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Household-based e-commerce demand modeling for an agent-based urban transportation simulation platform

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Abstract:	E-commerce market has grown rapidly in the past two decades and this trend has accelerated tremendously due to the ongoing coronavirus pandemic. The need for predicting e-commerce demand and evaluating relevant policies and solutions is increasing. However, the existing simulation models for e-commerce demand are still limited and do not consider the impacts of delivery options and their attributes that shoppers face on multiple dimensions of e-commerce demand. We propose a novel framework involving disaggregate behavioral models which jointly predict e-commerce expenditure, purchase amount per transaction, delivery mode and option choices. The proposed framework can simulate the changes in e-commerce demand attributable to the changes in delivery options and be used to evaluate the impacts of a range of policies and solutions. We specify the model parameters based on various sources of relevant information, integrate the model into an urban freight simulator, and conduct a demonstrative simulation for a prototypical North American city. The results of the analysis highlight the capability and applicability of the proposed modeling framework.

January 4, 2021

Dear Dr. Meng, Co-Editor-in-Chief

On behalf of my co-authors, I am pleased to submit the paper titled **Household-based e-commerce demand modeling for an agent-based urban transportation simulation platform**. This paper presents a novel modeling framework involving disaggregate models of e-commerce expenditure, order value, delivery mode and option choices. In the paper, we also integrate these models within an agent-based simulation framework, SimMobility Freight (Sakai et al., 2020, *Transportation Research Part E: Logistics and Transportation Review)*, and demonstrate an application in a metropolitan-scale urban freight simulation. We use the simulation analysis for estimating e-commerce-derived transportation demand at a metropolitan scale and obtaining insights on how the growth of two key factors under the post-pandemic situation, specifically e-commerce adaptation and the availability of pickup delivery options, could impact on transportation demand.

Existing e-commerce demand models for freight transportation analysis consider primarily consumers' characteristics, and delivery option attributes, which is of critical importance to evaluate the impacts of urban logistics solutions, are not taken into account. Also, despite the e-commerce demand analysis is increasingly important due to the rapid growth of e-commerce, which the 2020 coronavirus pandemic has accelerated, only a few studies integrate e-commerce demand models with urban freight simulations. The paper will fill these research gaps. We believe our research will significantly advance the research in e-commerce demand modeling and urban freight simulation explicitly considering e-commerce-driven freight transportation demand.

Sincerely,

Takanori Sakai

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Highlights

- E-commerce expenditure, order value, delivery mode and option are jointly modeled.
- Novel e-commerce models are integrated into an agent-based urban freight simulator.
- A demonstrative simulation is conducted for a prototypical North American city.
- A large contribution of e-commerce shipments to urban freight traffic is predicted.
- Proposed framework can replicate the intricate impacts of demand/supply changes.

Household-based e-commerce demand modeling for an agent-based urban transportation simulation platform

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Household-based e-commerce demand modeling for an agent-based urban transportation simulation platform

Abstract

E-commerce market has grown rapidly in the past two decades and this trend has accelerated tremendously due to the ongoing coronavirus pandemic. The need for predicting e-commerce demand and evaluating relevant policies and solutions is increasing. However, the existing simulation models for e-commerce demand are still limited and do not consider the impacts of delivery options and their attributes that shoppers face on multiple dimensions of e-commerce demand. We propose a novel framework involving disaggregate behavioral models which jointly predict e-commerce expenditure, purchase amount per transaction, delivery mode and option choices. The proposed framework can simulate the changes in e-commerce demand attributable to the changes in delivery options and be used to evaluate the impacts of a range of policies and solutions. We specify the model parameters based on various sources of relevant information, integrate the model into an urban freight simulator, and conduct a demonstrative simulation for a prototypical North American city. The results of the analysis highlight the capability and applicability of the proposed modeling framework.

Keywords:
E-commerce; Freight delivery; Freight demand modeling; Urban freight; Agent-based simulation

1. Introduction

E-commerce market has been growing worldwide for the past two decades. In the United States, the share of e-commerce sales for the fourth quarter of 2019 was 11.4% compared to only around 4% in 2009 (U.S. Department of Commerce, 2020). Furthermore, the coronavirus pandemic in 2020 has triggered a significant increase in demand for e-commerce deliveries (Fortune, 2020). To cater to the demand increase, large investments have been made by major e-commerce vendors (The New York Times, 2020). Along with the demand growth, there have been growing discussions among transportation researchers and practitioners on the measures to handle the increasing parcel deliveries to residential locations. Logistics solutions such as last-mile consolidations, collection points/drop zones, cargo cycles, crowd-shipping, drones, and delivery robots have been proposed and discussed (e.g., Allen et al., 2018a). Furthermore, the relationship between delivery service characteristics and consumers' purchase decisions has been studied from the e-commerce vendors' perspective, including services such as free shipping and same-day deliveries (Nguyen et al., 2019). It should be emphasized that the delivery options to be offered to e-commerce consumers rely on transportation network/systems and are expected to evolve even more rapidly than before, due to the changes in shopper's preferences toward e-commerce triggered by the pandemic. It should be noted that "delivery options" in this paper include both home delivery and pickup options.

Despite its importance for evaluating the impacts of logistics solutions to e-commerce demand, there is a lack of a modeling framework that considers the sensitivity of delivery demand to delivery options, specifically, delivery mode, fee, speed, and time slot, which depends on the performance of transportation systems. Such a framework should also be capable of measuring the impacts of vendor's policies such as free shipping, which is offered typically when the order value exceeds a pre-defined threshold (e.g., $25). The past studies on e-commerce demand models mainly focus on the characteristics of individuals and households as explanatory variables but not those of delivery options. This is a critical research gap, as, for example, the delivery fee is known to have a significant influence on e-commerce expenditure, order sizes, and frequency (Lewis et al., 2006; Lepthien and Clement, 2019). Our aim is to develop a modeling framework considering the consumers' reactions to e-commerce vendor's policy on delivery service options. We propose a theoretical demand model framework that predicts e-commerce demand (i.e., expenditure, frequency, order size, and delivery mode and option choices) given the household characteristics and the delivery modes/options offered. The fragmentation of commodity flows (i.e., the shift from Business-to-Business (B-to-B) to Business-to-Consumer (B-to-C) flows) is suspected of leading to greater congestion and environmental impacts (Morganti et al., 2014). The proposed framework is capable of simulating e-commerce delivery demand to evaluate impacts of, for example, the increase in the purchase share on online shopping against in-store shopping, new delivery options made available by novel transportation modes, and the increase/reduction in delivery fees. While the main contribution of this paper is conceptual, i.e., the development of modeling framework of the household-based e-commerce demand model, we also integrate the model with an agent-based urban freight simulator, SimMobility Freight (Sakai et al. 2020a), and demonstrate the capability of the framework. We specify the model parameters based on available data and use the integrated simulator to simulate e-commerce orders and shipments and associated transportation demand at a metropolitan scale under the pre-Covid-19 and the post-pandemic scenarios.

The rest of the paper is organized as follows; a literature review that covers existing e-commerce demand prediction models and the studies on the consumer preferences to delivery options; a description of the modeling framework for e-commerce demand and the specification of the household-based e-commerce demand model; an overview of SimMobility Freight; the demonstrative e-commerce and associated freight transportation demand simulation using SimMobility Freight integrated with the e-commerce demand model; and conclusions.

2. Literature Review

Although there are increasingly more studies on e-commerce demand modeling, they are mostly limited to the characterization of the demand. For example, some studies estimate models to shed light on the interactions between online and in-store shopping (e.g., Shi et al., 2019; Xi et al., 2020; Suel et al., 2018). The following literature review focuses on the research on e-commerce demand modeling for city-wide simulations. A broader review of e-commerce models is available in the literature, for example, Suel and Polak (2018).

