Title
Evaluating Delivery Service Preference for Online Shopping During the Early Phase of the COVID-19 Pandemic

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Evaluating Delivery Service Preference for Online Shopping During the Early Phase of the COVID-19 Pandemic

By

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THESIS

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Abstract

The COVID-19 pandemic rapidly accelerated the adoption of online shopping in early 2020. This increase raises questions about whether there are changes in e-shopping behavior, the characteristics of online shoppers, and the frequency of online purchases by different types of delivery services during that period. The e-shopping patterns during the COVID-19 pandemic also bring into question whether everyone has the accessibility to engage in online shopping and use various delivery services. This study addresses the above questions through exploratory data analyses, the estimation of binomial logistic regression models, and market segmentation using the Latent Class Cluster Analysis (LCCA) on the Spring 2020 COVID-19 Mobility Study survey data. The results show that age, educational background, type of neighborhood where the respondents live, household income, and attitudes toward technology strongly influence e-shopping behavior. The LCCA results revealed three well-defined latent classes: 1) *Occasional Shoppers*, who shopped not very frequently, generally used both *fast* and *standard* delivery services more than the other delivery options and often live in suburban areas, 2) *Non-Shoppers*, who made very few or no online purchases at all, tend to belong to the older age group, have lower education and income level, and have negative attitudes toward technology, and 3) *Super Shoppers*, who made more frequent purchases (usually three or more purchases in a month with any type of delivery services) tend to be younger and wealthier, live in urban areas, and usually have positive attitudes toward the adoption of technology. The results indicate that e-shopping and some delivery services during the early phase of the COVID-19 pandemic might only be available and benefit some groups, as people who had lower digital literacy and did not live in urban areas had less access to those services.

Keywords: E-shopping, COVID-19, Shopping Behavior, Delivery Services, Exploratory Data Analysis, Logistic Regression, Latent Class Cluster Analysis

1. Introduction

Technology advancement has changed the way people move and conduct their activities, including their shopping behavior. E-shopping provides the convenience of meeting people's needs from anywhere and anytime as long as users have access to smartphones, laptops, or other similar devices and a connection to the internet. In the US, e-commerce penetration has increased across all retail sectors, and retail e-commerce sales have grown steadily over the last decade (COWEN, 2022; USDC, 2022). The growth in e-commerce has forced logistic providers to think creatively and improve their delivery infrastructure and services to be able to handle the increasing volume of deliveries and compete with other providers to meet the demand and consumers' expectations. For example, one notable trend in online shopping is the increasing expectation for fast shipping and logistics to allow consumers to get their orders as quickly as possible. Therefore, a variety of delivery services has emerged and has been adopted by many shipping companies and stakeholders of delivery services, including sellers, third-party logistic providers, and crowdshipping platforms.

During the early stages of the global COVID-19 pandemic, the US government enforced restrictions on in-person gatherings, limited trips to malls and stores, and other non-essential travel (Spiegel & Tookes, 2021; Devi, 2020). These restrictions immediately impacted the transportation of people and goods (USITC, 2021). This situation led to a sharp increase in the popularity of online shopping (Mischa et al., 2021) because it allowed people to meet their shopping needs while reducing the risk of COVID-19 exposure. Thus, online shopping has become more than just having the convenience of shopping from home or anywhere without putting effort into traveling to the stores or spending time in traffic and money on gas. It has become an essential part of individuals' lives during the pandemic to meet their needs.

With the rapid growth in e-commerce sales during the early phase of the COVID-19 pandemic, online shopping patterns by different delivery services might have changed at the same time. The consumers' characteristics and e-shopping frequencies by type of deliveries could also be different during the early months of the pandemic. The COVID-19 pandemic impacted everyone regardless of their sociodemographic or economic status. However, only a few studies focused on the impact of COVID-19 on home delivery services (Figliozzi & Unnikrishnan, 2021), delivery limitations by home locations, and lessons learned on delivery services from the COVID-19 pandemic. Therefore, this study focuses on the following questions:

1. What were the online shopping patterns for various delivery services during the COVID-19 pandemic?
2. Who shopped online, and how often did they do that during the pandemic? Did the use of various types of delivery services differ by major demographic characteristics?
3. Were there limitations associated with online shopping and delivery services for people who do not live in urban areas? What are the lessons learned from the analysis of the use of various delivery methods during the COVID-19 pandemic?

2. Background

Online shopping sales have grown steadily in many parts of the world, including the US, over the past decade (Statista, 2021, USDC, 2022). Many studies have focused on understanding the variables that affect online shopping behavior. Some factors that may affect the adoption of online shopping range from access to the internet and smartphones to the role of sociodemographic characteristics and social connectedness (Naseri & Elliott, 2011). In general, factors that directly influence the use of e-commerce are technology adoption, internet use, and product interest. Cao et al. (2012) concluded that the internet opens access to a large amount of online information about products, generating more shopping demand.

As for demographic features, age is arguably a significant factor in online shopping frequency, as young adults are more likely to adopt new technologies and have access to and skills to use the internet than older adults (Lee et al., 2015, Crocco et al., 2013, Cao et al., 2012). On the other hand, Jusoh & Ling (2012) concluded that income and education only have a modest positive impact on online shopping decisions, whereas previous online purchases are the most important determinant. Meanwhile, gender effects on online shopping behavior are still unclear. Hasan (2010) found that women have more negative cognitive attitudes toward e-shopping, indicating they value the e-shopping utility less than men, which explains the low e-shopping activities of women. Women are also found to be less willing to adapt to online buying due to a lack of emotional experience from e-shopping (Dittmar et al., 2004). Farag (2007) found that men tend to have more internet experience, which affects e-shopping positively, while other studies argue that gender has no effect on online shopping behavior (Lee et al., 2015, Lian & Yen, 2014).

There is ambiguity in neighborhood effects on online shopping patterns. While Lee et al. (2015) found that the built environment is not a significant predictor of online shopping behavior, some studies have shown a strong correlation between neighborhood type and e-shopping adoption. Cao et al. (2013) explained how shopping barriers in exurban areas promote the use of e-shopping. Mokhtarian (2004) and Ren & Kwan (2009) also concluded that shopping accessibility influences e-shopping patterns; for example, low shopping accessibility in exurban areas will positively influence the adoption of e-shopping. However, Ren & Kwan (2009) discovered that the influence is low for a community with a higher car ownership rate. Zhen et al. (2018) concluded that this influence only applies to specific commodities. Zhen et al. (2018) did not find that effect on clothing, perhaps because the trial and experience of buying clothes are more important than other commodities such as books.

Cao et al. (2013) found that internet users in urban areas are more likely to shop online than those in rural and suburban areas, as urban residents are, on average, better educated and use the internet more than people in other areas. Another study also showed a positive correlation with e-shopping for people living in urban areas (Jaller & Pahwa, 2020). Despite having the same positive correlation in the two metropolitan areas, the authors found that San Francisco and Dallas have different shopping patterns because of the demographic variation in those cities, resulting in different negative externalities (*e.g.*, traffic congestion and pollution).

