVs.

In the case where 40% of the population had an initial PBC (IPBC) of 1 by far had the most significant results in relation to the number of participating SVs and how quickly the given demand was completed. As seen in Figure 2b, the number of volunteers with an IPBC was approximately double that of those without an IPBC. Note that when 40% of the population has an IPBC of 1, the number of volunteers plummets after about two weeks. This could be attributed to the allotted demand being fulfilled and thus volunteers no longer being needed. These two results could inform a number of possible interventions and policies. For example, it could be assumed that if communities were to implement disaster preparedness or skills courses within the community, more agents would be motivated to volunteer.

3.3 Site Choice and Volunteer Engagements Results and Discussion

When comparing site choice policies by Δwork remaining with the distance policy as the baseline, as seen in Figure 2c, choosing a volunteer site based on where a volunteer's friends go underperforms compared to a score or demand-based site choice policy. When an agent chooses a volunteer site, utilizing more standard and objective information would lead to a better long-term outcome, in terms of work remaining. Listening to your friends' experiences would be less useful than taking in information such as volunteer site distance and a volunteer site's request for aid.

Over the 30-day simulation period, the total work remaining at the volunteer sites differs between messaging policies. As seen in Figure 2d from day 3 onwards, there is less work remaining for a random initial message. Using a targeted messaging approach is not effective when looking at demand completion [18,19]. If a volunteer site were to message a few influential people, the information dissemination would not reach as many agents according to the model results.

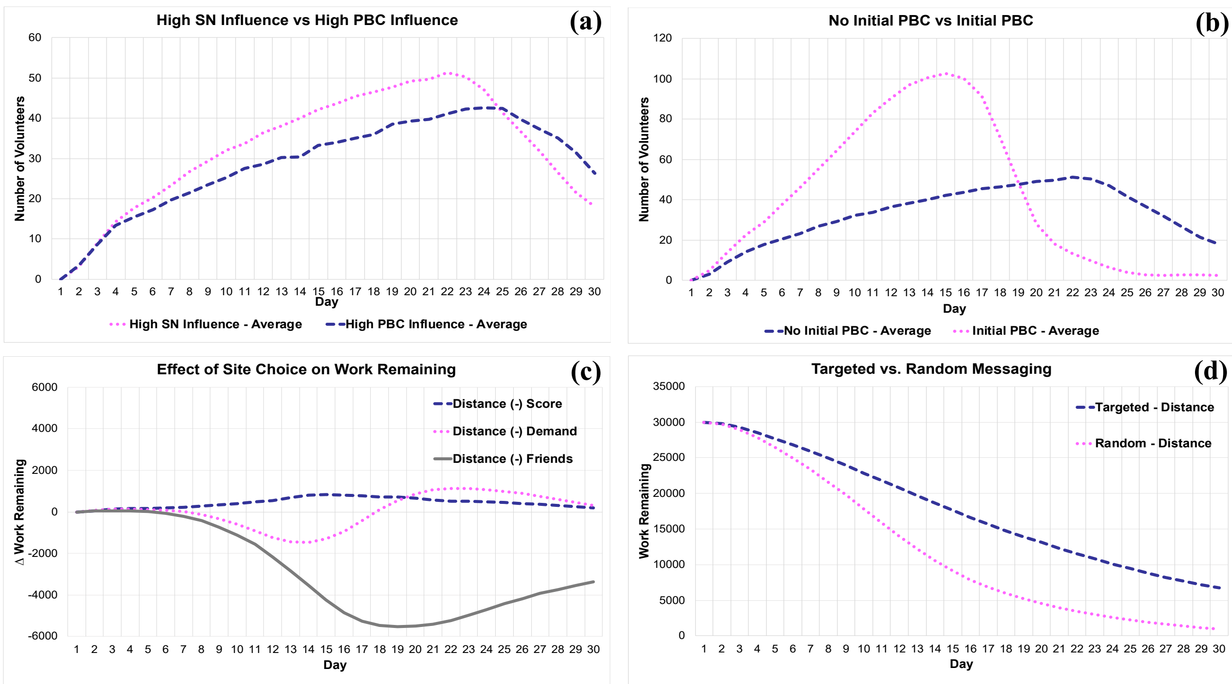

Figure 2. Graphical depiction of volunteer motivations where (a) compares cases of a high weightSN and a high weightPBC and (b) compares a case where 40% of the population begins with a PBC of 1 and a case where 0% of the population has a PBC of 1. Change in (Δ) work remaining between the distance and various policies is depicted (c) and work remaining between targeted and random messaging is plotted (d). Experiments are expressed over a 30-day period.

4. Conclusion

We present an agent-based model of spontaneous volunteer convergence in a post disaster setting. The model was developed to investigate the effects of agent motivation, information sharing, and engagement on effectiveness of disaster response. Using the Theory of Planned Behavior, we show that SV response to disasters is dependent upon the agent's internal motivations. This was most significantly seen when comparing those with a high initial perceived behavioral control and those with a low initial perceived behavioral control. In addition, we analyzed four different behaviors for site choice selection based on literature and subject interviews with previous spontaneous volunteers. Site choice based on social connections, although popular in practice, results in suboptimal work completion. Finally, we quantify volunteer engagement through messaging. Targeted messaging of influential (hub) agents is not cost-effective when compared with random messaging of equivalent cost. Overall, it is evident that certain parameters significantly change motivation and demand completed. Therefore, more rigorous sensitivity analysis is required to further evaluate influential parameters. Additional research includes verification and validation of the model. This would allow for eventual educational implementation; the model can be used as a tool to help teach the community the importance of training and preparing for a disaster. Furthermore, the model could serve as a basis for evaluating current SV engagement policies. This model serves as a foundation for additional research into simulation models of spontaneous volunteer convergence behaviors.

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