Assessing the Potential of Crowd-Shipping for Food Rescue Logistics Using Agent-Based Modeling

Anuj Mittal, Nilufer Oran Gibson, and Caroline C. Krejci

Abstract Food insecurity in the U.S. is a national concern. More than 30% of available food supply at the retail and consumer level in the U.S. is wasted each year and sent to landfills. This wholesome food could help address food insecurity problem by feeding the hungry families. Restaurants are a major source of food waste in the U.S. However, less than 5% of the more than 1 million restaurants in the U.S. currently donate food to the hungry. One of the biggest barriers to food donation from restaurants is transportation. Crowd-sourced transportation, known as "crowd-shipping," is a potential solution, in which individual volunteers use their personal vehicles to collect donated surplus food from restaurants and deliver it to food-insecure recipients. However, viability and effectiveness of such a program require that the number of participating restaurants and crowd-shippers are appropriately balanced and grow over time. This paper describes a conceptual agent-based model that was developed to examine the impact of initial restaurants and crowd-shipper participation levels on the number of meals delivered to food-insecure people over time. Preliminary experimental results demonstrate that increasing the initial participation levels does not necessarily lead to a uniformly better system performance over time—maintaining the right ratio of crowd-shippers to restaurants is critical to success.

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1 Introduction

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 [1]. This number is particularly concerning, given that approximately 30–40% of the U.S. food supply is wasted [2]. To address the problem of food insecurity, the U.S. Department of Agriculture supports multiple initiatives, including food distribution programs, child nutrition programs, the Supplemental Nutrition Assistance Program (SNAP), and a special SNAP for women, infants, and children (WIC). However, 27% of individuals who are food-insecure may not qualify for federal assistance because their gross monthly income is higher than the maximum allowed income for eligibility to participate in these programs [3].

Another approach to reducing food insecurity is by rescuing food, in which surplus food that is still edible is collected and delivered to food-insecure people. Food rescue activities in the U.S. are typically performed by extra-governmental, community-based charitable programs, such as food banks and pantries [4], which rescue donated surplus food from farms, manufacturers, and retailers [5]. Restaurants are a major source of food waste in the U.S., generating 11.4 million tons each year, of which 390,000 tons could be recovered to yield 643 million meals [6]. However, less than 5% of the more than 1 million restaurants in the U.S. currently donate surplus food [7]. For restaurants, one of the biggest barriers to donating surplus food is logistics. Because the restaurant sector consists of many independent locations with relatively small volumes of rescuable food per location, efficient collection and distribution of restaurant food surplus is particularly challenging [8]. While the donors receive tax benefits for their donations, it is the non-profit food rescue organizations that are typically responsible for managing and covering the cost of transporting surplus food to food-insecure recipients [8].

Crowd-shipping offers a potential solution to the challenge of food rescue logistics. *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" [9]. Examples of commercial crowd-shipping services include Uber Eats and DoorDash, in which customers use an online platform to order food, and a willing driver from a pool of available drivers (i.e., the crowd-shippers) delivers the order from restaurant (typically using his/her personal vehicle) for a predetermined price. The appeal of crowd-shipping lies in its ability to provide a low-cost delivery service with greater flexibility and shorter lead times than conventional transportation service providers.

Using crowd-shipping to rescue surplus food from restaurants and deliver it to food-insecure individuals is a relatively new idea. The non-profit organization Food Rescue US uses an app to recruit volunteer drivers ("Food Rescuers") to pick up surplus food from participating local donors and transport it to receiving agencies, such as soup kitchens and shelters. The service is currently operating in 17 U.S.

locations [10]. Goodr is a for-profit start-up company that uses third-party commercial crowd-shipping services to distribute surplus restaurant food throughout a large network of non-profit recipient organizations in Atlanta. Postmates, a commercial crowd-shipping company, has piloted an initiative in which it uses its own crowd-shippers to transport surplus food from participating restaurants in Los Angeles to local shelters [11].