Uzun and Poturak (2014) showed that trust and convenience are the most important variables that affect online consumer behaviors, followed by prices and the quality of products. Trust is one subjective variable yet critical, as cheating and fraud issues on the internet are becoming more common over time (FBI, 2020). Crocco et al. (2013) emphasized that the variety of available products, the ability to acquire more product information and to compare prices and savings positively affect the usage of online shopping. In contrast, the inability to see goods before buying them reduce consumers' trust. This could be why Italians hesitated to use e-commerce around 2002 or only a few years after the internet became widely available (De Blasio, 2008). Lee et al. (2015) analyzed the survey data of some internet users in Minneapolis and Saint Paul that also shared the same preference in a trying-then-buying product mindset. Xu (2017) added that e-shopping offerings affect online sellers' cumulative ratings by the type of products that eventually affect e-shopping behaviors.

Types of Delivery Services

The increasing online shopping demand has reshaped logistics and delivery services. Delivery and shipping companies race to provide their customers with the fastest, most reliable, and most affordable delivery options. As a result, many shipping options are provided to customers, such as locker pickup (*e.g.*, Amazon locker) and curbside or in-store pickup (*e.g.*, Target, Costco). Other options are *standard* delivery (in three or more days), same-day delivery, or even within one or two hours.

Locker pickup offers a variety of benefits that are not provided by conventional home delivery services. For example, customers can either have someone secure their packages in a locker or a 24/7 parcel locker system with a temporary access code on the electronic locker, which provides a safer and more secure delivery than traditional home delivery (Keeling et al., 2021). Morganti et al. (2014) found that parcel lockers benefit transportation operators by increasing the number of successful first-time deliveries, optimizing delivery routes, and lowering operational costs. This benefit is also related to the potential CO_2 emission savings from the reduction in failed home deliveries and repeated re-delivery attempts (Edwards et al., 2010) and the impact on traffic and congestion problems.

Despite having high satisfaction rates from its users (Iwan et al., 2016), the locker pickup service has relatively few enthusiasts. Morganti et al., 2014 found that less than 10% of e-shoppers in Germany chose delivery to pickup points, even though they have a dense pickup point network there (more than 36,000 pickup points all over the country; DHL pickup stations were within 10 minutes radius to 90% of the German population in 2009). The reason may be that the service requires customers to make extra effort to come to the locker locations to get the package (Faugere and Montreuil, 2016), even though most sites are relatively close to the customers' homes leading to moderately short trips (Ulmer and Streng, 2019).

Crowdshipping also emerged as a new form of freight transportation that provides social, economic, and environmental benefits while using the "crowd" to provide a cheaper and faster delivery (Le et al., 2019). Le et al. (2019) outlined the crowdshipping concept where an operation and management party will match and connect customers with drivers who are close to customers, have unused space in their vehicles, and are willing to deliver packages through an online platform. Pourrahmani and Jaller (2021) discovered that the crowdshipping benefit in mitigating negative environmental impacts occurs when the delivery happens through already existing trips and the use of cleaner modes. Punel et al. (2018) added that both traditional logistic firms (Amazon Flex Services, DHL, Walmart) and start-ups are part of the crowdshipping market, with the Business to Customer (B2C) dominating the business model.

The shipping options also vary by the type of purchased commodities. Same-day delivery and crowdshipping are usually used to deliver groceries and food to avoid spoiled food as they need to be at a specific temperature and cannot be on the road for too long. Books, clothes, and electronics purchases usually do not need the fastest delivery option as these commodities are generally not required to be under a specific temperature or condition. However, some customers may still prefer the quickest delivery for personal reasons. Delivery is closely related to speed and timetable. Xu (2017) found that faster shipping influences e-shopping, and sellers of hedonic products should focus on this. Nguyen et al. (2019) outlined findings on consumers' preference for delivery attributes provided by online retailers. The study found that consumers made decisions based on how they value money (*i.e.*, product costs, delivery fees), followed by delivery time and convenience. Nguyen defined three segment orientations of consumers across product categories: price-, time-, and convenience-oriented, which vary by gender and income.

Rush delivery (*i.e.*, within one or two hours) provides the fastest delivery option for customers, but it also incurs more negative environmental impacts. Jaller and Pahwa (2020) found that consolidation of online orders is critical to reduce the negative externalities or negative environmental impacts of e-shopping. They further explain that longer delivery methods allow vendors or stores to consolidate their orders and manage the shipment activities, while consolidating orders for rush delivery orders is hard and would affect the operations of most companies. Jaller and Pahwa (2020) concluded that rush delivery worsens the environmental efficiency of deliveries compared to other longer delivery services.

E-shopping During the COVID-19 Pandemic

The situation in the early months of the COVID-19 pandemic caused an immediate impact on the transportation of people and goods. Sobieralski (2020) studied the reduction of major airlines' capacity by 60%-80% in summer 2020, and Nehiba, C. (2021) reported a 40 % reduction in monthly vehicle miles traveled (VMT) in Louisiana in April 2020. Zhang et al. (2021) found a remarkable modal shift from public transit to walking or bicycle in Europe, a 60% shift to cars in South Korea and China, and even a much higher shift to motorcycles in India and other Asian countries. The reasons range from the lockdowns, restrictions to out-of-home activities and non-essential trips, and the fear of contracting the COVID-19 virus. The US International Trade Commission reported disruption in maritime shipping and air freight services in early 2020 due to the COVID-19 pandemic led to cancellations in shipping, flights, port delays, and container shortages, which was particularly substantial for imports from Northeast Asia to the United States

(USITC, 2021). USITC further outlined how the COVID-19 pandemic caused an increase in maritime freight costs in the second half of 2020, a sharp rise in air freight rates, higher shipping costs for imported goods, and other negative impacts (*e.g.*, on shipping modes and routes, ports, and arrival time of cargo).

The COVID-19 pandemic accelerated the adoption of online shopping (see **Figure 1**). Data from the US Department of Commerce shows how the annual US retail e-commerce sales in the second quarter of 2020 increased by more than four percentage points during the COVID-19 pandemic, compared to only a 1% annual increase from the second quarter of 2016 (USDC, 2022).

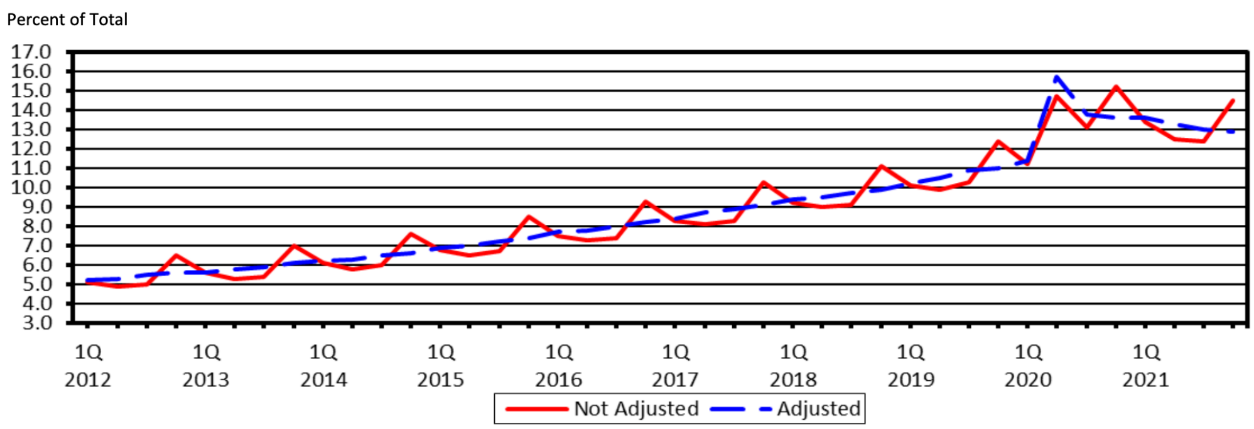

Figure 1. Estimated Quarterly U.S. Retail E-commerce Sales as a Percent of Total Quarterly Retail Sales: 1st Quarter 2012 – 4th Quarter 2021 (USDC,2022)

