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AN AGENT-BASED MODEL OF SURPLUS FOOD RESCUE USING CROWD-SHIPPING

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ABSTRACT

As climate change approaches a point of irreversibility, it is becoming increasingly important to find ways of preventing food waste from reaching landfills and emitting greenhouse gases. Food rescue programs offer a means of simultaneously diverting surplus food from landfills and addressing food insecurity. Recently, some food rescue organizations in the U.S. have begun leveraging crowd-shipping to more efficiently transport surplus food from donors to food-insecure recipients. However, the success of such initiatives relies on achieving a critical mass of donor and crowd-shipper participation. This paper describes a conceptual agent-based model that was developed to evaluate the design parameters of a volunteer-based crowd-shipping system for food rescue. Preliminary experimental results demonstrate the importance of generating sufficient awareness and commitment among potential volunteers in the early stages of the program's development to ensure consistent participation and service.

1 INTRODUCTION AND BACKGROUND

The Food and Agriculture Organization of the United Nations estimates that 1.3 billion tons (approximately one-third) of all food produced for human consumption worldwide is lost or wasted (Gustavsson et al. 2011). In developing countries, much of this waste occurs in the post-harvest and processing stages of the food supply chain, due to inadequate transportation and storage infrastructure. However, in industrialized countries, most food waste occurs at the consumption stage of the food supply chain, meaning that it is discarded even if it is still suitable for human consumption (Gustavsson et al. 2011). The U.S. Department of Agriculture estimates that 31% of the 430 billion pounds of available food supply at retail and consumer levels in the U.S. goes uneaten each year (Buzby et al. 2014).

Because agriculture and food production are resource-intensive activities, producing surplus food is an unnecessary strain on the environment. Hall et al. (2009) estimate that more than 25% of total freshwater use in the U.S. is used to produce food that is finally wasted. The energy embedded in wasted food represents approximately 2% of total annual energy consumption in the U.S. (Cuéllar and Webber 2010). Furthermore, the production of food that is wasted at the retail/consumer level in the U.S. generates greenhouse gas emissions equivalent to the emissions of 33 million passenger vehicles annually (Heller and Keoleian 2015). The disposal of food waste also has severe environmental consequences. The U.S. Environmental Protection Agency (EPA) estimates that 15.1% of all municipal solid waste (MSW) in the U.S. is food, which translates to 246.8 pounds of food waste generated per capita annually (U.S. EPA 2018). Only 5.3% of this food waste is recovered, leaving 30.3 million tons to be sent to landfills. As a result, food waste is the largest component of all landfilled MSW in the U.S., comprising a total of 22%. MSW landfills account for nearly 18% percent of anthropogenic methane emissions in the U.S. (U.S. EPA 2017a). With a global warming potential that is 28 times greater than carbon dioxide (Myhre et al. 2013), methane from food waste is, therefore, a major contributor to climate change. In response to these concerns, the United Nations has emphasized "reducing per capita global food waste at the retail and consumer levels" in its Sustainable Development Goals for 2030 (Grosso and Falasconi 2018).

There are sustainable alternatives to landfilling food waste, such as composting or converting it to fuel via anaerobic digestion. Another option is food rescue, in which surplus food that is still edible is collected and delivered to food-insecure people. Food insecurity in the U.S. is a serious humanitarian concern, with 15.6 million American families (12.3% of the U.S. population) lacking consistent access to sufficient nutritious food (USDA ERS 2018). Therefore, the EPA prioritizes food rescue over all other food waste management methods (besides source reduction) in its Food Recovery Hierarchy (U.S. EPA 2017b). Food rescue in the U.S. is typically performed by extra-governmental, community-based charitable programs, such as food banks and pantries (Tarasuk and Eakin 2005), who rescue donated surplus food from farms, manufacturers, and retailers (Feeding America 2018a). Restaurants are another major source of food waste in the U.S., generating 11.4 million tons each year (ReFED 2018). However, less than 5% of the more than 1 million restaurants in the U.S. currently donate food (Berkenkamp and Phillips 2017). One of the biggest barriers to donation is transportation because the restaurant sector consists of many locations and relatively small volumes of rescuable food per location, efficient collection and distribution of restaurant food waste are particularly challenging (Gunders and Bloom 2017).

Crowd-shipping offers a potential solution. *Crowd-shipping* is defined as "an information connectivity enabled marketplace concept that matches supply and demand for logistics services with an undefined and external crowd that has free capacity with regards to time and/or space, participates on a voluntary basis, and is compensated accordingly" (Rai et al. 2017). Examples of commercial crowd-shipping schemes include Uber Eats and DoorDash, in which food vendors use an online platform to find an available driver from a pool of drivers (i.e., the crowd-shippers) who is willing to pick up and deliver a customer's order (typically using his/her personal vehicle) for a predetermined price. The appeal of crowd-shipping lies in its ability to provide low-cost delivery service with greater flexibility and shorter lead times than conventional transportation service providers.