While still in early stages of development, these programs suggest that food rescue operations can be enhanced through the use of crowd-shipping, providing a potential new avenue for addressing food insecurity. However, as food rescue organizations consider crowd-shipping as a logistics solution, decisions about system design and the best strategy for launching the program will be critical. In particular, 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 [12]. 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. Modeling can help program designers to gain a better understanding of these factors, and then use this knowledge to increase the likelihood of system success, in terms of increasing the number of meals delivered to food-insecure people and number of restaurants that continue to participate in the program.

2 Models of Crowd-Shipping Systems

The objective of many existing models of crowd-shipping systems is to predict potential crowd-shippers' willingness to participate in a commercial crowd-shipping system. These are typically statistical models based on survey data and/or data collected from a crowd-shipping platform. A survey was conducted with 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 [13]. A similar statistical analysis was done using survey data in another study [14]. Service request records from a crowd-shipping company were statistically analyzed to determine how to increase the odds of successfully recruiting a crowd-shipper to fulfill a given service request [15]. Survey data on potential crowd-shippers' preferences and social network characteristics was used to develop a TRANSIMS model that evaluates the potential of using customers' social network contacts for last-mile delivery [16].

Agent-based modeling (ABM) has also been used to evaluate crowd-shipping systems. ABM is well-suited for this application, allowing potential crowd-shippers to be realistically modeled as autonomous and heterogeneous individuals. ABM was used to explore the relationship between crowd-shippers' characteristics, properties of crowd-shipping tasks, and system performance metrics [17]. Survey data from Amazon Mechanical Turk's service was used to validate the model. ABM was also used to investigate the use of crowd-shipping for last-mile parcel delivery for a case study in central London [18]. The purpose of the model was to understand how crowd-shippers' actions affect road usage. Likewise, ABM was used to simulate a crowd-sourced last-mile delivery service [19]. The model was used for capacity planning, observing the effects of varying the ratio of the number of crowd-shippers to the number of requested deliveries, as well as the maximum allowable crowd-shipper detour time, on system performance. In another study, survey data was used to inform the development of an ABM that examined the growth of a crowd-shipping system over time [20]. Experimental results show that the number of packages delivered is proportional to crowd-shipper flexibility, the monetary reward they receive for deliveries, and the initial number of crowd-shippers at the start of the simulation run.

This paper describes a conceptual 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., number of participants, number of meals delivered) that arise over time as a result of autonomous behaviors and interactions of crowd-shippers and restaurants. This conceptual model was developed from an earlier version of the model [21] and 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 (part of model description included in this paper is a © [2019] by IEEE and reprinted with permission from [21]). 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 conclusion and plans for future model development.

3 Agent-Based Model

The ABM was developed using NetLogo 6.0.4. The purpose of the model is to evaluate design parameters of a volunteer-based crowd-shipping system for rescuing food from restaurants. Texas has more food-insecure households than the average across all states in the U.S. (approximately 1.4 million) [22]. Therefore, the model 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 is located in a major metropolitan area with more than 1000 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 [23]. 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. Four shelters (one in census tract 1222 and the remaining three

