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Crowdsourcing the last mile delivery of online orders by exploiting the social networks of retail store customers

Aashwinikumar Devari [a], Alexander G. Nikolaev [a], Qing He [a,b,*]

[a] Department of Industrial and Systems Engineering, University at Buffalo, The State University of New York, Buffalo, NY 14260, United States
[b] Department of Civil, Structural and Environmental Engineering, University at Buffalo, The State University of New York, Buffalo, NY 14260, United States

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ABSTRACT

This paper demonstrates the potential benefits of crowdsourcing last mile delivery by exploiting a social network of the customers. The presented models and analysis are informed by the results of a survey to gauge people's attitudes toward engaging in social network-reliant package delivery to and by friends or acquaintances. It is found that using friends in a social network to assist in last mile delivery greatly reduces delivery costs and total emissions while ensuring speedy and reliable delivery. The proposed new delivery method also mitigates the privacy concerns and not-at-home syndrome that widely exist in last mile delivery.

1. Introduction

Last mile delivery is one of the largest challenges in Business to Customer e-commerce. With the increasing volume of purchases made online, retailers are under pressure to provide speedy, quality product delivery to customers (Barclays, 2014). At present, many retailers offer their customers the options of home delivery and store pickup. Last mile delivery service, in which the purchased products are delivered to the doors of consumers, is presently requested by the majority of online customers. Last mile product delivery, however, still remains an expensive option for retailers. The costs of the last mile delivery of products range between 13% and 75% of total supply chain costs (Gevaers et al., 2009). With many retailers attempting to find alternative solutions to the delivery of such orders, the challenges that emerge in these efforts include "not-at-home syndrome" and the "ping-pong" effect (when agreed-upon delivery times are not met by customers), leading to high economic and environmental costs incurred due to the extra miles driven, particularly in areas of low consumer density (Slabinac, 2016).

The majority of retailers are seeking options to deliver their products more efficiently. Traditionally, these deliveries are performed by commercial carriers (e.g., FedEx). Another perspective is that customers order online and pick up at a local store. In some cases, customers do not even exit their vehicles in the case of drive-through windows or when packages are loaded by store employees. Recently, many studies have been conducted on the level of customer expectations regarding the reliability and timely delivery of products ordered online, e.g., the idea of using drones for delivery (Slabinac, 2016).

One of the more recently emerging research ideas for resolving the last mile delivery issues in urban areas lies in the exploitation of crowd logistics. Crowd logistics, which may rely on crowdsourcing (mainly being defined as outsourcing a

* Corresponding author at: 313 Bell Hall, Buffalo, NY 14260, United States.
E-mail address: qinghe@buffalo.edu (Q. He).

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task to a crowd), designates the outsourcing of logistics services to a crowd, thereby achieving economic benefits for all parties involved (Mehmann et al., 2015). The proliferation of instant communication technologies enables logistics providers to seriously consider this new opportunity in last-mile logistics. The integration of end-to-end information sharing based on customers' smartphones within the logistics process promises a competitive advantage for e-commerce. Uber and Lyft, for example, are successful crowd logistics providers for passenger transportation. Other companies are also beginning to use crowds of taxis for last mile delivery (Chen and Pan, 2015). Amazon has investigated the notion of customers who, together with their own packages, pick up other packages (Reilly, 2015) and deliver these to recipients, who could be their neighbors.

Privacy protection concerns may arise when crowdsourcing delivery is implemented. People may wish not to disclose their shopping preferences and home addresses to strangers serving as couriers. Crowd workers typically prefer to remain anonymous; however, being anonymous may easily cause one to be or become unreliable (Varshney et al., 2014). Given an anonymous pool of a large number of workers, it is often difficult to enforce the quality of low-pay work performed (Varshney, 2012). Ensuring reliability and accountability is critical to the success of crowdsourced deliveries. These issues can be addressed by leveraging crowdsourced delivery on customers' friends and acquaintances who may have daily spatiotemporal overlaps, e.g., as co-workers and neighbors. By using friends and acquaintances chosen by individuals with a certain level of friendship from within their social networks, one alleviates the privacy concerns at least in part; and a customer will always be able to opt out of crowdsourced delivery. In this manner, one can maintain high levels of accountability and reliability while protecting privacy.

Further, assisting friends with deliveries can also result in an increase in the social capital of a community, particularly through the formation of new bonds. This aspect would help build up such tangible societal assets as goodwill, sympathy, and fellowship, among others, which all bring many potential benefits. The basic idea of "social capital" is that one's family, friends, and associates constitute an important asset, one that can be called upon in a crisis, enjoyed for its own sake, and/or leveraged for material gain (Woolcock, 2001). At present, consumers can use popular social network applications, such as Foursquare and Facebook Places, to easily communicate with friends, share information about recommended and frequently visited locations, and agree to assist each other. On one hand, social network applications can inform friends of each other's real-time locations and travel routes. On the other hand, extremely underutilized personal cars (as a means for delivery) can serve a new purpose as occasional delivery service providers. Integrating these two aspects, mobile-based social media platforms can be adopted to allow consumers to post and share the information of their online orders with friends, who, in turn, can help fulfill orders that can be picked up along their regular routes. We term this proposed delivery concept "Social Transportation", which can be viewed as being part of the broader concept of "Social Commerce" (Zhang and Wang, 2012). Social Transportation-driven order fulfillment has the potential to eventually transform the manner in which people deliver and receive packages and open new pathways to increasing the efficiency of transportation and logistics services.

The goal of this paper is to model and evaluate the potential benefits of using customers' social network contacts for last mile delivery under the umbrella of Social Transportation, which implies coordinated transportation systems facilitated/optimized through the use of software applications that rely on or gather data from sophisticated real-time sensors/GPS devices to compute optimal networks to connect individuals for optimized transportation applications. The paper showcases that the times and costs of last mile product delivery can be reduced by allowing friends/acquaintances to pick up and deliver small orders to each other as part of their routine trips to the store/work/home, as represented in Fig. 1. A case study is conducted to analyze this concept in detail for the city of Alexandria, VA. This paper raises and begins to address multiple novel questions associated with implementing this idea: these questions touch on the level of friendship required for the two parties to feel comfortable delivering orders for each other, the willingness of people to perform deliveries altogether, the extra time that they would agree to spend providing this service, and the incentives that they would require or appreciate.

The rest of this paper is organized as follows. The related literature is reviewed in Section 2. Section 3 discusses the survey conducted to analyze the relationship levels required to perform the delivery and the readiness of people to assist in product delivery based on other factors such as the extra travel time involved and the incentives sought, among others. Section 4 addresses simulating the delivery process, i.e., expressing the probabilities of successful delivery events and modeling

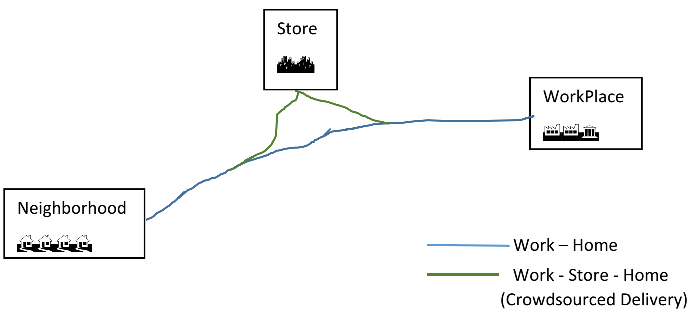

Fig. 1. Route for crowdsourced delivery.

delivery crowdsourcing on a city scale. The implementation of these ideas is realized in the transportation simulation tool, with the benefits of crowdsourcing delivery assessed thereafter, in Section 5. Section 6 summarizes the findings, discusses the limitations of this study, and outlines the future research scope.

