Adoption of delivery services in light of the COVID pandemic: Who and how long?

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A B S T R A C T

A significant growth in demand for online shopping in light of the Coronavirus Disease (COVID) crisis has received attention from transportation practitioners, policy-makers, and researchers. However, an important question arises in this increase in online shopping and resulting deliveries: How long will this last? Very little is known whether this popularity would last a long time. To address this question, the authors conducted a survey of 915 individuals residing in the U.S. and classified them into the four distinctive consumer types (i.e., the prior adopter, temporary adopter and permanent new adopter, and non-adopter) depending on their usage of delivery services before, during, and after (expected) the COVID crisis. This research aims to gain behavioral insight by exploring the differences between the four consumer types and investigating factors affecting the initial adoption and continuance intention of using delivery services. The descriptive analysis revealed that there are clear differences not only between the four types of consumers but also between the four product types (i.e., grocery, food, home goods, and other packages) considered in the survey. The models found that factors affecting the initial adoption and continuance intention are different from the previous studies conducted before the COVID pandemic. Implications for planning and policymaking are also discussed.

1. Motivation

The Coronavirus Disease (COVID) crisis has transformed how people eat, work, travel, shop, and entertain. Moreover, it has reshaped not only passenger transportation but also freight systems. Particularly, the increased online shopping is a notable effect. Retail sales via e-commerce in the United States (U.S.) increased by 31.8% from the first quarter to the second quarter in 2020, while total retail sales decreased by 3.9% during the same period (U.S. Census Bureau, 2020). During Black Friday in 2020, online shopping sales increased by 21.6%, while in-store shopping sales decreased by 52.1% compared with 2019 (Thomas, 2020). According to global surveys conducted by McKinsey. (2020a,b), Boston Consulting Group (2020), and Deloitte (2020), consumers around the world revealed a tendency toward online shopping from offline shopping in response to the COVID. This shift has resulted in an increase in home deliveries, particularly grocery and food deliveries. For instance, 22.5% of respondents have increased the frequency of food delivery services during the pandemic due to its convenience and safety reasons (e.g., reduction in infection risk) (Deloitte, 2020). Even the U.S. Centers for Disease Control and Prevention (CDC) now recommends to use online shopping and delivery services and

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avoid shopping in stores (Centers for Disease Control and Prevention, 2020b).

There is a great need for deliveries and the statistics shows that delivery services are booming during the pandemic. An important question arises in this unprecedented popularity of online shopping: *How long will it last?* Answering this question is essential to estimate the current and future demand for deliveries. Many surveys have assumed that people would still rely on delivery services even after the COVID crisis is over. However, in reality, consumers' technology acceptance is much more dynamic and complex during a pandemic than during usual days, i.e., this is not a 'to adopt or not to adopt' problem. A survey by the Rensselaer Polytechnic Institute found out that over 90% of respondents would switch back to original shopping channel once the COVID is over (Rensselaer Polytechnic Institute, 2020). The likely reason is that the increased use of e-commerce is not the result of market competition, where the most efficient competitor outperforms the others. In this case, an external disruption — a large disaster — significantly altered the playing field. It is likely that once this external effect is removed, some of the spins made by e-commerce will be reverted. Thus, there is heterogeneous behavior in the adoption and continuance intention. Accordingly, consumers can be classified into the four types depending on their behaviors as shown in Table 1.

The *non-adopters* would not adopt delivery services no matter what. The *prior adopters* have already adopted them before COVID and would continue to use during and after COVID. The *new adopters* are those who adopted delivery services during the COVID. These new adopters can be classified into two distinct types depending on their continuance intention: the *permanent* and *temporary new adopters*. The *temporary new adopters* started using delivery services during COVID but would not continue to use them anymore after the pandemic is over. One of the possible reasons is that on-demand delivery services typically charge more to customers than in-store purchase, e.g., extra charge for service fee to maintain a delivery platform, delivery fee, and driver tips. Hand et al. (2009) argued that price and product quality may affect the decision for discontinuation of online shopping. Additionally, there are also concerns about lost items (Brown, 2020). Due to the behavior of *temporary new adopters*, the long-term effect of the COVID on delivery services will not be as large as the near-term effect. In contrast, the *permanent new adopters* would settle down their new shopping channel and continue to use delivery services even after the pandemic is over.

It is important to classify customers depending on their initial adoption and continuance intention when investigating the impacts of the pandemic and predicting future demand. They may have different characteristics which would affect not only the demand side but also the equity issues and health concerns. For instance, while most people are going virtual, there would still be some people left behind forced to shop in-stores at a great risk of infection. Despite the importance of the heterogeneity of consumers' behavior, there has been no detailed examination of it so far. The existing studies are limited and provide only fragmentary information without considering the heterogeneity of the initial adoption and continuance intention. Treating consumers as they behave in the same manner, would lead to inaccurate results.

Online shopping and the resulting deliveries are directly and indirectly tied to transportation systems, particularly truck activity, travel behavior, vehicle-miles-traveled (VMT), and freight demand management in urban areas (Cao, 2009; Chen et al., 2017a,b; Jaller and Pahwa, 2020; Lin et al., 2018; Schmid et al., 2018; Xi et al., 2020). Furthermore, transportation-related public agencies play a critical role in the pandemic era as described in Matherly et al. (2020). To minimize the spread of the virus and to mitigate issues resulting from the pandemic, e.g., equity issues, it is important for the transportation agencies to identify potential threats and issues associated with the pandemic. Thus, an understanding of shopping behaviors coupled with the pandemic is timely and worth investigating to obtain behavioral insights.

The overall goal of this research is to better understand consumers' behavior during the pandemic. To achieve the goal, the following objectives must be reached: (1) identify the differences between the four consumer types, and (2) gain insight into the factors affecting the initial adoption and continuance intention using a survey data collected by the authors. The contributions of this research are two-fold: First, this is the first comprehensive study to investigate the initial adoption and continuance intention of using delivery services during a pandemic for a wide range of product type (i.e., grocery, food, home goods, and other packages). An understanding of both the adoption and post-adoption behavior provides an important behavioral insight into freight transportation planning and policy-making in light of the COVID situation. Secondly, the insights into adoption and continuance behavior are not limited to delivery services during the COVID pandemic. They shed light on future research on other new transportation service forms (e.g., autonomous vehicle, unmanned delivery services) and other upcoming disruptive events (e.g., disaster, recession).

The remainder of this paper is organized as follows: the next section reviews the existing studies on technology acceptance, determinants of deliveries, and changes in shopping behaviors during disruptive events. The third section describes a survey design. The fourth section presents the description of the survey data collected. Section five presents a modeling approach. Sections six and seven present the results and implications for planning and policy. The last section concludes this research.

Table 1
Consumer types by usage of delivery services.

Before COVID	During COVID	After COVID	Type	
No	No	No	*Non-adopter*	
No	Yes	Yes	*New adopter*	*Permanent*
		No		*Temporary*
Yes	Yes	Yes	*Prior adopter*	

2. Relevant literature

2.1. Technology adoption and continuance theory

With the advent of various Information and Communication Technology (ICT) in 1990′s, researchers paid attention to the acceptance of ICT, i.e., how various factors such as satisfaction, perceived usefulness, attitude towards technology, etc lead to the adoption of technology by consumers (Davis, 1985, 1989; Venkatesh, 2000; Venkatesh et al., 2003; Venkatesh and Bala, 2008; Venkatesh and Davis, 2000). Later, the focus has been shifted to post-adoption behaviors, i.e., consumers' continuance intention towards technology. For instance, some studies developed the technology continuance models to investigate what factors affect the consumers' intention to continue to use ICT on a regular basis in the future (Bhattacherjee, 2001; Liao et al., 2009; Zhou, 2013). In the transportation field, the technology continuance theory has been applied to many areas such as bike-sharing (Peng et al., 2019), online flight check-in (Lin and Filieri, 2015), and taxi reservation app (Weng et al., 2017).