The idea of using crowd-shipping to rescue surplus food from restaurants and deliver it to food-insecure individuals is relatively new and has not yet been widely adopted. However, a few food rescue programs using crowd-shipping have been implemented in the U.S. For example, Food Rescue US, a non-profit organization founded in 2011, uses an app to recruit volunteer drivers ("Food Rescuers") to pick up surplus food from participating local donors (including restaurants) and transport it to receiving agencies such as soup kitchens and shelters. The service is currently operating in 17 U.S. locations (Krejci and Oran Gibson 2019). Postmates, a commercial crowd-shipping company, piloted a social impact initiative in 2017 in which it uses its own crowd-shippers to transport surplus food from participating restaurants in Los Angeles to local shelters (Chatlani 2019).

The success of any crowd-shipping initiative requires acquiring a critical mass of customer and crowd-shipper participation. If there are too few participants, customers will be dissatisfied by unfilled service requests, crowd-shippers will have insufficient opportunities, and the initiative may never get off the ground (Frehe et al. 2017). Therefore, it is critical for a nascent crowd-shipping organization to build up its network as quickly as possible, which requires an understanding of the factors that influence potential customers' and crowd-shippers' willingness to participate. Miller et al. (2017) surveyed potential crowd-shippers to develop a statistical model that predicts the likelihood of a crowd-shipper accepting a delivery assignment, given crowd-shipper demographic attributes, the time required to complete the delivery, and the amount of compensation. Le and Ukkusuri (2019) performed a similar statistical analysis, also using survey data. Ermagun and Stathopolous (2018) statistically analyzed service request records from a crowd-shipping company to determine how to increase the odds of successfully recruiting a crowd-shipper to fulfill a given service request. Devari et al. (2017) collected survey data on potential crowd-shippers' preferences and social network characteristics and then used this data to develop a TRANSIMS model that evaluates the potential of using customers' social network contacts for last-mile delivery.

These existing studies are primarily focused on the development of statistical models that predict crowd-shippers' willingness to participate in commercial crowd-shipping systems, using data collected from surveys or directly from a crowd-shipping platform. By contrast, there is very little existing work that uses simulation modeling to study the dynamic evolution of a crowd-shipping system over time. Furthermore, the authors of this paper are unaware of any simulation models that simultaneously capture both customer and crowd-shipper behavior, nor are there any existing models that have been designed to study crowd-shippers who provide service on a voluntary basis.

Agent-based modeling is a powerful computation tool to model complex systems involving human decision-making (Mittal and Krejci 2015; Mittal 2016). This paper describes a conceptual agent-based model (ABM) that was developed to provide a better understanding of how to design and launch a successful volunteer-based crowd-shipping system for food rescue. The model can help predict emergent properties of a volunteer-based crowd shipping system (e.g., system growth, responsiveness, and service levels) that arise over time as a result of autonomous behaviors and interactions of crowd-shippers and restaurants. This conceptual model provides a basis for the future development of an agent-based decision-support tool that can assist non-profit and government organizations in initiating food rescue programs that leverage crowd-sourced transportation. The following sections provide a detailed description of the model, a set of preliminary experiments to demonstrate the model's performance, a discussion of the experimental results, and a conclusion and plans for future model development.

2 AGENT-BASED MODEL

The ABM was developed using NetLogo 6.0.4. The purpose of the model is to evaluate design parameters for a volunteer-based crowd-shipping system for rescuing food from restaurants. The model developed was designed to explore the potential implementation of such a program in The City of Arlington, which is located in North Texas. The City of Arlington was chosen as a case study to test the potential of a volunteer-based crowd shipping system in a major metropolitan area with more than one thousand restaurants and no existing program to rescue surplus food from these restaurants.

The City of Arlington is divided into 84 census tracts and 259 census block groups. A census block group is the smallest entity for which the U.S. Census Bureau collects and publishes demographic data of the residing population (ProximityOne 2019). Figure 1 shows the entire City of Arlington, containing 259 census block groups (represented by green houses), 1,066 restaurants (represented by yellow circles), and 5 homeless shelters (represented by red triangles). Geocoder from the U.S. Census Bureau was used to obtain the block groups and census tracts corresponding to each restaurant and shelter based on their street addresses (U.S. Census Bureau 2019a). The preliminary model described in this paper focuses on one of the 84 census tracts in Arlington (1224), which contains 5 census block groups and 18 restaurants, as shown in Figure 2. Four shelters (one in census tract 1222 and the remaining in census tract 1223) are considered as potential recipients of surplus food from the restaurants.

The ABM contains two types of agents: restaurant agents and crowd-shipper agents. The crowd-shipper agents represent the residents of the five block groups in census tract 1224, all of which are considered to be potential crowd-sourced transportation providers.

2.1 Description of Restaurant Agents

Each of the 18 restaurant agents is assigned a unique restaurant identification number r. It is assumed that each restaurant agent has surplus food available for donation thrice a week. Each agent's weekly donation schedule is represented by a set of seven binary availability index values ($V_{r,t}$). If restaurant agent r intends to donate at time-step t (where a time-step corresponds to one day), then $V_{r,t}$ will take a value of one. Each agent's $V_{r,t}$ values are assigned randomly at the start of the simulation run and are assumed to remain constant for the duration of the run.