As one of the earliest studies focusing on prediction of freight transportation demand, Wang and Zhou (2015) develop a binary choice model and a right-censored negative binomial model to predict delivery frequency, using individual, household, and urban characteristics as independent variables. Their model was estimated using the U.S. National Household Travel Survey (NHTS) data. The studies that follow assume the substitutability between shopping trips and deliveries. Stinson et al. (2019) develop a household-level e-commerce model, which predicts the participation in e-commerce and the ratio of delivery to on-site shopping. They use household characteristics and accessibilities as independent variables. Stinson et al. (2020), using the model in Stinson et al. (2019), estimate parcel delivery truck tours in POLARIS, an agent-based transportation model (Auld et al., 2016). Jaller and Pahwa (2020) develop a multinomial logit model that predicts a shopping decision in each day. Alternatives include "*no shopping*", "*in-store*", "*online*" and "*both*". The 2016 American Time Use Survey (ATUS) was used for model estimation. The independent variables include gender, age, education level, employment status, family income, mobility-related difficulty, region, the size of the Metropolitan Statistical Area (MSA) and season. They also study the impacts of different retail channel scenarios on traffic, using a series of assumptions on the relationships between shopping decisions and transportation demand based on available statistics, although the choices of channel are given in the analysis (i.e., the choices are not simulated for scenarios). Also, Comi and Nuzzolo (2016) propose a choice model considering the four alternatives for weekly purchases similar to those in Jaller and Pahwa. Only a few studies integrate e-commerce demand models with urban freight simulations. Also, the existing e-commerce demand models for freight transportation analysis consider primarily consumers' characteristics, and the delivery options presented by e-commerce vendors are not taken into account.

On the other hand, the consumer's preference for delivery options has been studied mainly in market research. Among them, those estimating choice models relevant to freight demand analysis are discussed next. Regarding the delivery option choice, Nguyen et al. (2019) conduct a conjoint analysis focusing on three product types – a personal care item, a pair of jeans, and a digital camera - and estimate a discrete choice model considering delivery option attributes including delivery speed, time slot, day/evening delivery, delivery date and delivery fee. Gawor and Hoberg (2019) also conduct a choice-based conjoint analysis asking delivery preferences for a digital camera, a laptop, and a smartphone to online shoppers in the US. Similarly, Garver et al. (2012) conduct an adaptive choice-based conjoint analysis, using the data from the students in a university market research class. The attributes such as price, delivery speed, availability of tracking, guaranteed delivery time, insurance, and shipping company are considered. Recently, Grashius et al. (2020) analyze e-commerce consumers' preferences for purchasing methods, time windows, minimum order requirements, and fees, given different COVID-19 pandemic scenarios. While several delivery option studies consider the effect of delivery fees among others, the studies on the relationship between the delivery fee and order size are limited. Lewis et al. (2006) is one of a few exceptions. They develop an ordered logit model for order value at online shopping considering the variables such as market and household-level variables and the delivery fee. They use the data from an online retailer specializing in nonperishable grocery and drugstore items. Furthermore, Lewis (2006) also develop an OLS regression model to predict an average order size (i.e., value) using the same data. Lepthien and Clement (2019) develop another OLS regression model of the order size considering delivery fee. They use data of an online retailer for streetwear and sportswear with the research interest on return behavior. The studies discussed above focus on only a single aspect of e-commerce demand independently from the others. For example, a delivery option selection model does not consider order size decisions. Considering the fact that the "free shipping" service is widely offered at present and that the order size is often influential to the delivery fee, those two decisions ("delivery option selection" and "order size selection") are related to each other in the real world.

The present research will fill existing research gaps on e-commerce demand modeling by (1) developing a modeling framework involving disaggregate models of e-commerce expenditure, order value, delivery mode and option choices, which takes the impacts of delivery options' characteristics into account, and (2) integrating these models within an agent-based simulation framework and demonstrating an application in a metropolitan-scale urban freight simulation.

3. E-commerce Demand Model

3.1 Simulation of e-commerce shipments

The e-commerce demand model we propose is household-based. A decision-maker in the model represents her/his household (this "decision maker" could consist of more than one online shopper who belongs to a single household) and the household characteristics are the input for the simulation. The simulation flow of the e-commerce demand is shown in Fig. 1. First, e-commerce adoption is determined. The "adoption" is defined here as the placement of at least one order in a given month. Following, (i) the total e-commerce expenditure in a month ("*total value*"), (ii) the purchase amount per transaction ("*order value*"), (iii) delivery mode (home delivery or pickup) ("*delivery mode*"), and (iv) delivery option ("*delivery option*") are simulated for the households that adopt e-commerce. The above simulations run independently across three item categories: groceries, household goods (i.e., goods for daily consumption such as detergents and toilet papers), and others (such as clothing, books, and electric appliances), and we acknowledge that there is room for future improvement by considering the interactions between these categories. Home delivery orders are converted to packages and, for each package, a distribution facility (the origin of package delivery) is assigned. The output, e-commerce shipments (i.e., package deliveries with origins and destinations), was put together with business-to-business (B2B) shipments and used as the input for the pre-day logistics planning model which generates goods vehicle operation plans (i.e., pickup and delivery schedules (or tours) for goods vehicles in a given day). The assignments of distribution facilities, the simulation of B2B shipments, and the pre-day logistics planning rely on SimMobility Freight (Sakai et al., 2020a), an urban freight simulator which is described in Section 4.

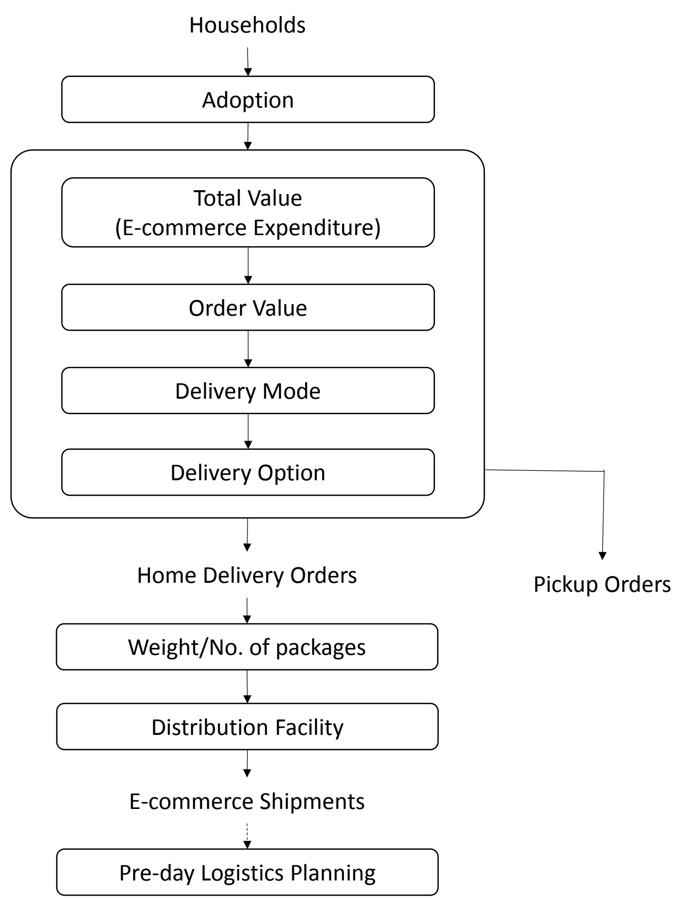

Fig. 1 Flow of e-commerce demand simulation

3.2 Adoption and order (total value, order value, delivery mode, delivery option) models

This subsection describes the e-commerce adoption and order models, which generate e-commerce orders. The model specification of each level is as follows.