2.2. Factors affecting demand for deliveries

Since the 1990s, there have been a number of studies investigating determinants of demand for deliveries as summarized in Table 2. With respect to the significant determinants of using delivery services, there has been consensus. In general, regardless of product type, individuals with high-income, high-education level, large household size were more likely to use delivery services than others. Age negatively affected the usage, i.e., young people tended to use more delivery services than others.

First in the literature, Hand et al. (2009) investigated the initial adoption and continuance intention of using online grocery shopping in London, U.K. They argued that situational factors may affect the decision for the adoption and discontinuation. However, only situational factors, not socio-demographic factors, were investigated.

2.3. Shopping behavior during pandemic

Consumers' shopping behavior during a pandemic is different from the ones in normal conditions. For instance, a number of unusual purchasing behaviors (for the necessities or medicine/vaccines) has been witnessed during the Avian flu, the Spanish flu pandemic, the Hong Kong flu pandemic, etc (Taylor, 2019). Behavioral scientists explain that such behaviors can be triggered by psychological effects such as "loss aversion", "the bandwagon effect", and "the neglect of probability" (Lappeman, 2020). Although it is an unusual behavior, a pandemic expert argued that such behavior helps us to feel a sense of control (Lufkin, 2020). According to a study by Chen et al. (2017a,b), consumers tend to buy "utilitarian products" rather than "hedonic products" when they feel a low perceived sense of control.

In addition to running out of stockpiles in every store, the crisis is also influencing consumers' shopping channel. According to

Table 2
Summary of literature on factors affecting demand for deliveries.

Reference	Area	Outcome	Type	Significant factors
Dias et al. (2020)	Puget Sound Region, WA	Frequency	Package	(+) Income, household size, residential density, in-person shopping; (−) Vehicle availability, households living in apartments
		Frequency	Grocery	(+) Income, household size, residential density, vehicle availability, in-person meal shopping; (−) Households living in apartments, in-person grocery shopping
		Frequency	Food	(+) Income, household size, residential density, vehicle availability
Spurlock et al. (2020)	Bay Area, CA	Shopping channel choice	Package	(+) Income, children; (−) Age
			Grocery	(+) Income
			Food	(+) Income, population density; (−) Age
			Household	(+) Income, children; (−) Age
Schmid et al. (2020)	U.S.	Frequency	All	(+) Household size; (−) Age, high income
Lee et al. (2017)	Davis, CA	Frequency	Package	(+) Income, positive perception; (−) Vehicle availability
Wang and Zhou (2015)	U.S.	Shopping channel choice	Package	(+) Internet usage, education, income, rural area, female, residential density, White, child; (−) Age, household size, African-American, Hispanic
		Frequency	Package	(+) Internet usage, education, female, race (white), income, vehicle count, residential density, rural area; (−) African-American, Hispanic
Hand et al. (2009)	U.K.	Initial adoption	Grocery	(+) Situational factors (no time to shop, convenience, no car, etc)
		Continuance	Grocery	(−) Situational factors (delivery fee, social contact, product quality, etc)
Ren and Kwan (2009)	Columbus, OH	Initial Adoption	All	(+) Female, internet usage, White; (−) Work hours, store density
		Frequency	All	(+) Age, female, income, internet usage, White, population density, number of children; (−) Store density
Farag et al. (2006)	Netherlands	Shopping channel choice	Package	(+) Education, urbanized area, internet usage; (−) Female
		Frequency	Package	(+) Worker status, internet usage; (−) Store density
Hiser et al. (1999)	College Station, TX	Willingness	Food	(+) Familiarity, education; (−) Age

Note: (+) and (−) refer to a positive and negative impact, respectively.

global consumer surveys conducted by McKinsey. (2020a,b), Boston Consulting Group (2020), and Deloitte (2020), consumers around the world revealed a tendency toward online shopping from offline shopping in response to the COVID. This shift has resulted in the use of grocery and food deliveries. For instance, 22.5% of respondents have increased the frequency of food delivery services during the crisis due to its convenience and safety reasons (e.g., reduction in infection risk) (Deloitte, 2020). Baig et al. (2020) found out that approximately 31% and 13% of respondents are the first-time users for online grocery and apparel shopping, respectively.

Disasters not only influence consumers but also businesses. Some vulnerable businesses experience loss in sales revenues or they may be forced to close due to governments' disaster-related restrictions (Tierney, 2007). According to U.S. Census Bureau (2020), retail sales (excluding e-commerce) in the U.S. significantly decreased due to the shift towards e-commerce during the COVID pandemic. Additionally, many major businesses in the U.S. ranging from retail stores, gym, car rental, cinema to department stores have filed for bankruptcy due to the substantial decrease in demand (Pandise, 2020).

Recently, there have been a significant amount of academic research. A survey by the Rensselaer Polytechnic Institute found out that 30% of respondents in the U.S. switched their shopping channel from offline to online during COVID (Rensselaer Polytechnic Institute, 2020). However, they also highlighted that over 90% of respondents would buy basic supplies in their original shopping channel, once the COVID is over. Shabanpour et al. (2020) developed a multivariate ordered probit model to identify factors affecting the number of grocery deliveries before, during, and after COVID. Education level positively affected the delivery frequency before and after COVID, while it did not affect during COVID. Low income households were less likely to receive grocery deliveries. Grashuis et al. (2020) developed multinomial logit models with different scenarios (COVID cases going up, constant, and down) and found out that an increasing number of confirmed cases in the region is associated with an increase in home deliveries and a decrease in curbside and in-store pick-up. Unnikrishnan and Figliozzi (2020) compared between home delivery purchases during COVID and those before COVID. In their study, higher income households were likely to receive more deliveries both before and during COVID. Those who were concerned about health issues were more likely to receive deliveries during COVID. Shamshiripour et al. (2020) surveyed residents in Chicago and argued that most respondents are likely to use more online grocery and food shopping after the pandemic situation than before.

2.4. Summary

In all the studies reviewed in Table 2, there remains a need for investigating the initial adoption and continuance intention which have not been studied in depth. Recently, advances in technology, e.g., convenient smartphone apps, same-day delivery, crowd-sourced delivery, are transforming online shopping environments. Thus, how consumers shop online and how they react to new technologies have been changed a lot compared with those in a decade ago. In light of the COVID crisis, there is another current need for studies investigating factors influencing the initial adoption and continuance intention of using delivery services. With respect to the previous studies related to the COVID, they have focused on trying to understand a shift in shopping channels from in-store to online. However, not only discontinuation behavior after a pandemic has yet been investigated but also the initial adoption can further be analyzed considering the heterogeneity of the continuance intention. Without taking into account consumers' discontinuance behavior, the current popularity of online shopping will mislead the post-pandemic planning. For instance, a survey in Shamshiripour et al. (2020) concluded that the current increasing trend of grocery and food deliveries would last a long time after the pandemic. Furthermore, most academic research focused on grocery deliveries. There is a need to investigate other types of deliveries as the pandemic has different impacts on necessary and non-necessary goods (Chen et al., 2017a,b; McKinsey, 2020b). The present research will fill these knowledge gaps.