2.2 Description of Crowd-Shipper Agents

There are a total of 4,579 crowd-shipper agents in the model, representing residents of census tract 1224. Each crowd-shipper agent belongs to one of the five census block groups in this tract and is assigned a unique identification number c. Population centroids (latitude and longitude coordinates) of these five block groups were obtained from U.S. Census Bureau. It is assumed that each crowd-shipper agent's residence is located at the population centroid of its respective block group.

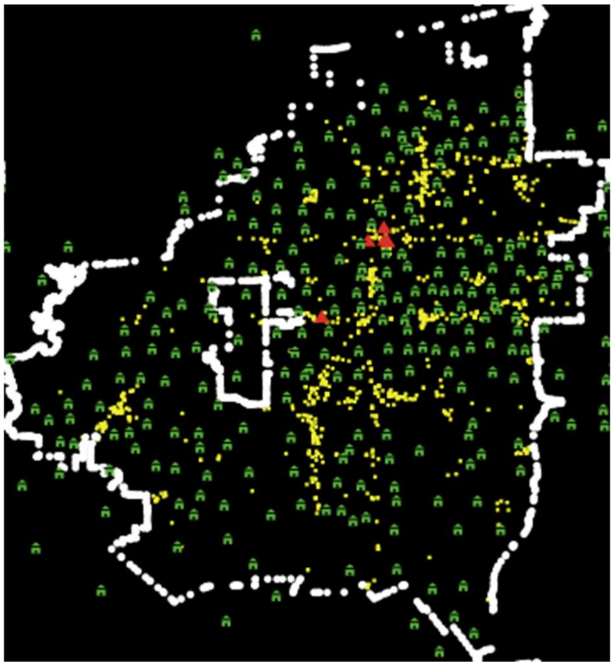

Figure 1: NetLogo representation of the City of Arlington, showing 259 census block groups, 1,066 restaurants, and 5 homeless shelters.

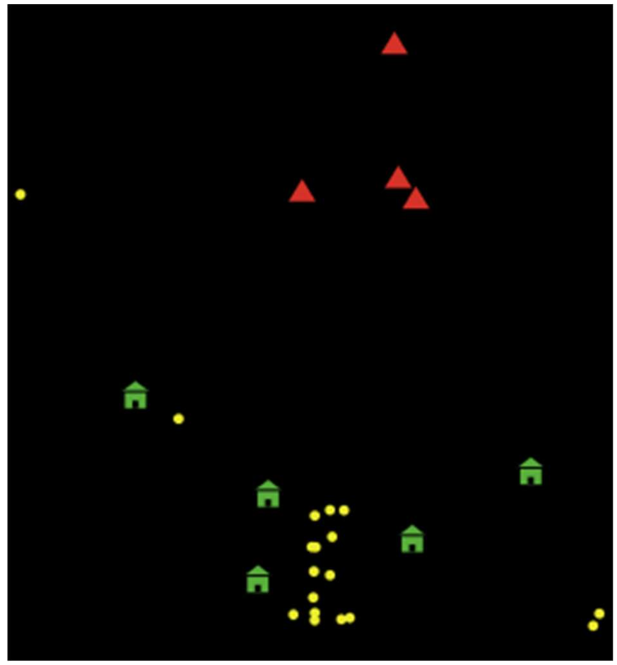

Figure 2: NetLogo representation of the modeled census tract, including 5 census block groups, 18 restaurants, and 4 homeless shelters.

Crowd-shipper agents are classified using five demographic factors, as per the classification of food rescue program volunteers by Mousa and Freeland-Graves (2017): age (18 - 25, 26 - 45, or 46 - 69), gender (male or female), ethnicity (Non-Hispanic White, African American, or Hispanic), education attainment (high school, partial college, college/university, or graduate school), and annual income (<\$17,500, \$17,500 - \$47,000, \$48,000 - \$66,000, or \$67,000 - \$80,000). Each agent's demographics are assigned based on 2017 U.S. Census Bureau statistics that correspond to the agent's block group (U.S. Census Bureau 2019b). An agent's demographics are assumed to remain constant throughout each simulation run. It is assumed that every crowd-shipper agent owns a vehicle and is capable of participating in the food rescue program.

2.3 Model Description

In each daily time-step, the restaurant agents decide whether or not to donate surplus food, and the crowd-shipper agents decide whether or not they will participate in the food rescue program by picking up donations from participating restaurants and delivering them to shelters. The ABM contains three sub-models: Restaurant agent decision-making, Shelter assignment, and Crowd-shipper agent decision-making. All three sub-models are executed sequentially in each time-step.

2.3.1 Sub-Model 1: Restaurant Agent Decision-Making

A restaurants' decision to donate its surplus food to a food rescue program depends on multiple factors. First, the restaurant must be aware that such a program exists. Once a restaurant learns of the program, its decision to participate may be motivated by sustainability goals (e.g., a desire to prevent food from being sent to the landfill) (Brahm et al. 2014) and financial considerations (e.g., tax deductions for charitable donations and reduced waste management fees) (Feeding America 2016). However, many restaurants are discouraged by food safety and liability concerns, being unaware of the Bill Emerson Good Samaritan Act, in which the donor is protected from liability when donating to a non-profit organization (Brahm et al. 2014; Feeding America 2018b). In addition, transportation constraints may prevent restaurants from donating (Berkenkemp and Philips 2017). For example, one restaurant stopped donating its surplus food to a food rescue program after the program's volunteers repeatedly failed to pick up donations at the agreed-upon time (Krejci and Oran Gibson 2019).