3.2.1. E-commerce Adoption

We use a binary logit (BL) model for e-commerce adoption for each item category similarly to the e-commerce participation model developed by Stinson et al. (2019). The systematic part of utility of e-commerce adoption $V_{n,adopt}^{item}$ for item category $item$ (groceries, household goods, or others) to a household n is:

$$V_{n,adopt}^{item} = ASC_{adopt}^{item} + \beta_{numadults}^{item} log\ (numadults_n) + \beta_{child}^{item} child_n\ + \sum_i \beta_{income,i}^{item} income_{i,n} + \beta_{hbsdist}^{item} \log(hbsdistance_n) \quad (1)$$

where

$numadults_n$:	Number of adults in household n.
$child_n$:	Variable for child(s) in household n. 1 if there is any child (less than 18 years old) in household n; 0 otherwise.
$income_{i,n}$:	Variable for the annual income category i (1: less than US$10k, 2: US$10k-15k, 3: US$15k-25k, 4: US$25k-35k, 5: US$35k-50k, 6: US$50k-75k, 7: US$75k-100k, 8: US$100k-125k, 9: US$125k-150k, 10: US$150k-200k, 11: US$200k or more). 1 if income category of household n is i; 0 otherwise.
$hbsdistance_n$:	The average distance (km) of home-based shop trips by the members of household n.

ASC_{adopt}^{item}, $\beta_{numadults}^{item}$, β_{child}^{item}, $\beta_{income,i}^{item}$, $\beta_{hbsdist}^{item}$: Model parameters

We define the "non-adoption" as the base-category (i.e., V_{n,non_adopt}^{item}=0); therefore, the probability $P_{n,adopt}^{item}$ of e-commerce adoption is:

$$P_{n,adopt}^{item} = \exp\left(V_{n,adopt}^{item}\right) / \exp(1 + V_{n,adopt}^{item}) \quad (2)$$

3.2.2. Total Value, Order Value, Delivery Mode and Delivery Option

The relationship between delivery modes/options and order and total values is bi-directional. Specifically,

- the characteristics of delivery modes/options, especially fee, affects the total value and order value; and
- delivery models/options' characteristics depend typically on order value, due to free shipping service or other marketing tactics.

Therefore, it is critical to consider the decisions on *total value*, *order value*, *delivery mode* and *delivery option* in a joint manner. We propose a multi-level model specification which considers the interrelations among these decisions using a nested structure; the first level is *delivery option*, the second level is *delivery mode*, the third level is *order value*, and the fourth level is *total value*. In this setting, the levels except the first one consider the expected utility from the lowers level through logsum measures (Fig. 2).

The model specification of each level, starting from the delivery option model, is described below. At each level, the model is specified as a multinomial logit (MNL) model. It should be noted that the notation for the item category $item$ is omitted for simplicity.

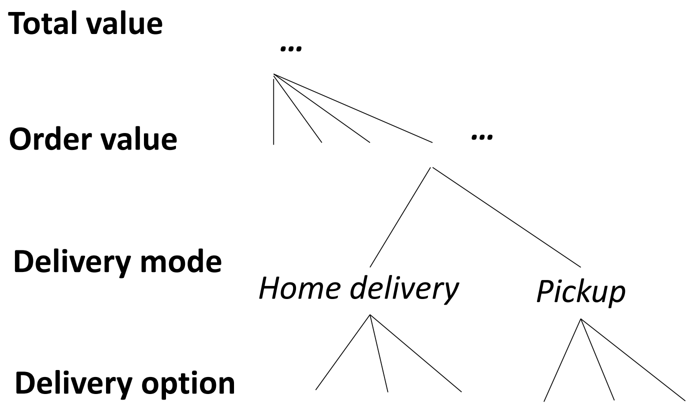

Fig. 2 A multi-level model structure

Total Value

Integer values in US$ are considered as alternatives for the total value choice. In this paper, we use the range 5 to 1000 per month, while this range is adjustable depending on simulation cases. The utility $U_{n,tv}$ of total value tv to household n and its systematic part $V_{n,tv}$ are defined as follows:

$$U_{n,tv} = V_{n,tv} + \varepsilon_{n,tv} \qquad (3)$$

$$V_{n,tv} = \beta_{logsumov} \cdot ln \sum_{ov} \exp\left(\hat{V}_{n,ov|tv}\right) + \beta_{hhs}\ (\alpha \cdot hhs_n - tv)^2 \qquad (4)$$

where

$\hat{V}_{n,ov\|tv}$:	The systematic part of the utility of order value ov given total value tv to household n (defined later in this section)
hhs_n :	Number of people in household n.
$\varepsilon_{n,tv}$:	Identically and independently Gumbel distributed random component.
$\beta_{logsumov}$, α:	Model parameters

The first term is the effect of the log-sum measure from the order value selection; the second term adjust the utility of the total value based on the "gap" between the household size and the total value.

The alternative specification of Equation (4) uses the total expenditure (combining both e-commerce and non-e-commerce) for the target item category, instead of the household size:

$$V_{n,tv} = \beta_{logsumov} \cdot ln \sum_{ov} \exp\left(\hat{V}_{n,ov|tv}\right) + \beta_{hhs}\ (\alpha' \cdot epdt_n - tv)^2 \qquad (4')$$

where $epdt_n$ is the total monthly expenditure of household n for the item category of interest; and α' is the fraction of the total expenditure (a model parameter).

The probability $P_{n,tv'}$ of total value tv' for household n is given by the following equation:

$$P_{n,tv'} = \exp\left(V_{n,tv'}\right) / \sum_{tv} \exp(V_{n,tv}) \qquad (5)$$

Order Value

Similar to the total value model, the set of order value alternatives consists of integer values in US$. We use the range 5 to 300 in this paper. The utility $U_{n,ov|tv}$ of order value (ov) given total value (tv) to household n and its systematics part $V_{n,ov|tv}$ are:

$$U_{n,ov|tv} = V_{n,ov|tv} + \varepsilon_{n,ov} \quad (6)$$

$$V_{n,ov|tv} = \beta_{logsumdm} \cdot \frac{tv}{ov} \cdot (\beta_{ref} + \ln \sum_{dm \in DM_{n|ov}} \exp(\tilde{V}_{n,dm|ov})) + \beta_{interval} \cdot \left(\frac{ov}{tv}\right)^2 + \beta_{storage} \cdot ov \quad (7)$$

where

$\tilde{V}_{n,dm|ov}$: The systematic part of the utility of delivery mode dm given order value ov to household n (defined later in this section)

$\varepsilon_{n,ov}$: Identically and independently Gumbel distributed random component.

$\beta_{logsumdm}$, β_{ref}, $\beta_{interval}$, $\beta_{storage}$: Model parameters.

The first term in Equation (7) captures the effect of the total expected utility from the delivery mode (home delivery/pickup). The log-sum measure from the delivery mode choice is adjusted with the intercept β_{ref} (which defines the reference point for the log-sum measure) and then multiplied by the frequency per month. The second term captures the effect of the interval between orders (i.e., the penalty for long order intervals); it is assumed that the longer interval is associated with the greater depreciation and the mismatch between purchased items and the future consumption need. The third term captures the effect of the storage cost, which is linear to the order value.

Delivery mode

We consider two delivery modes as alternatives: home delivery and pickup. The utility $V_{n,dm|ov}$ of delivery mode (dm) given order value (ov) to household n is:

$$U_{n,dm|ov} = V_{n,dm|ov} + \varepsilon_{n,dm} \quad (8)$$

where

$\varepsilon_{n,dm}$: Identically and independently Gumbel distributed random component.