2. Literature review

To the best of our knowledge, very few studies have discussed the idea of employing social networks to assist with last mile delivery (Suh et al., 2012). This section reviews the work that has been performed in the areas of reducing last mile delivery costs, modeling friendship levels, and activity-based travel demand modeling.

2.1. Last mile product delivery and crowdsourcing

Last mile product delivery is a crucial part of the supply chain of a product, and it can make or break the relationship between retailers and their customers. Indeed, this issue has become one of the bottlenecks of e-commerce (Wang et al., 2014). In their quest to reduce costs and improve operational efficiency, many companies try and test out different approaches to last mile delivery. In the present competitive scenario, to prosper, it is very important for companies to be ahead of, or on par with, their competitors. Since this paper mainly focuses on utilizing social networks for crowdsourced last mile delivery, we limit the overview of the relevant literature to the body of research on last mile delivery and crowdsourcing.

Freight activity brings major economic benefits (freight activity is a physical expression of the economy). There are various externality effects pertaining to last mile delivery in an urban setting (Slabinac, 2016). Last mile delivery transportation activities negatively impact the environment. The transportation of goods, through the use of service delivery vehicles, results in social, economic and operational impacts on the urban transportation infrastructure. Punakivi et al. (2001) discuss various other issues, such as unattended delivery and the "ping-pong" effect (when agreed-upon delivery times are not met by customers), that increase economic and environmental costs, depending on the miles driven, consumer density in a particular area, etc.

Speed and cost are the two factors that are crucial to the success of last mile delivery (Chen and Pan, 2015). There is an increasing amount of research being performed on the use of crowdsourcing as a solution to freight transport in city logistics. It is one of the key topics explored as an attempt to resolve logistics issues in urban areas (Mehmann et al., 2015). Since crowdsourcing has been conceived as relying on the Internet and an easily accessible crowd, multiple concerns about privacy and reliability are associated with its use in physical settings. Varshney (2012) discusses the issues of employing random people, who generally turn out to belong to low-income groups, to perform paid crowdsourced last mile delivery and proposes a mathematical model to determine the threshold conditions for such hires and to explore the tradeoffs between privacy, reliability and cost. One of the most important components of crowd logistics is the crowd itself; in this respect, trust, publicity and usability are the three influencing factors. Currently, however, there is no information available on the precise influence of these factors (Frehe et al., 2017). When using 'freelance crowds' in crowdsourced deliveries, it is important to ensure service quality. If the value of goods is high, then the risk of courier stealing may be increased (Peng and Xu, 2016). Another solution that can effectively address these issues lies in exploiting customers' own friendship networks, i.e., using friends whose daily routes have spatiotemporal overlaps such as those of co-workers and neighbors. Popular social network applications such as Foursquare and Facebook Places can be used to provide friends' real-time locations and travel routes, which can be used for assisting crowdsourced last mile delivery. One recent study has presented a framework for using social networks with a mobile and communication platform to assist in package pickup in last mile delivery (Suh et al., 2012). However, the fundamental research on assessing people's willingness to provide such a service and on its global impact under realistic assumptions about daily travel patterns has yet to be undertaken.

2.2. Friendship modeling

Multiple studies have been conducted by various other researchers with the objective of understanding and modeling the depth of friendship between people and within groups of people. These studies help us recognize the various levels and factors that affect the meaning of friendships, and they inform the modeling of an environment where the relationships between people let them perform crowdsourced delivery for those in their social networks. Indeed, the perceived level of trust depends on the level of friendship between people, measured on the friendship intensity scale (Rybak and McAndrew, 2006). Models of social tie formation have micro-foundations in the concept of homophily, i.e., the tendency of people to connect with peers with similar attributes (Currarini and Vega-Redondo, 2013); indeed, the dependence of social ties on the social attributes and relative locations of actors can easily be modeled. Markiewicz et al. (1999) analyze how the work context influences relationships between men and women. Van de Bunt et al. (1999) investigate random utility models that explain the choices people make with respect to the formation of affective relationships: in their study, (Van de Bunt et al., 1999) use rational choice theory, which claims that given constraints and opportunities, the actions of an individual can be quantitatively modeled if these actions are rooted in a cost-benefit analysis and that human behavior can be modeled *as though* it is rational. The dynamics of friendship between two individuals can be categorized into levels as Troubled,

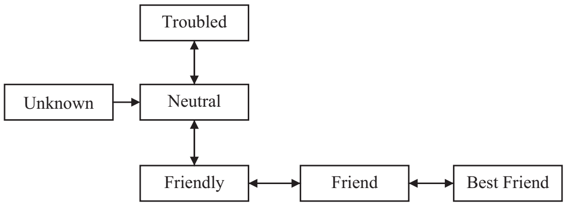

Fig. 2. Dynamics of the transitions between the friendship levels between individuals (Van de Bunt et al., 1999).

Neutral, Friendly, Friend, and Best Friend. The various levels of friendship between individuals and their transition are summarized in Fig. 2. In this paper, we have used these levels as a baseline to develop our friendship levels (i.e., close friend, friend, acquaintance, or anyone working/living nearby) to express the outcomes in a survey that we design and conduct to capture the friendship patterns exhibited by people at the workplace and in their neighborhoods; we then rely on the results of this survey when modeling the likelihood of crowdsourced product delivery.

2.3. Activity-based travel demand modeling and simulation

This paper also relies on the literature on activity-based modeling in transportation research. Activity-based modeling, as an alternative to trip-based travel demand modeling, captures the interrelated decisions regarding travel from home to one or more activity locations (Bowman and Ben-Akiva, 2001). Activity-based analysis has provided new methods of modeling travel demand and allowed for significant improvements in the understanding and forecasting of travel behavior (Auld and Mohammadian, 2009). This approach has been successfully applied in a variety of policy tests (McNally, 1996).

The basic characteristics of activity-based models are as follows: (1) travel demand is derived from activity selection, (2) activity selection involves generation, spatial choice, and scheduling, (3) activity and travel behavior are delimited (or even defined) by constraints, (4) activities, locations, times, and individual agendas are all interdependent, and (5) alternate decision paradigms are probable (McNally, 1996). Based on the selected activity, travel can be modeled on a transportation network such that each traveler chooses a route that is best for the entire population; the preferred travel modes can be refined with the help of consumer surveys. The main motivation behind the development of activity-based models is to understand the effects of new information, land use and growth management on travel behaviors and the response of travelers to various policies, which is critical to improving new design policies (Shiftan and Ben-Akiva, 2011). The explicit modeling of activities and the consequent tours and trips in activity-based modeling enable a more credible analysis of the responses to policies and the subsequent effects of policies on traffic and air quality (Shiftan, 2000). Exploiting all these features of the activity-based travel modeling paradigm, we adopt it to simulate and test the various parameters of crowdsourcing delivery operation since both the exact locations and travel activities of each traveler in the network can be assumed to be fixed and known.