These factors were incorporated into the restaurant agents' decision logic. In each daily time-step *t*, if a restaurant agent is aware of the existence of the food rescue program (i.e., its binary awareness variable $A_r = 1$) and it has food available to donate ($V_{r,t} = 1$), it will evaluate its willingness to donate ($W_{r,t}$) based on its total utility ($U_{r,t}$). Total utility is measured on a scale of 0 to 1, where larger values correspond to greater donation likelihood. A restaurant's total utility is evaluated as the weighted sum of four components: utility due to sustainability goals ($U_{r,s(t)}$), concerns ($U_{r,c(t)}$), past experiences ($U_{r,e(t)}$), and financial benefits ($U_{r,f(t)}$), as given by Equation (1). Each of these components is also defined on a 0-1 scale, and the sum of the weights ($\beta_{r,s}, \beta_{r,c}$, $\beta_{r,e}$and $\beta_{r,f}$) is equal to 1. Therefore, the total utility of a restaurant agent ($U_{r,t}$) is always between 0 and 1.

$$U_{r,t} = \beta_{r,s}U_{r,s(t)} + \beta_{r,c}U_{r,c(t)} + \beta_{r,e}U_{r,e(t)} + \beta_{r,f}U_{r,f(t)} \tag{1}$$

Each restaurant agent's utility due to sustainability ($U_{r,s(t)}$) is initially assigned a random value between 0 and 0.5. In each subsequent time-step, $U_{r,s(t)}$ may increase based on interactions with other restaurant agents, in which awareness of the positive social and environmental impacts of food rescue programs is enhanced. These interactions occur via the restaurant agents' social network, which is an Erdős-Rényi random network (Newman 2002) with an average degree of connection equal to four. In a given week, the probability of interaction between two socially-connected restaurant agents is assumed to be 5%. Upon interaction between two restaurant agents, if one agent is aware of the food donation program, the other agent also becomes aware. Furthermore, the agent with the lower $U_{r,s(t)}$ value will increase this value by 10% of the other agent's $U_{r,s(t)}$ value. The utility due to concern ($U_{r,c(t)}$) for a restaurant agent is given by Equation (2), where $c_{r,t}$ is the agent's concern level at time-step *t*. Each agent's $c_{r,t}$ value is initialized as a random value between 0.5 and 1. When two restaurant agents interact via their social network, the concern level of the agent with higher concern decreases by 10% of the concern level of the other agent.

$$U_{r,c(t)} = \frac{1}{e^{2c_{r,t}}} \tag{2}$$

A restaurant agent's utility due to past experiences is given by Equation (3), which is the ratio of the number of days ($N_{r,d}$) in which the agent sought and successfully found a crowd-shipper agent to pick up its donation, to the total number of days (d_r) in which the agent has food available to donate ($V_{r,t} = 1$) and aware of the food rescue program ($A_r = 1$).

$$U_{r,e(t)} = \frac{N_{r,d}}{d_r} \tag{3}$$

For each restaurant agent in each daily time-step, a random number is generated between 0 and 1. If the number is less than the agent's total utility value ($U_{r,t}$) at time *t*, the agent is willing to donate food ($W_{r,t} = 1$, or 0 otherwise) and will seek out a crowd-shipper agent for a pick-up. It is assumed that if a restaurant agent successfully finds a crowd-shipper to pick up its donation, it will remain willing to donate food ($W_{r,t} = 1$) in future time-steps until an attempt to find a crowd-shipper fails. If this occurs, the restaurant agent will re-evaluate its decision to participate, based on its current total utility ($U_{r,t}$).

2.3.2 Sub-Model 2: Shelter Assignment

In each time-step, if a particular restaurant agent r is willing to donate food ($W_{r,t} = 1$), the donation is randomly assigned to one of the four homeless shelters. It is assumed that shelters are able to receive food on any day of the week and have no capacity constraints.

2.3.3 Sub-Model 3: Crowd-Shipper Agent Decision-Making

Motivations for individuals to participate in food rescue programs include service requirements of a social organization, career improvement, and altruism (Mousa and Freeland-Graves 2017). Typically, food rescue volunteers are not financially motivated to participate. However, food rescue via crowd-shipping is a relatively new concept – traditionally, volunteer food rescue activities occur at food bank/pantry warehouses. Therefore, encouraging sufficient participation might require some financial incentives. For example, donor restaurants' tax deductions are used to run one of the largest fresh food donation programs in the North America (Food Donation Connection 2018). A similar scheme could be employed to incentivize food rescue crowd-shippers. Finally, the motivation to serve as a volunteer crowd-shipper may be impacted by previous experiences. For example, a lack of consistent opportunities to participate in the food rescue program could decrease a volunteer's motivation, as continuous participation and enthusiasm to volunteer are interrelated (Schanes and Stagl 2019).