The systematics parts of utilities of home delivery and pickup, $V_{n,dm=hd|ov}$ and $V_{n,dm=pu|ov}$ respectively, given order value (ov) to household n, are:

Home delivery: $V_{n,dm=hd|ov} = \beta_{logsum_{hd}} \cdot \ln \sum_{do \in DO_{n,ov}} \exp(\tilde{V}_{n,do|ov})$ (9)

Pickup: $V_{n,dm=pu|ov} = ASC_{pu} + \beta_{logsum_{pu}} \cdot \ln \sum_{po \in PO_{n,ov}} \exp(\hat{V}_{n,po|ov})$ (10)

where

$\tilde{V}_{n,do|ov}$, $\hat{V}_{n,po|ov}$: The systematic parts of the utilities of home delivery option do and pickup option po, respectively, given order value ov to household n (defined later).

$DO_{n,ov}$: The set of home delivery options (do) available to household n given order value ov.

$PO_{n,ov}$: The set of pickup options (po) available to household n given order value ov.

$\beta_{ASC_{pu}}$, $\beta_{logsum_{hd}}$, $\beta_{logsum_{pu}}$: Model parameters.

The utility functions for the delivery options under home delivery mode and those under pickup mode are defined differently as described below.

Delivery option under home delivery mode

The model considers the situation that a decision maker is solicited to select one option for home delivery, from multiple delivery options which differ in in terms of speed, slot, time, day, and fee, given the order value. The example of the alternatives is shown in Table 1. The set of alternatives $DO_{n,ov}(\ni do)$ is conditional to ov (e.g., free shipping for the standard delivery).

Table 1 Example of delivery options (home delivery mode)

Option	Speed	Time slot	Time	Date	Fee
1	2-5 days	No time slot	Daytime	Weekday only	US$0
2	One day	No time slot	Daytime	Weekday only	US$12
3	Same day	4 hr	Daytime and evening	Weekday and Saturday	US$18

Source: Adapted from Nguyen et al. (2019) ("Fee" is different from those presented in Nguyen et al.)

The utility $U_{n,do|ov}$ of delivery option (do) given order value (ov) for a decision maker n and its systematic utility $V_{n,do|ov}$ are:

$$U_{n,do|ov} = V_{n,do|ov} + \varepsilon_{n,do} \quad (11)$$

$$V_{n,do|ov} = \sum_i \beta_i^{speed} speed_{i,do} + \sum_j \beta_j^{slot} slot_{j,do} + \sum_k \beta_k^{time} time_{k,do} + \sum_l \beta_l^{date} date_{l,do} + \beta_{delivfee} fee_{do,ov} \quad (12)$$

where:

$speed_{i,do}$: Variable for speed *i* (1: 2-5 days, 2: one day, 3: same day). 1 if speed category of *do* is *i*; 0 otherwise.

$slot_{j,do}$: Variable for time slot (width) *j* (1: no time slot, 2: two hours, 3: four hours). 1 if time slot category of *do* is *j*; 0 otherwise.

$time_{k,do}$: Variable for time *k* (1: daytime, 2: daytime & evening). 1 if time category of *do* is *k*; 0 otherwise.

$date_{l,do}$: Variable for date l (1: weekday, 2: weekday & Saturday, 3: all days). 1 if date category of *do* is l; 0 otherwise.

$fee_{do,ov}$: Fee of *do* given order value *ov*.

$\varepsilon_{n,do}$: Identically and independently Gumbel distributed random component.

β_i^{speed}, β_j^{slot}, β_k^{time}, β_l^{date}, $\beta_{delivfee}$: Model parameters.

Equation (12) is the same with the model specification proposed by Nguyen et al. (2019) except that delivery fee is considered as a continuous variable, instead of a dummy variable.

Delivery option under pickup mode

For the pickup model, the three main options are considered: in-store, curbside, and locker. The utility $U_{n,po|ov}$ of pickup option (po) given order value (ov) for a decision maker n and its systematic part $V_{n,po|ov}$ are:

$$U_{n,po|ov} = V_{n,po|ov} + \varepsilon_{n,po} \quad (13)$$

$$V_{n,po|ov} = \beta_{curbside} curbside_{po} + \beta_{locker} locker_{po} + \beta_{pickfee} fee_{po,ov} \quad (14)$$

where:

$curbside_{po}$: Variable for curbside pickup. 1 if po is curbside pickup; 0 otherwise.

$locker_{po}$: Variable for locker pickup. 1 if po is locker pickup; 0 otherwise.

$fee_{po,ov}$: Fee of po given order value *ov*.

$\varepsilon_{n,po}$: Identically and independently Gumbel distributed random component.

$\beta_{curbside}$, β_{locker}, $\beta_{pickfee}$: Model parameters.

The proposed general modeling framework consisting of the above four levels allows the e-commerce demand prediction to be sensitive to delivery options' attributes on multiple dimensions, i.e., frequency, size, and delivery mode/option choices. The model also can consider varying fees depending on order size for each option. The example of fee setting is shown in Table 2.

Table 2 Example of fees by delivery option (home delivery and pickup)

Option (home delivery)	Speed	Fee (US$) Order size (US$) 0-25	25-50	50-100	100-	Other characteristics (same for all options)
1	2-5 days	6	0	0	0	No time slot, daytime delivery, and all days
2	One day	12	15	17	20	
3	Same day	18	20	22	27	

Option (pickup)	Instore/Curbside	Fee (US$) Order size (US$) 0-25	25-50	50-100	100-
1	In-store	6	0	0	0
2	Curbside	6	2	2	2

3.3 Subsequent models to translate e-commerce orders to e-commerce shipments

The output of the model described in 3.2.2 is e-commerce orders with the information of item category, value, and delivery option. These e-commerce orders are converted to e-commerce shipments with additional processes. The first process is the value-to-weight conversion and the assignment of the number of delivery packages to each order. As of now, we use the simple random assignments of weight-per-value and the number of packages to each e-commerce order based on pre-defined distributions (which are calibrated based on empirical data). The second process is the distribution facility assignment for each package. For this, the supplier selection model in SimMobility Freight (described in Section 4) is used, which is a logit mixture model considering e-commerce carriers' facilities and a subset of retail establishments as alternatives. The details of the supplier section model are available in Sakai et al. (2020b).

4. SimMobility Freight: Overview

SimMobility Freight is an urban freight model and a part of SimMobility, an agent-based urban transportation simulation platform (Adnan et al., 2016). SimMobility/SimMobility Freight simulates transportation-related decisions at three different temporal dimensions, i.e., long-term (LT), mid-term (MT), and short-term (ST) (Fig.3). In regard to SimMobility Freight, the LT model simulates the decisions of business establishments, including commodity contracts (which defines B2B shipments) and overnight parking locations. The MT model simulates *pre-day logistics planning* (*carrier selection* and *vehicle operation planning*) and *within-day vehicle operations* (*route choice* and *pickup/delivery parking choice*). Furthermore, the mesoscopic traffic simulator, a supply model, runs together with "within-day" models and computes network performance. The ST model is a microscopic simulator of vehicle behaviors on the road network (Azevedo et al., 2017). Traffic simulators in MT and ST models are common for freight and passenger analyses, jointly handling goods and passenger vehicles. The details of SimMobility Freight are available in Sakai et al. (2020a). The e-commerce demand model which we propose in this paper is positioned before the *pre-day logistics planning*. In the demonstrative simulation in the next section, we use the LT commodity contract model and the proposed e-commerce demand model to simulate B2B shipments and e-commerce shipments, respectively, and use pre-day logistics planning model to simulate goods vehicle tours.