To summarize, the last mile delivery problem presents a serious challenge to the operations of any supply chain network, and crowdsourcing appears to be emerging as a new potential approach to tackling this challenge. To date, no detailed study assessing the benefits of using friendship connections for performing last mile delivery has been conducted. This paper bridges the gap between crowdsourced last mile delivery research, friendship modeling in social networks and travel activity modeling. It also addresses the challenges associated with implementing this idea and evaluates several key expected values associated with city-scale crowdsourced delivery operations.

3. Consumer survey for social network-supported last mile delivery

An online survey was conducted in 2015 to gain a better understanding of the various factors that would play a role in implementing the concept of Social Transportation. The results of the survey were used in modeling the behavior of customers based on various parameters to be used in the transportation simulation. This section provides the survey overview as well as the results and critical findings.

3.1. Survey overview

We designed and distributed a survey to gauge the friendship levels required to support crowdsourced product delivery activities and to identify the number of such peers (friends) with whom an average citizen interacts on a regular basis and who can assist him or her with last mile product delivery. A paid survey using Survey Monkey and containing 12 questions was conducted. We managed to solicit responses from a total of 104 respondents in the U.S.; the differences between the respondents' attributes were characterized with the help of the following rubrics: employment, home ownership, education, and motor vehicle ownership. Based on the survey results, we attempted to characterize the minimum level of friendship required for people to accept (perform) product delivery by (for) their peers. The survey also provided data on the monetary compensation and maximum extra time that the persons asked to perform deliveries would count on to agree to do so.

3.2. Survey results and critical findings

The survey included responses from individuals of different genders, with approximately 59% female respondents, and individuals from different income and age brackets. The summaries of the survey respondent demographic characteristic distributions are presented in Figs. 3 and 4.

Fig. 5 shows the percentage distribution of the participants' responses for the minimum level of friendship that they need to have with someone to assist each other in making small package deliveries. As shown, the vast majority of people, 72%, will accept or deliver a product only for or to their friends or close friends (an additional 16% would also trust their acquaintances). We arrive at the conclusion that it is very important for individuals to know the people to or from whom they deliver or receive their products. These results also highlight the fact that people value their privacy in their shopping activities somewhat highly.

Figs. 6 and 7 show the percentage distributions in the responses regarding the number of close friends and not-so-close friends that the respondents claim they have, respectively. A majority of the respondents have 1–4 close friends and 5–9 not-to-close friends at the workplace or in their neighborhoods. One may refer to the Appendix for detailed data. In Question (7)

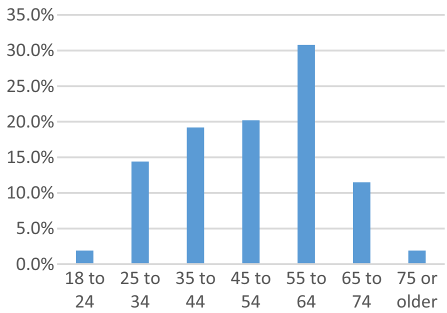

Fig. 3. Percentage distribution of age levels.

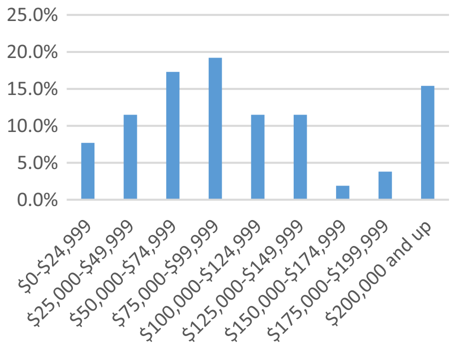

Fig. 4. Percentage distribution of income levels.

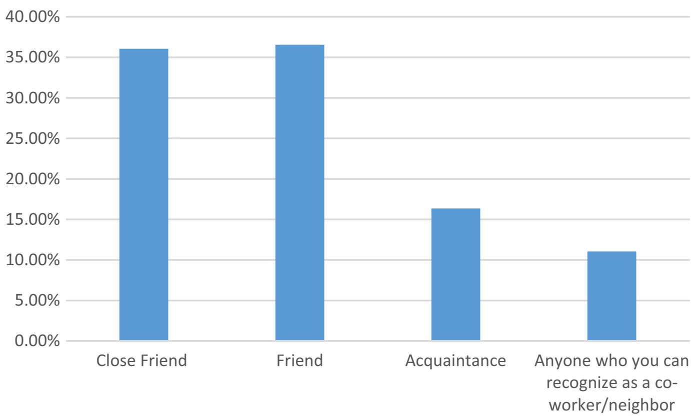

Fig. 5. Percentage distribution of friendship levels required for product delivery.

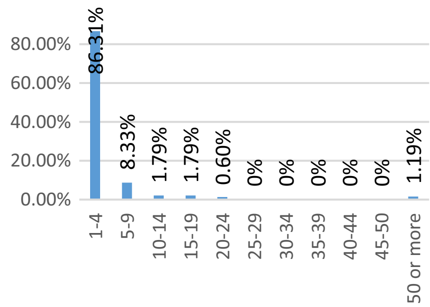

Fig. 6. Distribution of number of close friends in an individual's social network.

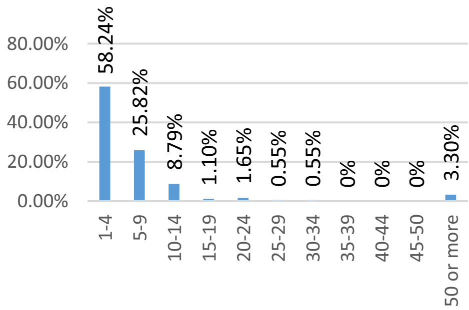

Fig. 7. Distribution of number of friends in an individual's social network.

of the Appendix, the participants report the number of people identified in four levels of friendship in their workplace: (i) close friend, (ii) friend, (iii) acquaintance, and (iv) others recognized as co-workers. Similarly, in Question (8), the participants report the numbers for the same four levels of friendships in respect to their neighbors. Further, the participants also indicate what level of friendship they require to make/receive delivery in Question (9) and (10).

By combining the answers to Questions (7)–(10), we calculate how many peers an individual can make/receive delivery to/from in their social network. First, we individually calculate the number of people from/to whom a person would accept/deliver products at the workplace and in their neighborhoods. Without loss of generality, we take the workplace as an example. Let f_{ik}^{w} be the number of friends from the workplace that individual i has at level k. For ease of notation, we set the lower friendship at a higher k value. Let $k \in \{1, 2, 3, 4\}$, representing the following four friendship levels: close friend, friend, acquaintance, and co-workers, ascendingly. Let $\alpha_i(\alpha_i \leqslant 4)$ be the required level of friendship (maximal k) for individual i to accept a package. Similarly, let $\beta_i(\beta_i \leqslant 4)$ be the required level of friendship (maximal k) for individual i to deliver a package. Therefore, the number of people from whom a person would accept products in the workplace is $N_i^{aw} = \sum_{k=0}^{k \leqslant \alpha_i} f_{ik}^{w}$. Similarly, the number of people to whom a person would deliver products in the workplace is $N_i^{dw} = \sum_{k=0}^{k \leqslant \beta_i} f_{ik}^{w}$. In a similar manner, we can calculate N_i^{an} and N_i^{dn} for their neighborhoods. The results show that for workplace N_i^{aw} is 17.33 and N_i^{dw} is 16.73 whereas for neighborhood N_i^{an} is 13.64 and N_i^{dn} *is* 14.21. Individuals make friends in their workplace/neighborhood over time. However, we assume that there is a steady state in which the number of friends with whom a person can maintain relationships remains constant and that the data that we observe accurately describe this steady state distribution.

