ONE STEP AT A TIME: IMPROVING THE FIDELITY OF GEOSPATIAL AGENT-BASED MODELS USING EMPIRICAL DATA

By

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THESIS

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ABSTRACT

One Step at a Time: Improving the Fidelity of Geospatial Agent-Based Models Using Empirical Data

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Agent-based modeling is frequently used to produce geospatial models of transportation systems. However, reducing the computational requirements of these models can require a degree of abstraction that can compromise the fidelity of the modeled environment. The purpose of the agent-based model presented in this thesis is to explore the potential of a volunteer-based crowd-shipping system for rescuing surplus meals from restaurants and delivering them to homeless shelters in Arlington, Texas. Each iteration of the model's development has sought to improve model realism by incorporating empirical data to strengthen underlying assumptions. This thesis describes the most recent iteration, in which a method is presented for selecting eligible volunteers crowd-shippers based on total trip duration, derived from real-time traffic data. Preliminary experimental results illustrate the impact of adding trip duration constraints and increasing the size of the modeled region on model behavior, as well as illuminating the need for further analysis.

DEDICATION

I dedicate this thesis to my family. Specifically my husband Cory who has supported me through many late nights and encouraged me to always put my best foot forward. I also dedicate this work to the faculty of the Industrial Engineering Department at the University of Texas at Arlington and Dunwoody College of Technology. This thesis is a direct result of their unparalleled support and understanding. I cannot express enough appreciation for their time or dedication in making my academic experience a success.

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1 INTRODUCTION

The sharing economy and crowdsourcing have experienced explosive growth in recent years. Crowdsourcing is a type of outsourcing in which an individual or organization (i.e., crowdsourcer) makes an open request to a pool of individuals (i.e., the crowd) through an online platform acting as an intermediary to perform a particular task or service voluntarily, often for monetary compensation (Mladenow, Bauer, and Strauss 2016). Crowdsourcing offers many benefits to businesses, customers, and society through its ability to leverage financial, intellectual, and material assets and resources from a crowd and share, redistribute, or reuse them to perform services more quickly and at a reduced cost than traditional counterparts (Carbone, Rouquet, and Roussat 2017). The central idea is to specifically optimize the usage of under-utilized assets from the crowd (i.e. vehicle capacity) and make them available to the crowdsourcer through a digital platform (Benkler 2012). Many challenges endured by crowd-sourced initiatives have been identified, which include a lack of trust among participants, crowdsourcer loss of autonomy with customers, poor service quality, and platform failure at launch (Mckinnon 2016). Perhaps the most prominent of these challenges is the capability of a system to survive past early stages of implementation due to diminished participation from one or multiple sides of the platform. For instance, 30 of the 57 platforms reviewed by Carbone, Rouquet, and Roussat (2017) failed, experienced decline, or were acquired during the researchers' 11-month exploratory period.

Crowd-shipping systems are part of the sharing economy domain in which the crowdsourcer (i.e., sender) can request services for the transport of goods from members of the crowd (i.e., carriers) via an online platform that acts as an intermediary to facilitate connection between the sender and carrier. Crowd-shipping systems have become a supplemental avenue to fulfill timely, flexible, and convenient deliveries for many organizations and often at a fraction of the cost of a traditional logistics system (Rougès and Montreuil 2014; Carbone, Rouquet, and Roussat 2017). Crowd-shipping has the potential to provide speedy, flexible, and lower-cost deliveries for consumers, enable brick-and-motor stores to compete with online retailers while widening their market channels, reduce the carbon footprints, and promoting a sense of community among participants (Rougès and Montreuil 2014; Mckinnon 2016). The concept of crowd-shipping has become more popular recently, due to consumer uptake in restaurant meal delivery and grocery delivery platforms driven by the COVID-19 pandemic. In crowd-shipping, excess capacity in personal vehicles belonging to members of the carrier crowd is used to perform logistics related activities (Mittal et al. 2021). The idea is that as the size of the carrier crowd grows, it should become more likely for a sender to find an available carrier to perform the logistical service in a timely manner at a competitive rate, and as an increasing number of senders receive satisfactory service and continue using the platform, it should be more likely that carriers can find tasks to fulfill (Rougès and Montreuil 2014). Thus the success of any crowd-shipping system is dependent on obtaining an initial critical mass of both senders and carriers to realize system growth via network effects. However, this can pose a dilemma for the platform designer: a critical mass of carriers is needed to attract senders and perform services rapidly at high service level, with flexibility, and low cost, while a critical mass of senders is needed to attract carriers and enlarge the available pool (Frehe, Mehmann, and Teuteberg 2017).

In order to predict whether a platform will be successful, it is necessary to understand why some crowd-shipping systems thrive while others do not. The studies that have been conducted to investigate long-term network effects are often one-sided. They either seek to understand how particular carrier characteristics impact system performance, determine the geographical location that reveals the most promising degree of participation, or analyze the behavioral attributes of senders and/or carriers independently from the system (Ermagun, Shamshiripour, and Stathopoulos 2020; Punel, Ermagun, and Stathopoulos 2018; Le and Ukkusuri 2019). The purpose of this research aims to integrate and extend these research strands by addressing the following research questions: 1) How does crowd-shippers' tolerance for trip time impact the system's performance and the span the program will cover? 2) How do crowd-shippers' demographics, geography, and population densities influence the viability of the platform? 3) To what degree does sender density, type, and location in relation to crowd-shippers impact system success?

This research seeks to answer the above questions via experimentation with an empirically-grounded geospatial agent-based model (ABM). ABM is a simulation modeling method that can be used to represent individual people as autonomous and adaptive software agents, which has made it attractive for geospatial and transport modeling (Castle and Crooks 2006; Anand, Duin, and Tavasszy 2016). For decades ABM has been used to represent phenomena at the individual-level in geospatial models by enabling internal entities within a population to have heterogeneity and autonomy based on a set of programmed rules that govern their reactions (Castle and Crooks 2006). Agents can be programmed to acquire new knowledge and adapt their behaviors, based on observations of their environment and/or former interactions with other agents (Macal 2016). Thus, allowing the agents to display 'emergent' properties and behaviors throughout the simulation run, sometimes resulting in unexpected global behavior (Mittal et al. 2021). This is critical to investigate macro-level network effects because often individuals within a collection do not behave in an identical manor, and have diverse personality traits and cognitive behaviors (Heppenstall, Malleson, and Crooks 2016). Therefore, ABM is a suitable vessel for exploring the interactions effects among sender and carrier agents, as it allows for adaptive behaviors to develop and become evident over time identifying which factors impact long-term network effects. Indeed, some recent literature describes the application of ABM to study the dynamic evolution of crowd-shipping systems over time, although the focus of these models has been strictly on the carriers' perspective (Wise et al. 2018; Chen and Chankov 2018; Devari, Nikolaev, and He 2017; van de Westelaken and Zhang 2017).

This thesis describes the progressive development of an agent-based model that studies the extent to which carrier demographics, sender and carrier locations and densities, and carrier social networks impact the long-term network effects and growth of a crowd-shipping system for food rescue. The paper is organized as follows: Section 2 presents a literature review and background on crowd-shipping and geospatial agent-based models, Section 3 provides an overview of the food rescue agent-based transport model, and Section 4 describes the evolution of the model over time, with a detailed explanation of how empirical data has been leveraged to improve the model in each iteration. Section 5 describes the data preparation method that has been employed in the most recent stages of model development to refine the model environment. Section 6 provides the results of some preliminary experiments that were performed using the current version of the model and then compares these results with results from previous versions, and Section 7 concludes the paper and discusses ongoing research.

2 LITERATURE REVIEW AND BACKGROUND

2.1 Crowd-shipping

Many factors influence sender and carrier participation decisions, and often their motivational and demotivational factors differ. Certainly, the economic advantage is motivating for both senders and carriers. Crowd-shipping enables senders to ship a parcel at less cost than with a traditional logistics provider. Carriers, on the other hand, are given the opportunity to earn secondary income with the flexibility to only accept the trips that they deem suitable (i.e. the monetary compensation outweighs the expense of time and fuel cost) (Mckinnon 2016). A study conducted by Punel and Stathopoulos (2017) suggests that senders' participation is primarily influenced by delivery cost, shipment duration, control over delivery conditions, driver training, and past experiences; however, the significance of each of these attributes varies based on shipment distance. The literature also denotes senders' liability concerns regarding trust issues and quality of service, and the importance of a rating system to review possible carriers (Le et al. 2019). By contrast, carriers' participation is influenced by monetary compensation, the amount of time required to complete the trip, time and day of the trip, and scheduling flexibility. It has also been indicated by survey results that a carrier is more likely to participate if he/she belongs to specific demographics groups, namely highly educated or low income (Punel, Ermagun, and Stathopoulos 2018; Punel and Stathopoulos 2017). However, whether a crowd-shipping system thrives is not only dependent of the behavioral attributes of the individual actors, but also the built-environment characteristics. Built environment characteristics can include, population densities, distances to origin and destination points, and accessibility to drop-off and pick-up locations in relation to program participants. Therefore, the success of a crowd-shipping system relies heavily on its area of operation, with performance often improving in urban areas (Punel, Ermagun, and

Stathopoulos 2018). Additionally, the spatial distribution of senders and carriers affect the matchmaking capabilities of the crowd-shipping platform, and due to network effects, there must be a critical mass of both senders and carriers in close proximity to each other for a crowd-shipping program to perform well, be economical, and socially accepted. In other words, the success of the crowd-shipping initiative is not solely a result of its individual participants, but rather having enough of the right type of participants located in the right place (Ermagun, Shamshiripour, and Stathopoulos 2020).

The literature suggests that there is increasing momentum in exploring crowd-shipping systems among the academic community. Carbone, Rouquet, and Roussat (2017) were among the first to offer a comprehensive review of 57 mobile and web-based crowd-logistics platforms. More recently, Punel, Ermagun, and Stathopoulos (2018) conducted a statistical study based on survey results to determine the differences among crowd-shipping users and non-users. It was the first attempt to model the link between a crowd-shipping system and built environment characteristics. They discovered that common attributes of crowd-shipping adopters were young, male, and employed full-time, and that urban areas are preferential for system development (Punel, Ermagun, and Stathopoulos 2018). Le and Ukkusuri (2019) also used a statistical and survey-based approach to investigate the different behavioral characteristics that govern whether an individual is willing to participate in a crowd-shipping system, and more importantly how long a carrier is willing to devote to making a delivery. Ermagun, Shamshiripour, and Stathopoulos (2020) further supported that crowd-shipping systems were more likely to flourish in suburban locations. Their nested logit models were the first to utilize empirical data from a crowd-shipping platform to understand the functioning and performance of crowd-shipping system from bidding to delivery, and for each phase analyzed the impact of geographic location (i.e., urban or suburban), socioeconomic factors, and built-environment factors on performance (Ermagun, Shamshiripour, and Stathopoulos 2020). They conclude that the performance of crowd-shipping systems is dependent on local network effects, and that suburban areas seem to have the population densities, carrier involvement, and changing labor markets that promote the growth of crowd-shipping platforms (Ermagun, Shamshiripour, and Stathopoulos 2020). Most studies are narrowed to a specific domain and seek to investigate only a single element of a crowd-shipping system (e.g. carrier motivations, geographical locations, characteristics of senders). There is a lack of existing literature that explores how multiple interdependent factors simultaneously affect system performance. Studying the perspectives of both senders and carriers, as well as the interactions among participants is necessary to realize network effects and behaviors at a system-wide level.