Some studies have focused on identifying the impacts of the COVID-19 pandemic on e-shopping behavior and whether the previous findings regarding the variables that affect e-shopping behaviors still hold during and after the pandemic. The World Economic Forum cited some US consumers' reviews on their websites, including the phenomenon of shifting to digital shopping channels and the type of purchased commodities. The page also shows that 75% of consumers have tried a new shopping behavior (*e.g.*, new shopping method, choosing different brands, different retailers, etc.) since the COVID-19 pandemic started, and about 40% of them intend to continue to engage in the new behavior. Young et al. (2022) found that e-shoppers who shopped at least once a week before COVID-19 increased nearly five times in the early pandemic in Spring 2020 but later decreased by half in Fall 2020. They further explained that consumers with higher education and income levels are still positively associated with higher adoption of e-shopping, while the age group is no longer a significant predictor of e-shopping behavior as everyone from any age group was impacted by the COVID-19 pandemic restrictions.

On the other hand, grocery shopping represents one of the essential trips that were allowed by governments also during the pandemic. Compostella et al. (*forthcoming*) found that, despite the ability to engage in in-person grocery shopping, some people still chose to do online shopping. These online grocery shoppers were mainly part of the middle- and high-income groups. Meanwhile, in-person shoppers were active people who were less likely to reduce their in-person shopping trips.

The previous studies provided a foundation of theoretical background and analysis methods for this thesis. Some variables that were found to affect e-shopping behaviors in the previous studies are also tested in this study to further complement and improve the current understanding of e-shopping behavior, with particular emphasis on the e-shopping behavior by type of deliveries during the early COVID-19 pandemic in the US, which is the focus of this thesis. The following section provides an overview and analysis of the online shopping patterns by various delivery services during the early COVID-19 pandemic between March and April 2020.

3. Data

The study uses data collected in Spring 2020 as part of the COVID-19 Mobility Study carried out at the University of California, Davis. The survey is part of a study involving an annual survey that is administered to understand individuals' changing lifestyles, preferences, and travel and activity patterns. The survey questions include a broad range of topics related to sociodemographic, household composition, economic background, vehicle ownership, and travel and shopping patterns. As the COVID-19 pandemic started in early 2020, beginning in that year, the research team used this survey to include questions related to the impacts of COVID-19 on their activity and mobility patterns. Thus, the survey data for the analyses in this thesis include information on telecommuting patterns, travel behavior, attitudes related to a variety of dimensions, the use of emerging transportation services, and e-shopping patterns during the early phase of the COVID-19 pandemic, *i.e.,* the period between March and April 2020. Young et al. (2022) describe three approaches that were used to recruit the spring 2020 COVID-19 mobility study respondents: 1.) Recontacted respondents from the previous surveys in 2018 and 2019 who agreed to participate in future surveys; 2.) Used a quota sampling approach through an online opinion panel vendor and targeted specific groups of respondents at a city-level basis based on their sociodemographic characteristics, such as age, gender, race, ethnicity, household size and income, and activities (student/employment status); 3.) Used a convenience sample collected by sending out survey invitations via professional listservs and social media.

Although the team recognized how the use of an online opinion panel might lead to certain forms of sampling biases, this method was chosen to prevent potential respondents from worrying about in-person interactions and as an acceptable tradeoff between the speed of the data collection and the quality of the collected data. Young et al. (2022) further explain the data limitations that include the use of a quota sampling approach which makes the dataset not fully representative of the characteristics of residents in the surveyed cities due to the nonrandom nature of the sampling process and sampling frame used for the data collection. Respondents' reported cities were Atlanta, Boston, Chicago, Washington DC, Denver, Detroit, Kansas, Los Angeles, New York City, Sacramento, Salt Lake City, San Diego, San Francisco, Seattle, and Tampa.

Overview of E-shopping Survey Section

In addition to the various sociodemographic, socioeconomic, and travel patterns data, the Spring 2020 survey data also collected information on e-shopping patterns during the early phase of the COVID-19 pandemic. For example, there were questions about the specific commodities that respondents bought online and the type of delivery options that they chose for online purchases in the previous 30 days between March and April 2020 (see **Table 1**). There are six delivery options provided in the survey: same-day delivery (*e.g.*, Amazon Prime Now, Instacart), fast delivery or 1-day/ 2-day delivery (*e.g.*, Amazon Prime), Standard delivery (three or more days), order online with pick-up at a local store (*e.g.*, Costco, Target), order online with delivery to pick-up locker (*e.g.*, Amazon locker), and international shipments with longer delivery time. With this information, the study explores the online shopping frequencies by various delivery options during the early COVID-19 pandemic and e-shoppers' attributes such as age, educational background, employment, income groups, and type of neighborhood. In the same survey section, there were also questions related to attitudes towards online shopping, shopping patterns (online or store visits) before and during the COVID-19 pandemic, questions about whether respondents have made changes to their grocery shopping patterns, and how respondents expected their shopping patterns to change in the future compared to their current practices.

Table 1. The survey question about the number of online purchases using various delivery options in the last 30 days.

Variables	Question/ Statement	Variable Type	Response Scale
Same-day delivery	During the past 30 days, how many times have you purchased any products online with the following delivery option? Please enter "0" if you did not use that type of delivery option.	Count variable	Any integer
Fast delivery	During the past 30 days, how many times have you purchased any products online with the following delivery option? Please enter "0" if you did not use that type of delivery option.	Count variable	Any integer
Standard delivery	During the past 30 days, how many times have you purchased any products online with the following delivery option? Please enter "0" if you did not use that type of delivery option.	Count variable	Any integer
Local pickup	During the past 30 days, how many times have you purchased any products online with the following delivery option? Please enter "0" if you did not use that type of delivery option.	Count variable	Any integer
Locker pickup	During the past 30 days, how many times have you purchased any products online with the following delivery option? Please enter "0" if you did not use that type of delivery option.	Count variable	Any integer
International delivery	During the past 30 days, how many times have you purchased any products online with the following delivery option? Please enter "0" if you did not use that type of delivery option.	Count variable	Any integer

Final Data Set

The original data were collected, reviewed for quality control, and recoded by researchers in the 3 Revolutions Future Mobility Program at UC Davis. For this study, I further reviewed and tested the data to remove cases that may create potential issues in the analyses in this study. Some of the cases that are tested, questioned, and potentially may be removed from the data set are as follows:

1. Respondents who gave no information about their online shopping patterns were removed from the data set.
2. Respondents who gave no information about their background and sociodemographic, including age, gender, household income, employment, and many more. Without this information, the respondents cannot be classified and grouped in the model, and their online shopping information cannot be analyzed further. Thus, these respondents were removed from the data set.
3. Respondents who mistyped answers and no other valid information were available to recode their answers. These respondents were flagged as potentially suspicious and further reviewed. For example, one respondent reported they were born in the year 0.196, and there was no other information in the survey to help correct this answer. Therefore, this respondent's age was questioned, but their other information was still used for the initial exploratory analysis. However, this respondent was later removed as the age variable was required for further analysis.
4. Respondents who are extreme outliers for the number of deliveries for online purchases in the last 30 days. Respondents who reported extremely high numbers of purchases and/or deliveries were reviewed on a case-by-case basis. Investigating each extreme case helps avoid dropping legitimate cases just because they are outliers. However, a few unrealistic and rare cases were also dropped from the data set, even if they can be rationalized. For example, a respondent who reported 500 deliveries for online purchases in a month was further reviewed based on other information to justify the answer. This respondent was the one and only respondent in a group that reported 500 deliveries by one delivery option in a month. This respondent was removed from the data set because this case was hard to

study or further analyze unless there were more respondents and information available. In this study, I assumed 30 purchases per month to be a reasonable cut-off number based on the distribution of the purchases of each delivery option. This number can also be interpreted as daily purchases, where respondents would use any delivery option for one online purchase every day in a month (if one month = 30 days, then one purchase/day will be 30 purchase/month). Another reason is that respondents who made more than 30 purchases were very rare, totaling only 0.4% of the cases (35 respondents), and the variance above 30 purchases is also high.

After passing through the above tests and reviews, a total of 8,593 responses were used in the final data set of this study. The distribution of relevant socio-demographic variables in the dataset can be seen in **Table 2**. The Spring 2020 survey respondents were rather evenly distributed across age groups and dominated by women (almost 60%), with only about 40% of respondents being men, and a small number of respondents who identified as non-binary. Meanwhile, white respondents dominated the survey with almost 70% share, followed by 13% black, 10% asian, and 7.4% from other races. Moreover, only about 10% of respondents were full-time students, and a few respondents took part-time school or online courses, but most of them were not students. While more than 50% of respondents had a bachelor's degree, only 42% of respondents had full-time employment, 12% did not work, and the remaining either had part-time employment, other types of work (*e.g.*, multiple jobs), or were already retired.

Table 2. Distribution of relevant socio-demographic variables (N=8,593 observations).

Variables	Respondents (N)	Relative Frequency (%)	Variables	Respondents (N)	Relative Frequency (%)
Personal Attributes			**Ownership Attributes**		
Gender			Own car	6,331	73.7
Female	5,085	59.2	Have access to car	7,724	89.9
Male	3,459	40.2	Own smartphone	8,236	95.8
Other	49	0.6	Own laptop	7,145	83.1
Age group			Own desktop computer	4,471	52.0
18-34	3,129	36.4	Own tablet	5,930	69.0
35-54	2,891	33.6	Own smartwatch	3,210	37.4
55+	2,573	30.0	Fast internet	7,979	92.9
Race			**Household Attributes**		
White	5,891	68.6	*Type of Neighborhood*		
Black	1,159	13.5	Urban	3,028	35.2
Asian	904	10.5	Suburban	4,941	57.5
Other	639	7.4	Small Town	372	4.3
Education level			Rural	252	2.9
Some Grade/ High School	187	2.2	*HH Income*		
Completed High School/GED	1,196	13.9	< $25K	1,193	13.9
Some College/ Technical School	2,531	29.5	$25K - $50K	1,699	19.8
Bachelor's Degree	2,905	33.8	$50K - $75K	1,441	16.8
Graduate Degree	1,410	16.4	$75K - $100K	1,198	13.9
Professional Degree	364	4.2	$100K - $150K	1,773	20.6
Student status			> $150K	1,289	15.0
Full-time Student	868	10.1	*HH Size*		
Part-time Student	358	4.2	1 person	1,438	16.7
Taking online courses	448	5.2	2 persons	2,755	32.1
Not a student	6,919	80.5	3 persons	1,576	18.3
Employment			4 persons	1,623	18.9
Full-time employed	3,633	42.3	5 or more persons	1,201	14.0
Part-time employed	1,150	13.4	*HH # of children (age < 18)*		
Retired	1,170	13.6	0 kid	5,565	64.8
Other work type	1,572	18.3	1 kid	1,447	16.8
No Work	1,068	12.4	2 kids	1,104	12.8
Have Driver License	7,852	91.4	3 or more kids	477	5.6

Variables	Respondents (N)	Relative Frequency (%)	Variables	Respondents (N)	Relative Frequency (%)
Attitude traits			*HH # of adults (ages 18-64)*		
Like to be the first to use the latest technology			0 person	1,448	16.9
Strongly disagree	1,305	15.2	1 person	1,610	18.7
Somewhat disagree	1,961	22.8	2 persons	3,516	40.9
Neither agree nor disagree	2,124	24.7	3 persons	1,154	13.4
Somewhat agree	2,086	24.3	4 or more persons	865	10.1
Strongly agree	1,117	13.0	*HH # of elders (ages > 64)*		
Like new things			0 person	6,668	77.6
Strongly disagree	254	3.0	1 person	1,146	13.3
Somewhat disagree	693	8.0	2 persons	736	8.6
Neither agree nor disagree	1,229	14.3	3 or more persons	43	0.5
Somewhat agree	4,159	48.4	*HH # with health risk*		
Strongly agree	2,258	26.3	0 person	5,155	60.0
Like driving			1 person	2,095	24.4
Strongly disagree	383	4.5	2 persons	949	11.0
Somewhat disagree	501	5.8	3 or more persons	394	4.6
Neither agree nor disagree	1,158	13.5	*HH # with licenses*		
Somewhat agree	2,741	31.9	0 person	768	8.9
Strongly agree	3,810	44.3	1 person	2,059	24.0
			2 persons	3,898	45.4
			3 or more persons	1,868	21.7

Another notable attribute was that more than 90% of respondents have driver's licenses, and almost 90% had access to a car even though only about 70% of them owned one. Owning several high-technology devices and services such as smartphones, fast internet, and laptops were common attributes that survey respondents had, with about 95%, 92%, and 90% of total respondents having those devices or services, respectively. While only about 40% of respondents owned smartwatches, more than 50% of them had either tablet or desktop computers.

Attitudes towards technologies are other valuable and interesting variables to understand the survey respondents better. Based on the survey data, more than 70% of respondents agreed with the statement that they like driving and they like trying new things, while about 37% of them agreed that they like to be among the first group to use the latest technology. To summarize, most survey respondents tend to have positive attitudes toward technology and are open to trying new things and technologies.

Most of the Spring 2020 survey respondents lived in suburban (about 58%) and urban (35%) areas, and only a small group of respondents lived in small towns (4.3%) and rural areas (2.9%). However, about 35% of them lived in a household with more than $100K annual income, 35% lived with a yearly income lower than $50K, and the remaining group lived between $50K and $100K. Household composition is another important feature in understanding the demographic background of the survey respondents. Almost half of the respondents lived alone, or with another person, about 65% had no kids, and about 80% stayed without elders. Moreover, in 40% of the households, at least one member had a health risk.