Fig. 8 depicts the summary of the responses to the question about the credit/monetary rewards that people would expect in return for delivering a product to anyone in general. The results show an interesting heavy-headed and heavy-tailed

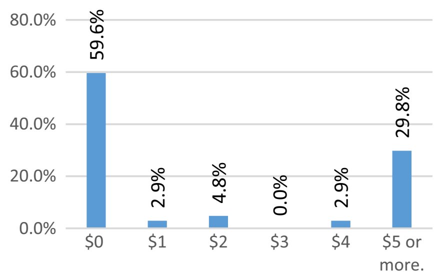

Fig. 8. Percentage distribution of compensation for product delivery.

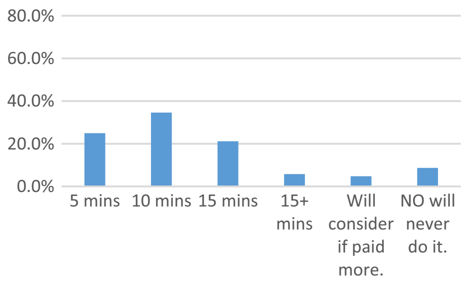

Fig. 9. Percentage distribution for willingness to spend extra time.

distribution: 60% of the participants would agree to deliver packages without any reward or benefit expectation. However, another 30% of responses would only agree if rewarded 5 USD or more per delivery.

The survey also inquired about the maximum extra time that each person would be ready to spend while helping anyone perform a delivery: according to Fig. 9, more than 80% of the participants would be content with allocating 15 extra minutes (or less) for delivery. Additionally, it can be anticipated that as the time required to assist with a delivery increases, the chances of delivery decrease. These results are used to model the probability that a product will be delivered in the simulated environment. The impact of additional time can be better understood from the logistic regression model presented in the next section.

4. Simulation

This section discusses the simulation procedure adopted for the analysis and validation of the crowdsourced delivery scheme. The built simulation framework allows for flexibility in assessing the utility of the proposed innovation, in concept, across various scenarios and in studying the sensitivity of the outputs to multiple model parameters.

4.1. Modeling the probability of making/performing a delivery for a friend

A logistic regression model is developed to model the dichotomous indicator variable for the event that an online order of a retail store customer is delivered to a particular friend. To comply with the survey data, the predictors of this response variable include age, income levels, gender and the extra time that the friend would need to invest in performing the delivery[2]. Note that extra time is modeled cumulatively to model the incremental effect for four time brackets: less than or equal to 5 min (T_0), greater than 5 min but less than or equal to 10 min (T_1), greater than 10 min but less than or equal to 15 min (T_2), and greater than 15 min (T_3). For example, a 10-min time requirement is modeled by setting the variable T_0 to one (to reflect the impact of the friend's committing the first 5 min to the delivery) and setting the variable T_1 to 1 (to reflect the impact of the friend's committing an *additional* 5 min to the same delivery). This setting will result in an "all 1 column" for variable T_0. Therefore, T_0 will be removed from the modeling.

Let **Y** be the response variable for the binary outcome of 1/0 (Agree/Disagree) for product delivery and p be the probability that **Y** will take the value of 1. Let scalar α denote the value of the intercept and vector $\boldsymbol{\beta}$ denote the vector of the coefficients for the predictor vector **X**. The probability of an outcome in the *logit* modeling takes the form

$$P(Y = Outcome|X = x) = \frac{e^{\alpha+\boldsymbol{\beta}x}}{1 + e^{\alpha+\boldsymbol{\beta}x}}. \tag{1}$$

Table 1 summarizes the selected predictor variables comprising vector **X**. Note that both age and gender are removed from the final model since they were found to be insignificant in the initial fitting attempt. According to (1), the probability that a given friend will agree to perform a delivery can be expressed as

Table 1
Logistic regression model summary.[a,b]

	Notation	Estimate	Std. error	z value	Pr(>|z|)
(Intercept)	α	1.3915	0.5507	2.527	0.0115*
Income \$125,000 and up (**I1**)	β_1	1.0594	0.5339	1.984	0.0472*
Income \$25,000–\$74,999 (**I2**)	β_2	1.1702	0.5446	2.149	0.0317*
Income \$75,000–\$124,999 (**I3**)	β_3	1.0547	0.5382	1.960	0.0500
Extra time (min) ∈ (5, 10] (**T1**)	β_4	−1.7553	0.4100	−4.281	1.86e−05***
Extra time (min) ∈ (10, 15] (**T2**)	β_5	−1.4279	0.2980	−4.791	1.66e−06***
Extra time (min) greater than 15 (**T3**)	β_6	−2.0395	0.4714	−4.326	1.52e−05***

[a] Null deviance: 576.35 on 415 degrees of freedom; residual deviance: 366.22 on 409 degrees of freedom; McFadden's Pseudo R^2 = 0.3645.
[b] Using compensation as a variable in the regression resulted in its being non-significant and hence omitted.

$$p = \frac{e^{\alpha+\sum_{i=1}^{3}\beta i * Ii+\sum_{i=4}^{6}\beta i * Ti}}{1+e^{\alpha+\sum_{i=1}^{3}\beta i * Ii+\sum_{i=4}^{6}\beta i * Ti}}. \tag{2}$$

Note that the income level coefficients β_1, β_2, and β_3 are all positive, reflecting the fact that the delivery probability for people with a medium and high income level (above $25,000) is higher than that for people with a low income level (below $25,000). Further, the amount of extra time required for a delivery plays a significant role: the estimated coefficients β_4, β_5, and β_6 are all negative, indicating that the probability of willingness to deliver decreases as the extra time required to make the delivery increases.

The probability of order delivery by one friend for another can now be used to calculate the probability of the order's being delivered by any – at least one – friend, based on the order pick-up location and the number of friends available to make a feasible detour to perform the delivery.

4.2. Activity-based modeling tools

To simulate how the proposed delivery operation would function in real-world everyday traffic, an agent-based transportation simulator TRANSIMS (TRANsportation Analysis and SIMulation System) is adopted. TRANSIMS can be used to model individual travelers and their multi-modal trips using agents in synthetic populations and their everyday activities. TRANSIMS allows one to collect somewhat detailed outputs from each simulation run, including the simulated origins and destinations of travelers and the travel times, based on the time of day and routes taken.

TRANSIMS takes as inputs the transportation network, transit lines, census data for the population, household activity surveys, itinerant travelers and trips, and vehicle characteristics. Fig. 10 summarizes the steps required to set up a TRANSIMS model environment:

(1) The population synthesizer uses census data to generate synthetic households with income and member characteristics. It also places each synthetic household in a link in the transportation network (activity location). Vehicles are assigned to these households using the population synthesizer.
(2) The activity generator takes a detailed activity survey of the area as input. It assigns activities to household members in the network. The start and end times of each activity are determined, and the location and travel mode for each activity are chosen.