In the model, it is assumed that each crowd-shipper agent will not volunteer more than once a week (i.e., once in every seven time-steps) to rescue food from a restaurant. Each crowd-shipper agent c has a binary awareness variable (A_c), which takes a value of one if the agent is aware of the food rescue program, or zero otherwise. If A_c = 1, the agent evaluates its willingness to volunteer ($W_{c,t}$) at time-step t based on its current total utility ($U_{c,t}$). $U_{c,t}$ for each crowd-shipper agent is defined on a scale of 0 to 1 and is a weighted sum of three components: utility due to motivation ($U_{c,m(t)}$), financial benefits ($U_{c,f(t)}$), and past experiences ($U_{c,e(t)}$), as given by Equation (4). Each of these components is also defined on a scale of 0 to 1, and the sum of the weights ($\beta_{c,m}$, $\beta_{c,f}$ and $\beta_{c,e}$) is equal to 1.

$$U_{c,t} = \beta_{c,m} U_{c,m(t)} + \beta_{c,f} U_{c,f(t)} + \beta_{c,e} U_{c,e(t)} \tag{4}$$

The initial value of $U_{c,m(t)}$ for each crowd-shipper agent is derived from the motivation scale defined by Mousa and Freeland-Graves (2017), which is based on survey data collected from volunteers who participate in food rescue programs. The motivation score mean, standard deviation, and range for each demographic factor level of the volunteers surveyed is shown in Table 1. These statistics were used to define probability distributions (as shown in Table 1), from which the initial $U_{c,m(t)}$ values were drawn for each crowd-shipper agent. The five motivation scores from each demographic factor were averaged, normalized to a value between zero and one, and then assigned to the agents.

Crowd-shipper motivation is assumed to be influenced by social interactions. Results from a national survey indicate that, on average, a person knows approximately 13 people in his/her neighborhood (McCarty et al. 2001). Thus, an Erdős-Rényi random social network with an average degree of 13 is used to connect the crowd-shipper agents residing within the same census tract. The probability of an interaction between any two connected crowd-shipper agents in a given week is assumed to be 0.5%. If a crowd-shipper agent is aware of the food rescue program (A_c = 1) and interacts with an agent in its social network, the other agent also becomes aware. Upon interaction, the crowd-shipper whose utility due to motivation value ($U_{c,m(t)}$) is less will increase this value by 1% of the $U_{c,m(t)}$ value of the other crowd-shipper.

Utility due to past experiences ($U_{c,e(t)}$) is based on the regularity of a crowd-shipper's participation in food rescue program. $U_{c,e(t)}$ is evaluated using Equation (5), where $N_{c,w}$ is the total number of weeks a crowd-shipper has participated in food rescue program and w_c is the total number of weeks that the crowd-shipper has been aware of the program (when $A_c = 1$).

$$U_{c,e(t)} = \frac{N_{c,w}}{w_c\ (\forall A_c = 1)} \tag{5}$$

The value of $U_{c,f(t)}$ for each crowd-shipper agent is varied experimentally (as described in the following section). In each time-step, a random number is generated between 0 and 1 for each aware crowd-shipping agent, and if the number is less than the agent's total utility value ($U_{c,t}$), the agent is willing to rescue food from a restaurant agent ($W_{c,t}$ = 1, or 0 otherwise).

Table 1: Summary statistics and probability distributions used to determine crowd-shipper agent initial motivation utility values (average of motivation score from each demographic factor was normalized between 0 and 1 to assign to each crowd-shipper agent).

Demographic factor: level	*M*	*SD*	Range	Assumed distribution
Age: 18 - 25	8.97	2.97	[1,14]	Truncated normal (1,14)
Age: 26 - 45	7.94	4.31	[1,14]	Truncated normal (1,14)
Age: 46 - 69	10.93	0.87	[10,13]	Truncated normal (10,13)
Gender: Men	7.96	2.96	[1,14]	Truncated normal (1,14)
Gender: Women	9.78	2.94	[1,14]	Truncated normal (1,14)
Ethnicity: Non-Hispanic White	9.27	2.97	[1,14]	Truncated normal (1,14)
Ethnicity: African American	8.26	21.97	[3,14]	Uniform (3,14)
Ethnicity: Hispanic	9.65	2.13	[6,12]	Truncated normal (6,12)
Education: High school	6.05	6.36	[1,12]	Uniform (1,12)
Education: Partial college	8.67	1.30	[7,10]	Truncated normal (7,10)
Education: College/university	9.36	2.84	[1,14]	Truncated normal (1,14)
Education: Graduate school	3.63	10.24	[1,8]	Uniform (1,8)
Annual income: <17,500	8.79	2.83	[1,14]	Truncated normal (1,14)
Annual income:17,500 - 47,000	7.53	4.64	[1,14]	Truncated normal (1,14)
Annual income:48,000 - 66,000	11.24	1.48	[10,14]	Truncated normal (10,14)
Annual income:67,000 - 80,000	10.67	1.59	[8,12]	Truncated normal (8,12)