The interactions between participants with heterogeneous preferences and characteristics causes a crowd-shipping system to evolve and dynamically change over time, which makes capturing these complexities and analyzing how various factors impact the growth of the system challenging. As a result, from a modeling perspective, crowd-shipping systems are both interesting and complex. It has been suggested that the network effects of crowdsourced systems differ among regions, and some studies have been conducted to evaluate varying demographics of crowd-shipping agents across geographic locations, how crowd-shipper agents are motivated by certain inherent behavioral characteristics, and to analyze the attributes of senders on system performance (Ermagun, Shamshiripour, and Stathopoulos 2020; Punel, Ermagun, and Stathopoulos 2018). However, a system-level approach that encompasses multiple aspects of the system to understand how the roles of sender and carrier agents are connected has not been performed. It is necessary to study the interactions between agents as well as the system as a whole to understand the impact that various built-environment factors and agent behaviors have on long-term network effects.

The research described in Mittal, Krejci, Oran Gibson, and Marusak (2021) pioneered the exploration of interactions between heterogeneous entities within a crowdsourced system by developing the first ABM model to capture both the sender and carrier perspectives in a crowd-shipping system. The purpose of their research was to better understand how a platform could achieve a critical mass of senders and carrier crowd participants to satisfy the networks effects that are necessary for a platform to grow and thrive. The preliminary experimental results demonstrated that increasing the initial participation levels does not necessarily lead to a uniformly better system performance over time, but maintaining the right ratio of carriers to senders is critical to success (Mittal et al. 2021).

The purpose of the models described in this thesis is to extend the previous work by using ABM to study multiple regions of a city to determine which district displays the most promising potential of success in implementing a food rescue startup via a crowdsourced delivery scheme. In the models described in this thesis, the heterogeneity of restaurant agents plays a role, including their densities, types, and how they are geographically situated with respect to crowd-shippers. These models also incorporate multiple empirical datasets to represent a more accurate system to further evaluate the effects of geography (geographical region, crowd-shipper and restaurant locations), resident demographics, travel times, population densities, and crowd-shipper social networks on the success and longevity of the system. The literature on crowd-shipping initiatives indicates that they are often unsuccessful, and many dissolve within months of launch. Thus there is a need for a systematic way to better understand which factors contribute the most to the success of crowd-shipping systems. This research is particularly important for crowd-shipping platform designers, helping them to have a better understanding of the intricacies of what could make or break their new endeavor.

2.2 Geospatial Agent Based Models

Over the years, researchers and practitioners alike have used geospatial simulations to analyze complex systems, including urban development, policy planning, land cover issues, traffic patterns, and transportation models. Geospatial simulations are models that have location-dependent features, where changes to locations can yield changes in model results (Castle and Crooks 2006). For decades, cellular automata and agent-based modeling have been used to represent individual-level phenomena in geospatial models (Castle and Crooks 2006). Agent-based modeling in particular is attractive for geospatial and transport models because of its ability to model people and objects realistically (Anand et al. 2016; Castle and Crooks 2006). However, aspects of such models are often abstracted to accommodate computational requirements, which can potentially compromise the model's validity, with respect to the real-world systems they represent.

The smallest level of geographic detail captured in the model environment defines the fidelity of its spatial resolution, which translates directly to the spatial scale of the system. For example, if the spatial scale of the system under study is at the neighborhood level, the model must realistically capture the intrinsic behaviors of neighborhoods. Likewise, the temporal resolution is defined by each discrete time step for which the model records information (e.g., months or years), and the time scale reflects the overall time period for which system behavior is captured. The relationships established between the temporal and spatial scales and the model agents determine how realistically the real-world environment is represented in the digital workspace (Castle and Crooks 2006). However, establishing appropriate spatial and temporal scales can be challenging, especially when modeling a system that contains complex interactions that cause it to evolve, since small fluctuations in the model scales can drastically impact model outputs (Heppenstall et al. 2016). Therefore, it is critical to determine a proper balance between spatial and temporal resolutions, and to understand how expanding them will impact model design.

Transport models naturally revolve around space and time, yet the spatial relationships are often highly abstracted (Dueker and Peng 2007). For example, NetLogo's embedded coordinate system corresponds to the number of cells in each dimension. This may be appropriate for abstract models, but when agents' movements depend on their position within a particular spatial setting, using geospatial input data is necessary (Mayrhofer 2015). The recent uptake in integration of Geographic Information Systems (GIS) into transport models and modeling software has increased the capabilities of capturing and managing spatial data that is scalable, dynamic, and adaptable. However, accurate, timely, and dynamic data is rarely implemented in agent-based models (ABM) of traffic demand, emergency evacuation, and pedestrian networks (Loidl et al. 2016). The computational power necessary to store and manage this complex data can lead to extended processing times. Furthermore, a lack of standardization around the optimal use of spatial data sets, a lack of access to suitable data, and cost associated with capturing complex dynamic sets hinder the utilization of quality data in transport models (Loidl et al. 2016). Thus, one of the major challenges of transport models is striking a balance between generality, realism, and model validity (Loidl et al. 2016). In particular, artificial closure and spatial scale of the modeling environment can affect the emergent properties displayed by agents, potentially yielding an unrealistic picture of global behavior (Batty and Torrens 2001).

This paper describes how integrating real-time spatial datasets into an agent-based transport model can improve the spatial scaling of the simulation environment to better represent the true system. In particular, this paper presents a new and systematic approach to defining realistic travel boundaries for agents based on travel times. The model described in this paper has been developed and refined over time via an iterative approach, in an effort to improve its integrity. According to Bert et al. (2014), if each progression taken in model development incorporates and documents additional empirical data that strengthens the accuracy of underlying assumptions, the model will transform to concretely represent the true system and become more useful and less disputed in practical applications. Researchers have stressed the importance of structured conceptual mapping in the initial stages of model development such that the relationships described between agents are verified and validated (Anand et al. 2016; Hansen et al. 2019). However, there is no consensus on how validation of agent behaviors and their environment should occur between each iteration of model development (Hansen et al. 2019). This work presents an iterative methodology that supports the evolution of model development from an abstract description to a more authentic representation of a real-world transport system that can be used to investigate and predict the performance of a crowd-shipping system in various regions.

3 MODEL OVERVIEW

The purpose of the ABM described in this paper is to explore the potential of a volunteer-based crowd-shipping system for rescuing surplus meals from restaurants and delivering them to homeless shelters in the city of Arlington, Texas. The ABM, developed in NetLogo, encompasses two agent types: crowd-shipper agents and restaurant agents. In each daily time step, restaurant agents located within the modeled region decide whether they will donate surplus food, and potential crowd-shipper agents decide whether they will volunteer to pick up surplus food from the restaurants and deliver it to a homeless shelter. A restaurant agent can participate in the donation program at most three times per week based on four primary motivational factors: their sustainability goals, financial considerations, liability concerns, and past experiences associated with successfully finding a crowd-shipper in previous time steps (Mittal et al. 2021). If a restaurant agent decides to donate in a particular time step, then the delivery is assigned to one of the four homeless shelters randomly. Similarly, crowd-shipper volunteers can choose to participate in the program at most once a week, and their participation is influenced by four primary motivational factors: preference for novel experiences, social life, altruism, and past experiences with the food rescue program (Mittal et al. 2021). If a crowd-shipper agent decides to volunteer, it will select a particular delivery assignment based on total trip duration. An overview of the restaurant and crowd-shipper agents' decision logic is presented in Figure 1 below.