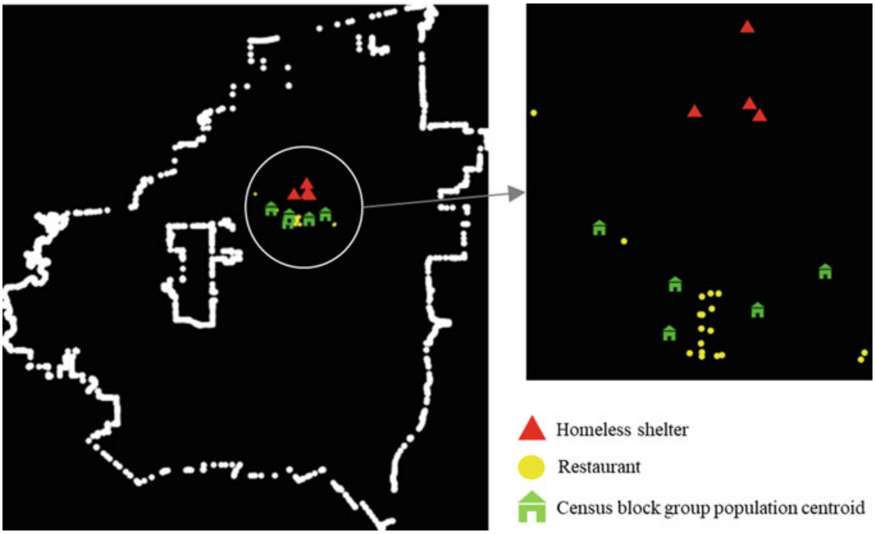

Fig. 1 NetLogo representation of the City of Arlington, showing population centroids of 5 census block groups, 18 restaurants, and 4 homeless shelters (part of the figure on the right is a © [2019] by IEEE. Reprinted, with permission, from [21])

in census tract 1223) are considered as potential recipients of surplus food from the restaurants. U.S. Census Bureau geocoding services were used to obtain the census tracts and block groups corresponding to each restaurant and shelter, based on their street addresses [24]. The locations of population centroids of the 5 census block groups, 18 restaurants, and 4 shelters on the map of the City of Arlington are shown in Fig. 1.

3.1 Model Overview

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 (if above age 18) are considered to be potential transportation providers. In each time-step (where a time-step corresponds to one day), 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 the assigned 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.

3.2 Sub-Model 1: Restaurant Agent Decision-Making

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 an array of seven binary availability index values ($V_{r,t}$). If restaurant agent r has food available to donate at time-step t, then $V_{r,t}$ will take a value of one, or zero otherwise. 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.

A restaurant's 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 landfills) [25] and financial considerations (e.g., tax deductions for charitable donations and reduced waste management fees) [26]. However, many restaurants are discouraged from donating 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 [25, 27]. In addition, transportation constraints may prevent restaurants from donating [7]. 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 [10].

All of these relevant factors were incorporated into the restaurant agents' decision-making 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 evaluated as the weighted sum of four components and is defined on a scale of -1 to 1: 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 (1). Larger values of total utility ($U_{r,t}$) correspond to greater donation likelihood.

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

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. In the event of a failure, the restaurant agent will re-evaluate its decision to participate, based on its current total utility ($U_{r,t}$). Also, if a restaurant agent has surplus food available ($V_{r,t} = 1$) and is willing to donate food ($W_{r,t} = 1$) but does not find a crowd-shipper for pick-up three times consecutively, it will stop participating in the food rescue program, with no possibility of rejoining in future time-steps.

Restaurant agents' utility due to sustainability goals ($U_{r,s(t)}$), concerns ($U_{r,c(t)}$), and financial benefits ($U_{r,f(t)}$) are defined on a scale of 0 to 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 assumed as an Erdős-Rényi random network [28] 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 (2), where $c_{r,t}$ is the agent's r 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. Utility gained due to financial benefits from food donation ($U_{r,f(t)}$) has been assigned a value of 0.5 for each restaurant agent, and it remains constant over the duration of the simulation run.

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

A restaurant agent's utility due to past experiences ($U_{r,e(t)}$) is defined on a scale of -1 and 1 and is a combination of the agent's personal experiences with the food rescue program and the number of interactions (i_r) with other restaurant agents who have stopped participating in the program due to inability to source deliveries from the crowd-shippers. The agent's personal experiences are evaluated using 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 was aware of the food rescue program ($A_r = 1$) and had food available to donate ($V_{r,t} = 1$). $U_{r,e(t)}$ for a restaurant agent is evaluated using (3).

$$U_{r,e(t)} = \frac{N_{r,d}}{d_r} - \frac{i_r}{10} \tag{3}$$

The weights on utility due to sustainability goals ($\beta_{r,s}$), concerns ($\beta_{r,c}$), past experiences ($\beta_{r,e}$), and financial benefits ($\beta_{r,f}$) for the restaurant agents are assumed as 0.1, 0.2, 0.5, and 0.2, respectively. Higher weight is assigned to utility due to past experiences ($U_{r,e(t)}$) based on the assumption that restaurants will be more likely to participate in the food rescue program if they have previously experienced more successful deliveries and have received less negative feedback from restaurants that have stopped participating in the program.