Figure 2 illustrates the number of purchases by various delivery options of each respondent in 30 days between March and April 2020. Each dot represents each respondent's use of each delivery option. Y-axis with high density shows that many respondents reported the same number of purchases in that delivery option, while low density means how rare respondents made such a number of purchases. The figure shows that people used *fast* and *standard* delivery the most and made fewer purchases with *locker pickup* and *international* delivery.

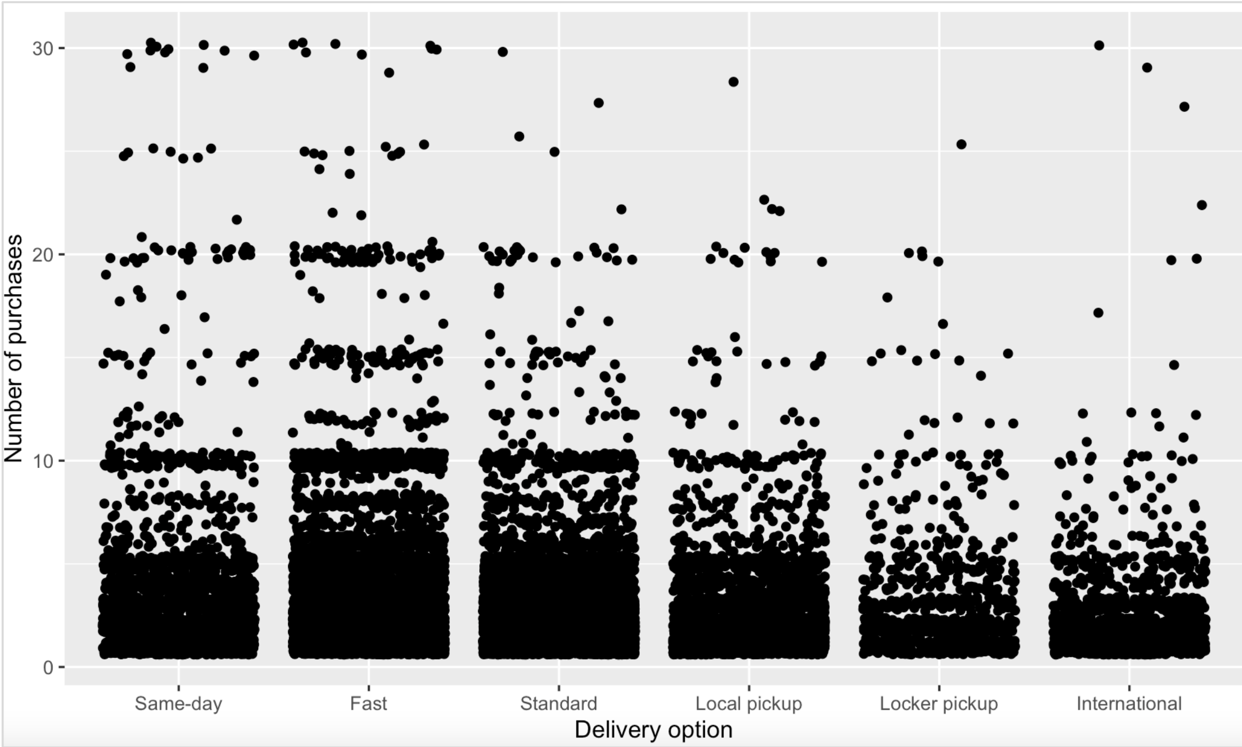

Figure 2. Number of purchases by various delivery options (N=8,593 observations)

Table 3. Summary statistic of the number of purchases by various delivery options (N=8,593 observations)

# Deliveries	Same-day	Fast	Standard	Local pickup	Locker pickup	International
Including 0 value cases (N=8,593 obs.)						
Minimum	0.0	0.0	0.0	0.0	0.0	0.0
1st quartile	0.0	0.0	0.0	0.0	0.0	0.0
Median	0.0	1.0	1.0	0.0	0.0	0.0
Mean	0.9	2.2	1.8	0.8	0.3	0.4
3rd quartile	1.0	3.0	3.0	1.0	0.0	0.0
Maximum	30.0	30.0	30.0	28.0	25.0	30.0
Not including 0 value cases						
N (# obs.)	***2,161***	***4,644***	***4,852***	***2,598***	***766***	***1,463***
Minimum	1.0	1.0	1.0	1.0	1.0	1.0
1st quartile	1.0	2.0	1.0	1.0	1.0	1.0
Median	2.0	3.0	2.0	2.0	2.0	2.0
Mean	3.7	4.0	3.1	2.8	3.1	2.3
3rd quartile	4.0	5.0	4.0	3.0	4.0	3.0
Maximum	30.0	28.0	30.0	28.0	25.0	30.0

While **Figure 2** only shows e-shopping frequencies at a glance,

Table *3* reveals a more detailed look into the online shopping frequencies with and without zero value cases (*i.e.*, respondents who made no purchases with each delivery option). As discussed in the previous section, 30-purchases per delivery option is used as the cut-off limit for a reasonable number of purchases with a sufficient group of respondents. Thus, some delivery options have 30 purchases as their maximum number. When including zero value cases, *fast* and *standard* deliveries have the highest average number of purchases with more than one purchase on average, while the mean for *same-day* and *local pickup* is slightly below one purchase per respondent, and *locker pickup* and *international* delivery have the lowest average number of purchases. The average number of purchases excluding zero value cases is three purchases in almost every delivery option. The *fast* and *same-day* delivery options have the highest average number of purchases, or around four, in a month. The analysis of the mean and median number of purchases helped inform the next phase of the study in deciding the classification of online shopping frequencies that will be used for the analysis and modeling.

4. Methodology

This study implements three statistical analyses to answer the research questions using data from 8,593 respondents. The first portion of the analyses employs exploratory data analysis to define a set of variables that influence the online shopping behavior of respondents. The second method of analysis is centered on the estimation of a set of binomial logistic regression models to analyze the behaviors of respondents who used each delivery option for online purchases and those who did not use it. Then, the results from the exploratory data analysis and the model estimation are used to identify the covariates that can be used to understand the sociodemographic of each latent class in the subsequent analysis. Finally, latent class cluster analysis (LCCA) is the third analysis to segment respondents into groups based on their online shopping behavior in terms of their number of deliveries for online purchases made in the previous 30 days (*i.e.*, during the early COVID-19 pandemic between March and April 2020).

4.1 Exploratory Data Analysis

Exploratory data analysis helps discover patterns and check hypotheses and assumptions through summary statistics and graphical representation. In this section, the exploratory data analysis focuses on the following groups of variables: 1) Person attributes: age, gender, race, activities (worker/student), employment, educational background; and 2) Household attributes: type of neighborhood, household income, and household size; 3.) Ownership attributes: car ownership and access to a car, and high-technology devices and services, such as smartphones, laptops, fast internet, desktop computer, tablet, or smartwatches; and 4.) Attitude traits: like driving, like new things, and like to be among the first people to have the latest technology. The relationship between each variable and e-shopping frequencies is analyzed to see if any variable is associated with the online shopping behavior of respondents.