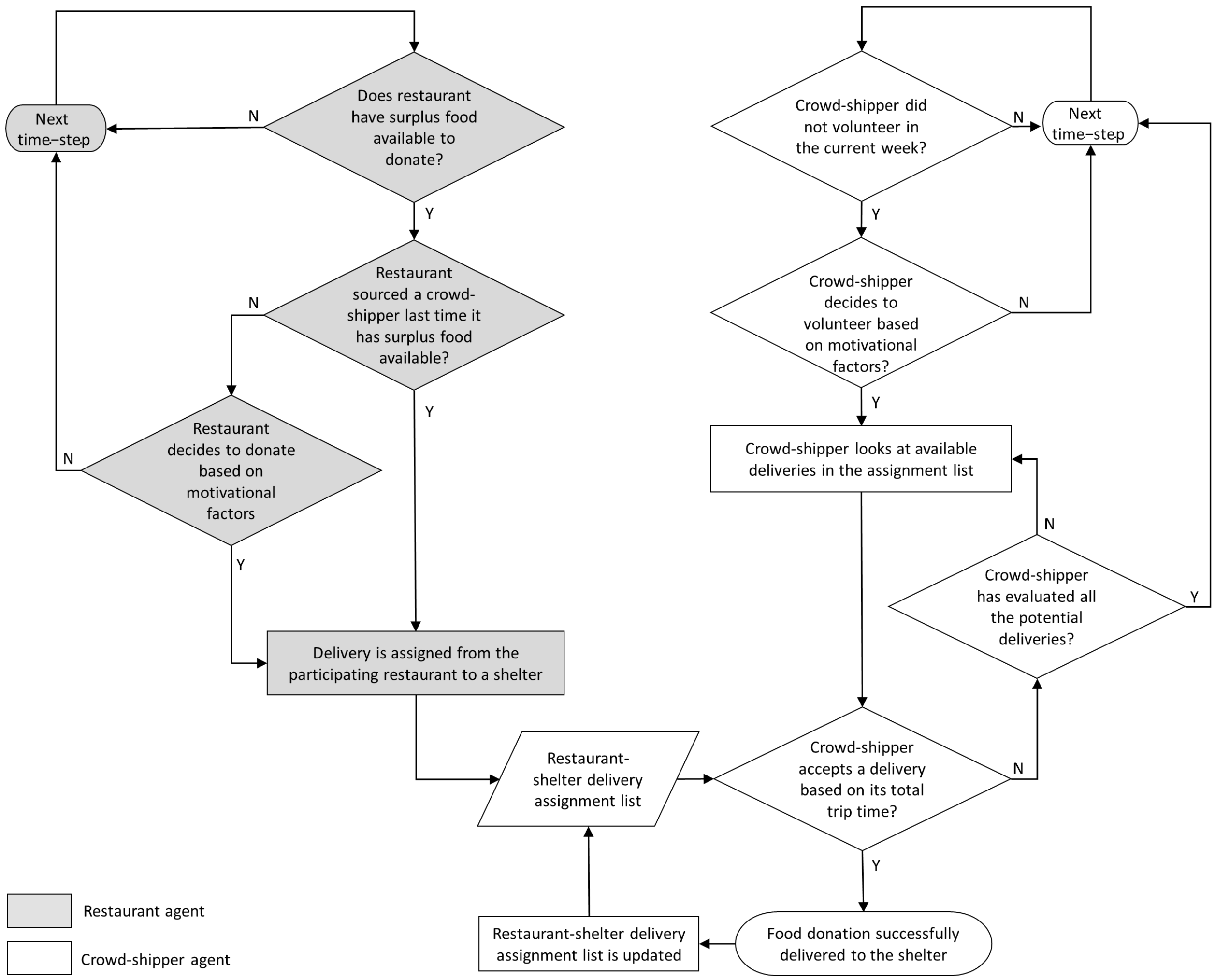


Figure 1: Restaurant and crowd-shipper agents decision-making logic

The city of Arlington consists of 84 census tracts, housing 259 individual block groups. A block group is the smallest geographic unit for which the US Census Bureau publishes data, and thus is used to set the spatial scale of this model (*Census Block Groups and Block Group Codes* 2021). Crowd-shipper agents are assigned demographic characteristics that correspond to the block group in which they reside, according to 2017 US Census Bureau statistics, including age, gender, ethnicity, education attainment, and annual income. Geocoding services via the US Census Bureau were used to collect data to determine which census tracts and block groups were associated with certain restaurants and shelters, according to their street addresses (*United States Census Bureau* 2021).

In this model, potential crowd-shipper agents that are not currently involved in the program can be motivated to participate based on their interactions with other crowd-shipper agents that have already adopted the program. These interactions allow the system to grow over time and enable participating crowd-shippers to influence nonadopters. A large body of research demonstrates that people typically share more connections at the local level (i.e. close geographic proximity) than at the non-local level, which is often depicted in ABM as a small world network structure that is scalable to the model space (Rai and Robinson 2015). This model uses a small world social network structure generated using random interactions in which crowd-shipper agents are connected and can be influenced by other agents that belongs to the same social network.

4 EVOLUTION OF CROWD-SHIPPING ABM DEVELOPMENT

The model described in the previous section has been developed iteratively over time in order to reduce the level of abstraction in the model. Figure 2 shows how empirical data was incrementally incorporated at each iteration of model development to strengthen underlying assumptions. This section will provide a detailed explanation of each iteration.

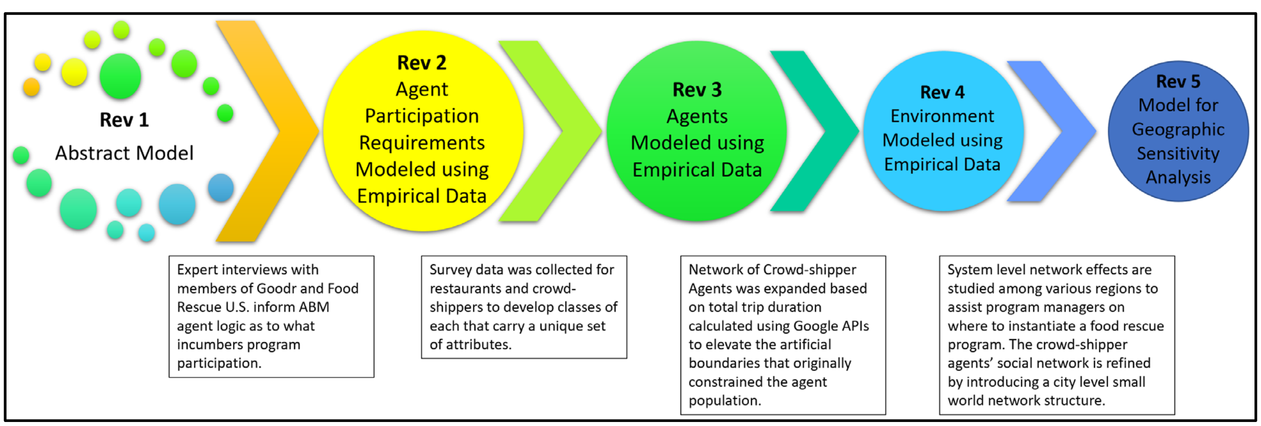


Figure 2: Summary of the evolution of crowd-shipping ABM development

4.1 Abstract Model: Rev 1

The abstract ABM (Rev 1) on which this research is based was first presented at the 2019 Winter Simulation Conference (Mittal et al. 2019a). This version of the ABM depicts the crowd-shipping network for a single census tract (tract 1224), which is composed of 5 census block groups containing 18 restaurants and 4,579 crowd-shipper agents, as well as four homeless shelters located outside census tract 1224.

Although motivational factors that informed whether agents participate in the food rescue program were derived from the literature, the model does not account for the factors that would cause restaurants and crowd-shipper agents to cease participation in the program (i.e., if they decide to participate, it is assumed that they continue to do so indefinitely).

4.2 Rev 2

The next iteration in model development (Rev 2) sought to improve the realism of the restaurant and crowd-shipper agents' decision-making constructs by incorporating empirically-derived factors that would influence their long-term participation in a food rescue program (Mittal et al. 2019b). Empirical data was collected via interviews with experts involved with existing food rescue programs, including Goodr and Food Rescue US. Goodr is a for-profit company that leverages commercial crowd-shipping services to distribute surplus restaurant food among non-profit organizations in Atlanta, Georgia. The interview with Goodr provided insights into the challenges restaurants face with respect to surplus food donation. Food Rescue US is a non-profit organization operating in 17 US cities that utilizes an app to recruit volunteers who are willing to pick up surplus food from local donors and deliver it to agencies that serve people suffering from food insecurity. The interview with Food Rescue US provided information about factors that could hinder volunteer crowd-shipper participation.

Takeaways from both interviews provided the basis for agents' decision logic on terminating their participation in the program: restaurant agents cease participation if they experience three consecutive failed pick-ups from crowd-shipper agents, and crowd-shipper agents stop participating if they were willing to volunteer three times consecutively but were unable to do so as a result of insufficient restaurant participation. The Rev 2 model was used to evaluate the potential of such a program to grow and sustain itself over time, in terms of maintaining sufficient and balanced crowd-shipper and restaurant participation; however, it only represents a small geographic region (census tract 1224), and some of the agents' decision logic was still based on the modelers' assumptions.

4.3 Rev 3

The next iteration of the model (Rev 3) integrated two empirical data sets that were used to better understand the motivating factors of restaurants and volunteer crowd-shippers (Mittal et al. 2021). A comprehensive list of all 1,066 foodservice establishments located in Arlington was requested from the city. Initially, this list was sorted into four categories (single location, multi-location, institutional, and entertainment), to reflect the authority granted to each establishment to make autonomous decisions on food donation policies. Single-location restaurants are defined as establishments that lack affiliation with other organizations, whereas multi-location restaurants have several locations owned by a managing company. The establishments that were categorized as entertainment and institutional were excluded, based on the assumption that they did not have enough authority to make independent decisions regarding the donation of surplus food. Thirty-nine restaurants located in the city of Arlington were surveyed on their willingness to donate food, perceived challenges to donation, and how decision-making authority is structured in their organization. The survey results indicated that single-location restaurants have direct authority to make decisions about the donation of surplus food, while over half of multi-location restaurants would require consent from a managing authority (e.g., corporate headquarters) before commencing participation. This logic was incorporated into the model by requiring multi-location restaurant agents to wait 12 weeks after being invited to participate in the food rescue program before actively requesting donation pick-ups. In addition, the survey results revealed that single-location restaurants were more motivated to donate in effort to support their local community, while multi-location restaurants were frequently motivated by financial reasons. Therefore, single-location restaurant agents were assigned greater significance on the “sustainability” motivational factor in their decision logic function. Based on survey results, factors representing liability concerns and transportation constraints were also incorporated into the restaurant agents’ decision logic.

The crowd-shipping agent decision-making logic was also refined, using survey data from 300 food rescue volunteers in Texas (Mousa and Freeland-Graves 2017). The survey included demographic questions and also inquired about four factors that motivated participation: “service requirement,” “novel experience,” “social life,” and “altruism.” The survey data was clustered using Ward’s method of hierarchical clustering on age, annual income, and motivation to volunteer. Four distinct clusters emerged, and each was used to create a unique crowd-shipper agent persona: students/new graduates, young professionals, mature professionals, and retirees. Each persona was used to translate behavioral representations indicative of the persona to the agents. For example, retiree agents have more flexible pickup time windows and are more willing to accept longer trip assignments because they have more time available to volunteer. The demographics from the Census Bureau data and the four personas were used to proportionally upscale the crowd-shipper agent population to realistically represent the true population. Finally, the total eligible crowd-shipper agent population was reduced to 23% of the total resident population of census tract 1224, because on average, 23% of Texas residents volunteer (National and Community Service 2019). Additionally, the small world social network structure was executed at the local level, and represented by neighborhoods, corresponding to the five census block groups in the model. Crowd-shipper agents were qualified to establish local connections with other crowd-shipper agents within the block group in which they reside.

4.4 Rev 4

In Rev 4, the geographic scope of the modeled region of interest is increased, and the eligible crowd-shipper agent population is determined based on total trip time, rather than census tract boundaries. This revision was made to better reflect reality: residents travel throughout a city without attention to census tract positioning, and therefore it is unrealistic to assume that only residents within a particular census tract are the only individuals who are willing and eligible to volunteer.

A crowd-shipper's trip includes three legs: driving from the centroid of the census block group in which it resides to a donor restaurant, then driving to a shelter to deliver the donated food, and finally returning to its origin. In Rev 3, the modeled region is a single census tract containing five block groups. Because this region is relatively small, it was reasonable to assume that any crowd-shipper residing within the census tract would be eligible to pick up donations from any of the 16 donor restaurants and deliver to any of the 4 shelters located within the region.