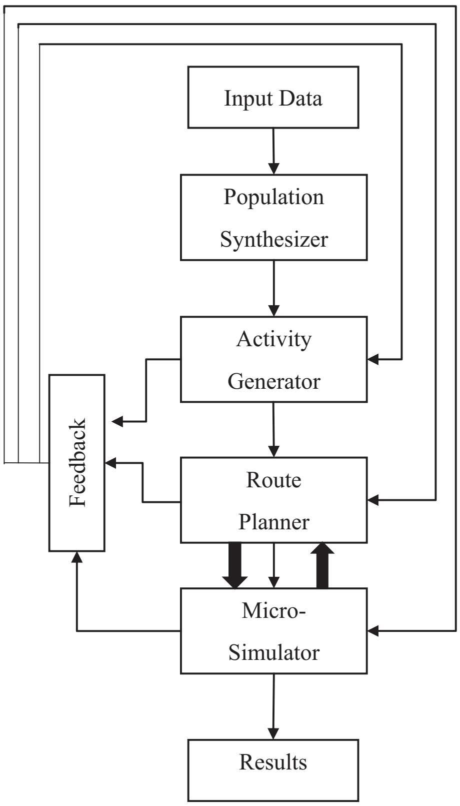

Fig. 10. TRANSIMS methodology for activity-based modeling.

(3) The route planner builds a step-by-step trip plan for each individual traveler to travel from his or her origin to destination based on the activities and trip tables.
(4) The micro-simulator simulates the second-by-second movement of vehicles through the network and precisely follows the travel plans scheduled by the route planner for each individual traveler. It is used to generate performance statistics, track individual travelers and summarize the observed events.
(5) The route planner and micro-simulator are run iteratively in the feedback procedure to eliminate potential problems due to routing conflicts: the procedure keeps running until equilibrium is achieved such that each traveler has chosen the route that is best for the entire population. It returns routing and microsimulation outputs that, as realistically as possible, represent normal trips and congestion.

4.3. Simulation of crowdsourced last mile delivery

We report on the simulated study conducted with the data for the city of Alexandria, Virginia, with a synthetic population of 229,371. The city has demographics that are similar to those of the survey population, shown in Questions (1)–(4) of the Appendix. The city network contains 3606 links, 8656 activity nodes, and 26,623 daily trips taken by individual travelers. This paper assumes a single store location for online order pick-up, as shown in Fig. 11, in a shopping mall and analyzes the benefits of the adoption of the crowdsourced delivery scheme by this store. The use of a single store location helps us prove the concept in an uncomplicated manner.

We consider three scenarios with the objective of testing the utility of the proposed delivery scheme, calculating the costs and performance metric values across these simulated scenarios. Scenario 1 utilizes only traditional truck delivery in which all orders are delivered from the store using delivery trucks routed between the target locations in a close-to-optimal manner; we determine the minimal number of trucks required to perform an average day delivery. Scenario 2 tests the use of crowdsourcing to deliver products to customers, with the rest of the orders delivered using trucks. Scenario 3 allows only customers to pick up their online orders at the local store. Fig. 12 summarizes the steps involved in setting up each of these simulated scenarios.

The orders in the city are randomly distributed among the synthetic population at the rate of 13.6 per capita (per person per year) (Statista, 2013), which amounts to approximately 8600 orders delivered daily. In Scenario 1, because the number of target nodes (delivery addresses) is very high, to avoid computational problems in solving a Vehicle Routing Problem (VRP), we solve a Travelling Salesman Problem (TSP) with the Lin-Kernighan-Helsgaun heuristic (Helsgaun, 2006) to first derive the shortest routes that would cover all delivery locations.

Based on the total distance covered in the TSP, the number of trucks required in the VRP is calculated. We assume that the truck operates for 8 h per day and that the optimal TSP route is partitioned into segments based on the 8-h operating limit for each truck, with one truck subsequently allocated per segment, to perform deliveries. The time taken by each truck to travel from and to the store in a TSP segment is also considered in this calculation. Assuming an average delivery truck speed of 15 miles per hour (considering stops at intersections) and an average stop time of two minutes for each delivery, the total number of trucks is calculated to cover the entire length of the TSP.

Fig. 13 presents a simple example of how the number of trucks is calculated. In this example, one can observe that the TSP tour is sliced into four segments to be covered by four trucks separately, with each truck traveling from the store to the beginning of the segment and returning back to the store and the end of the segment.

Fig. 11. The study area in the city of Alexandria, Virginia.

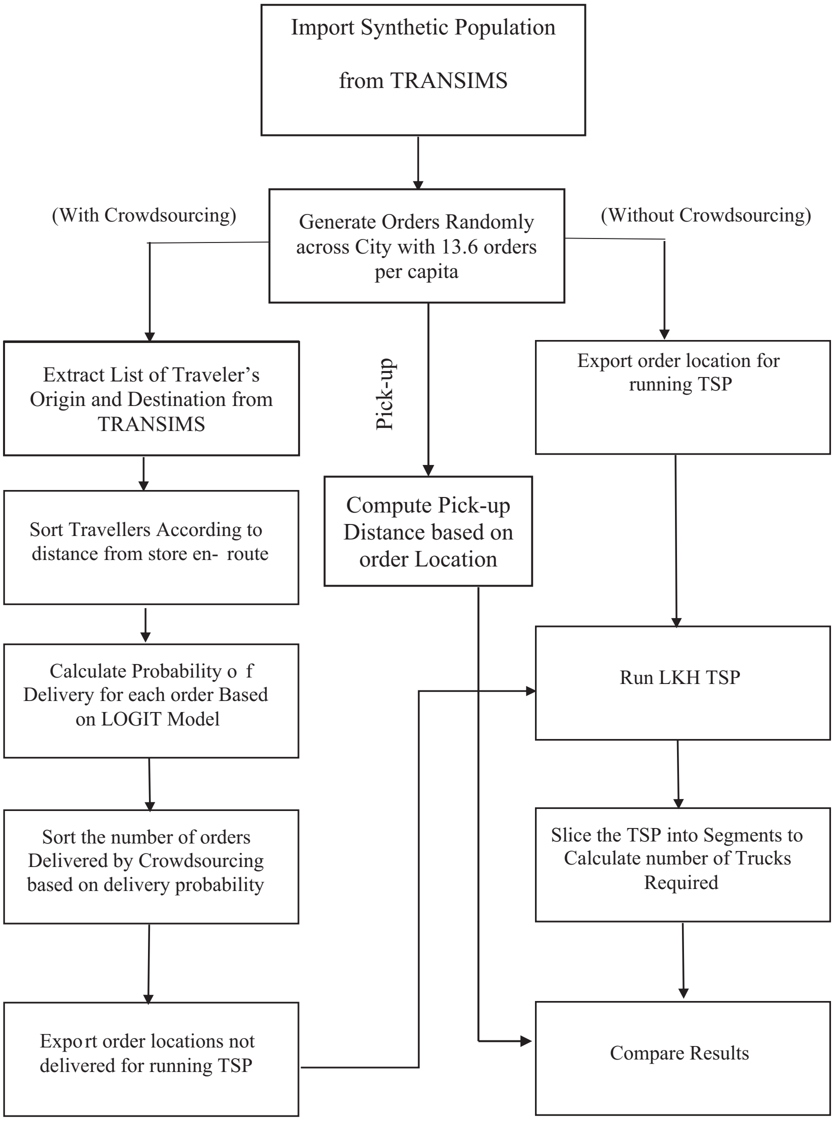

Fig. 12. The flow chart of the entire simulation process.