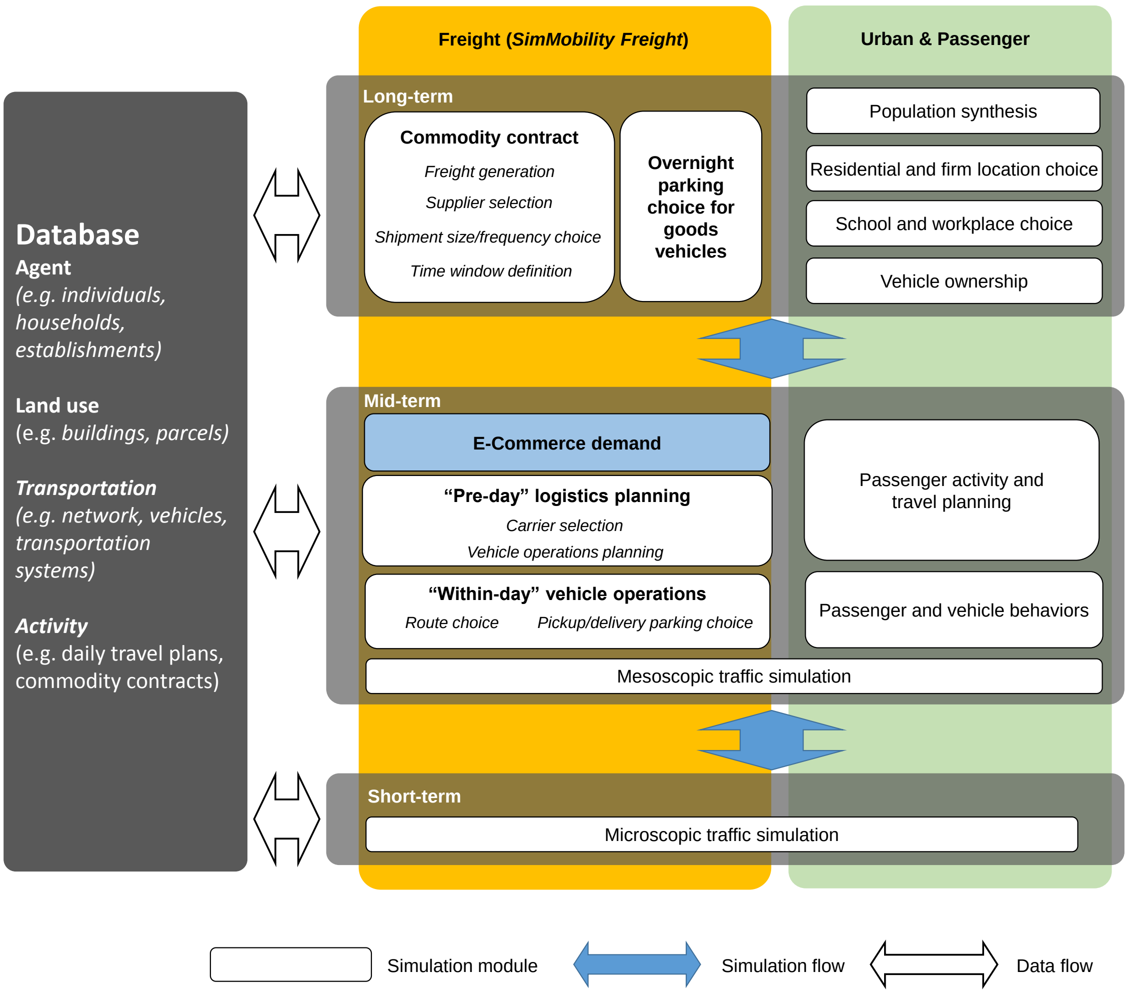

Fig. 3 Main components of SimMobility

5. Demonstrative Application using Auto-Innovative City

5.1 Overview

Despite the rapid increase in e-commerce deliveries in recent years, the impact of B2C e-commerce deliveries to urban traffic, compared against other freight traffic, is not well-known. One of the reasons for this is that the widely used surveys for classified traffic counts do not differentiate goods vehicles for e-commerce deliveries and those for other purposes. As a demonstrative analysis, we use SimMobility Freight enhanced with the proposed e-commerce model for estimating e-commerce-derived transportation demand at a metropolitan scale. Also, we use this analysis to obtain insights on how the growth of two key factors under the post-pandemic situation, specifically e-commerce adaptation and the availability of pickup delivery options, could impact on transportation demand. For the analysis, we generate and simulate an Auto-Innovative prototype city, which uses Boston as an archetype (Fig. 4). The prototype city is a model of a class (or typology) of cities. Among the 12 typologies identified by Oke et al. (2019), the Auto-Innovative prototype represents a dense auto-dependent North American city with high transit mode share and population density (Oke et al., 2019; Oke et al., 2020). The synthetic household and establishment data were developed for the Auto-Innovative prototype city and we use them as inputs. The synthetic establishments include 58 last-mile distribution facilities for e-commerce, of which 4 are for groceries. We also assume that 348 large scale retail establishments (> 3000 m^2) can serve as the origins of grocery deliveries. In this demonstration, we do not consider the pickup option using a locker distinctively from in-store and curbside pickups due to the data limitation for setting the relevant model parameters.

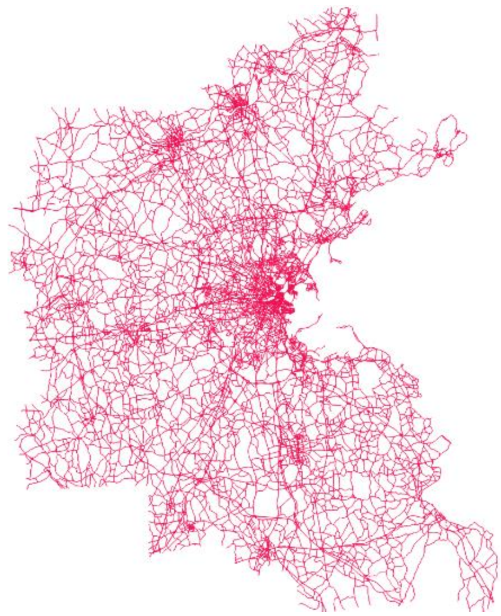

Fig. 4 Network in Auto Innovative city

5.2 Model parameter specification

Ideally, the model parameters should be calibrated for the four levels using a single data in a joint manner; however, there is no real-world data available for us to estimate model parameters altogether. Instead, we specify model parameters by estimating and/or calibrating them based on the synthetic data or by using parameters from past studies. We acknowledge that, while we attempt to use realistic model parameters as much as possible, the model sensitivities are not based on empirical data from Boston or another Auto Innovative city. Further calibration will be required for more accurately replicating various types of elasticities, which the proposed model specification is capable of simulating. Below, we describe the methods to set model parameters in the order of (1) delivery option model, (2) delivery mode model, (3) order value model, (4) total value model and (5) e-commerce adoption model.

Delivery option: The model parameters of delivery option model (mode: home delivery) (Equation (12)) are obtained from the estimated model in Nguyen et al. (2019). They conducted a conjoint analysis to estimate the part-worth utilities for the delivery option choice. Their analysis used the data from 1012 respondents in the Netherlands, who expressed delivery option preferences for the purchase of three different items. We used the parameters estimated for personal care item while we make changes on the delivery fee term. In the original model, the delivery fee was treated as a categorical variable. We replaced this with a function that treats the delivery fee as a continuous variable as shown in Equation (12). The coefficient for the delivery fee was calibrated to replicate the part-worth utility in the original model and the unit of currency is converted from € to US$. Similarly, the model parameters of delivery option model (mode: pickup) (Equation. (14)) are obtained from Grashuis et al. (2020). They estimated a delivery option choice model which covers in-store and curbside pickup options using a stated preference survey data collected from 900 respondents in the U.S., during 2020.