By contrast, the geographic region modeled in Rev 4 extends to the entire Arlington City Council District 2, encompassing five census tracts totaling 11 block groups and 65 restaurants. While it would be convenient to use the District 2 boundary as a proxy for the boundary for crowd-shipper agents that are eligible to make trips within District 2, this assumption is likely unreasonable: a census block group from a neighboring district might actually be closer in proximity to a particular District 2 restaurant than a block group located within District 2. Figure 3 illustrates this concept. District 2 is represented by the shaded green region, while potential donor restaurants are represented as blue triangles and each orange circle depicts a census block group centroid. The figure indicates that crowd-shippers located in the census blocks north of Interstate 20 would be closer to pick up from restaurants just south of the interstate than those located in the far south of District 2.

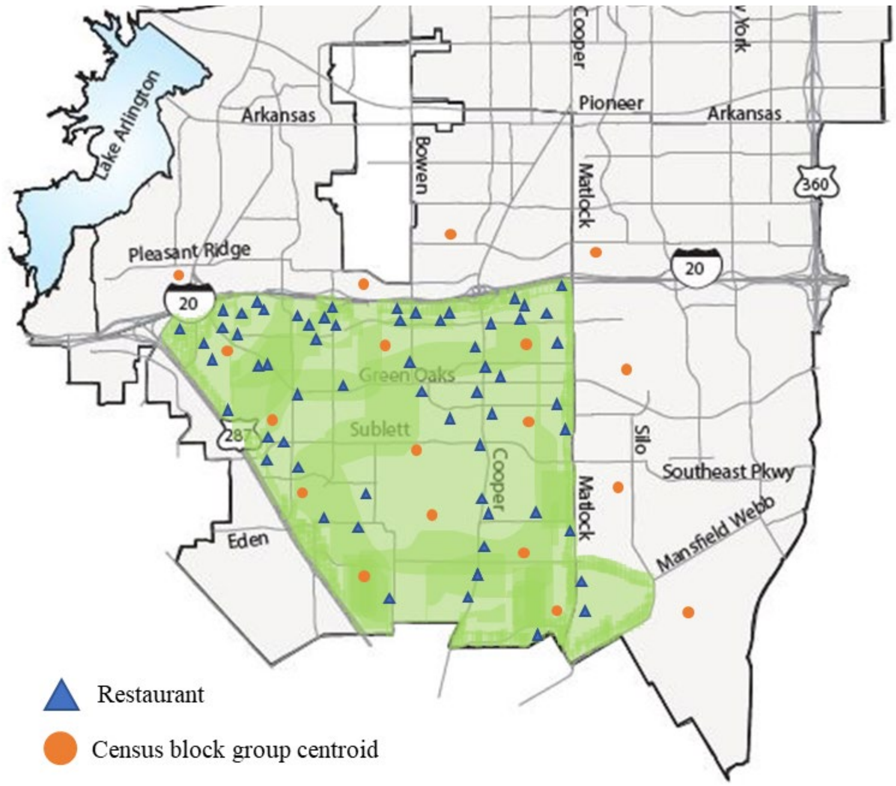


Figure 3: Potential eligible crowd-shipper agents in neighboring regions

Therefore, it was necessary to define criteria for determining which residents were eligible to make particular trips. This approach also had to be sufficiently generalizable to be easily adapted to other regions of interest. Taking this into account, crowd-shipper agent eligibility is instead determined based on total trip time, which is grounded in data extracted using Google Maps APIs. A demonstration of this methodology as applied to a single district of the city of Arlington is described after the model evolution section.

4.5 Rev 5

In the most recent version of the model (Rev 5), the crowd-shipper agent population was modeled differently to increase the model's realism. The system was still simulated at the district level; however the entire population of Arlington was considered as the potential crowd-shipper agent pool, resulting in a total of 308,939 agents. The effects of this change were two-fold: 1) this allowed the top 23% of all residents

(71,052 agents) to be eligible to perform deliveries based on total trip time regardless of district, and 2) enabled a more authentic representation of the interactions between crowd-shipper agents to be accounted for in the model through a small-world social network structure.

Crowd-shipper agent eligibility was still constrained by total trip time. Total trip duration was based on the summation of each of the three segments of the crowd-shipper's trip. A restaurant agent was considered as a potential participant as long as it was located in the district under consideration. Table 1 below displays the total number of restaurant agents and eligible crowd-shipper agents for each district for total trip durations of 20, 25, and 30 minutes. It is meant to provide an example of the variation in the number of eligible crowd-shipper agents as total trip duration is decreased. For most districts, the eligible crowd-shipper population is cut in nearly half when the allotted trip time is reduced from 30 to 20 minutes.

Table 1: Restaurant and crowd-shipper agent population per district based on total trip duration

		Total eligible crowd-shipper agents		
District	**Total restaurant agents**	**30 minutes**	**25 minutes**	**20 minutes**
1	195	66,516	53,860	35,699
2	94	54,283	27,185	8,690
3	65	65,409	48,009	20,175
4	185	68,222	52,121	24,620
5	182	71,048	63,690	43,019

One advantage of the Rev 5 ABM is that the eligible crowd-shipper population is derived from the entire resident population of the city of Arlington. Although only the best 23% (71,052 of 308,920 agents) are considered as eligible to participate as crowd-shippers, the demographics for all 308,920 agents were used as an input into the model. By leveraging the city wide demographic attributes, a crowd-shipper's small-world social network could be designed more realistically. In previous versions of the model it was assumed that crowd-shipper agents could only interact with other crowd-shipper agents from their neighborhood (i.e. census block group). However, in reality people interact with other people in the city (e.g. at work, school, clubs, etc.) and not only their neighbors. The small world social network structure allows for a majority of social links to occur locally and a minority to be established nonlocally. By modeling the entire resident population, crowd-shipper agents in Rev 5 can connect and interact with other crowd-shipper agents within close geographic proximity from their corresponding census block group as well other agents throughout the city within their cluster (designated by age and income). In other words, each agent that was aware of the program already was allowed to connect with a specified number of other agents inside their region and outside their region but within their cluster. Hence adopters of the program can influence nonadopters at both the local and nonlocal levels, enabling further growth to the program.

However, NetLogo is notorious for struggling to run large complex models in a reasonable amount of time (Railsback et al. 2017). Instead of increasing runtime by forcing NetLogo to create all the links for each agent during the simulation, the crowd-shipper social network links were established as attributes in the input data set. Since the computational time required to establish the social network links would increase exponentially as more crowd-shippers become aware of the program, eliminating the need for links to be established throughout the simulation run could be one alternative to reduce runtime. The data preparation methodology described in the next section was initially utilized in Rev 4 and then tailored to accommodate the larger data set used in Rev 5.

5 DATA PREPARATION METHODOLOGY

The data preparation methodology to select the eligible crowd-shipper population is grounded in integrating GIS data into the ABM. Integrating GIS data within the modeling paradigm enables a realistic environment to capture agent movement that resembles that of humans (Groeneveld 2011). NetLogo coupled with its GIS extension allows geographic coordinates to be read in from an input dataset; however, the modeled environment must be resized to correspond to the imported coordinate system (Mayrhofer 2015). This is a feasible approach when all distance calculations are computed internally within the model.

By contrast, the approach taken in the crowd-shipping ABM (Rev 4 and 5) uses Google Distance Matrix APIs to precompute the shortest path for crowd-shipper agents' trips. The implementation of the Google APIs offers two main advantages. Firstly, deriving the shortest path for all unique pairs of origin and destination points on a crowd-shipper's route before running the model allows each path to be predetermined and the subset corresponding to the region of interest loaded as an input in the ABM, resulting in decreased model runtime. An additional benefit of this approach is incurred when running the ABM for a different region of interest, since more data would not have to be fetched to re-compute the shortest paths for the new region. Secondly, NetLogo employs a single-source shortest path selection, such as Dijkstra's algorithm, which takes less time to run than other shortest path algorithms, but generates fewer shortest path combinations (Groeneveld 2011). The Google Distance Matrix API computes an average travel time for each segment of a path, and by generating all potential combinations of segments over a specific path, the actual shortest travel distance is computed contingent on time. Therefore, when compared to other shortest path algorithms, leveraging the Google Distance Matrix API returns the best route when given a specific origin and destination point (Charoenporn 2018).

Figure 4 shows the six steps that comprise the approach that was taken to determine the total eligible crowd-shipper agent population for Rev 4 and 5 of the ABM, which are described in detail below.

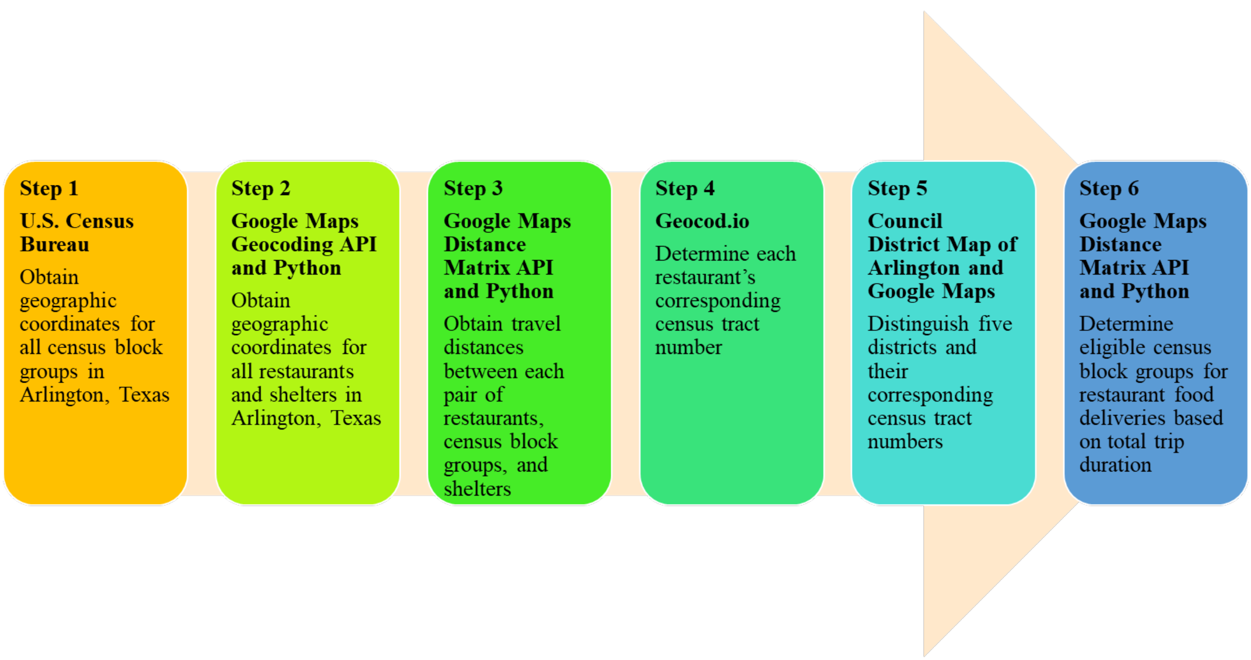


Figure 4: Summary of data preparation methodology for Rev 4 in crowd-shipping ABM development

Step 1 - First, the latitude and longitude coordinates for each of the 259 block groups in the city of Arlington were extracted from 2017 US Census Bureau data (*United States Census Bureau* 2021). Each pair of geographic coordinates represents the population centroid of its corresponding block group. It is assumed that all crowd-shipper agents within a particular block group are located at the population centroid. Although this assumption may not capture actual individual resident locations, the block group centroid is commonly used as a point of origin in distance calculations (Biba et al. 2010). The locations of the centroids are used in subsequent steps for determining accurate average travel times.