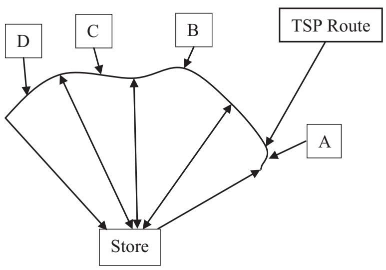

Fig. 13. Number of trucks calculated from the TSP.

In Scenario 2, based on the probabilities calculated with the logistic regression model (2), the number of orders to be delivered by friends to friends is generated. The probability of delivering by all possible individuals in the social network who could assist in the delivery is calculated based on their attributes such as income levels and the extra time that delivery would take using Eq. (2). To determine whether an order is delivered using crowdsourcing, we consider all possibilities of how the order can be delivered: if the order owner has N friends, then the probability that the order will be delivered can be obtained as

$$P = 1 - \left(\prod_{i=1}^{N}(1 - P_i)\right), \quad (3)$$

where P_i is the probability that the delivery will be performed by friend i.

For example, suppose a particular order can be delivered by any of two friends (meaning that the required re-routing to execute the order pick-up is feasible for each of them), with probabilities P_1 and P_2. To determine whether an order is delivered by either of the friends, we first calculate the probability that the order will not be delivered, $(1 - P) = (1 - P_1) * (1 - P_2)$, and subtract it from one to obtain P. Given P, a Monte Carlo method is then used to generate the successful deliveries in the simulation. Using this method, we consider all friends who could assist in the delivery and eliminate the problem in which an order may be picked up by multiple friends.

The remaining orders, those that are not delivered using crowdsourcing, are sorted and exported to the LKH TSP tool for Scenario 1, and the number of trucks required to deliver the remaining orders is obtained as described above.

In Scenario 3, all orders are assumed to be picked up from the store by the respective customers either by taking a detour along one of their regular trips or by taking an extra trip. For each order pick-up performed by a customer, the (extra) distance traveled (for the respective best route) is found as the minimum among the following three distances: (1) that for a direct trip from home to the store and back, (2) that for a direct trip from work to the store and back, and (3) the extra distance that the customer would have to cover if he or she decided to pick up the package by taking a re-route on his or her commute from home to work.

5. Results

This section presents the results of the comparative analysis of the simulated scenarios described in Section 4. Section 5.1 details the calculations of the amount of savings expected to be achieved due to a reduction in the number of employed delivery trucks when crowdsourced delivery is exploited. Section 5.2 discusses the sensitivity of the results to consumer behavior-related model parameters. Section 5.3 quantifies the impact of the crowdsourced delivery scheme on vehicular emissions.

5.1. Observed reduction in the number of trucks

Using the simulated experiments, each with 50 replications, we calculate the average number of trucks needed to perform delivery in the two scenarios – one with crowdsourced delivery and the other without it. Additionally, we compare the average total miles traveled by trucks in the first two scenarios versus the extra miles traveled by cars in the third scenario. Table 2 presents these results.

Table 2 suggests that the amount of savings obtained due to the reduction in the number of trucks achieved by exploiting crowdsourcing can be expected to be very substantial. Assuming that the average cost of operating a commercial truck is approximately \$1.7/mile (DAT-Solutions, 2016) and that the average cost of operating a personal automobile is \$0.6/mile

Table 2
Comparisons of crowdsourced and non-crowdsourced delivery miles traveled.

Scenario	Number of trucks	Average miles per truck	Total truck miles	Total car miles	Carrier cost	Car cost	Total cost
Without crowdsourced delivery (truck)	147	60 miles	8820 miles	0 miles	\$14,994	\$0	\$14994
With crowdsourced delivery	69	55 miles	3752 miles	3366 miles	\$6378	\$2020	\$8398
Without crowdsourced delivery (pick-up)	0	0 miles	0 miles	34,610 miles	\$0	\$20766	\$20,766

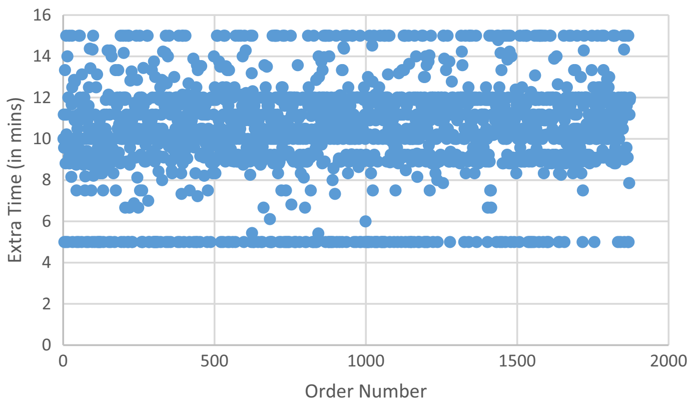

Fig. 14. Scatter plot of the extra time taken for each delivery using crowdsourcing.

(AAA, 2016), the approximate savings for a retailer per day under Scenario 2 amount to \$8600, compared to Scenario 1 (in which only trucks are used to perform deliveries). The net cost reduction with the increased car operating cost (to be borne by the car owner/friend delivering the order) would be \$6400. This result is due to the reduction in truck miles traveled of 5068 miles – a reduction in total truck miles of as much as 57%.

From the simulated experiments, we also find that in performing an average crowdsourced delivery for his or her friend, an individual spends approximately ten extra minutes on his or her trip, on average, including the time spent collecting the order at the store. Fig. 14 gives a detailed account of the amount of extra time spent in making the delivery for each order in one of the simulated replications (with a total number of 8600 deliveries being close to 1900). We assume that a minimum of 5 extra minutes is required to assist in a delivery: this assumption is reflected in a lower bound in Fig. 14. Additionally, we assume an upper bound of 15 min for the extra time spent in delivery; indeed, Fig. 9 indicates that the surveyed individuals would be very unlikely to agree to assist a friend with a delivery if they had to spend more than 15 min doing so. It is assumed that whenever the extra time for a delivery exceeds 15 min, the delivery is performed by a store truck.

The total amount of additional travel time that people devote to helping their friends with order deliveries comes to an average of approximately 10,100 min. Converting this number to additional miles traveled, at an average speed of 20 mph in the city, we obtain 3366 extra car miles driven to perform the deliveries. In the third scenario, in which customers pick up all orders on their own, they cover a total distance of approximately 34,610 miles, on average. It can be concluded that by relying on friend-driven crowdsourcing for last mile product delivery, the city can reduce the total number of car miles driven to execute order pick-ups by as much as 90%.

5.2. Sensitivity analysis

The results presented above are obtained under the assumption that all of the friends of every individual are necessarily available for performing any delivery, more precisely, that they all consider being of service for each delivery. However, this may not be the case due to various personal reasons, vacations, sick time, etc. Understanding such friendship-driven behavior at a more granular level is a subject of future research; such research could help us more accurately establish how many times one would be ready to assist his or her friends with deliveries in a steady state condition, e.g., over a year, to subsequently refine our simulation-based insights. Nonetheless, to gauge the potential impact of such new information on our results in this paper, we introduce the parameter α as the probability that a person will be ready to deliver on a particular day and make the probability that friend i will *consider and agree* to make a delivery be equal to αP_i. By conducting the sensitivity analysis of our results with respect to α, we also implicitly measure the error that can be induced by an incorrect specification in (2). Table 3 summarizes the total truck miles and the number of trucks required, adjusted as the parameter α varies in the range of 0–100%.