Delivery mode: To estimate the model parameters for delivery mode choice model (Equation (9-10)), synthetic data was generated using the model presented in Grashuis et al. (2020). First, we generated 240 profiles of delivery option, following the survey design of Grashuis et al., and randomly picked a profile for each of in-store pick-up, curbside pick-up, and home delivery option, made a choice set of the three, and repeated the process. Then, we applied the MNL model of Grashuis et al. to replicate the choices and the generated synthetic data is used for estimating the model parameters. The logsum measure of home delivery options and pickup options was calculated based on Equation (12) and Equation (14), respectively, with the model parameters mentioned above. Since Grashuis et al. do not consider/assume the details of the delivery options under home delivery mode such as delivery speed and the associated fee in their survey and model, we assumed the availability of three home delivery options (2-5 days, one day, or same day). The home delivery fee in the synthetic data (which is set following the method of Grashuis et al.) was assumed as that of 2-5 days. The home delivery fee for the one day was set at twice the 2-5 days fee and the fee for the same day was set at triple.

Order value: We relied on Lewis et al. (2006) to generate synthetic data for estimating parameters of the order value model (Equation (7)), specifically $\beta_{logsumdo}$ and β_{ref}. Lewis et al. estimated an ordered logit model to predict order size, using the data from an online retailer. The data collection year and location are not disclosed but supposedly the data is from the US in 2003 or earlier. We generated the synthetic data using their model, which consider the relationship between delivery fee and order size. To generate the data, we assumed four fee structures for small (\$0-\$50), medium (\$50-\$75) and large (\$75-) order size (i.e., \$5/\$7/\$0, \$5/\$7/\$9, \$3/\$5/\$5, and \$6/\$8/\$10). Since the responses by the Lewis et al.'s model are categorical ($\leq$ \$50, \$50 - \$75, $>$ \$75), randomly selected continuous values were assigned instead of categorical values. To compute the logsum measure from the lower level, we used the model parameters of the delivery option and mode models mentioned above, while pickup mode/pickup delivery options were assumed unavailable for the synthetic samples. The availability of express home delivery options (one day or same day) was assumed similarly to the parameter estimation for the delivery mode choice model.

$\beta_{logsumdo}$ and β_{ref}, which capture the influence of the logsum from the lower level and were estimated using the above method, are used for all three item categories. On the other hand, $\beta_{interval}$ and $\beta_{storage}$ were re-calibrated for each item category. We generated another synthetic data generated using data fusion. The base samples are from 2017 National Household Travel Survey (2017 NHTS) (U.S. Federal Highway Administration, 2017). 2017 NHTS includes the count of times purchased online for delivery, i.e., the count of e-commerce orders, in last 30 days, at a household level. One limitation is that the count data does not include information such as item category and order value.

- To enrich this data, first, we assigned one of the three item categories (*groceries*, *household goods*, or *others*) to each order. This assignment was random but guided to achieve the following two targets: (a) the share of the households which have at least one order for groceries is around 16% (this 16% was set referring to Etumnu and Widmar (2020), which conducted a survey of online grocery shopping in 2019); and (b) the ratio of the order counts between *household goods* and *others* is 0.39 (this 0.39 was set referring to Holguin-Veras and Wang (2020), which estimates the monthly delivery frequency before the pandemic).

- Next, order value was assigned to each of the orders. For this, we used the earlier-mentioned synthetic data generated using the model of Lewis et al. and generated the order value – order frequency pair samples. An order value was randomly selected for each NHTS sample from the group of order value – order frequency pairs which order frequency corresponds to the NHTS sample. Then, the assigned order values were multiplied by an adjustment factor defined for each item category so that the average total value (i.e., monthly e-commerce expenditure) per household (including those do no adopt e-commerce) match the reference values. We set the reference per-month total value per household for each item category as follows: US\$16.7 for *groceries*, US\$38.5 for *household goods*, and US\$62.3 for *others*, based on Digital Commerce 360 (2020a), The Atlantic (2019) and U.S. Bureau of Labor Statistics (2020).

This NHTS based synthetic data was used to re-estimate $\beta_{interval}$ and $\beta_{storage}$ for each item category, with the fixed $\beta_{logsumdo}$ and β_{ref}. For this, the above-mentioned parameters for delivery option and mode models were used. Furthermore, three home delivery options (2-5 days, one day, and same day) are assumed available while the pickup options (in-store and curbside) are assumed available only for 7%[1] of orders regardless of item category.

Total value: The model parameters of the total value model (Equation (4)) were estimated for each item category using the NHTS-based synthetic data with the model parameters set for the lower levels and the available delivery options assumed earlier (three home delivery options (always available) and two pickup options (available only for 7%).

Adoption: Similarly, the parameters of the e-commerce adoption model were estimated for each item category using the NHTS based synthetic data.

The model parameters used for the simulation are summarized in Table 3 and 4. The comparison between the e-commerce demand-related reference and simulated values (using the parameters determined using the above-mentioned method) is summarized in Table 5.

Table 3 Summary of the model parameters (Delivery Option, Delivery Mode, Order Value, and Total Value)

Parameter	Value	Parameter	Value
Delivery option choice		**Order value choice**	
Home delivery mode		$\beta_{logsumdm}$	0.471
β_i^{speed}		β_{ref}	-0.550
- same day	0.177	$\beta_{interval}$ [groceries]	-0.970
- next day	0.082	$\beta_{storage}$ [groceries]	-0.00504
- 2-5 business days	-0.259	$\beta_{interval}$ [household goods]	-0.467
β_j^{slot}		$\beta_{storage}$ [household goods]	-0.0709
- no time slot	-0.157	$\beta_{interval}$ [others]	0
- 2 hr	0.113	$\beta_{storage}$ [others]	-0.226
- 4 hr	0.040		
β_k^{time}		**Total value choice**	
- daytime	-0.090	$\beta_{logsumov}$ [groceries]	501×10^3
- daytime & evening	0.090	β_{hhs} [groceries]	-44.7
β_l^{date}		α [groceries]	0
- weekday	-0.063	$\beta_{logsumov}$ [household goods]	1300×10^3
- weekday & Saturday	0.054	β_{hhs} [household goods]	-14.6
- all days	0.009	α [household goods]	56.4
$\beta_{delivfee}$ (US$)	-0.183	$\beta_{logsumov}$ [others]	298×10^3
Pickup mode		β_{hhs} [others]	-18.1
$\beta_{curbside}$	0.532	α [others]	36.3
β_{locker}	n/a		
$\beta_{pickfee}$ (US$)	-0.110		
Delivery mode choice			
$\beta_{ASC_{pu}}$	-0.461		
$\beta_{logsum_{pu}}$	0.407		
$\beta_{logsum_{hd}}$	0.930		

[1] Since the data on the pickup option availability for e-commerce orders is not available, we use this ballpark figure based on "% of Top 500 retailers with stores offering curbside pickup in December 2019" (6.9%) (Digital Commerce 360, 2020b).