3.3 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.

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

There are a total of 4579 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 the 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. Using the centroid of a census block group as a point of origin is a common assumption when calculating travel distances for the population residing within the block group to a particular destination [29].

Crowd-shipper agents are classified using five demographic factors, as per the classification of food rescue program volunteers by [30]: 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 [31]. 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.

Motivations for individuals to participate in food rescue programs include service requirements of a social organization, career improvement, and altruism [30]. 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 fund one of the largest fresh food donation programs in the North America [32]. 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 [33].

In this 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. Similar to the restaurant agents, 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. It is also assumed that crowd-shipper agents are available to volunteer three times a week. Each agent's availability schedule is represented by a set of seven binary availability index values ($V_{c,t}$). If a crowd-shipper agent c is available to volunteer at time-step t, then $V_{c,t}$ will take a value of one, or zero otherwise. Each agent's $V_{c,t}$ values are assigned randomly at the start of the simulation run and are assumed to remain constant for the duration of the run. If A_c and $V_{c,t}$ are equal to 1, and if the agent has not volunteered previously for the food rescue program in the current week, 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 -1 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 (4). 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 assumed to be willing to rescue food from a restaurant agent ($W_{c,t} = 1$, or 0 otherwise).

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

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 choose a particular food donation delivery d is based on its availability at the time of the pick-up of the delivery, given by an agent's pick-up availability index (P_c) and the total time required (T_d) to complete the delivery. The total required time (T_d) 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. Travel times between census blocks, restaurants, and homeless shelters are estimated using the Google Maps API. The total waiting time involved at restaurants and homeless shelters is assumed as 10 min in the model. The pick-up availability index of a crowd-shipper (P_c) is assigned based on its age level, where a higher index value corresponds to a greater probability that the agent will participate. The pick-up availability index (P_c) 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 willing crowd-shipper agent will look at available deliveries in the list and make its final decision to make a delivery d based on its availability at the pick-up time (P_c) and convenience utility ($C_{c,d}$), which is given by (5). Convenience utility ($C_{c,d}$) for a delivery d is a function of total time involved in completing the delivery (T_d), with greater the time, lesser the utility value.

$$C_{c,d} = \frac{1}{e^{2T_d}} \tag{5}$$

Two random numbers are generated between 0 and 1 and if each of the numbers are less than P_c and $C_{c,d}$, 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. Also, if a crowd-shipper has been willing to volunteer three times consecutively but was unable to make any delivery due to time constraints (lack of availability at the time of pick-up determined by an agent's P_c and/or lack of convenience determined by $C_{c,d}$), it will stop participating in the program in future time-steps.

Crowd-shipper agents' utilities due to motivation ($U_{c,m(t)}$) and financial benefits ($U_{c,f(t)}$) are defined on a scale of 0 to 1. The initial value of $U_{c,m(t)}$ for each crowd-shipper agent is derived from the motivation scale defined by [30], which is based on survey data collected from volunteers who participate in food rescue programs. The motivation score means, 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 initial $U_{c,m(t)}$ values are drawn for each crowd-shipper agent. The five motivation scores from each demographic factor are then averaged, normalized to a value between zero and one, and 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 [34]. 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 $U_{c,m(t)}$ value is lower 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 defined on a scale of -1 to 1, and is based on the regularity of a crowd-shipper's participation in food rescue program and its interactions with other crowd-shippers who have stopped participating in the food rescue program. $U_{c,e(t)}$ is evaluated using (6), where $N_{c,w}$ is the total number of weeks a crowd-shipper has participated in the food rescue program, w_c is the total number of weeks that the crowd-shipper has been aware of the program (when $A_c = 1$), and i_c is the number of interactions a crowd-shipper has had with other agents who have stopped participating in the food rescue program.