Step 2 - Google Maps Geocoding API using a Python script were then used to extract the latitude and longitude coordinates of each of the 721 restaurants and four shelters located in Arlington according to their physical street addresses (*Google Maps Platform Geocoding API* 2021).

Step 3 - Using the geographic coordinates for each census block group centroid, restaurant, and shelter, a Google Maps Distance Matrix API was leveraged via a Python script to obtain the travel distances between all unique pairs of locations (*Google Maps Platform Distance Matrix API* 2021). The resulting travel distances are needed to determine accurate travel times for crowd-shippers on each segment of their routes.

Step 4 - Geocodio was used to determine in which census tract in Arlington a restaurant was located. The Geocodio software and their RESTful API enables both forward and reverse geocoding lookups (*Geocodio* 2021). It is assumed that only restaurants in the modeled region of interest are permitted to join the donation program; therefore, it is necessary to know which of the 721 total restaurants are located in the region of interest and should be included in the model.

Step 5 - The next step was to determine the boundaries for the larger geographic region. Rev 4 expands the geographic region of the ABM by partitioning Arlington into five City Council Districts. Google Maps and the map of the districts published on the City of Arlington website were used to determine which census tracts are located in each district (*District Map* 2021). Although these boundaries were not used to constrain the selection of eligible crowd-shippers, it was assumed that only restaurants located in the census tracts within the district of interest would be modeled as restaurant agents in the ABM.

Step 6 - Finally, a Python script was used to establish the total eligible crowd-shipper agent population to be included in Rev 4 and 5 of the model. The API enables accurate estimation of travel times by averaging real-time traffic data to determine the time required to travel from one location to another under light, normal, and heavy traffic conditions. Commonly, people use travel duration, rather than distance, to determine their willingness to make a trip. According to the interview with Food Rescue US, trips are planned such that they take less than 30 minutes to complete, in order to increase the likelihood of volunteer crowd-shipper participation. Therefore, it was assumed that a crowd-shipper agent would not accept a trip assignment if the expected completion time was 30 minutes or longer. It was also assumed that a crowd-shipper agent would spend five minutes at both the restaurant picking up the donation and at the shelter dropping it off. Hence, the total driving time must be less than 20 minutes for the trip to be acceptable.

Rev 4- The travel distances for each of the individual trip segments that were calculated in Step 3 were then combined to determine the durations of every possible combination of roundtrips originating from and ending at each census block group centroid. With 721 restaurants, 259 census block groups, and 4 shelters, there were approximately 1.2 million possible combinations. Python script was used to generate these combinations and output the census block group number (1 to 259), restaurant number (1-721), shelter number (1 to 4), and total trip duration (in seconds) for each unique combination. This output was then filtered to eliminate any combinations having a total trip time longer than 20 minutes. The list of remaining feasible trips could then be used to identify the eligible crowd-shipping agent population for a given district.

Rev 5- The data to determine eligible crowd-shipper agents for Rev 5 was prepared similarly to Rev 4 in the previous steps, but Step 6 was modified to reduce model runtime for the city level population, as well as prepare a single dataset that could be used to model any desired region. The travel distances for each of the individual trip segments that were calculated in Step 3 were recorded and loaded as an input into the model prior to initialization. During the simulation, NetLogo was then used to compute the unique travel durations for each of the possible combinations that included a restaurant in the particular district being modeled, and next filtered out those crowd-shipper agents with a total trip duration that exceeded the allotted time. As in Rev 4, the list of remaining feasible trips was used to select the eligible crowd-shipper agent population for a given district.

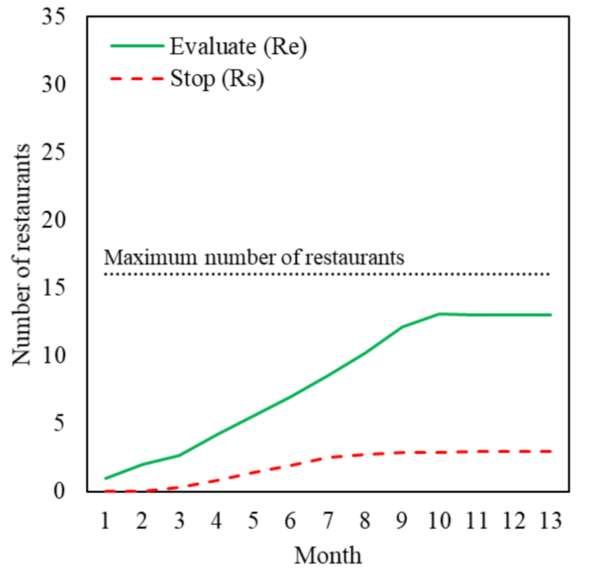
By these methods, the constraint of selecting crowd-shipper agents from a single census tract that existed in previous versions of the ABM is relaxed to consider eligible crowd-shipper agents from neighboring census tracts, thus reflecting a more realistic portrayal of the potential crowd-shipper population.

6 EXPERIMENTS, RESULTS, AND DISCUSSION

The Rev 4 version of the model was used to investigate the effects of expanding the geographic region of participating restaurants to City Council District 2, as well as considering residents from District 2 and its neighboring census block groups as potential crowd-shippers. District 2 was chosen for preliminary experimentation, since it is the smallest of the five districts. The following metrics were captured in each time-step: restaurant agents currently evaluating participation in the program, restaurant agents that stopped participating in the program, crowd-shipper agents currently evaluating participation, and crowd-shipper agents that stopped participating. Intuitively, by increasing the size of the modeled region and thus increasing the number of potential crowd-shippers, it was expected that more delivery requests would be fulfilled, thus increasing crowd-shipper and restaurant agent participation over time. However, prior experimentation with Rev 3 demonstrated that if there is not an adequate balance of restaurants to potential crowd-shippers, the system will not be able to sustain itself, due to a lack of participation from one side of the network (Mittal et al. 2021). For the sake of this analysis, the behavior of the system is compared to experimental results from Rev 3 since a volunteer food rescue program does not exist in Arlington and therefore outputs cannot be compared to empirical data.

In Rev 3, the model encompassed a single census tract, 16 restaurants agents, and 1,053 crowd-shipper agents centrally located in five census block groups. There was no constraint placed on trip distance or travel time for the crowd-shipper agents to complete their trip. In Rev 4, the model encompasses all of District 2, which houses 65 restaurants and 11 census block groups. After introducing the 20-minute total trip duration constraint, 6,367 potential crowd-shippers were found to be eligible from 26 census block groups within and adjacent to District 2. However, only 33 of the 65 restaurants were eligible to participate – the remaining 32 restaurants were too distant from the eligible crowd-shippers' origins to meet the 20-minute transport duration constraint. For the experiments presented in this paper, all other input parameters were held constant between Rev 3 and Rev 4. Also, similar to Rev 3, model was run for 100 replications of 364 daily time steps.

Results for Rev 3 yielded a system that was successful and viable over the course of one year, in terms of both restaurant and crowd-shipper participation (Mittal et al. 2021). This can be observed in Figure 5 and Figure 7. The system is considered to be successful because the number of restaurants that continue to evaluate participation over the course of one year exceeds the number that stop participating, and the number of crowd-shippers that continue to evaluate participation and those that stop participating remain balanced throughout the course of the year. By contrast, the results of the same experiments with Rev 4 (shown in Figure 6 and Figure 8) indicate that the program is unsuccessful because it does not continue to grow over the course of the year. In fact, number of restaurants that cease participation outweighs the number that continue to participate after the sixth month.



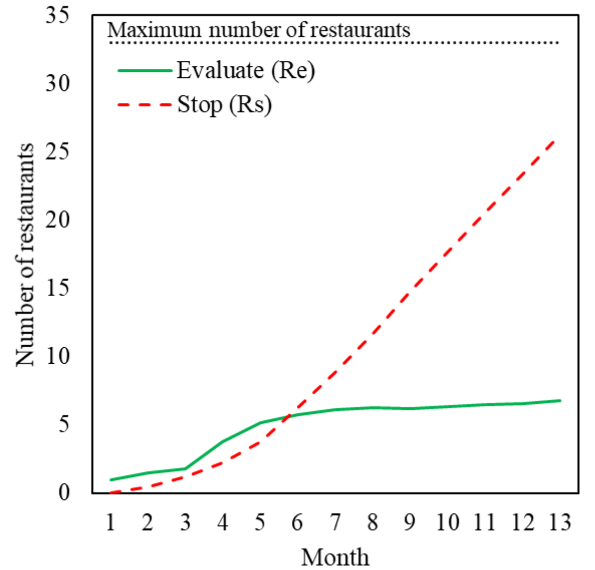
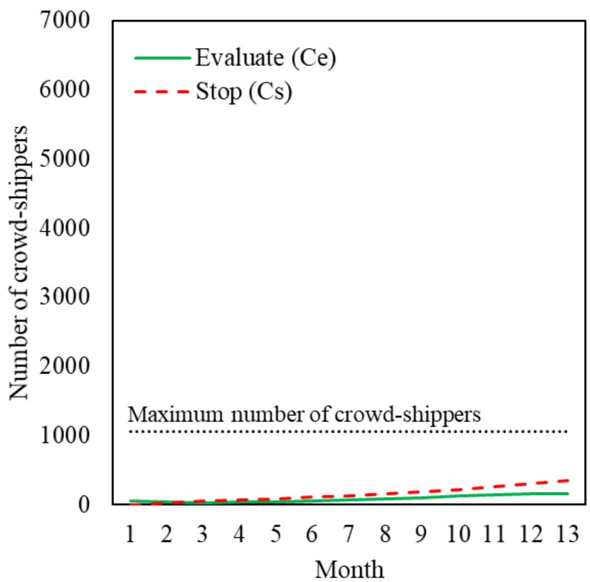


Figure 5: Number of restaurants evaluating (R_e) and stop participating (R_s) in Rev 3.