Table 3
Summary of the sensitivity analysis of total truck miles in crowdsourced delivery.

Scenario crowdsourced delivery	Number of trucks	Average distance per truck (in miles)	Total truck miles
(α = 100%)	69	55 miles	3752 miles
(α = 90%)	89	57 miles	5029 miles
(α = 80%)	96	56 miles	5431 miles
(α = 70%)	101	56 miles	5751 miles
(α = 60%)	109	57 miles	6185 miles
(α = 50%)	110	57 miles	6196 miles
(α = 40%)	119	57 miles	6753 miles
(α = 30%)	120	57 miles	6875 miles
(α = 20%)	130	57 miles	7382 miles
(α = 10%)	137	57 miles	7744 miles
(α = 0%)	147	60 miles	8820 miles

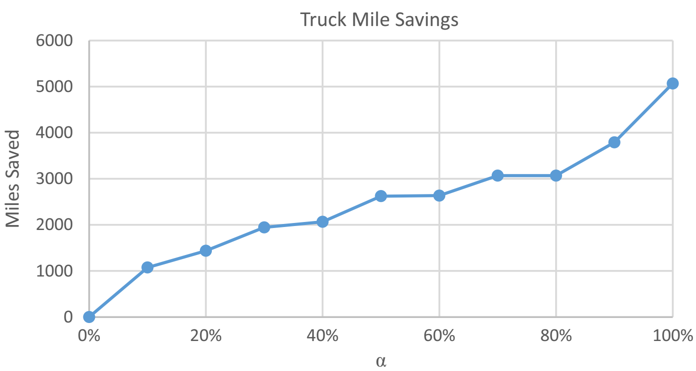

Fig. 15. Sensitivity analysis of truck mile savings in crowdsourced delivery.

Table 4
Emissions comparison with and without crowdsourcing.

Pollutant	Truck emissions (grams/mile)	Cars emissions (grams/mile)	Truck emissions savings (grams)	Car additional emissions (grams)	With crowd-sourcing (grams)	Without crowd-sourcing (grams)
THC	0.453	1.077	2295.804	3625.18	5324.84	3995.46
CO	2.311	9.4	11712.148	31640.4	40311.3	20383
NOx	8.613	0.693	43650.684	2332.64	34648.6	75966.7
PM2.5	0.202	0.0041	1023.736	13.8006	771.705	1781.64
PM10	0.219	0.0044	1109.892	14.8104	836.498	1931.58

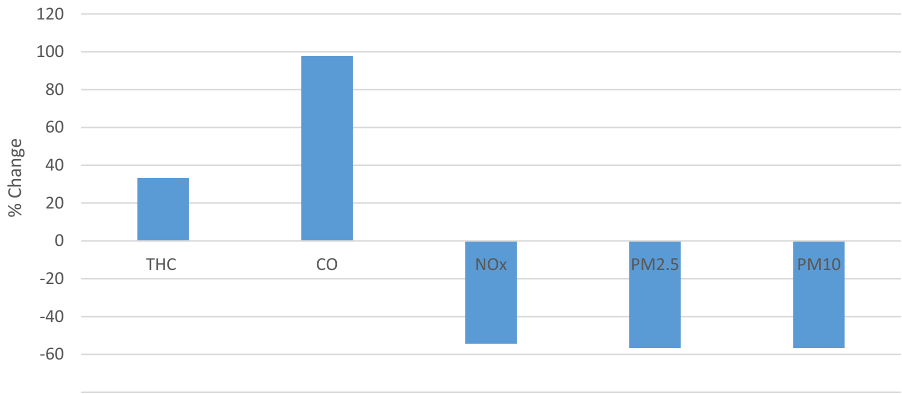

Fig. 16. % Change in the emissions volumes of pollutants in Alexandria per day in comparison to those for last mile delivery without crowdsourcing.

Fig. 15 shows that as α increases, the number of truck miles saved also increases. Observe that there exists a close-to-linear relationship between α and truck miles saved.

5.3. Effect on environmental emissions

The impact of crowdsourced last mile delivery on the environment is calculated based on the total emissions volume savings as a function of the reduction in truck miles driven, adjusted for the additional emissions attributed to the extra distance traveled by passenger cars. The emissions, in grams per mile, are calculated based on the computer models by the U.S. Environmental Protection Agency, which provides emissions estimates for different types of vehicles (US-EPA, 2008). In our calculations, we assume that heavy-duty small diesel trucks are used for store-operated delivery. The results of the emissions volume calculations are given in Table 4.

According to Fig. 16, substantial savings can be achieved in the emissions of nitrogen oxides (NOx) and particulate matter (PM), which are the major pollutants in urban areas. It is well known that $PM_{2.5}$ is harmful to humans because it can remain lodged in the lungs for extended periods of time, causing chronic health problems. It is a well-known fact that these pollutants are a major cause of respiratory tract-related illnesses in urban areas. Reducing the PM level in the atmosphere is of great advantage to reducing pollution-related health issues in urban areas. However, there is also a substantial increase in Total Hydrocarbon Emissions (THC) and Carbon Monoxide (CO) due to extra car miles since we consider that passenger cars run on gasoline-powered engines, which emit more CO and THC compared to the diesel engines powering delivery trucks. With stronger emissions control imposed on passenger cars and the introduction of electric/hybrid vehicles, we could expect a higher reduction in emissions levels.

6. Conclusions and future research

6.1. Conclusions

This paper presents a scenario-based analysis of the benefits of exploiting a particular type of crowdsourced last mile delivery for retail store order pick-ups – a delivery scheme that relies on friendship/acquaintance networks. A survey with 104 participants reveals that a vast majority of people – 72% of the respondents – would agree to perform a delivery of a package to their friends or close friends. The inferred counts of friends to/from whom an individual would accept/deliver products at their workplace and in the neighborhood turn out to be, on average, 17.33 and 14.21, respectively. It is also found that more than 60% of people are willing to make a delivery to their friends for free and 80% of the participants can afford to spend up to 15 min extra in providing this assistance.

Based on the survey results, a logistic regression model is built to model the probability for each friend's agreeing to make a delivery. The paper proceeds to conduct a comparative analysis of the impact of last mile deliveries in a city, under different scenarios, and evaluates the benefits of exploiting social networks for crowdsourced last mile delivery. The total impact on daily emissions in an urban area is reported as the key analysis outcome. The insights provided by this paper help us gauge the promise of using social networks to achieve a reduction in last mile delivery costs and in the volumes of pollutants from diesel-powered delivery trucks. It is found that retailers could reduce their total truck mileage by 57% (which is equivalent to reducing delivery costs by 8600USD per day) by using crowdsourcing, with the individual drivers (who provide the delivery assistance to their friends) taking an average of 10 min extra per delivery. Additionally, the achieved reduction in the volumes of pollutants – NOx, $PM_{2.5}$, and PM_{10} – emitted by delivery trucks amounts to as much as 55%.