Figure 3 displays the strong relationship between the average e-shopping frequency by options. The highest numbers of average purchases are found to be made by respondents in the 35-40 age group using *fast* delivery, followed by a *standard*, *same-day*, and *local pickup* options. As for the older group, *standard* delivery appears to be the most popular among others. The most notable differences in e-shopping frequency by car access can only be seen in the *local pickup* option (see **Figure 4**). This is reasonable as people who have access to cars will have easier access to go to a nearby local store to pick up their online orders compared to those without access to cars.

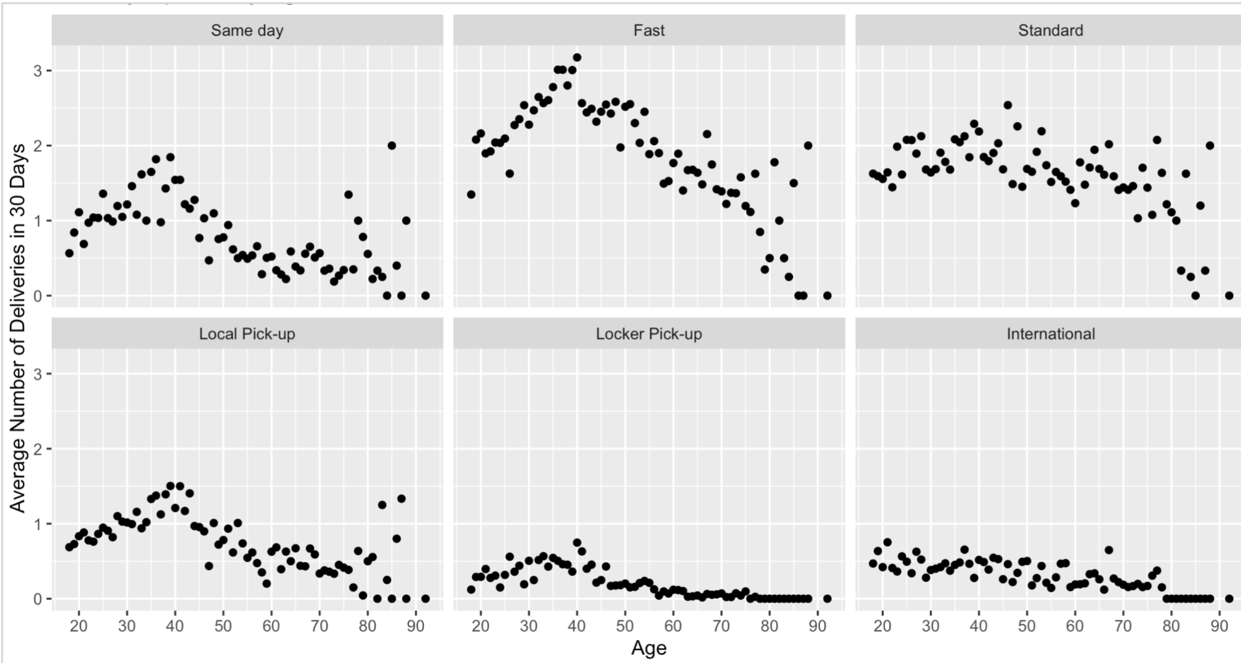

Figure 3. Average e-shopping frequency by type of deliveries by age by delivery option (N=8,593 observations)

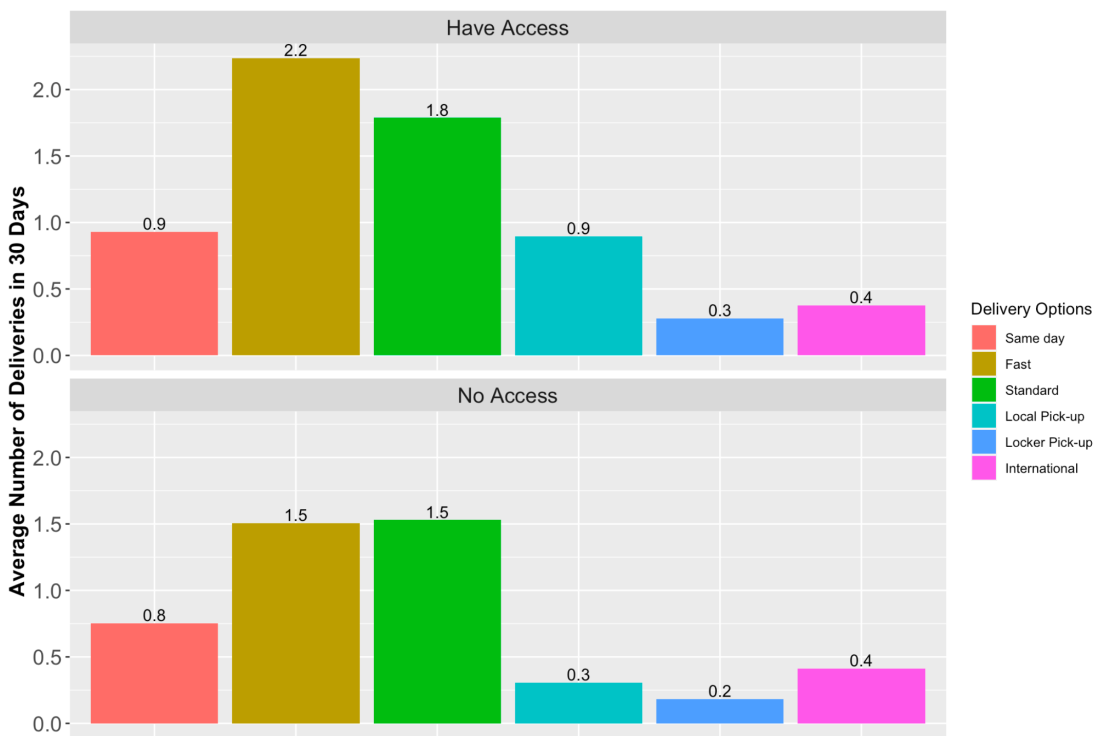

Figure 4. Average e-shopping frequency by accessibility to cars by delivery option (N=8,593 observations)

Educational background is another variable that is highly associated with e-shopping frequency. **Figure 5** displays how e-shopping frequency is higher for respondents with a higher educational background for almost every delivery option. In addition, the *fast* delivery option is the most popular shipping option at every education level, except the High School level. On the other hand, **Figure 6** shows a higher purchase frequency for every delivery option in correlation with respondents who agree they like to be among the first people to have the latest technology.