Figure 6: Number of restaurants evaluating (R_e) and stop participating (R_s) in Rev 4.



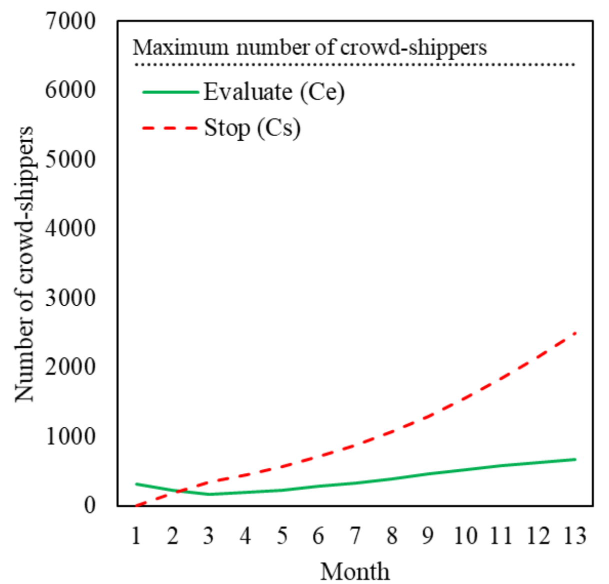


Figure 7: Number of crowd-shippers evaluating (C_e) and stop participating (C_s) in Rev 3.

Figure 8: Number of crowd-shippers evaluating (C_e) and stop participating (C_s) in Rev 4.

The observed results are due to the fact that even though restaurant agents are willing to donate at a certain time step, there are no crowd-shipper agents available within the constrained proximity to make the requested pick-up and delivery. Consequently, restaurant agents cease participation in the program because their requests for delivery are not being assigned to crowd-shipper agents, and crowd-shipper agents stop participating because they cannot accept deliveries. It was observed that very few crowd-shippers from the enlarged pool were actually qualified to make deliveries, given the new constraint of being limited by travel distance and time. In addition, the location of crowd-shipper agents in relation to restaurants and shelters plays a critical role in system success. If the potential crowd-shipper population is denser in one area of a district while significant restaurant density is elsewhere, then accepting donations from restaurants might be infeasible due to the time required to complete the trip. Moreover, since all shelters are located on the north side of Arlington, a district that is too far from the shelters will yield very few crowd-shippers that qualify to make the deliveries because the trip duration is too long. The preliminary experiments with the Rev 4 version of the model have provided some insights into the extent to which geographical conditions can impact the viability and longevity of a crowd-shipping network. The system was successful for a smaller region of interest (Rev 3), however, the results from Rev 4 suggest that expanding the region of interest while constraining crowd-shipper's allotted trip duration diminished the system's performance. Therefore, a thorough geographic sensitivity analysis is warranted to decipher which factor explicitly has the greater effect on model performance.

The Rev 5 version of the model was used to assess which districts would be most and least favorable to implement a food rescue program in Arlington. Rev 5 was initially developed to understand the impact that the crowd-shipper's social network has on network effects and system performance. As such, crowd-shippers that were aware of the program upon model initialization were allowed to interact weekly with three other agents within their region and two others outside their region. Likewise, in subsequent time steps any crowd-shipper agent that was aware of the program was allowed to interact weekly with other agents under the same conditions. This resulted in an exponentially increasing computation time in every seventh time step. Implementing a social network to facilitate agent interactions yielded a model with an exorbitant runtime, taking approximately 13 hours to complete a single iteration. Therefore, crowd-shipper's social networks and interactions with other crowd-shipper agents were omitted for further experimentation with the Rev 5 model. However, as determined in Rev 3, a critical mass of both restaurant agents and crowd-shippers agents is necessary for the system to be successful. As a result of omitting the interactions among crowd-shipper agents, the ability for information to be diffused between crowd-shippers and the awareness of the program to rise over the course of the year was now excluded from the model. To account for this, the initial percentage of the eligible crowd-shipper population that knows about the program upon model initialization was experimentally varied. Likewise, the travel time allotted to crowd-shippers to make the trip was also varied to better understand the impact that crowd-shipper, shelter, and restaurant locations have on system performance.

City Council District 2 was selected as one candidate for experimentation such that the results could be compared to the preliminary analysis conducted with the Rev 4 version of the model. City Council District 5 was also selected for experimentation because it is located closest to the four shelters located in the north side of Arlington. It was hypothesized that this region would outperform District 2 due to the reduced trip time required to get from a restaurant located within that region to a shelter. In Experiment 1 the crowd-shipper's initial awareness about the program within the modeled region was increased from the 5 percent mark used in Rev 3 and Rev 4 experimentation to 10 percent, and a total trip duration of 30 (Experiment 1a) and 45 (Experiment 1b) minutes was allowed. Aside from increasing initial awareness of crowd-shippers and extending the geographic scope such that the best 23 percent of the entire population of Arlington was included as potential crowd-shippers, all other model parameters were held constant between Rev 3 and Rev 4. Table 2 below summarizes how different factors have been varied in the previous experiments and the ones to follow presented in this section.

Table 2: Summary of experiments

	Rev 3	Rev 4	Rev 5 Experiment 1a	Rev 5 Experiment 1b	Rev 5 Experiment 2a	Rev 5 Experiment 2b
Region under study	Census Tract 1224	District 2	District 2 District 5	District 2 District 5	District 2 District 5	District 2 District 5
Crowd-shipper initial awareness	5%	5%	10%	10%	15%	15%
Crowd-shipper total trip duration	None	30 minutes	30 minutes	45 minutes	30 minutes	45 minutes
Interactions between crowd-shippers modeled	Yes	Yes	No	No	No	No

Due to the size of the model and the runtime limitations, only five replications were executed for each region for Experiments 1 and 2. Results for Experiment 1a are given in Figures 9-12.

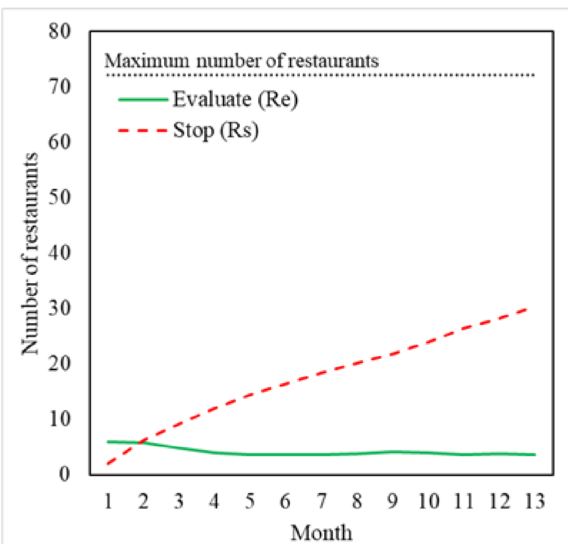


Figure 9: Number of restaurants evaluating (R_e) and stop participating (R_s) in Experiment 1a with 30 minute trip duration for District 2.

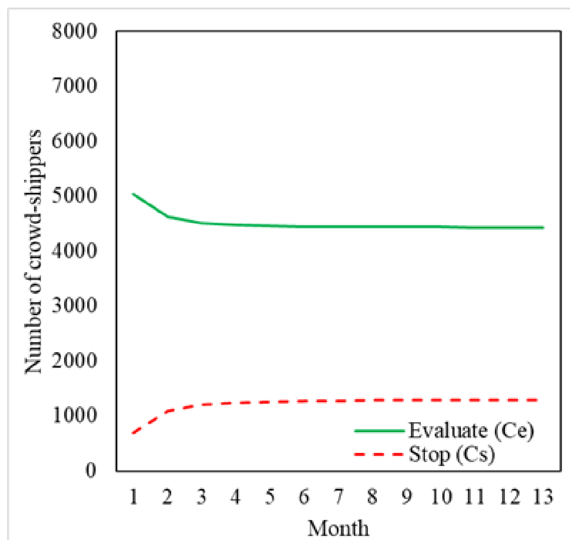


Figure 10: Number of crowd-shippers evaluating (C_e) and stop participating (C_s) in Experiment 1a with 30 minute trip duration for District 2.

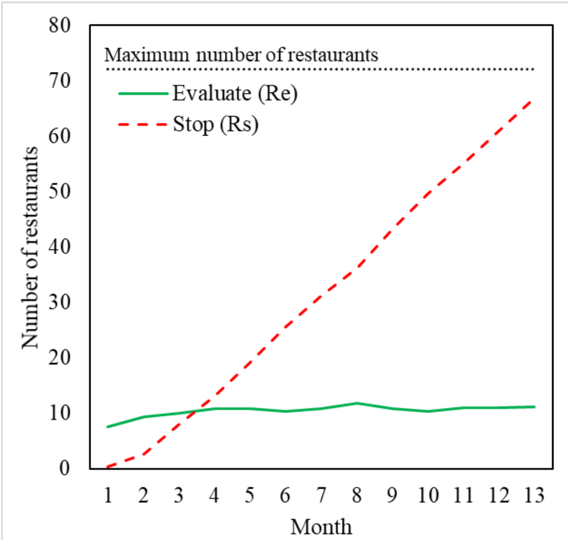


Figure 11: Number of restaurants evaluating (R_e) and stop participating (R_s) in Experiment 1a with 30 minute trip duration for District 5.

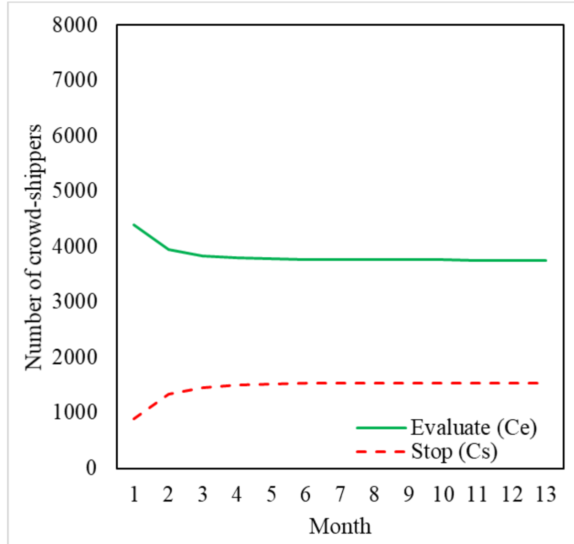


Figure 12: Number of crowd-shippers evaluating (C_e) and stop participating (C_s) in Experiment 1a with 30 minute trip duration for District 5.