Table 1 Summary statistics and probability distributions used to determine crowd-shipper agent's 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) (© [2019] by IEEE. Reprinted, with permission, from [21])

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)

$$U_{c,e(t)} = \frac{N_{c,w}}{w_c\ (\forall A_c = 1)} - \frac{i_c}{10} \tag{6}$$

It is assumed in this model that the crowd-shipper agents are not financially incentivized to participate in the food rescue program. Therefore, utility gained due to financial benefits ($U_{c,f(t)}$) is assigned a value of 0 for all crowd-shipper agents and it remains constant over the duration of the simulation run. The weights on utility due to motivation ($\beta_{c,m}$), financial benefits ($\beta_{c,f}$), and past experiences ($\beta_{c,e}$) are assumed as 0.25, 0.25, and 0.5, respectively. It was assumed that the crowd-shippers' utility due to past experiences ($U_{c,e(t)}$) was the most influential of the three elements, based on research that suggests that volunteer participation tends to increase with accumulating experience [35] and fewer negative interactions with former volunteers.

3.5 *Initialization*

The initial number of restaurant and crowd-shipper agents who are aware of food rescue program (i.e., restaurants with $A_r = 1$ and crowd-shippers with $A_c = 1$) is varied experimentally to identify the effect of initial starting population on the system metrics over the simulation runtime. Figure 2 shows the flowchart representing the three sub-models executed at each time-step in the ABM.