3. Survey description

The source of data for this research is a survey on the effect of the COVID pandemic on travel, shopping, and communications activities in the United States. The survey was conducted by the authors through Amazon Mechanical Turk platform (Amazon, 2020). Two separate batches of data were collected, one in mid-May 2020 and the other in late June 2020. Between these two batches, 1,163 observations were collected, which reduced to 915 after data cleaning to remove incomplete and faulty observations. Observations were removed from the dataset if the respondent left the survey before answering all questions or if the respondent provided values that were not logical. In general, distributions of key variables were consistent with those in Census data. However, certain demographic groups (e.g., low education level, low- and high-income groups) were under-represented, i.e., they did not match demographics of the entire population. Thus, sampling weights were generated using the Iterative Proportional Fitting procedure in Stata (Bergmann, 2011) to improve results. This command generates sampling weights by comparing the distribution of specified variables to specified population statistics. In our survey, weights were generated using the respondent's gender, education level, age, and household income.

In this research, the authors consider three separate time periods: "before", "during", and "after" the pandemic. "Before pandemic" refers to the respondent's activities before shutdowns began and "during pandemic" refers to activities at the time of the survey. Additionally, the authors asked respondents to predict their activity level once the pandemic is over, so "after pandemic" represents a time after all shutdowns and restrictions are lifted and all normal activities can resume. While the authors did not specify beyond this in the survey and left "after pandemic" open to interpretation, it can be assumed that such would only be the case after a vaccine or treatment for COVID is found.

As part of this survey, respondents were asked questions in four areas: shopping activity, employment information, online activities, and demographics. To elaborate on the shopping activity section, respondents reported their average number of shopping trips

Table 3
Summary statistics of the key variables (mean/percentage).

	Grocery delivery				Food delivery				Home goods delivery				Other packages delivery			
Weighted N	176	110	88	541	475	27	48	365	260	95	91	469	745	3	27	140
Variable	**Prior**	**Temp**	**Perm**	**Non**	**Prior**	**Temp**	**Perm**	**Non**	**Prior**	**Temp**	**Perm**	**Non**	**Prior**	**Temp**	**Perm**	**Non**
Age	43.54	49.32	45.32	46.43	43.69	51.10	45.87	48.93	45.34	52.31	45.80	45.36	45.42	36.54	52.52	48.73
Gender (male)	0.54	0.51	0.64	0.46	0.50	0.59	0.48	0.51	0.50	0.46	0.56	0.50	0.50	0.52	0.51	0.50
Hispanic status	0.18	0.07	0.08	0.04	0.09	0.09	0.12	0.05	0.08	0.03	0.16	0.06	0.08	0.00	0.02	0.06
Household size	3.23	3.34	2.35	2.69	3.19	2.55	3.17	2.36	3.12	2.66	2.95	2.70	2.94	2.85	2.38	2.37
Employment (full-time)	0.62	0.49	0.41	0.44	0.48	0.43	0.55	0.47	0.60	0.47	0.50	0.41	0.47	0.92	0.47	0.51
Household income ($1,000)*	92.69	96.18	64.18	75.45	89.98	92.78	98.18	64.11	84.32	94.82	101.5	70.79	82.42	86.09	97.34	64.73
Home (apartment)	0.00	0.17	0.35	0.13	0.20	0.13	0.22	0.14	0.16	0.08	0.21	0.19	0.15	0.31	0.31	0.26
Home (one-family detached)	0.63	0.70	0.54	0.75	0.68	0.85	0.69	0.71	0.69	0.80	0.54	0.72	0.73	0.69	0.41	0.60
Education level																
Less than high school	0.0%	0.0%	18.2%	17.8%	11.1%	0.0%	0.0%	16.3%	7.0%	0.0%	0.0%	20.1%	12.9%	0.0%	0.0%	11.5%
High school degree	36.0%	41.8%	41.1%	47.6%	45.6%	22.9%	34.6%	44.9%	38.3%	44.3%	48.0%	46.4%	43.4%	0.0%	24.6%	51.8%
Associate degree	14.0%	20.6%	7.8%	12.2%	11.6%	13.3%	21.4%	14.0%	13.5%	20.9%	12.0%	11.6%	13.4%	20.8%	22.8%	9.5%
Bachelor's degree	33.6%	23.7%	24.7%	13.0%	20.5%	41.7%	16.5%	16.5%	24.8%	22.7%	30.7%	13.5%	18.2%	38.3%	43.9%	20.4%
Graduate degree	16.5%	13.9%	8.2%	9.4%	11.1%	22.1%	27.6%	8.3%	16.4%	12.2%	9.3%	8.4%	12.0%	40.9%	8.7%	6.8%
Race group																
White	75.0%	84.5%	87.2%	87.0%	80.0%	79.3%	81.2%	90.9%	79.5%	87.8%	85.2%	86.2%	83.7%	72.3%	87.6%	87.7%
African-American	13.1%	2.6%	5.5%	4.5%	8.4%	7.2%	6.2%	2.8%	11.8%	1.9%	4.2%	4.0%	5.4%	19.5%	9.6%	8.7%
Asian	9.1%	9.8%	3.2%	6.0%	8.4%	10.7%	11.6%	3.8%	6.6%	5.7%	8.2%	6.8%	7.9%	8.2%	2.8%	1.7%
Others	2.6%	3.0%	4.1%	2.5%	3.1%	2.8%	1.0%	2.5%	1.9%	4.6%	2.4%	2.9%	3.0%	0.0%	0.0%	1.9%
Number of trips on a workday (before)	3.45	2.80	2.83	2.66	2.95	3.41	3.06	2.63	3.72	2.38	2.75	2.45	2.95	2.16	2.25	2.56
Number of trips on a non-workday (before)	2.00	2.61	1.73	2.21	2.46	2.30	2.01	1.80	2.33	2.28	1.86	2.12	2.25	1.99	2.12	1.75
In-store shopping freq.																
No change	0.29	0.24	0.14	0.32	0.29	0.22	0.26	0.28	0.27	0.27	0.20	0.31	0.28	0.31	0.28	0.31
Shop more frequently during COVID	0.14	0.03	0.06	0.04	0.08	0.03	0.09	0.03	0.10	0.02	0.04	0.05	0.06	0.11	0.06	0.03
Shop less frequently during COVID	0.57	0.73	0.80	0.65	0.63	0.75	0.64	0.69	0.63	0.72	0.76	0.64	0.66	0.58	0.66	0.66

Note:

1) Non, Temp, Perm, and Prior refer to the non-adopters, temporary new adopters, permanent new adopters, and prior adopters, respectively.

2) * Household income was reported as a categorical variable (under $15 k; between $15 k and $25 k; between $25 k and $35 k; between $35 k and $50 k; between $50 k and $75 k; between $75 k and $100 k; between $100 k and $150 k; between $150 k and $200 k; $200 k or higher). Then, the average value in the category was taken.

per month, as well as the average number of deliveries per month for four separate types of items. Item types respondents were asked to provide frequencies for included groceries, prepared food, home goods (e.g., household supplies including paper products, cleaning supplies, etc), and other package deliveries (e.g., clothing, books, accessories, electronics, etc.). These four categories were chosen because they not only account for the universe of items people may have delivered to their home, but because purchasing patterns for these four categories may be significantly different. For example, a person may have prepared food delivered to their home but will not order groceries online for delivery. The questions focused on an individual-level decision rather than a household-level decision. By developing an individual-level model, one can investigate in more detail what factors affect the usage of delivery services, e.g., gender, age, race, employment status, educational attainment, etc. The corresponding policy-makings can target specific groups effectively.

Based on the average number of deliveries before, during, and after COVID, it was possible to categorize respondents into one of three groups for each type of delivery. For instance, if a respondent reported zero deliveries before, during, and after COVID, s/he can be reasonably assumed to be a non-adopter.

- "Prior adopters": those who received deliveries of a given type prior to the COVID pandemic.
- "New adopters": those who did not use e-commerce prior to the COVID pandemic, but began using e-commerce during the COVID pandemic
- "Non-adopters": those who did not receive any deliveries for a given item type before, during, and after the COVID pandemic. Interestingly, a handful of respondents reported that they would start using delivery services after COVID. Those respondents were worth investigating, but they were classified as the non-adopters in the current study due to a very small number of observations.