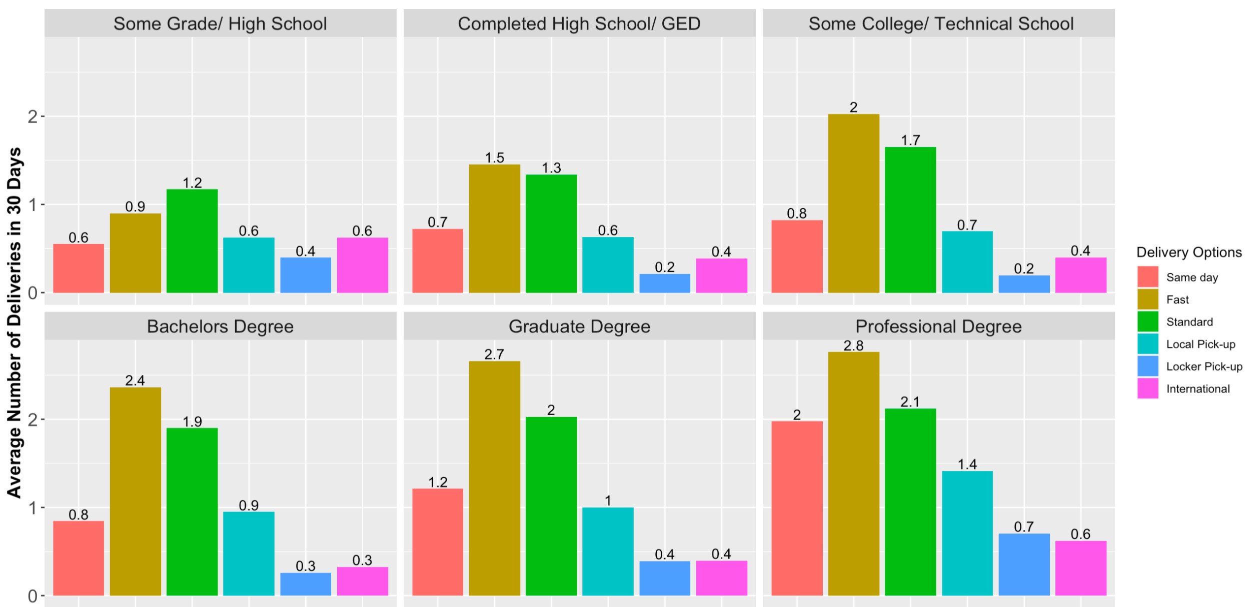

Figure 5. Average e-shopping frequency by educational background by delivery option (N=8,593 observations)

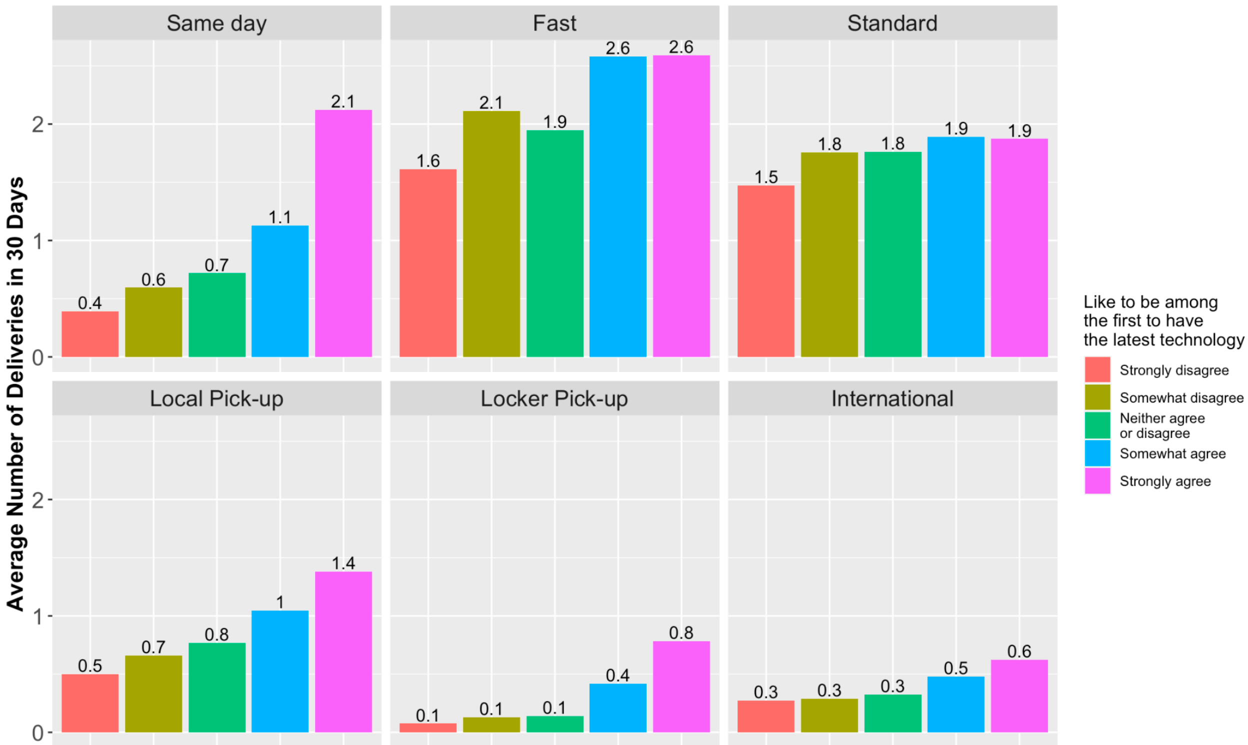

Figure 6. Average e-shopping frequency by attitude towards technology - Like to be among the first people to have the latest technology by delivery option (N=8,593 observations)

As for household attributes, the type of neighborhood where respondents live is remarkably correlated with online shopping frequency. The e-shopping frequencies using *same-day* delivery, *local pickup*, and *locker pickup* are higher in urban areas than in other neighborhoods (see **Figure 7**). Respondents who live in suburban areas and small towns have the highest average e-shopping frequency using *fast* and *standard* delivery, respectively. This pattern shows that some delivery options are more common in certain types of neighborhoods; for example, *locker pickup* is more commonly used in urban areas. The *same-day* delivery orders may be harder to complete if the destination is far away from the stores that need to fulfill the orders. Thus, those stores may only offer *fast* or *standard* delivery options to individuals located in lower-density and farther-located neighborhoods.