In reality, even if a potential crowd-shipper is willing ($W_{c,t} = 1$) to participate, other obligations and time constraints may prevent him/her from doing so. To allow for these factors, a willing crowd-shipper agent's final decision to participate is based on an availability index ($V_{c,t}$) and time required (T) to complete the pick-up and delivery. The required time (T) is estimated using the Google Maps API and includes four components: travel time from the population centroid of the crowd-shipper's census block to the restaurant location, travel time from the restaurant to the assigned homeless shelter, travel time from the homeless shelter back to the census block centroid, and the total time spent in waiting, loading, and unloading food at the restaurant and homeless shelters. The availability index of a crowd-shipper ($V_{c,t}$) is assigned based on its age level, where a higher index value corresponds to a greater probability that the agent will participate. The availability index ($V_{c,t}$) is assigned a value of 0.5 for crowd-shipper agents that have an age level of 18 - 25 or 26 - 45, and a value of 0.75 is assigned for agents with an age level of 45 - 69. This logic is based on the assumption that senior crowd-shippers (i.e., retired persons) have more availability for volunteer activities.

A crowd-shipper agent will look at available deliveries randomly in the list and evaluate its willingness to volunteer ($W_{c,t}$), availability (based on its availability index ($V_{c,t}$)) and convenience utility ($C_{c,T}$) due to total time (T) for the delivery, given by Equation (6). Three random numbers are generated between 0 and 1 and if each of the numbers are less than $W_{c,t}$, $V_{c,t}$ and $C_{c,T}$, respectively, the crowd-shipper agent will participate in the food rescue program, and the particular delivery will be removed from the list of potential deliveries for the other crowd-shipper agents. This randomness is introduced to represent heterogeneity in crowd-shipper agent behaviors that is not explicitly represented by the state variables in the model.

$$C_{c,T} = \frac{1}{e^{2T}} \tag{6}$$

2.4 Initialization

Total 5% of the restaurants are initialized with the awareness to donate food ($A_r = 1$) through the volunteer-based crowd-shipping system. This assumption is based on the statistics that currently less than 5% of the U.S. restaurants donate surplus food (Berkenkamp and Phillips 2017). Also, the initial number of crowd-shipper agents who are aware of food rescue program ($A_c = 1$) is varied experimentally to identify the effect of initial starting population on the system metrics over the simulation runtime.

3 EXPERIMENTATION AND RESULTS

The ABM was used to investigate the factors affecting the capacity and the rate of growth of a food rescue program in which volunteer crowd-shippers collect surplus food from restaurants and deliver it to shelters. The three key performance metrics of interest are the number of successful and failed deliveries over time and the number of restaurant donation requests. A *failure* corresponds to a situation in which a restaurant is willing to donate food in a particular time-step, but none of the crowd shippers chooses to fulfill its request. A *success* corresponds to a donation that is picked up by a crowd shipper and delivered to the assigned shelter. The total number of restaurant donation requests is, therefore, the sum of the number of successful and failed deliveries. Upon experiencing a failed delivery, a restaurant's willingness to participate in the food rescue program in future time-steps decreases. Maintaining and increasing restaurant donations, therefore, requires consistent active participation by a sufficient number of crowd shippers.

A key determinant of a crowd shipper's willingness to participate is the wait time that it experiences when responding to a donation request. Therefore, the ABM was used to test the sensitivity of the three performance metrics for different values of wait time ($t_{c,w}$) during pick-ups and deliveries. The total number of active crowd shippers will also likely depend on initial conditions; to test this, the initial number of crowd shippers that are aware of the food rescue operations (i.e., $A_c = 1$) at the start of the simulation run was experimentally varied. Finally, sensitivity analysis on the utility gained due to financial incentives by both crowd shippers $U_{c,f(t)}$ and restaurants $U_{r,f(t)}$ through participation in the food rescue program is performed. This analysis represents a potential policy implementation in which tax dollars saved by the restaurants through participation in the food donation program can be shared with the crowd shippers for their volunteering endeavors. Table 2 summarizes the seven experimental scenarios. For each experiment, 100 replications of 364 time-steps (52 weeks) each were run. Also, utility functions for restaurant and crowd-shipper agents as defined in equations (1) and (4) are considered equally weighted from each factor.

Scenarios 1 through 3 demonstrate the effect of increased wait times on delivery success and restaurant participation. From Scenario 1 (the baseline scenario) through Scenario 3, the total time a crowd shipper waits at restaurants and shelters ($t_{c,w}$) is set to 5, 15 and 30 minutes, respectively, while the values of the three remaining factors were kept constant. Figure 3 shows the total number of successful and failed deliveries for experimental scenarios 1 through 3 (error bars represent 95% confidence interval) at the end of one-year time-period. As the total waiting time ($t_{c,w}$) was increased from 5 to 15 minutes, no statistically significant difference was observed (at $\alpha = 0.05$) in the total number of successful (Scenario 1: $M = 995.83$, $SD = 401.92$; Scenario 2: $M = 889.74$, $SD = 436.86$; $t = 1.79$, $p = 0.075$) and failed deliveries (Scenario 1: $M = 260.16$, $SD = 142.42$; Scenario 2: $M = 289.67$, $SD = 167.51$; $t = -1.34$, $p = 0.181$). However, the number of successful deliveries were significantly reduced in Scenario 3 ($M = 618.13$, $SD = 334.41$) when the total waiting time ($t_{c,w}$) was increased to 30 minutes.