New adopters could be further subdivided into "temporary new adopters", i.e., respondents who began receiving deliveries of an item type during the pandemic but expect to stop receiving deliveries once the pandemic is over; and "permanent new adopters", i.e., respondents who began receiving deliveries of an item type during the pandemic and expect to continue receiving deliveries once the pandemic is over. This subdivision was made based on the respondent's predictions for how they would shop after the pandemic is over.

Table 3 presents a summary of statistics of the key variables. Only key variables are presented due to the space limit. Other variables including the number of stores in an area (US Census Bureau, 2016) and the number of COVID cases at state level (Centers for Disease Control and Prevention, 2021) were also investigated.

It should be noted that the accuracy of the classification can be improved by directly asking respondents whether they never used delivery services for a given time frame (before, during, and after COVID). When investigating the initial adoption of a technology, in some literature, they directly asked respondents whether they have never used services before (Alemi et al., 2018). Some other literatures used a similar method with the present paper, e.g., if time spent on online shopping in a typical week is greater than zero, then adoption = 1; otherwise, adoption = 0 (Ren and Kwan, 2009). Due to the length of the survey, further detailed information could not be collected. To reduce burden and fatigue for respondents, the authors collected the limited amount of information per category since the present research collected a long and broad range of information including work- and travel-related information (e.g., work-from-home behavior, shopping behavior, travel behavior, etc.).

4. Descriptive analysis

In the section, the similarities and differences between groups (the prior adopters, temporary and permanent new adopters, and non-adopters) are discussed.

4.1. Share of each adopter type

Table 4 exhibits the share of each consumer type. Delivery services for other packages had been most widely adopted by respondents even before the pandemic, i.e., the prior adopters accounted for the largest share for other packages compared with other types of goods, followed by deliveries for food, home goods, and grocery. In general, the evidence showed that the initial adoption and continuance intention varies by goods type. Grocery deliveries had the highest proportion of new adopters including the temporary and permanent new adopters at 21.8%, followed by home goods at 20.3%, food at 8.1%, and other packages at only 3.3%. These results imply that the COVID pandemic had a larger impact on the purchase channels for essential items (grocery and home goods) than less essential items (food and other packages). In addition, for essential items, the temporary new adopters accounted for a larger portion than the permanent new adopters, while the permanent new adopters made up a larger portion than the temporary new adopters for less essential items.

Table 4
Share of each adopter type (N = 915).

Type of adopter	Grocery	Food	Home goods	Other packages
Prior adopter	19.2%	51.9%	28.4%	81.5%
Temporary new adopter	12.1%	2.9%	10.4%	0.3%
Permanent new adopter	9.7%	5.2%	9.9%	3.0%
Non-adopter	59.1%	39.9%	51.3%	15.3%

4.2. Profiles of the four adopter types

The distributions of key socio-economic variables are discussed in this section to gain insights into similarities and differences among the four consumer types. The average age for the temporary new adopters of grocery, food, and home goods ranged from 49 to 52. These numbers were higher than the other consumer types. On the other hand, the prior adopters tended to be younger than the other consumer types. With respect to income, the permanent new adopters and non-adopters (of food, home goods, and other packages) reported the highest and lowest income than the other consumer types, respectively. In contrast, the permanent new adopters of grocery deliveries had the lowest income level than the other types. The permanent new adopters were more likely to live in an apartment than the others regardless of product type. As for education level, the prior adopters of essential goods (grocery and home goods) tended to be highly educated (i.e., those with a bachelor's or graduate degree). On the other hand, the new adopters of less essential goods (food and other packages) were more likely to be highly educated than the other consumer types. Overall, the non-adopters were not likely to be highly educated regardless of product type.
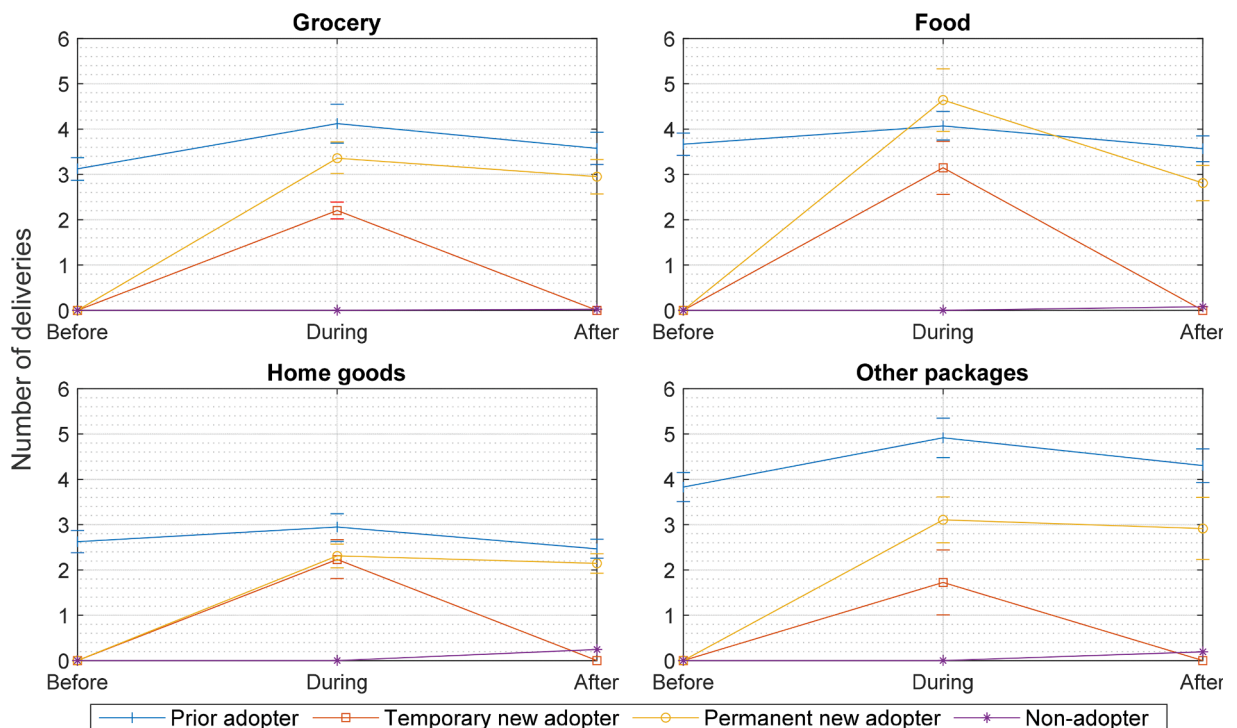
4.3. Average number of deliveries

Fig. 1 presents the average number of deliveries per month received by each consumer type. Overall, the number of deliveries received by the prior adopters was not likely to be affected much by the COVID. The average numbers for the prior adopters slightly increased during COVID for all types of goods, then they would drop to the previous level after the pandemic is over. The average numbers for the permanent new adopters were expected to be slightly higher than those for the temporary new adopters.

With respect to the average number of grocery deliveries, the prior adopters used to receive 3.1 deliveries per month. This number increased to 4.1 during COVID, while the permanent and temporary new adopters started to receive 3.4 and 2.2 deliveries, respectively. After the pandemic is over, the average number of deliveries for the prior adopters and the permanent new adopters were expected to drop to 3.6 and 3.0, respectively.

Food deliveries showed a different pattern from that of any other types of goods. The number of deliveries for the permanent new adopters increased at a great pace, overtaking that of the prior adopters during COVID. However, after the COVID is over, the average number for the permanent new adopters would sharply decrease and they would receive fewer deliveries than the prior adopters. The average number for the temporary new adopters during COVID also increased to 3.2 which is close to that for the prior adopters.