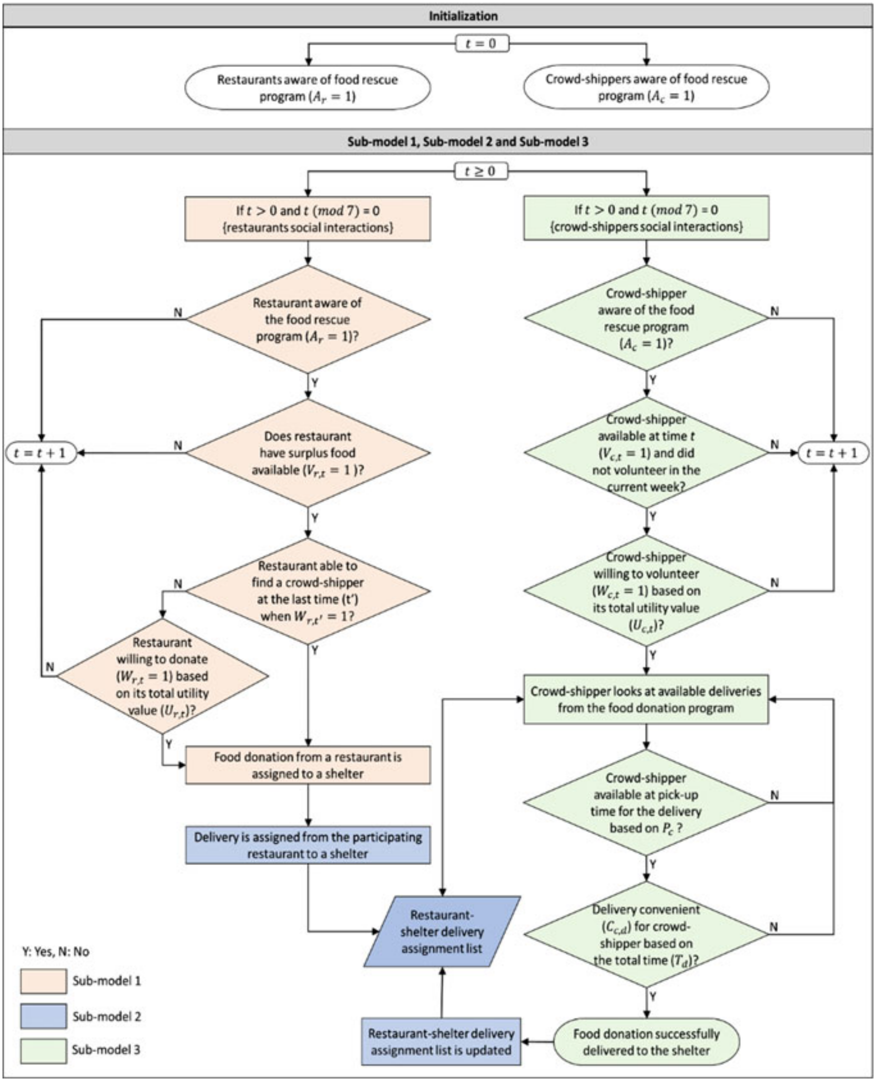

Fig. 2 Flowchart of the three sub-models executed at each time-step in the ABM

4 Experimentation and Results

The ABM was used to investigate factors affecting the viability of a crowd-based volunteer food rescue program. System viability is achieved when the amount of food donated by restaurants and the number of participating crowd-shippers are sufficient to fulfill food donation requests, and this balance is successfully maintained over time. Users who request service via a crowd logistics platform (i.e., restaurants) will only find the platform useful if there are sufficient service providers (i.e., volunteer crowd-shippers), and vice versa. Therefore, it is important to ensure that there is an appropriate balance between the number of service requesters and providers when the program is initially launched, to avoid immediate program failure.

To gain a greater understanding of how to determine the right initial balance, the initial percentages of crowd-shippers (C_0) and restaurants (R_0) who are aware of the food rescue program (i.e., restaurants with $A_r = 1$ and crowd-shippers with $A_c = 1$) were experimentally varied. In each experimental scenario, three key output metrics are captured in each daily time-step: the number of meals rescued and the number of restaurants (R_c) and crowd-shippers (C_c) who are aware of the food rescue program and continue to evaluate participation. On average, each restaurant in the U.S. generates approximately 50,000 lb of surplus food per year and this value was used to determine the potential food donation (three times every week for the 52-week period) for each restaurant in the model [36]. Also, it has been assumed that each pound of food being rescued corresponds to 0.83 meals [6]. For each experimental scenario, 100 replications of 364 daily time-steps were run.

First, the initial percentage of restaurants aware of the program (R_0) was assigned a value of 5%, and the initial percentage of aware crowd-shippers (C_0) was assigned values of 0.5%, 1%, 1.5%, and 2%. Figure 3 shows the total number of meals rescued at the end of one year for the four different values of C_0.

The results indicate that more meals are rescued as the initial value of C_0 is increased, which suggests that increasing C_0 has a positive effect on total restaurant participation. This observation is supported by the data in Fig. 4, which shows the

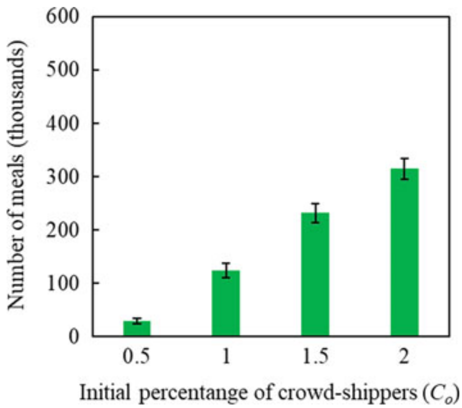

Fig. 3 Number of meals rescued at the end of one year when 5% of restaurants (R_0) were initially assumed to be aware of the food rescue program, with C_0 varied from 0.5% to 2%