Table 2: Seven experimental scenarios.

	Crowd shipper total wait time ($t_{c,w}$)	Percentage of crowd shippers with $A_c = 1$ at $t = 0$	Financial utility of crowd shipper ($U_{c,f(t)}$)	Financial utility of restaurant ($U_{r,f(t)}$)
Scenario 1	5	0.1	0	0.5
Scenario 2	15	0.1	0	0.5
Scenario 3	30	0.1	0	0.5
Scenario 4	5	0.3	0	0.5
Scenario 5	5	0.5	0	0.5
Scenario 6	5	0.1	0.25	0.25
Scenario 7	5	0.1	0.5	0

As the total wait time ($t_{c,w}$) is increased from 5 to 30 minutes, the total number of restaurant donation requests (represented by the sum of successful and failed deliveries) decreased by 20% in Scenario 3 as compared to the baseline scenario. Figure 4 shows the number of successful and failed deliveries each week over 52 weeks for scenarios 1 to 3. Initially, the number of failed deliveries exceeded the number of successful deliveries in all three scenarios. However, successful deliveries began to consistently outnumber failures in weeks 16, 20, and 31 for Scenarios 1, 2, and 3, respectively. This is a consequence of the diffusion of awareness that occurred over time via social interactions, which increased the number of crowd shippers available (i.e., having $A_c = 1$) to make deliveries.

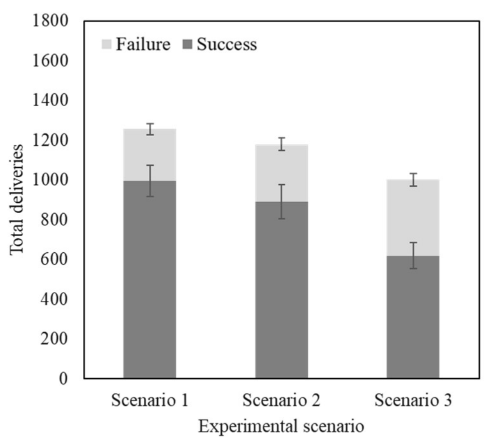

Figure 3: Total number of successful and failed deliveries at the end of one-year simulation run in experimental Scenarios 1, 2 and 3.

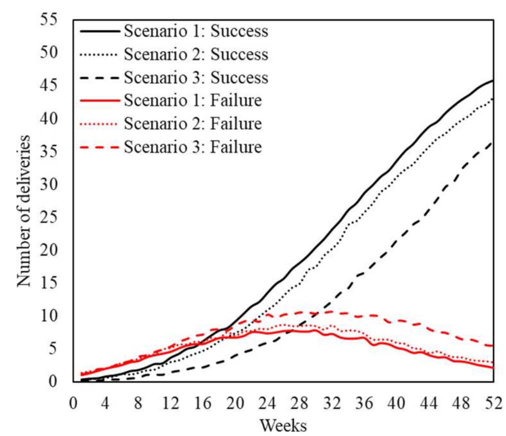

Figure 4: Number of successful and failed deliveries each week in experimental Scenarios 1, 2 and 3.

In Scenarios 4 and 5, the initial percentage of crowd shippers that are aware of the possibility of rescuing food was increased from the baseline level of 0.1% (Scenario 1) to 0.3% and 0.5 %, respectively. Figure 5 compares the total number of scheduled deliveries in each of these scenarios after 52 weeks. Scenarios 4 and 5 yielded 23% and 25% more participation by the restaurants, respectively, as compared to the baseline scenario, as well as significantly more successful deliveries (Scenario 4: M = 1,567, SD = 361, t = -10.58, $p < 0.001$; Scenario 5: M = 1,658, SD = 461, t = -10.83, $p < 0.001$) and fewer failures (Scenario 4: M = 70.5, SD = 61.7, t = 12.22, $p < 0.001$; Scenario 5: M = 20.9, SD = 19.9, t = 16.64, $p < 0.001$). Figure 6 shows that successful deliveries immediately outnumbered failures (i.e., in week 1) in both Scenarios 4 and 5. Furthermore, by the end of 52-week simulation run, failed deliveries still occurred in Scenario 1, while they stopped occurring in Scenarios 4 and 5 by weeks 46 and 33, respectively. The large ratio of potential crowd-shippers to potential restaurant donors led to very few failed deliveries in Scenarios 4 and 5.

Scenarios 6 and 7 test the effects of increasing the utility from financial incentives for crowd shippers to volunteer ($U_{c,f(t)}$) by 0.25 and 0.50, respectively, and decreasing this utility for restaurants ($U_{r,f(t)}$) by 0.25 and 0.50, respectively. Figure 7 shows the total number of successful and failed deliveries in experimental Scenarios 6 and 7 and the baseline scenario (Scenario 1). There was no major system improvement observed in terms of increase in successful deliveries or reduction in failed deliveries between Scenarios 1 and 6 or Scenarios 1 and 7. Figure 8 shows that the break-even of successful and failed deliveries occurs in week 14 for Scenario 6, and in week 4 for Scenario 7. Arriving at the break-even week sooner in Scenario 7 indicates that increasing the utility of financial incentives for crowd shippers increased their overall participation in the food donation program in the earlier time-steps.