Deliveries of home goods exhibited the smallest differences between consumer types during and after COVID. The average number did not differ much by consumer type during COVID. The temporary and permanent new adopters received almost the same number of deliveries during the pandemic (approximately 2.3 deliveries). After the pandemic, the permanent new adopters would receive the similar number of deliveries to the prior adopters.

Fig. 1. Average number *of deliveries* per month.

During this pandemic, people work from home, learn remotely, or hang out remotely. Time spent at home, of course, has nearly doubled and the corresponding household supplies, groceries, food, etc. at home has increased. Furthermore, due to the restrictions of physical shopping in stores, consumers rely on online shopping more than before the pandemic. However, a slight decrease in online shopping is expected after COVID. This is partly due to a less reliance on online channel. As physical shopping has its' own unique advantages (Mokhtarian, 2004), online shopping can never dominate and consumers would go back to the physical channel. Another possible reason is a decrease in supplies/groceries/food needed at home as people don't work from home or e-learning anymore, i.e., time spent at home will be cut in half.

In contrast to essential items, according to McKinsey, we are less likely to use other packages (e.g., clothing, cosmetics) during the pandemic (McKinsey, 2020a). This is probably the reason why there were the largest differences among consumer types for other packages. The prior adopters received 3.2 and 1.8 more deliveries than the temporary and permanent new adopters during COVID, respectively. After the pandemic situation is over, there would still be a notable difference between the prior adopters (4.3 deliveries) and the permanent new adopters (2.9 deliveries). However, it should be interpreted with caution due to the small number of observations for the temporary new adopters.

4.4. Aggregate number of users and deliveries

Table 5 exhibits the aggregate number of users and deliveries. The growth rate was worth examining to see how many users and deliveries in population increase or decrease over time. Before the pandemic, only the prior adopters used delivery services. During the pandemic, however, the number of users and deliveries increased as the new adopters started using delivery services. After the pandemic, only the prior adopters and permanent new adopters would remain to use delivery services. In general, a substantial increase in the number of users and demand during COVID does not seem likely to last a long time. The long-term effects (i.e., differences between before and after COVID) were expected to be approximately half of the near-term effects (i.e., differences between before and during COVID). This is because the current increase in online shopping is driven by a disruptive event, not by a market competition. It is likely that once this pandemic is over, some of the spins made by e-commerce will be reverted. However, the growth rate varied much by the type of goods. The growth rates for essential goods (grocery and home goods) were higher than those for less essential items (food and other packages).

Although grocery deliveries had the smallest number of users and deliveries before COVID among other types, it increased at the highest rate during COVID. Later, however, it would decrease at the highest rate after COVID. The evidence suggests that grocery deliveries are likely to be most affected by the pandemic. Food delivery was the second most popular type of deliveries before COVID. The number of users for food deliveries during COVID increased by only 15.7% and it would slightly decrease after the pandemic is over. Although the growth of users was minimal, the number of deliveries increased by 28.6% during COVID. Delivery for home goods had the second highest growth rate. The numbers of users and deliveries increased by over 70% during COVID. Although the numbers would decrease after COVID, there would still be a net increase of users and deliveries with the situation before COVID. Other packages delivery was the most popular type of deliveries before COVID. However, the number of users increased by only 4% during COVID and it would remain almost the same after COVID. Interestingly, despite it's almost steady state, the number of deliveries increased by 31.5% during COVID. It implies that the pandemic does not affect much the initial adoption of other package deliveries, but the existing users increase their shopping frequency due to the pandemic.

5. Modeling approach

The modeling effort relied on binary logistic regression models from two different decisions: initial adoption due to COVID, and continuance intention. The first model identifies significant factors influencing the initial adoption to answer the following questions: who will newly adopt delivery services during the COVID pandemic? and who will fall behind? The second model was developed to investigate the post-adoption behavior of those who newly adopted delivery services in light of the COVID pandemic, i.e., to identify factors affecting the continuance intention to use delivery services after the COVID crisis is over. The conceptual framework of this research is presented in Fig. 2.

For the modeling part, a binary logistic regression is estimated with the data. When a dependent variable is binary coded, a logistic and Probit regression models are two of the most commonly used model forms (Washington et al., 2020). In the present study, a logit

Table 5
Aggregate number of users and deliveries.

		Before COVID	During COVID	After COVID
Grocery	Number of users	176	374 (+113.3%)	264 (+50.4%)
	Total number of deliveries	548.7	1265.0 (+130.6%)	903.6 (+64.7%)
Food	Number of users	475	550 (+15.7%)	523 (+10.1%)
	Total number of deliveries	1743.5	2243.0 (+28.6%)	1859.7 (+6.7%)
Home goods	Number of users	260	446 (+71.2%)	351 (+34.8%)
	Total number of deliveries	683.8	1186.4 (+73.5%)	951.8 (+39.2%)
Other packages	Number of users	745	775 (+4.0%)	773 (+3.6%)
	Total number of deliveries	2856.7	3757.0 (+31.5%)	3316.5 (+16.1%)

Note: Percentages in parentheses show the growth rate compared with before COVID.
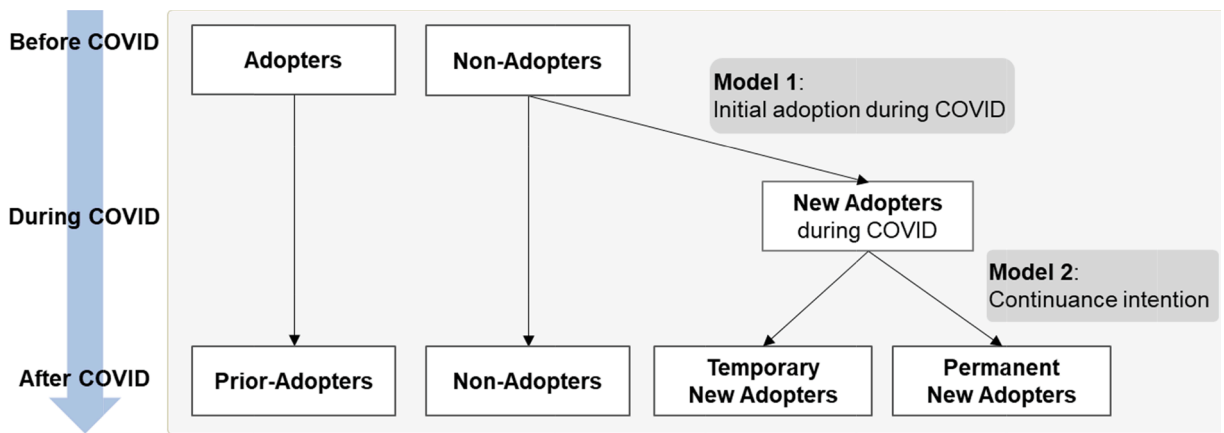
Fig. 2. Conceptual framework.

framework was selected due to its advantage of an easier interpretation over a probit model. Using odds ratio (which will be discussed in later in this section), the impact of each variable can be easily computed. Different model forms including a simple binary logistic regression model and a nested logit model were compared. When selecting the best model form, the authors considered the significance of each coefficient (using a p-value and intuition of coefficients' magnitudes) as well as the model's overall performance (using a chi-square test and the Pseudo R-squared value). At the end, a simple binary logistic model was chosen as it performed the best among others. A nested logit model did not perform well due to the lack of observations at the second level for some product types (e.g., only a few temporary new adopters for other packages). In other words, small sample size at the second level ended up worsening the entire model performance. In all cases, the authors conducted a systematic and comprehensive testing of meaningful variables, including interaction terms. As for the variable selection process, it should be noted that the value of alpha (significance level) was increased to 0.30 when selecting significant variables. Due to the relatively small sample size in the present study, this was inevitable to accommodate more type 1 errors. This strategy is sometimes used by studies suffering from the small number of observations (please see Zou et al. (2016) as an example).