Figures 9 and 11 show restaurant participation in the program over time for Experiment 1a. The results indicate that both District 2 and District 5 fail in the second and third months, respectively, due to a lack of restaurant agents that continue to evaluate participation in the program. This is due to the fact that restaurant agents are unable to successfully find crowd-shipper agents within their district to accept their delivery requests. In both districts, there is initial drop in the number of crowd-shipper agents because those that are willing to participate in the early stages of the program cannot secure a delivery due to the lack of restaurant agents enrolled in the program. Restaurants continue to be recruited over the course of the year, but many of the crowd-shippers have ceased participation prior to that point. Since crowd-shipper agents' awareness of the program is fixed within a region and interactions between them are not being modeled, awareness of the program cannot grow and attract eligible crowd-shippers from other districts. As illustrated in Figure 10 and Figure 12, crowd-shipper agent participation begins to stabilize as restaurant agents begin to discontinue participation. This suggests that there are still eligible crowd-shippers in the program, but they may be participating infrequently or there are not enough residing within a proximity close enough to the restaurants offering deliveries to allow them to complete the trip under the allotted travel duration.

In Experiment 1b, the allowable trip duration for crowd-shipper agents was increased to 45 minutes. The results are shown in Figures 13-16.

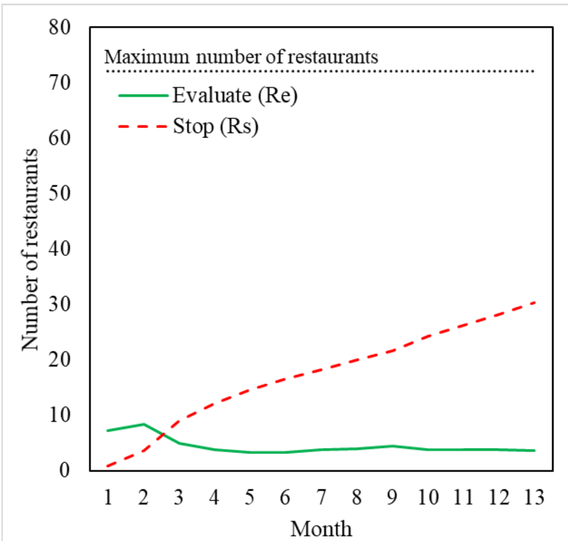


Figure 13: Number of restaurants evaluating (R_e) and stop participating (R_s) in Experiment 1b with 45 minute trip duration for District 2.

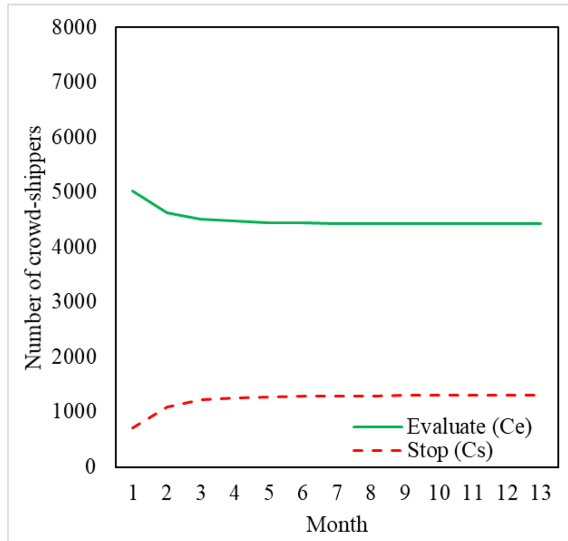


Figure 14: Number of crowd-shippers evaluating (C_e) and stop participating (C_s) in Experiment 1b with 45 minute trip duration for District 2.

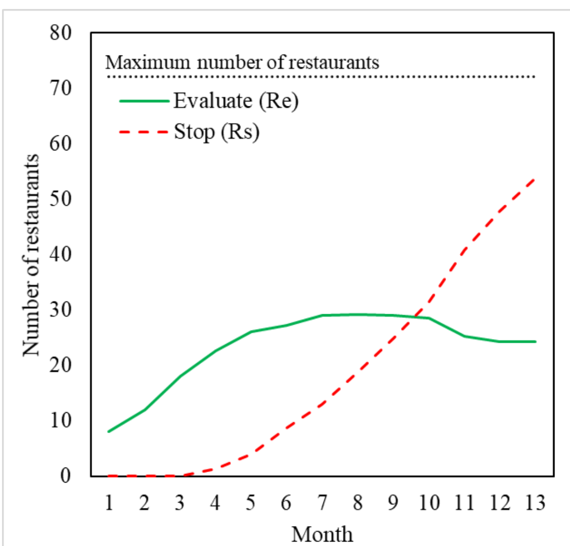


Figure 15: Number of restaurants evaluating (R_e) and stop participating (R_s) in Experiment 1b with 45 minute trip duration for District 5.

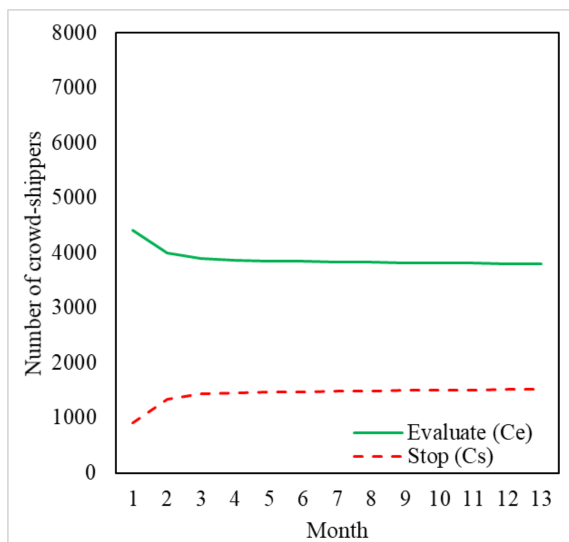
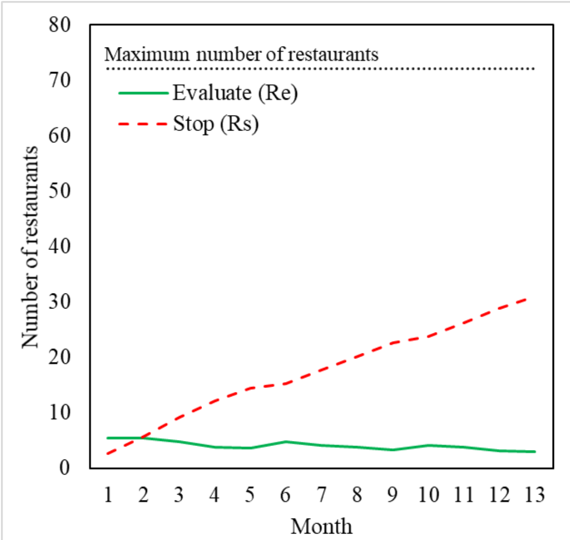


Figure 16: Number of crowd-shippers evaluating (C_e) and stop participating (C_s) in Experiment 1b with 45 minute trip duration for District 5.

It is still observed in Figure 13 and Figure 15 that the programs in both District 2 and District 5 are unsuccessful; however, District 2 fails much earlier than District 5, between months two and three versus months nine and ten. This is a consequence of the types of restaurants housed in each district. Sixty-five restaurants are located within District 2, as opposed to 182 restaurants in District 5. Moreover, restaurants are classified as either single location or multi-location, and it is assumed that single location restaurants can offer deliveries immediately after recruitment but multi-location restaurants must wait 12 weeks before commencing participation. Currently, four single location restaurant agents and two multi-location restaurant agents are recruited each month. However, District 2 only houses six single location type restaurants, and therefore after the second month no more single location restaurant agents can be recruited. As a result, there are insufficient restaurant agents participating in the early stages of the program to sustain growth, regardless of if they are able find a crowd-shipper agent to make the requested deliveries or not. Conversely, District 5 has 68 single location restaurants, and therefore single location restaurant agents can continue to be recruited over the course of the year. Figure 15 illustrates this growth through the ninth month. After month nine, the number of restaurant agents that stop participating steadily outweighs those that do as a result of not being able to locate eligible crowd-shipper agents within the region to fulfill requested deliveries within the allotted trip duration. Trends for crowd-shipper agent participation are similar to Experiment 1a for the aforementioned reasons, as shown in Figure 14 and Figure 15.

To further explore the importance of achieving a critical mass of participants, the initial awareness of the crowd-shippers was increased to 15 percent of the region's crowd-shipper population for Experiment 2. Again, the total allotted trip time was set to 30 (Experiment 2a) and 45 (Experiment 2b) minutes and District 2 and District 5 were modeled. Results are given in for Experiment 2a in Figures 17-20.



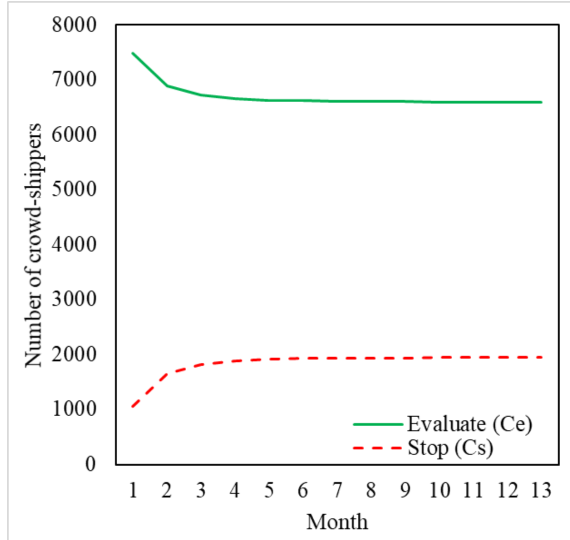
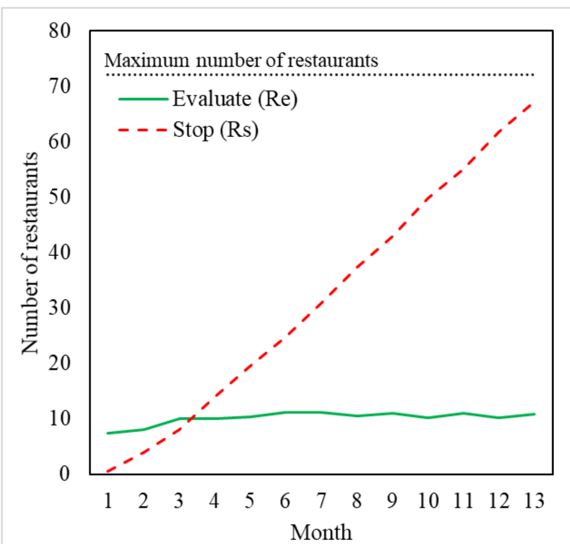


Figure 17: Number of restaurants evaluating (R_e) and stop participating (R_s) in Experiment 2a with 30 minute trip duration for District 2.