One of the major issues in the various methods of using crowdsourcing to perform last mile delivery is to ensure reliability and accountability, particularly in responding to the privacy concerns of consumers. The use of social networks for crowdsourced deliveries, analyzed in this paper, has the potential to attenuate these issues to a large extent since, in such a setting, only the people sharing a particular level of friendship are relied on to perform deliveries. Additionally, various other issues, including not-at-home syndrome, which requires repeated delivery runs or specified time windows, are mitigated. It is found that using friends in a social network to assist in last mile delivery greatly reduces delivery costs and total emissions while ensuring speedy and reliable delivery. Therefore, "Social Delivery" can also be exploited for same-day delivery in e-commerce practice – such deliveries could be more heavily incentivized.

Finally, policy issues relating to the sustainability and social inequality of crowd logistics with regard to the sharing economy should be identified, quantified and evaluated. Some studies have shown that there may exist a "paradox of openness and distinction" (Schora et al., 2016) between the actual practice and the widely articulated goals of openness and equity of the sharing economy. The government and legal regulations play a major role in mitigating the potential risks of crowd logistics services.

6.2. Future research

In calculating the probabilities of delivering a product, this paper assumes that a person would do so every time, which may not be the case. In real-world scenarios, further research must be conducted to determine the number of times that a person would help assist per unit of time. In this paper, we have conducted a sensitivity analysis to gain a broad understanding of effects. However, a more detailed study must be conducted to understand the delivery behavior of friends. The possibility of providing store credits or rewards to people assisting in delivery must be studied in more detail. This aspect could positively impact consumers' willingness to perform a delivery. This paper currently considers order delivery in a city and intends to prove this concept by assigning all orders to a single location; this aspect has its limitations, and a more detailed analysis must be conducted.

Considering environmental emissions and the resultant reduction in pollution, we must also consider the rebound effects of such an idea, in which, due to lower costs or benefits, people may actually start ordering more or driving more to achieve deliveries, which consequently could negate the potential benefits. Additionally, it must be understood that the cost savings in crowdsourced deliveries are primarily to the retailer and that the transferred cost would be borne by the car owner/participants in crowdsourced deliveries.

Presently, we have considered only single-hop delivery, i.e., when only one friend can be involved in performing last mile delivery. The possibility of multi-hop delivery, in which a package can change hands on its way to the target person or a single person performs deliveries for multiple friends, can be analyzed in future studies. It is expected that such a scheme would further increase the probability of shipment delivery.

Appendix A. Survey Questions and Responses

Survey Monkey Questions and Responses:

1) What is your approximate average household income?

Answer Options	**Response Percent**	**Response Count**
$0-$24,999	7.7%	8
$25,000-$49,999	11.5%	12
$50,000-$74,999	17.3%	18
$75,000-$99,999	19.2%	20
$100,000-$124,999	11.5%	12
$125,000-$149,999	11.5%	12
$150,000-$174,999	1.9%	2
$175,000-$199,999	3.8%	4
$200,000 and up	15.4%	16
answered question		**104**

2) What is your gender?		
Answer Options	**Response Percent**	**Response Count**
Female	58.7%	61
Male	41.3%	43
answered question		**104**

3) What is your age?		
Answer Options	**Response Percent**	**Response Count**
18 to 24	1.9%	2
25 to 34	14.4%	15
35 to 44	19.2%	20
45 to 54	20.2%	21
55 to 64	30.8%	32
65 to 74	11.5%	12
75 or older	1.9%	2
answered question		**104**

4) How many people currently live in your household?		
Answer Options	**Response Percent**	**Response Count**
1	16.3%	17
2	42.3%	44
3	20.2%	21
4	14.4%	15
5 or more	6.7%	7
answered question		**104**

5) How many employees currently work at the location where you work?		
Answer Options	**Response Percent**	**Response Count**
1 to 4 employees	6.7%	7
5 to 19 employees	8.7%	9
20 to 99 employees	26.9%	28
100 to 499 employees	25.0%	26
500 to 999 employees	10.6%	11
1000 employees or more	22.1%	23
answered question		**104**

6) What is the number of individuals you regularly communicate with at your workplace		
Answer Options	**Response Percent**	**Response Count**
0 to 9	26.0%	27
10 to 19	34.6%	36
20 to 29	17.3%	18
30 to 39	2.9%	3
40 to 49	2.9%	3
50 or more	16.3%	17
answered question		**104**

7) Please indicate the number of people you communicate regularly at your workplace according to level of relationship:

Answer Options	**1-4**	**5-9**	**10-14**	**15-19**	**20-24**	**25-29**	**30-34**	**35-39**	**40-44**	**45-50**	**50 or more**	**Response Count**
Close Friend	78	8	1	0	1	0	0	0	0	0	1	89
Friend	44	31	8	2	3	0	1	0	0	0	3	92
Acquaintance	21	19	26	7	9	2	2	1	1	3	5	96
Others who you can recognize as co-workers	22	15	13	13	4	3	2	0	2	0	22	96
answered question												**104**

8) Please indicate the number of people you communicate regularly in the vicinity of your home (neighbors) according to level of relationship:

Answer Options	**1-4**	**5-9**	**10-14**	**15-19**	**20-24**	**25-29**	**30-34**	**35-39**	**40-44**	**45-50**	**50 or more**	**Response Count**
Close Friend	67	6	2	3	0	0	0	0	0	0	1	79
Friend	62	16	8	0	0	1	0	0	0	0	3	90
Acquaintance	51	25	14	3	0	0	0	0	1	0	3	97
Others who you can recognize as neighbors	41	20	15	9	5	0	1	0	1	1	2	95
answered question												**104**

9) What level of relationship do you need to have with a co-worker/neighbor so as to allow them to assist with the delivery of your online order (pick it up and pass it to you whenever you get to meet)?

Answer Options	**Response Percent**	**Response Count**
Close Friend	35.6%	37
Friend	38.5%	40
Acquaintance	14.4%	15
Anyone who you can recognize as a co-worker/neighbor	11.5%	12
answered question		**104**

10) What level of relationship do you need to have with a co-worker/neighbor so as to agree to deliver a small online order?

Answer Options	**Response Percent**	**Response Count**
Close Friend	36.5%	38
Friend	34.6%	36
Acquaintance	18.3%	19
Anyone who you can recognize as a co-worker/neighbor	10.6%	11
answered question		**104**

11) Would you pick-up a package in a store for your neighbors/co-workers on your way home/to work? What is the minimal amount of compensation/incentive that you would consider enticing to participate in delivery?

Answer Options	Response Percent	Response Count
$0 Would do it for environmental considerations or friendship enhancement.	59.6%	62
$1	2.9%	3
$2	4.8%	5
$3	0.0%	0
$4	2.9%	3
$5 or more.	29.8%	31
answered question		**104**

12) If you were to pick-up a package in a store for your neighbors/co-workers on your way home/to work, under how much extra travel time, would you do it considering you were offered for this delivery the reward that is to your liking:

Answer Options	Response Percent	Response Count
Would do it if extra travel time is Less than 5 mins	25.0%	26
Would do it if extra travel time is Less than 10 mins	34.6%	36
Would do it if extra travel time is Less than 15 mins	21.2%	22
Would do it if extra travel time is more than 15 mins	5.8%	6
Will consider if paid more.	4.8%	5
NO will never do it.	8.7%	9
answered question		**104**

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