The probability of the dependent variable having $y = 1$ in a logit model can be expressed as in Equation (1) (Washington et al., 2020):

$$P(y = 1) = \frac{exp\left[\beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p\right]}{1 + exp\left[\beta_0 + \beta_1 x_1 + \cdots + \beta_p x_p\right]} \tag{1}$$

In addition to coefficients, the odds ratio, $exp(\widehat{\beta_p})$, was also computed for better interpretation of the results. One unit increase in the independent variable, x, is associated with an increase (if odds ratio is greater than 1.0) or a decrease (if odds ratio is smaller than 1.0) in the odds of an outcome.

To model the initial adoption of deliveries in model 1, the dependent variable takes a value of one if the respondent is a new adopter and zero if the respondent is a non-adopter. To model the continuance intention in model 2, the dependent variable is one and zero if the respondent is a permanent new adopter and temporary new adopter, respectively.

6. Modeling results

This section presents the final models' specifications. Models with different combinations of variables were developed and compared to determine the best model considering correlations between variables, the goodness-of-fit measures and statistical

Table 6
Final model for the initial adoption of grocery deliveries.

Variables	Coef.	Odds Ratio	Robust Std. Err.	z	P > z
Gender (male)	0.356	1.428	0.282	1.265	0.206
Hispanic status	0.526	1.692	0.461	1.141	0.254
Home (apartment)	0.529	1.697	0.441	1.200	0.230
Number of people over 65 years old in the household	0.346	1.413	0.190	1.821	0.069
Log of population density	0.147	1.158	0.069	2.139	0.032
(constant)	−2.463		0.536	−4.598	0.000
Summary					
Unweighted N	660		Log-pseudolikelihood		−408.9
Prob>chi2	0.02		Pseudo-R2		0.05

significance of coefficients. Odds ratios, i.e., exponentiated coefficients, were also computed to better interpret the impact of a variable.

6.1. Grocery delivery

Tables 6 and 7 present the final models for the initial adoption and continuance intention of grocery deliveries during COVID, respectively.

The results in Table 6 show can be interpreted as that males are 1.413 times more likely to newly adopt grocery deliveries than females during COVID. Interestingly, Hispanic respondents were nearly two times more likely to adopt grocery deliveries than non-Hispanic respondents. This finding was the opposite result of the previous studies (Ren and Kwan, 2009; Wang and Zhou, 2015). Typically, disadvantaged groups are less likely to use delivery services than White individuals. In addition, one additional senior (over 65 years old) in the household was associated with an increase in the initial adoption of grocery deliveries. The plausible reason is that they try to avoid visiting stores due to the risk of the infection. This was also contrary to the previous studies which have suggested that age is negatively associated with the usage of delivery services. These new findings can be interpreted as that the disadvantaged race group or high-risk group, i.e., those who require extra precautions against the virus, are more likely to start receiving deliveries for essential goods such as groceries to avoid visiting stores. Centers for Disease Control and Prevention (2020a) argued that (a) adults over 65 years old have a greater risk of death and hospitalization than those between 18 and 29 years old, and (b) disadvantaged races are at a greater risk due to limited access to healthcare systems. A possible reason for the adoption of deliveries is that they may have limited safe channels for shopping other than deliveries. Due to the highly skewed distribution of population density in ZIP code, the variable was log-transformed. Population density positively affected the initial adoption of grocery deliveries. This is possibly due to the reason that respondents may want to avoid visiting grocery stores in densely-populated areas due to the COVID risk. It is worth noting that the variables income and education level which were the significant factors in most previous studies was not significant in the model. In previous studies, household income and education level were associated with an increase in the usage of delivery services as can be seen in Table 2. Regardless of household income and education level, however, people newly adopted grocery deliveries due to the necessity during the COVID pandemic.

The model for the continuance intention exhibits different result from that for the initial adoption. The impact of the variable age was consistent with the previous studies. Age was negatively associated with the continuance intention. In other words, among the new adopters, young respondents were likely to continue their behavior after COVID. Male new adopters were 1.8 times more likely to continue receiving grocery deliveries. Household income was not relevant to the initial adoption, but it negatively affected the continuance behavior. Higher income led to less probability of continuing behavior. In other words, those with higher income tended to temporarily adopt grocery deliveries during COVID and they would go back to their original shopping channel. The density of grocery stores in their area was associated with a decrease in the continuance intention. Respondents who had higher accessibility to the grocery stores were more likely to give up receiving grocery deliveries. Those who made more trips on a non-workday would less likely to continue to receive grocery deliveries after the pandemic is over.

6.2. Food delivery

Tables 8 and 9 present the final models for the initial adoption and continuance intention of food deliveries during COVID, respectively.

In general, the results were different from those for the initial adoption of grocery deliveries. This is possibly due to the difference between essential and less essential spending. Dining out is typically considered as less essential spending while grocery shopping is essential for household.

In Table 8, the number of people under 18 years old in the household increases the likelihood of the initial adoption of food deliveries. This impact was similar to the impact of children in the household in the previous studies which suggested that children positively affects the usage of delivery services (Spurlock et al., 2020; Wang and Zhou, 2015). The impact of education level was also consistent with previously known impact of education level (Hiser et al., 1999). Those with high education level (graduate degree) were 3.2 times more likely to start receiving food deliveries than other population segments. In contrast, Hispanic and African-

Table 7
Final model for the continuance intention of grocery deliveries.

Variables	Coef.	Odds Ratio	Robust Std. Err.	z	P > z
Age	−0.020	0.980	0.012	−1.681	0.093
Gender (male)	0.572	1.772	0.402	1.425	0.154
Household income ($1,000)	−0.009	0.991	0.004	−2.093	0.036
Grocery store density	−0.041	0.960	0.035	−1.162	0.245
Number of trips on a non-workday	−0.144	0.866	0.093	−1.549	0.121
(constant)	1.524	–	0.806	1.891	0.059
Summary					
Unweighted N	213		Log-pseudolikelihood		−122.5
Prob>chi2	0.01		Pseudo R2		0.10

Table 8
Final model for the initial adoption of food deliveries.

Variables	Coef.	Odds Ratio	Robust Std. Err.	z	P > z
Hispanic status	1.153	3.168	0.572	2.014	0.044
Number of people under 18 years old in the household	0.333	1.395	0.148	2.243	0.025
Education level (graduate degree)	1.178	3.248	0.434	2.717	0.007
Race (African-American)	1.017	2.765	0.605	1.683	0.092
Household income ($1,000)	0.005	1.005	0.003	1.589	0.112
(constant)	−2.438	–	0.299	−8.146	0.000
Summary					
Unweighted N	412		Log-pseudolikelihood		−182.1
Prob>chi2	0.00		Pseudo R2		0.09

Table 9
Final model for the continuance intention of food deliveries.

Variables	Coef.	Odds Ratio	Robust Std. Err.	z	P > z
Number of people over 65 years old in the household	−1.125	0.325	0.409	−2.754	0.006
Restaurant density	−0.021	0.979	0.016	−1.349	0.177
(constant)	1.125	–	0.339	3.322	0.001
Summary					
Unweighted N	90		Log-pseudolikelihood		−44.0
Prob>chi2	0.01		Pseudo R2		0.10

Note: The result may not be reliable due to the small number of observations.

American respondents were more likely to adopt food deliveries than other races. Typically, in the previous studies, disadvantaged races were less likely to use delivery services. This implies that they are constrained to safely dine in stores or pick-up their food at restaurants. Unlike grocery deliveries, income was relevant to the initial adoption of food deliveries. The final model shows that income positively affected the initial adoption of food deliveries during COVID. This income effect is consistent with the previous studies on the determinants of food deliveries during usual days. Those who used to make more trips to the restaurants (i.e., dine out more frequently) were more likely to newly adopt food deliveries during COVID.