Table 4 Summary of the model parameters (Adoption)

Parameter	Value		
	Groceries	Household goods	Others
ASC_{adopt}^{item}	-3.02	-1.67	-1.17
$\beta_{numadults}^{item}$	0.725	0.711	0.669
$\beta_{hbsdist}^{item}$	-0.00405	0.00494	0.0153
β_{child}^{item}	0.348	0.512	0.648
$\beta_{income,i}^{item}$			
- 0-10k US$	-0.00585	0.00268	0.130
- 10k-15k US$	0.180	0.361	0.418
- 15k-25k US$	0.450	0.582	0.764
- 25k-35k US$	0.681	0.874	1.18
- 35k-50k US$	0.908	1.21	1.58
- 50k-75k US$	1.15	1.52	1.98
- 100k-125k US$	1.30	1.75	2.29
- 125k-150k US$	1.44	1.90	2.57
- 150k-200k US$	1.59	2.11	2.80
- 200k- US$	1.75	2.37	2.93

Table 5 Comparison between the reference and simulated values of e-commerce demand

Indicator	Source	Reference value	Simulated value (Auto Innovative City)
• Orders per household-day	2017 NHTS (U.S. Federal Highway Administration, 2017).	0.155 [all]	0.152 [all]
• Adoption rate	Etumnu, C. E., & Widmar, N. O. (2020).	16% [groceries] n/a [household goods] n/a [others]	16.6% [groceries] 45.8% [household goods] 60.9% [others]
• Expenditure (e-commerce) per household-month	Digital Commerce 360 (2020a), The Atlantic (2019) and U.S. Bureau of Labor Statistics (2020)	$16.7 [groceries] 1) $38.5 [household goods] 2) $62.3 [others] 3)	$17.5 [groceries] $39.2 [household goods] $64.8 [others]
• Expenditure per order	Brick Meets Click (2020)	$72 [groceries] n/a [household goods] n/a [others]	$70.5 [groceries] $31.7 [household goods] $20.7 [others]

Note: 1) 4.3% of the total expense for *groceries* is assumed as the e-commerce expense; 2) 26% of the total expense for *household goods* is assumed as the e-commerce expense; 3) 26% of the total expense for *others* is assumed as the e-commerce expense.

5.3 Calibration of other models

The key information on the model calibration for other models are as follows:

No. packages per order: Since there is no available data for estimating no. of packages for each order based on order characteristics, we set, for the simulation, the probability distributions of the number of packages per order (Table 6) so that the number of e-commerce deliveries per household-day becomes 0.226[2].

[2] This is based on the number of online retailer parcel deliveries (10.6 billion) and the number of households (128.58 million) in the U.S., 2019 (Barron's, 2020).

Table 6 Assumption on no. of packages per order

Item category	No. of packages per order 1	2	3	Total
Groceries	100%	0	0	100%
Household goods	50%	38%	12%	100%
Others	45%	33%	22%	100%

Vehicle operation planning: The vehicle operations planning model in the MT model of SimMobility Freight, which is a heuristics which assigns shipments to vehicles and generates daily vehicle operation schedules (refer to Sakai et al. (2020a) for details). The two key settings were calibrated for parcel deliveries:

- Dwell time: Average dwell time per parcel delivery was set as 2.3 minutes. (Allen et al. (2018b) report that the mean parking time per parcel is 2.3 minutes based on a survey in London.)

- Vehicle capacity: The vehicle volume capacity and the weight-to-volume conversion is set so that average number of parcel deliveries per tour becomes around 11 for groceries and 37 for non-grocery items.

Fig. 5 shows the number of deliveries per driver-day (As a rough indication, Kuo (2018) reported that an average FedEx driver can delivery around 75-125 packages per day while the average of the home delivery industry is 15-35 packages per day (Jaller and Pahwa, 2020). The result is more or less consistent with this anecdotal evidence.

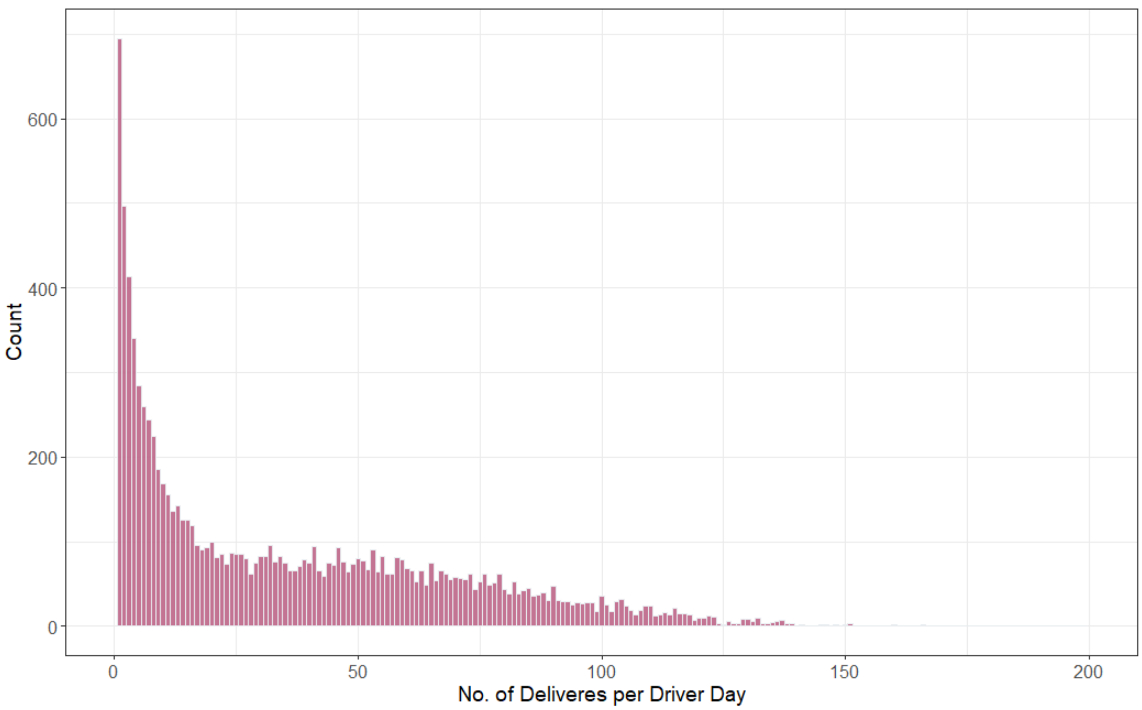

Fig. 5 Number of deliveries per driver day (e-commerce deliveries)

B2B shipments: The LT model in SimMobility Freight generates B2B shipments. The initial model parameters were estimated using the data from 2013 Tokyo Metropolitan Freight Survey, which has large sample size and detailed information of shipments, including shipper and receiver information. The detailed information of the data and parameters is available in Sakai et al. (2020a). We re-calibrated the model parameters based on the 2012 Commodity Flow Survey – Public Use Microdata (2012 PUM) (U.S. Census Bureau, 2012). The shipment records with shipper industry type and commodity type information are available from 2012 PUM but the data is mainly for manufacturers and wholesalers; therefore, we used Freight Analysis Framework (FAF4) data, which provides aggregate OD flow, to complement 2012 PUM. Models were calibrated so that aggregate freight generation matches the survey data. Furthermore, shipment size model parameters were calibrated for shipments from manufacturing and wholesale industries for each commodity type.

5.4 Scenarios

For the simulation, we consider three different scenarios in terms of e-commerce adaptation and the availability of pickup delivery options, aiming to understand the magnitude of e-commerce transportation demand, especially, goods vehicle traffic for e-commerce deliveries. The scenarios considered are:

- Scenario Base (Scn. Base): This scenario uses the model and inputs used for the calibration mentioned in Section 5.2.
- Scenario 1 (Scn. 1): This scenario assumes the increase of e-commerce adoption by 70%, 50% and 20% for groceries, household goods, and others, respectively. These growth rates are determined considering Holguin-Veras and Wang (2020). They present the expected growth of delivery frequencies per individual for groceries (67%), household goods (43%), medicines (60%)[3], and other packages (16%) from the pre-pandemic to the post-pandemic time, based on an interview survey in the U.S. (938 samples). We acknowledge that these figures of Holguin-Veras and Wang are not specifically for “adoption” and they might not take into account pickups, although we refer to them for setting our assumption of adoption rates. We also assume pickup options are available for 40% of grocery orders, 30% of household goods orders, and 20% of other orders.
- Scenario 2 (Scn. 2): This scenario assumes the same adoption rates with Scn. 1 with higher pickup mode availabilities: 60%, 45% and 30% for groceries, household goods, and others.