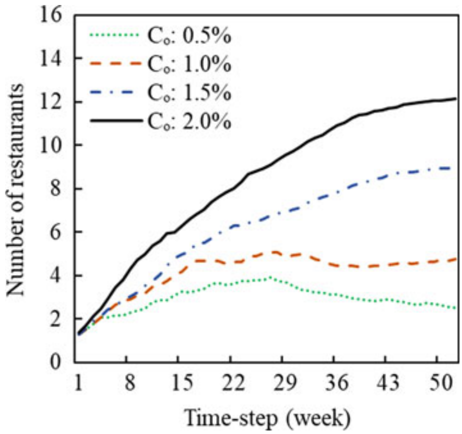

Fig. 4 Number of restaurants that continue to evaluate participation in the food rescue program (R_c), when 5 percent of restaurants (R_o) were initially assumed to be aware of the program with C_0 varied from 0.5% to 2%

number of restaurants every week that continued to evaluate participation (R_c) when C_0 was varied. The number of crowd-shippers available to make deliveries (C_c) followed a similar pattern (Fig. 5), although the value of C_c drops early on in all four cases. The reason for this drop in participation is likely related to the low value of R_c in the initial time-steps—with few delivery requests, crowd-shippers find few opportunities to participate. However, C_c increases in the later time-steps, indicating the mutually positive effect of the increasing number of participating restaurants and the increasing number of crowd-shippers on each other.

The higher initial percentage of aware crowd-shippers (C_o) increases the rate of information diffusion among other potential crowd-shippers, improving food rescue operations by reducing the number of restaurants that stop participating due to repeated failed pick-ups. This suggests that number of crowd-shippers available in the beginning of the program (C_0) is an important aspect of the program design,

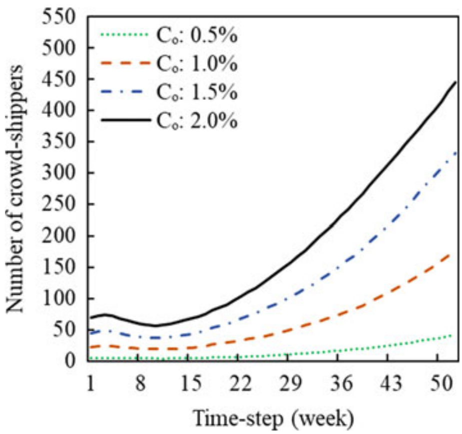

Fig. 5 Number of crowd-shippers (C_c) that continue to evaluate participation in the food rescue program, when 5 percent of restaurants (R_o) were initially assumed to be aware of the program with C_0 varied from 0.5% to 2%

and a higher C_0 value leads to higher number of restaurants who continue to evaluate participation (R_C) in the program.

Given that greater values of C_o tend to yield better system performance, the next set of experiments was performed with C_0 set to 1.5% or 2%, while the initial number of restaurants aware of the program (R_0) was varied. Figure 6 shows the number of meals rescued at the end of one year when R_o was varied and was set to 5%, 25%, 50%, and 75% for these two different values of $C_{0.}$ In all cases, increasing R_o has a positive effect on the number of meals rescued.

However, Fig. 7a shows that for C_0 =1.5%, increasing R_0 resulted in fewer restaurants that continued to evaluate participation (R_c) at the end of one year. By

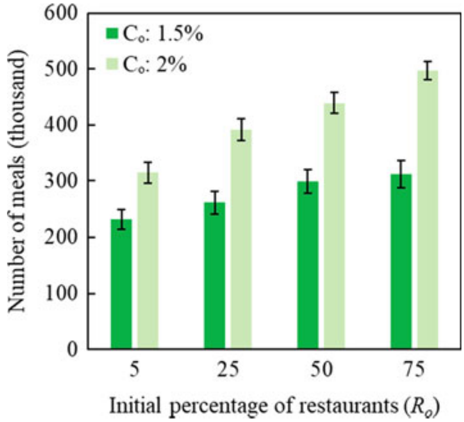

Fig. 6 Number of meals rescued at the end of one year when initial number of restaurants aware of the program (R_o) is varied from 5 to 75%, with C_0 set to 1.5% and 2%