The final model for the continuance intention in Table 9 shows that the number of seniors in the household negatively affected the continuance intention. Restaurant density, as a measure of accessibility to restaurants, negatively affected the continuance intention. In other words, those who had better access to restaurants were less likely to continue to use delivery services after COVID. The results in Table 9 should be taken with caution due to a small number of observations.

6.3. Home goods delivery

Tables 10 and 11 present the final models for the initial adoption and continuance intention of home goods deliveries during COVID, respectively.

In Table 10, similar to the impact of seniors on grocery deliveries which are essential spending, the impact of age was different from that in the previous studies. Age positively affected the initial adoption of home goods deliveries during COVID as older adults have a greater risk of infection and severe illness. Same as the previous two deliveries (grocery and food), Hispanic respondents were two times more likely to adopt home goods deliveries than non-Hispanic respondents. Those with higher income were more likely to adopt home goods deliveries. This result is consistent with the previous studies indicating that income has a positive impact on deliveries. However, on the other side of it, low-income households were still not likely to adopt deliveries for essential home goods including paper products or cleaning supplies during the pandemic. This suggests that the gap between socio-demographic groups becomes larger, worsening the inequality issue, during a pandemic.

Table 10
Final model for the initial adoption of home goods deliveries.

Variables	Coef.	Odds Ratio	Robust Std. Err.	z	P > z
Age	0.022	1.022	0.009	2.470	0.014
Hispanic status	0.614	1.848	0.565	1.085	0.278
Household income ($1,000)	0.008	1.008	0.002	3.213	0.001
(constant)	−2.661	–	0.515	−5.162	0.00
Summary					
Unweighted N	588		Log-pseudolikelihood		−369.8
Prob>chi2	0.00		Pseudo R2		0.05

Table 11
Final model for the continuance intention of home goods deliveries.

Variables	Coef.	Odds Ratio	Robust Std. Err.	z	P > z
Number of people under 18 years old in the household	0.334	1.396	0.204	1.636	0.102
Home (apartment)	1.361	3.899	0.546	2.490	0.013
Retail store density	−0.002	0.998	0.001	−1.201	0.230
(constant)	−0.381	–	0.257	−1.482	0.138
Summary					
Unweighted N	197		Log-pseudolikelihood		−121.8
Prob>chi2	0.05		Pseudo R2		0.04

The final model in Table 11 shows that the impacts of the variables are consistent with the previous studies. The number of people under 18 years old in the household was positively associated with the continuance intention. Those living in an apartment were four times more likely to continue their behavior than others. Same as the models for the continuance intention of grocery and food deliveries, the accessibility to stores (retail store density) negatively affected the continuance intention.

6.4. Other packages delivery

Tables 12 and 13 present the final models for the initial adoption and continuance intention of other package deliveries during COVID, respectively.

Although only a few variables were significant in the final model, they were consistent with the previous studies. In Table 12, those living in a one-family detached house were not likely to adopt other package deliveries. A higher density of clothing and accessory stores led to less likelihood of the initial adoption. In other words, those who had better access to physical stores for clothing, accessories, etc. were not likely to use delivery services. Similar to food and home goods deliveries, income positively affected the initial adoption. Overall, most variables identified as significant ones in the previous studies (e.g., age, gender, and race) were not significant in the final model. This highlights that factors affecting other package deliveries during a pandemic are different from those during normal conditions.

The result in Table 13 should be interpreted carefully due to the relatively small number of observations. Full-time workers were less likely to continue receiving other package deliveries. Household size was negatively associated with the continuance intention. Income positively affected the continuance intention of receiving other package deliveries after COVID. The density of clothing and accessory stores was negatively associated with the continuance intention.

7. Implications for planning and policy

The results from this research provide critical implications for planning and policymaking in response to the current pandemic and upcoming disruptive events. First, the findings from descriptive analysis highlight the importance of differentiating the four consumer types: the prior adopter, temporary and permanent new adopter, and non-adopter. The analysis confirmed that there are similarities and clear differences not only between goods types but also between the four consumer types. In normal conditions, there would be the same four types of consumers. However, a better understanding of such consumer types during a pandemic is much more important as it could be associated with the equity issue and health concerns. Interestingly, the changes in the aggregate number of users and deliveries showed that the current increase in demand is a bubble that will burst once the pandemic ends. If transportation planners and researchers rely solely on the current popularity of delivery services without considering (a) a substantial amount of people who will not continue to use delivery services after the pandemic is over and (b) different growth rates for the four types of goods, demand for deliveries after the pandemic would be overestimated.

The results from the modeling effort show that a traditional point of view does not work in a pandemic situation due to psychological and behavioral reasons, i.e., the evidence highlighted that demand modeling, planning, and policymaking during a pandemic should be different from those during normal conditions. For instance, socio-economic factors previously identified as determinants of online shopping do not necessarily have the same impact during a pandemic. The effects of some variables (e.g., income and store

Table 12
Final model for the initial adoption of other package deliveries.

Variables	Coef.	Odds Ratio	Robust Std. Err.	z	P > z
Home (one-family detached)	−1.336	0.263	0.574	−2.330	0.020
Household income ($1,000)	0.010	1.010	0.005	2.120	0.034
Clothing and accessories stores density	−0.186	0.830	0.110	−1.686	0.092
(constant)	−1.324	–	0.551	−2.403	0.016
Summary					
Unweighted N	182		Log-pseudolikelihood		−68.5
Prob>chi2	0.03		Pseudo R2		0.11

Table 13

Final model for the continuance intention of other package deliveries.

Variables	Coef.	Odds Ratio	Robust Std. Err.	z	P > z
Employment (full-time)	−2.005	0.135	1.347	−1.488	0.137
Household size	−0.377	0.686	0.248	−1.524	0.128
Household income ($1,000)	0.011	1.011	0.010	1.030	0.303
Clothing and accessories stores density	−0.201	0.818	0.075	−2.689	0.007
(constant)	4.437	84.52	1.176	3.774	0.000
Summary					
Unweighted N	39		Log-pseudolikelihood		−5.8
Prob>chi2	0.00		Pseudo R2		0.24

Note: The result may not be reliable due to the small number of observations.

density) on the adoption of delivery services were consistent with the previous studies as summarized in Table 14. However, the effects of some other variables (e.g., age and disadvantaged groups) were contrary to the previous studies which have suggested that they are negatively associated with the usage of delivery services. The model results in the present study showed that age and the elderly positively affect the adoption of delivery services. Continuance intention is very important as much as the initial adoption particularly given pandemic fears and restrictions. The models for the continuance intention provide new insights as it has not been discovered so far. The significant factors were different from the models for the initial adoption. Accessibility to stores was one of key driving factors to determine the continuance intention. Those who have better access to stores would give up online shopping once the pandemic is over.