While the assumptions for Scn.1 and Scn.2 are not aiming for the high accuracy prediction of the post-pandemic situation due to the limited information available at this point of time, this analysis allows us to understand the level of transportation demand sensitivities against the key changes in consumers and retailing businesses.

5.5 Result

The result of the simulations using the e-commerce demand model is shown in Table 7. We would like to re-emphasize that the results could depend on the assumptions and the methods we used in the parameter setting mentioned earlier and that our main purpose is to demonstrate the simulation capability of the model. For obtaining more certain description of e-commerce demand, the calibration of the full model using the single data source is required, which we consider as a future task.

For both Scn.1 and Scn. 2, the change in the expenditure per household-month is greater than that of adoption rate for any item category, as the increase in pickup availability affects the expenditure positively at the same time. The influence of the pickup availability is especially high for *household goods*, for which the logsum measure from the lower level has a stronger effect on the total value choice than the other item categories. This highlights the advantage of the model specification, simulating varying effects of delivery options by item category. The increase in pickup availability, which makes it more convenient to receive items, has the effect of reducing the expenditure per order. Such effect also varies by item category. The comparison between Scn. 1 and Scn. 2 indicates that the order size of *household goods* is relatively insensitive to the change in pickup availability. The comparison also indicates that, while the increased pickup availability (in Scn.2) leads to the less home deliveries (478.0 thousand (Scn. 2) vs. 490.0 thousand (Scn. 1)), the difference is minor and not as significant as that of no. of pickup orders (84.8 thousand (Scn. 2) vs. 52.2 thousand (Scn. 1)). The model specification allows us to replicate “induced” e-commerce demand attributable to higher convenience due to the delivery option availability.

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[3] We treat household goods and medicines as one item category (“*household goods*”), while Holguin-Veras and Wang (2020) treat them separately.

Table 7 Simulated e-commerce demand

Indicator		Scn. Base	Scn.1	Scn.2
Scenario setting (parentheses: change from Scn. Base)				
• Adoption rate (%)	Groceries	16.6	28.7 (+70%)	28.7 (+70%)
	Household goods	45.8	68.7 (+50%)	68.7 (+50%)
	Others	60.9	73.0 (+20%)	73.0 (+20%)
• Pickup availability (%)	Groceries	7	40	60
	Household goods	7	30	45
	Others	7	20	30
E-commerce demand (parentheses: change from Scn. Base)				
• Expenditure (e-commerce) per household-month (US$)	Groceries	17.5	30.0 (+71%)	30.1 (+72%)
	Household goods	39.2	65.4 (+67%)	72.0 (+84%)
	Others	64.8	79.2 (+22%)	81.1 (+25%)
	Total	121.5	174.6 (+44%)	183.2 (+51%)
• Expenditure per order	Groceries	70.5	67.5 (-4.3%)	65.4 (-7.2%)
	Household goods	31.7	31.5 (-0.6%)	31.5 (-0.6%)
	Others	20.7	20.3 (-1.9%)	19.9 (-3.9%)
• No. of home deliveries (thou.)	Groceries	15.4	22.6 (+47%)	20.1 (+31%)
	Household goods	107.4	155.4 (+45%)	153.7 (+43%)
	Others	271.4	312.9 (+15%)	304.2 (+12%)
	Total	394.2	490.9 (+25%)	478.0 (+21%)
• No. of pickup orders (thou.)	Groceries	0.7	7.0 (+900%)	11.2 (+1500%)
	Household goods	2.8	20.7 (+639%)	34.7 (+1139%)
	Others	6.7	24.5 (+266%)	38.9 (+481%)
	Total	10.2	52.2 (+412%)	84.8 (+731%)

The indicators of freight transportation demand - the results of "*pre-day" logistics planning* in SimMobility Freight - is shown in Table 8. Number of tours, number of deliveries per tour, and vehicle kilometers traveled (VKT) are calculated for three tour types: (1) only e-commerce shipments, (2) mixed (e-commerce shipments and B2B shipments which are parcels), and (3) others (B2B shipments which are not parcels). For computing these indicators, the simulation was run five times for each scenario and the average values were calculated. It must be noted that a tour could be generated jointly for non-grocery e-commerce shipments and B2B parcel shipments while these shipments cannot be paired with other B2B shipments in a tour.

The contribution of e-commerce-derived home deliveries to freight transportation demand is high. In the base scenario, 9% (11.1 thousand) of freight vehicle tours and 22% (1.86 mil.) of VKT are only for e-commerce shipments. While the validation with observed data is required in the future, the result indicates that e-commerce-derived home delivery traffic has grown to the level which is no longer negligible. On the other hand, results of Scn.1 and Scn.2 indicate that the growth of home delivery traffic would not be proportional to that of no. of home deliveries. For example, in Scn. 1, the number of home deliveries increases by 25% but VKT of e-commerce shipment-dedicated tours increased only by 18.5%.

Table 8 Simulated freight transportation demand (in a given day)

Indicator	Tour type	Scn. Base	Scn.1	Scn.2
Tours (thou.)	Only e-commerce shipments	11.1	13.5 (+20.9%)	12.9 (+15.4%)
	Mixed	1.42	1.53 (+7.7%)	1.55 (+9.0%)
	Others	111.3	110.9 (+0.5%)	112.3 (+1.8%)
	Total	122.9	125.9 (+2.5%)	126.7 (+3.1%)
No. of deliveries per tour	Only e-commerce shipments	31.9	32.9 (+3.3%)	33.4 (+4.9%)
	Mixed	22.3	23.2 (+4.4%)	23.5 (+5.6%)
	Others	1.70	1.70 (-0.10%)	1.69 (-0.60%)
VKT (mil.)	Only e-commerce shipments	1.86	2.21 (+18.5%)	2.13 (+14.2%)
	Mixed (e-commerce & other parcels)	0.24	0.25 (+5.4%)	0.26 (+10.8%)
	Others	6.44	6.44 (+0.0%)	6.44 (+0.0%)
	Total	8.54	8.90 (+4.2%)	8.83 (+3.3%)

6. Conclusions

This research developed the framework of household-based e-commerce demand modeling, integrated the e-commerce demand models with SimMobility Freight, and conducted a demonstrative simulation of e-commerce and associated freight transportation demand for a prototypical North American city. The proposed framework jointly predicts the total e-commerce expenditure, order value, delivery mode and option choices. In the framework, the demand is sensitive to delivery option attributes, which is of critical importance to evaluate the impacts of urban logistics solutions that affect delivery speeds and costs. Using the model parameters selected based on available data and knowledge, we demonstrated how the model performs. The simulations highlight that the model can replicate the intricate impacts of the changes in adoption rate and delivery mode/option (pickup, specifically) availability on e-commerce and freight transportation demand.

This research contributes as a key step in developing a comprehensive modeling framework of e-commerce demand. As for the proposed framework, there is room for incorporating heterogeneity attributable to household characteristics and the different order situations (e.g., a shopper who requires some specific item immediately vs. a shopper who places recurring orders). Furthermore, developments on supply-side simulations, which simulate the characteristics and decisions of e-commerce vendors and carriers, are required to rigorously evaluate the impacts of supply improvement. Moreover, the interaction between e-commerce orders and in-store shopping trips is, as identified in other studies (Suel and Polak, 2018), important for comprehensively evaluating the transportation impacts of the growth in e-commerce. While the proposed model predicts pickup orders, the evaluation of the passenger transportation demand change is not in the scope of this research.

Lastly, together with the theoretical development of the model, the improvement in data collection and data fusion methods are also required for e-commerce. The generation of an integrated data which covers the information of consumers, delivery options, package receiving, and shopping and pickup trips, is required to accurately understand the e-commerce-derived transportation demand characteristics.

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