Figure 18: Number of crowd-shippers evaluating (C_e) and stop participating (C_s) in Experiment 2a with 30 minute trip duration for District 2.



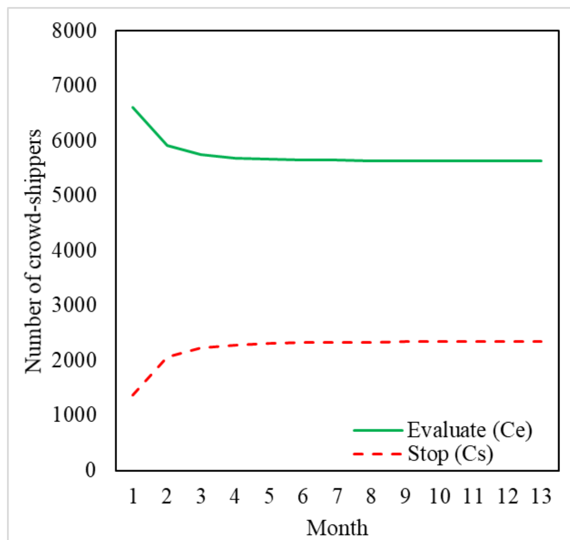


Figure 19: Number of restaurants evaluating (R_e) and stop participating (R_s) in Experiment 2a with 30 minute trip duration for District 5.

Figure 20: Number of crowd-shippers evaluating (C_e) and stop participating (C_s) in Experiment 2a with 30 minute trip duration for District 5.

The results of Experiment 2a are similar to those of Experiment 1 for District 2. The only difference is that since more crowd-shipper agents have been added at the onset of the program, more continue to evaluate over the course of the year, widening the gap between those that continue to participate and those that stop. This can be observed when comparing Figure 18 to Figure 10 . Likewise, the results for Experiment 2a for District 5 remain the same, yielding an unsuccessful system in the third month under a trip restriction of 30 minutes. The results for Experiment 2b are presented in Figure 21-24.

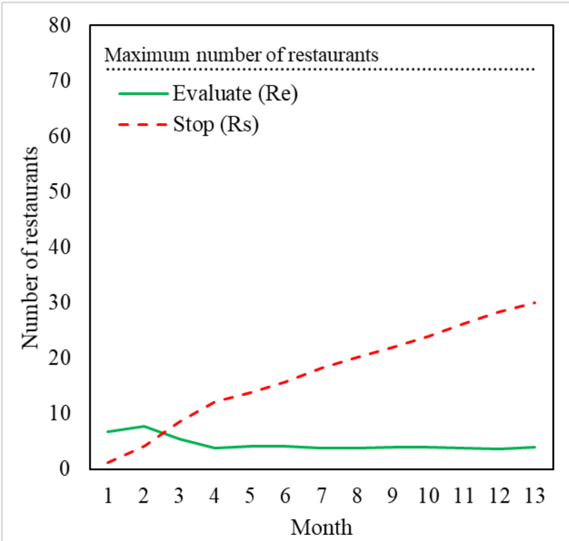


Figure 21: Number of restaurants evaluating (R_e) and stop participating (R_s) in Experiment 2b with 45 minute trip duration for District 2.

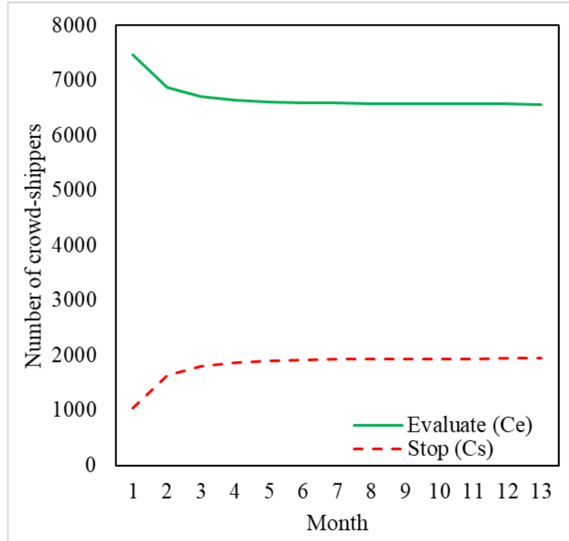


Figure 22: Number of crowd-shippers evaluating (C_e) and stop participating (C_s) in Experiment 2b with 45 minute trip duration for District 2.

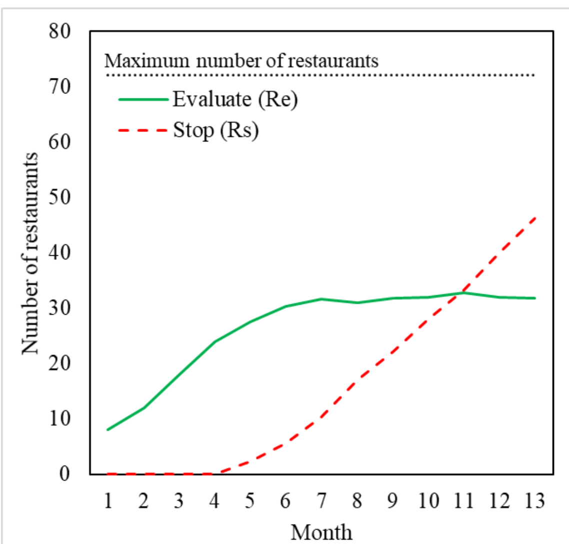


Figure 23: Number of restaurants evaluating (R_e) and stop participating (R_s) in Experiment 2b with 45 minute trip duration for District 5.

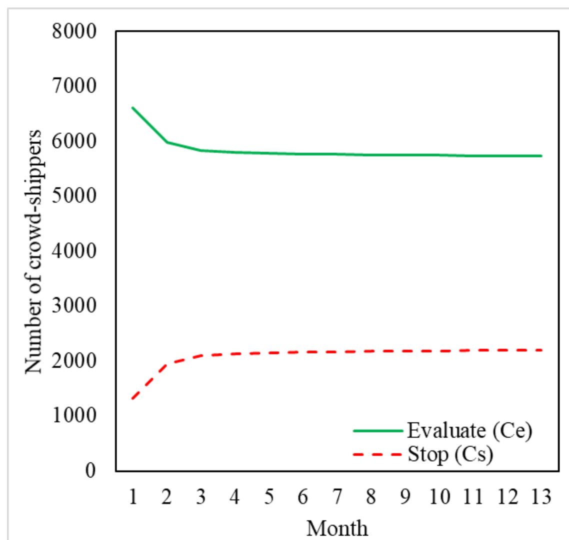


Figure 24: Number of crowd-shippers evaluating (C_e) and stop participating (C_s) in Experiment 2b with 45 minute trip duration for District 5.

District 2 performs similarly to previous experiments, continuing to fail between the second and third months. However, in District 5, the addition of more crowd-shipper agents and the increased trip duration of 45 minutes further delays the point of failure to the eleventh month, as depicted in Figure 23. This is due to the fact that restaurant agents are more likely to find an eligible crowd-shipper agent from the enlarged pool to make a successful delivery. In addition, although the number of restaurants that stop participating overtakes those that are still evaluating in the eleventh month, the number that continues to participate starts to steady. This may be due to the fact that restaurant agents that have been recruited in the later months have secured successful deliveries and have not ceased to participate or they are located closer to eligible crowd-shippers that are still willing to accept deliveries.

The caveat to these results remains in the runtime issue present when incorporating the crowd-shipper agents' social network. The power of using ABM is its ability to capture behavior complexities and decision making among heterogeneous agents. In this model, the interactions that enable to system to grow over time are established through the crowd-shipper's social network. By omitting this component the model is not leveraging the full capacity of ABM. These preliminary results conclude that indeed total travel duration, crowd-shipper and restaurant locations, and their proximity to each other are critical factors in system performance. However, without realistic interactions between crowd-shipper agents and diffusion of information it is hard to predict to what extent each of these factors affects the overall success of the system.

7 CONCLUSION AND ONGOING WORK

This thesis presents an approach to model development in which an abstract version of an ABM evolves over time to become a more realistic representation of a crowd-sourced transport system, demonstrating how a geospatial ABM can be iteratively improved via the inclusion of empirical data. In the most recent version of the model, the selection of eligible crowd-shipper agents is based on total trip duration derived from real-time traffic data, rather than census tract boundaries, and the entire population of the city has been targeted as a potential eligible crowd-shipper.

The runtime issue when the crowd-shippers' social network is implemented remains an immense limitation of the Rev 5 model. A way to represent crowd-shipper's interactions and the diffusion of information about the program realistically with computational efficiency needs to be determined. This is necessary to understand the role the social network has on the network effects. If a social network could be implemented in such a way that runtime was significantly reduced, this would allow further experimentation with different social network types as well as determining how many interactions among crowd-shippers within their region and outside their region need to be established to ascertain and sustain a critical mass of platform users. In addition, the critical mass for restaurants should be further analyzed by varying the recruitment strategy and the number of restaurants that are recruited monthly. The initial intent of this thesis posed to answer these questions, but has unintentionally rendered to be out of the scope of this work.

Each of the five regions of interest is different, in terms of geographic size and location, as well as demographic characteristics of resident populations and number of restaurants. Rev 5 of the ABM was used to assess the most and least favorable regions for strategically implementing a food rescue program. In future work, a thorough sensitivity analysis for each of the five City Council districts located in Arlington should be performed with this model. The purpose of the sensitivity analysis will be to determine how varying the geographic region of interest and crowd-shipper agents' allowable trip duration impact the behavior of the model. This will allow further study of the allotted trip time for crowd-shippers to determine whether it is the same for each region, or if a single duration exists that would be feasible for every district. Moreover, once the crowd-shippers' social network is in place, the relationship between where crowd-shipper interactions occur and trip duration should be explored. The outputs of these sensitivity analyses will be illustrated through a live interactive dashboard in a public domain such that it can be leveraged by practitioners as a decision support tool.

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