Further insights into policy-making can be drawn from this research. Equity is becoming more important as the market share of online shopping increases (Dias et al., 2020). During a pandemic, however, it is more important as the existing gap between socio-demographic groups becomes larger worsening the inequality issue. Low-income households, seniors, and disadvantaged race groups lacking access to resources during COVID are a great concern of public agencies (Goger, 2020). The results from the current study support this view. A high-risk group (seniors over 65 years old) positively affected the initial adoption of grocery deliveries and the variable age was positively associated with home goods deliveries. In contrast, a high-risk group seemed to have a negative impact on the continuance intention. On the one hand, an increase in the likelihood of the initial adoption for essential goods and a decrease in the continuance intention imply that they have limited alternatives during the pandemic, i.e., no safe access to physical shopping. On the other hand, this evidence can also be viewed as a positive sign as they have, at least, an alternative way of physical shopping. A further investigation is needed to see a logic behind the adoption of delivery services. For instance, a future survey can investigate whether a respondent have a safe and secure access to resources during a pandemic. Although the argument regarding seniors is disputable, there would evidently still be those who fall behind, not being able to use delivery services during COVID. An income gap indeed worsens inequality issues, i.e., the existing income gap becomes larger during the pandemic. As in the previous studies, low-income households were still not likely to adopt delivery services during the pandemic. This is partly due to high monetary cost of deliveries. Many studies have proved that costs associated with delivery (e.g., delivery fee, service fee, handling fee, driver tip, etc) negatively affect the usage of delivery services (Huang and Oppewal, 2006; Lewis, 2006; Marcucci et al., 2021). Thus, they have a greater potential risk exposure than others. In other words, they have no choice left and they are forced to shop in brick-and-mortar stores taking a risk of infection.

As highlighted in Matherly et al. (2020), cities and transportation-related agencies can play an important role in a variety of ways to provide an equitable service to everyone in the pandemic. For instance, the evidence in the present study suggests that a temporary expansion of designated spaces for curbside pick-up (see Montgomery County DOT, 2020; Seattle DOT, 2020 as examples) may offer a safer way for those who have limited alternatives for shopping other than relying only on delivery services.

In addition to a provision of spaces for pick-up, a collaboration across a wide range of agencies is also needed during a pandemic. For instance, the City of New York runs special programs to keep both social-distancing and running businesses. New York City Department of Transportation (NYC DOT)'s Open Restaurants program allows restaurants in the city to expand their seating to the adjacent outdoor areas, e.g., on sidewalks or roadways, while dine-in service is restricted to keep social distancing (NYC DOT, 2020a). Another similar program by NYC DOT, called the Open Storefronts, allows establishments including retail stores to run their business in outdoor space adjacent to the store (NYC DOT, 2020b). These programs offer a wide range of choices in shopping to consumers while keeping the community safe. These strategies can effectively work especially for those with low income. As (a) vehicle ownership is positively associated with income in the U.S. (FHWA, 2017) and (b) low-income individuals are reluctant to use delivery services due to high cost, such policies can provide low-income individuals with a safe and secure access to resources.

Besides offering wider shopping channels to people, some cities have made an effort to deliver essential items directly to the targeted people including low-income households, seniors, and those with disabilities. For instance, San Francisco is running a free food delivery program, called Great Plates Delivered Meal Program, for vulnerable people including seniors, people with disabilities, and low-income households during COVID (San Francisco Human Services Agency, 2020). The city of Smyrna in Georgia and LA county in California run a similar program to deliver groceries, household goods, and medicine to vulnerable people (City of Smyrna, 2020; WDACS, 2020). A collaboration with delivery companies to offer special benefits or with Transportation Network Companies (TNC) or transit authorities to assist the vulnerable people for a safer trip to the stores can also be a way of mitigating negative impacts of the pandemic from the transportation perspective. For instance, seniors using a special transit card in San Francisco pay a discounted

Table 14
Results comparison.

| | Literature | | This research | | | |
| | | | Initial adoption | | Continuance intention | |
	Positive	Negative	Positive	Negative	Positive	Negative
Grocery	Income, household size, residential density	Apartment	Male, Hispanic, apartment, seniors, pop density		Male	Age, income, store density, physical trips
Food	Education, income, household size, pop density	Age	Hispanic, education, African-American, income, children			Seniors, store density
Home goods	Income	Age	Age, Hispanic, income		Children, apartment	Store density
Other PKG	Income, education, household size, internet usage, female, White	Age, vehicle availability, store density, Hispanic	Income, one-family house	Store density	Income	Full-time worker, household size, store density

price for a taxi trip to grocery stores (SFMTA, 2020). Taxi drivers in Los Angeles and New York City deliver groceries and food to the vulnerable people during the COVID pandemic in collaboration with the city authorities (Carpenter, 2020; Rivoli, 2020).

8. Conclusions

Online shopping and resulting deliveries are an integral part of daily life in the pandemic era to avoid visiting stores. Although delivery services are booming everywhere, the current popularity of them may not last a long time due to the heterogeneity of consumers' behavior. This research conducted a survey and analyzed the initial adoption and continuance intention of using delivery services which have not been investigated in depth.

The results from the descriptive analysis presented clear differences not only between the four types of consumers (i.e., the prior adopter, temporary and permanent new adopter, and non-adopter) but also between the four product types (grocery, food, home goods, and other packages). In terms of the average number of deliveries by consumer type, the average number for the prior adopter was greater than that for other types in general. The average number of home goods deliveries did not exhibit significant differences between the four consumer types. On the other hand, the average number of other package deliveries differed much between the consumer types. The prior adopters would receive significantly more package deliveries than the new adopters during and after COVID. With respect to the aggregate number of users and deliveries over time, it is expected that the long-term effects of the COVID on delivery services would be approximately half of the near-term effects. For instance, the number of users for grocery deliveries increased by 113% during COVID. However, almost half of these new adopters would not continue to use it once the pandemic is over. This is because the increased demand for deliveries is not the result of market competition, but the result of an external disruption, or a large disaster. The near- and long-term effects also varied by the product type. For instance, the growth of essential goods (grocery and home goods) was faster than that of less essential goods (food and other packages). Interestingly, the number of users for other package deliveries did not differ much across time, but the existing users were likely to increase the package delivery frequency during and after COVID. The analysis confirmed that there are similarities and clear differences between the four consumer types and highlighted the importance of considering all the four types in planning and policy.

The logistic regression models were also developed to examine factors influencing the initial adoption and continuance intention of using delivery services. As a result, the contributing factors were different not only from those in the previous studies but also between the four product types. For instance, the effects of income and store density were consistent with the previous studies. However, the effects of some variables including disadvantaged races, seniors, and age were contrary to the previously known effects. This implies that consumers' behavior during a pandemic is different from behaviors during normal conditions. Unlike during normal conditions, many psychological factors (e.g., perceived risk of infection in stores) possibly affect the consumers' behaviors during a pandemic.

The results also highlighted the importance of an understanding of the gap between an increase in online shopping and the equity issues. Low-income households or disadvantaged groups are a great concern of policymakers during a pandemic. As they have limited choices during a pandemic, it is important to provide them an equitable and fair access to resources. This paper discussed ways to mitigate negative impacts of the COVID considering the research findings, e.g., a provision of curbside spaces for pick-up, a special delivery to the vulnerable people in collaboration with other transportation-related agencies.

The modeling results in the present study can be further improved by increasing the sample size. It should be noted that this study increased the significance level to 0.3 when selecting variables to accommodate more type 1 errors due to the small number of observations. In addition, future research should consider various factors including observable variables (e.g., vehicle ownership, a primary mode to the stores) and unobservable factors (e.g., attitudes towards online shopping, perception on the pandemic). The authors collected and tested the number of positive cases in a region as an independent variable in the models (Centers for Disease Control and Prevention, 2021). However, the variable was significant in none of the models. This implies that the unobservable factors (e.g., individual's perception on the pandemic) rather than superficial numbers (i.e., the number of cases in a region) can possibly play a significant role in the adoption of delivery services.

Notwithstanding the limitations, this research offers valuable behavioral insights into not only the current freight planning and policymaking but also future studies on other new transportation service forms and other upcoming disruptive events.

CRediT authorship contribution statement

Xiaokun Cara Wang: Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Project administration. **Woojung Kim:** Conceptualization, Methodology, Formal analysis, Writing – original draft. **José Holguín-Veras:** Writing – review & editing, Project administration. **Joshua Schmid:** Data curation, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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