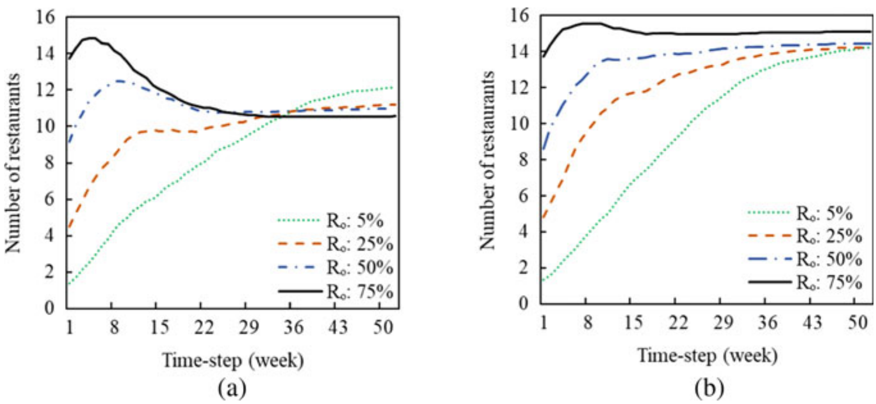

Fig. 7 Number of restaurants that continue to evaluate participation in the food rescue program (R_c) when C_0 is **a** 1.5%, **b** 2.0%

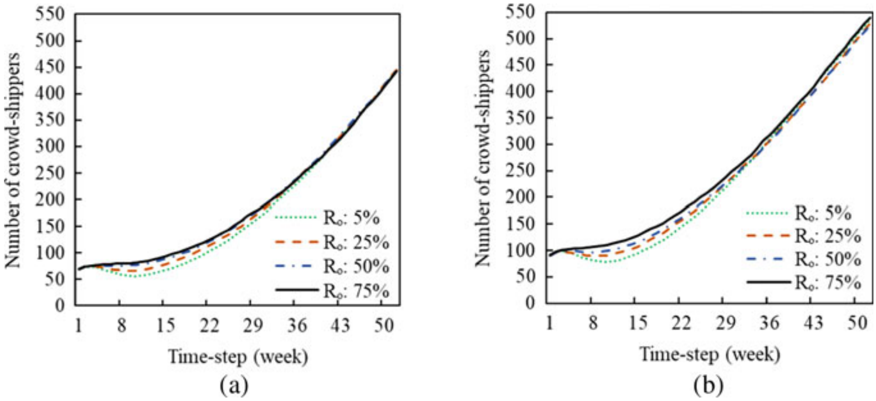

Fig. 8 Number of crowd-shippers that continue to evaluate participation in the food rescue program (C_c) when C_0 is **a** 1.5%, **b** 2.0%

contrast, Fig. 7b shows that when $C_0 = 2.0\%$, the number of participating restaurants (R_c) was always higher when R_0 was higher. In both cases, the number of crowd-shippers available to participate (C_c) in the initial time-steps are greater when the initial percentage of restaurants aware of the food rescue program (R_0) is greater (Fig. 8a, b). Increased availability of restaurants provided greater opportunities for crowd-shippers to deliver food donations, thereby reducing the number who stopped participating in the program due to a lack of available deliveries in the initial time-steps.

5 Conclusion

This paper describes a conceptual ABM that was designed to study the viability of a volunteer-based crowd-shipping program for food rescue. Preliminary experimental results from the model demonstrate the importance of achieving the right balance between the initial number of restaurant and crowd-shipper participants on the program's effectiveness, in terms of the number of meals rescued and number of restaurants who continue to participate in the program. The conceptual model described in this paper will serve as a starting point for future research. Empirical data on crowd-shipper and restaurant behavior will be collected to gain a greater understanding of crowd-shippers' behaviors and preferences, as well as insights into restaurants' decision-making processes. Using this data, the existing model will be enhanced, such that it will be capable of supporting design decisions for new food rescue programs. For example, the model can help to identify the degree to which providing monetary incentives to crowd-shippers supports program effectiveness and long-term sustainability. Developing viable crowd-sourced transportation programs to rescue surplus food will help alleviate food insecurity as well as reduce the food waste and its accompanying environmental impacts: greenhouse gas emissions from landfills.

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