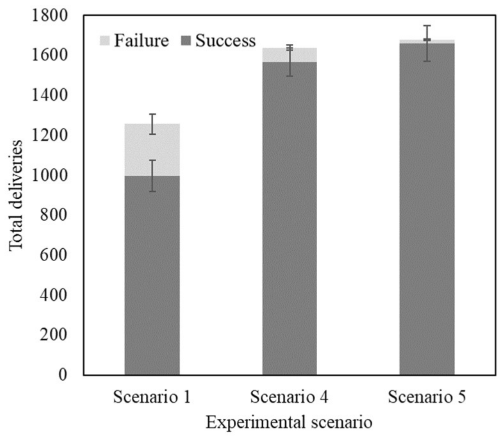

Figure 5: Total number of successful and failed deliveries at the end of one simulated year in experimental Scenarios 1, 4 and 5.

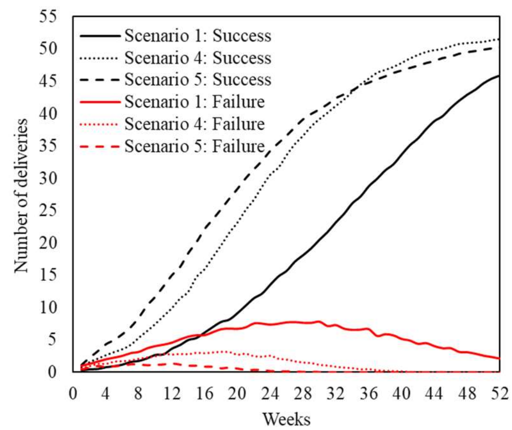

Figure 6: Number of successful and failed deliveries each week in experimental Scenarios 1, 4 and 5.

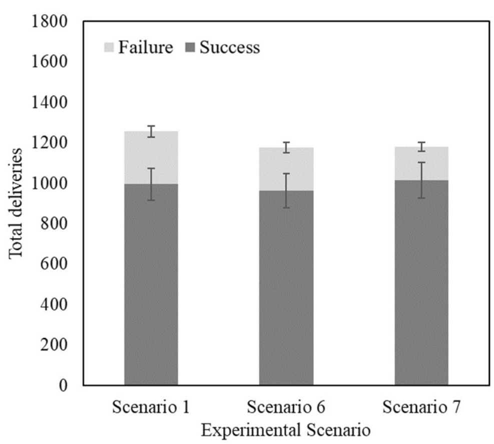

Figure 7: Total number of successful and failed deliveries at the end of one-year time period in experimental Scenarios 1, 6 and 7.

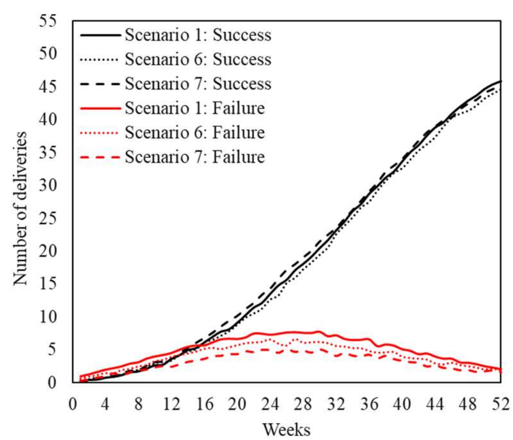

Figure 8: Number of successful and failed deliveries each week in experimental Scenarios 1, 6 and 7.

4 CONCLUSION AND FUTURE WORK

This paper demonstrates the value of an agent-based modeling approach in informing the design parameters of a volunteer-based crowd-shipping system for rescuing surplus food from restaurants. Preliminary experimentation with the conceptual model described in this paper demonstrates the importance of reducing crowd shippers' wait time in maintaining restaurant and crowd-shipper participation in the system. The model also suggests that food rescue organizations should invest in creating and increasing awareness among individuals to participate as crowd-shippers for restaurant food donations before implementing the volunteer-based crowd-shipping system. In addition, it is observed that decreasing restaurants' financial incentives to participate only slightly discourages their participation. On the other hand, participation by crowd-shippers increases earlier in the presence of financial incentives as compared to when there are no incentives.

The model described in this paper serves as a starting point for the development of a system, in which the restaurant surplus food is diverted from landfill and provided to people in need. While this model does not study the prevention of surplus food creation, it can be useful to eliminate its accompanying environmental effect: greenhouse gas emissions from landfills. To further capture the capabilities of this ABM, a larger sample of population needs to be modeled. Incorporating an estimated amount of food per donation into the model will help track the positive environmental impact of this volunteer-based crowd-shipping system for rescuing the surplus food from restaurants. This is a conceptual model incorporating motivation of participants that determines their utility based on factors that could be of primary importance to them and thus captures their decision-making process. The model could be used to further investigate specific motivations of these participants by collecting empirical survey data from them and thus strengthen the factors determining their utility for the specific application.

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