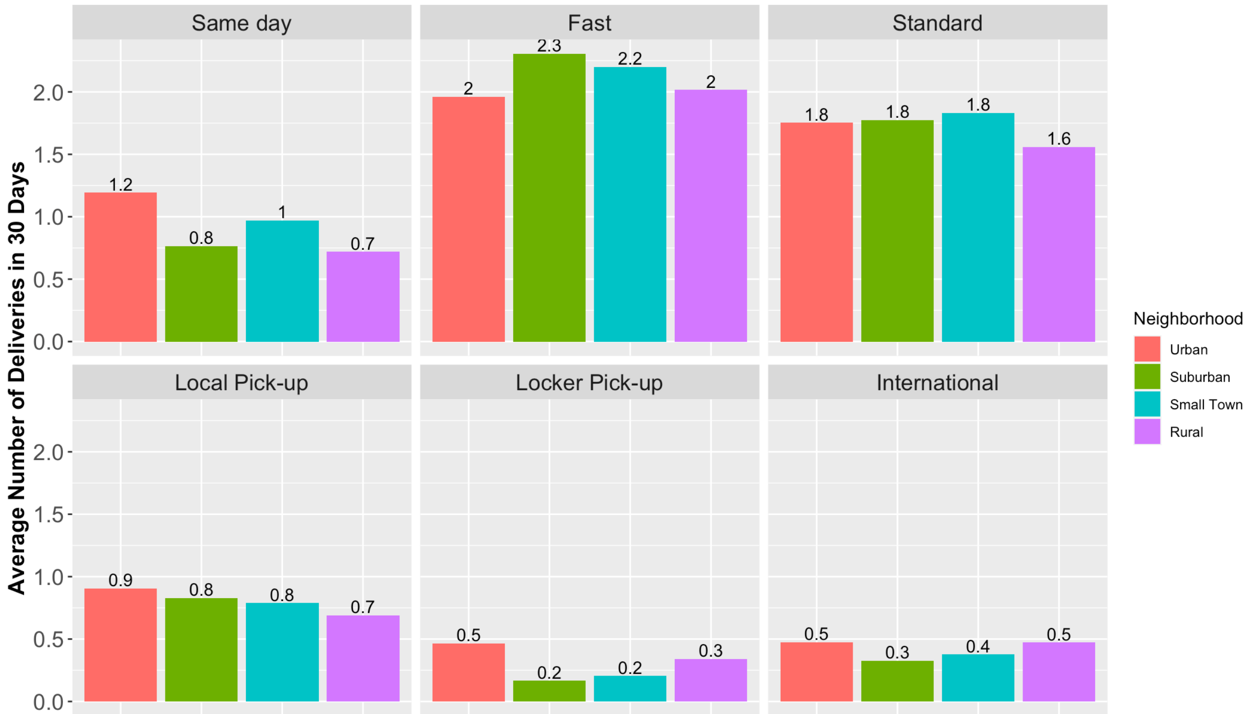

Figure 7. Average e-shopping frequency by type of neighborhood (N=8,593 observations)

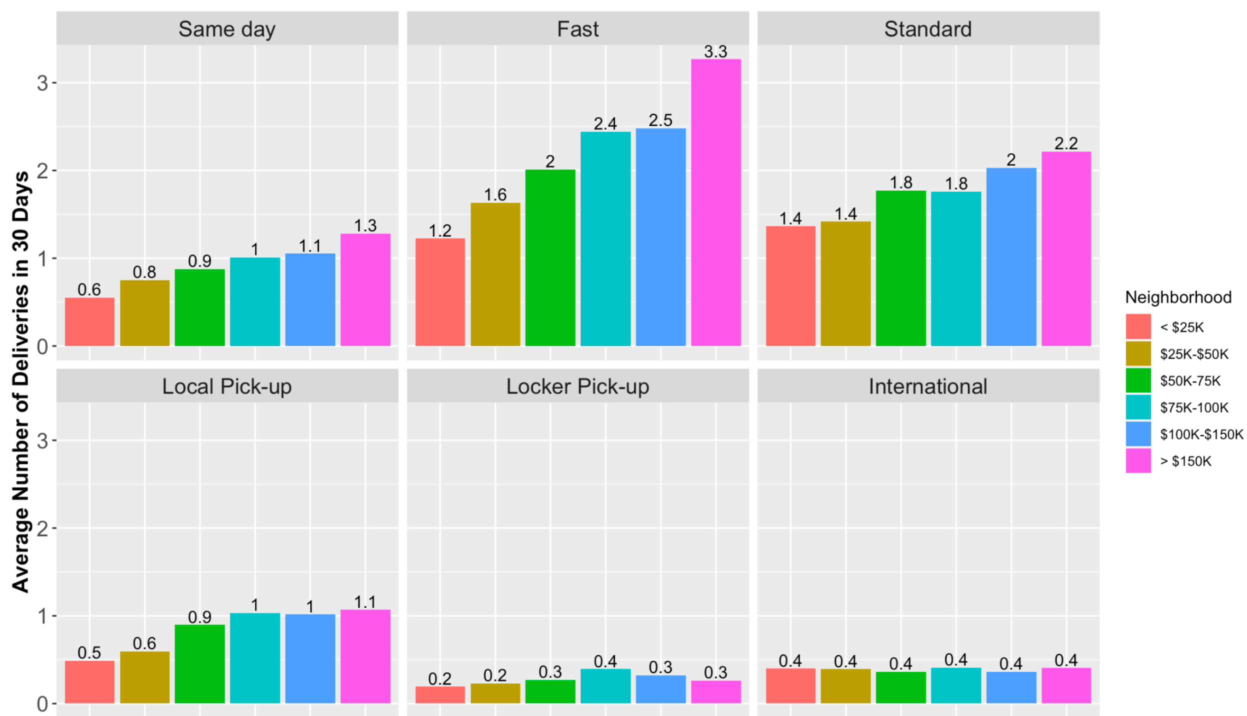

Figure 8. Average e-shopping frequency by household income (N=8,593 observations)

Another prominent household attribute highly associated with e-shopping frequency is household income (see **Figure 8**). The figure shows how higher-income individuals tend to have a higher number of purchases in almost every delivery option, especially for *fast* delivery. *Fast* delivery appears to be the most popular shipping option for higher income groups, while lower income groups prefer *standard* or *fast* delivery, among others.

To summarize, variables that have high and positive correlations with e-shopping frequency are age group, educational background, household income, type of neighborhood where respondents live, and attitudes towards technology (like to be among the first to have the latest technology). Other than the displayed variables, I also analyzed many other variables measuring personal and household attributes for which data is available. Some other variables like gender, race, and driving attitudes are not found to show strong correlations with online shopping behavior and the use of various delivery methods.

4.2 Binomial Logistic Regression

While exploratory data analysis provides insights into what variables are highly associated with e-shopping frequency, binomial logistic regression is useful to analyze and predict whether one or more variables influence e-shopping behavior (using certain delivery options). This model measures the relationship between multiple independent variables and the likelihood that a certain outcome will be observed in a dependent (categorical) variable. In this case, the independent variables are the individual and household characteristics of respondents, while the dependent variable is the binary outcomes (*i.e.*, whether the respondent used or did not use a certain delivery option to make online purchases). The independent or explanatory variables can either be continuous or categorical. This model specifically helps to see whether someone used a delivery option for online purchases or not. The model was applied to each delivery option separately and for all delivery options together (*i.e.*, whether a respondent used any of the delivery options or did not use them at all). The six delivery options are *same-day* delivery, *fast* delivery (1- or 2-day), *standard* delivery (three or more days), *local pickup*, *locker pickup*, and *international* delivery.

I used two criteria to guide the model specification in the study: the Akaike information criterion (AIC) and p-value were used to evaluate the significance of variables. Even though the p-value < 0.05 shows that a variable is statistically significant, Najmi et al. (2021) argued that it should not be the sole reason to remove variables, and further analysis should be conducted. Thus, the p-value of 0.1 is chosen as a threshold to discover which variables would be highly significant and impact the decision to use a delivery option. The model used stepwise regression in both directions using the "lmtest" package in the R program to see the best fitting model. The stepwise regression removed a variable one at a time by choosing a model with a lower AIC value. Then, the stepwise regression model shows the most fitted model with the lowest AIC. This method was conducted along with interpretability considerations, which means some variables need to be quite reasonable and able to be interpreted to be included in further analysis.

4.3 Latent Class Cluster Analysis

Latent Class Cluster Analysis (LCCA) is chosen to provide a powerful alternative approach to subgroup analysis. LCCA helps identify the latent (unobserved) classes in samples based on responses of observed variables that often share certain outward characteristics (Weller et al., 2020). **Figure 9** below shows the conceptual model of LCCA as implemented in this study.

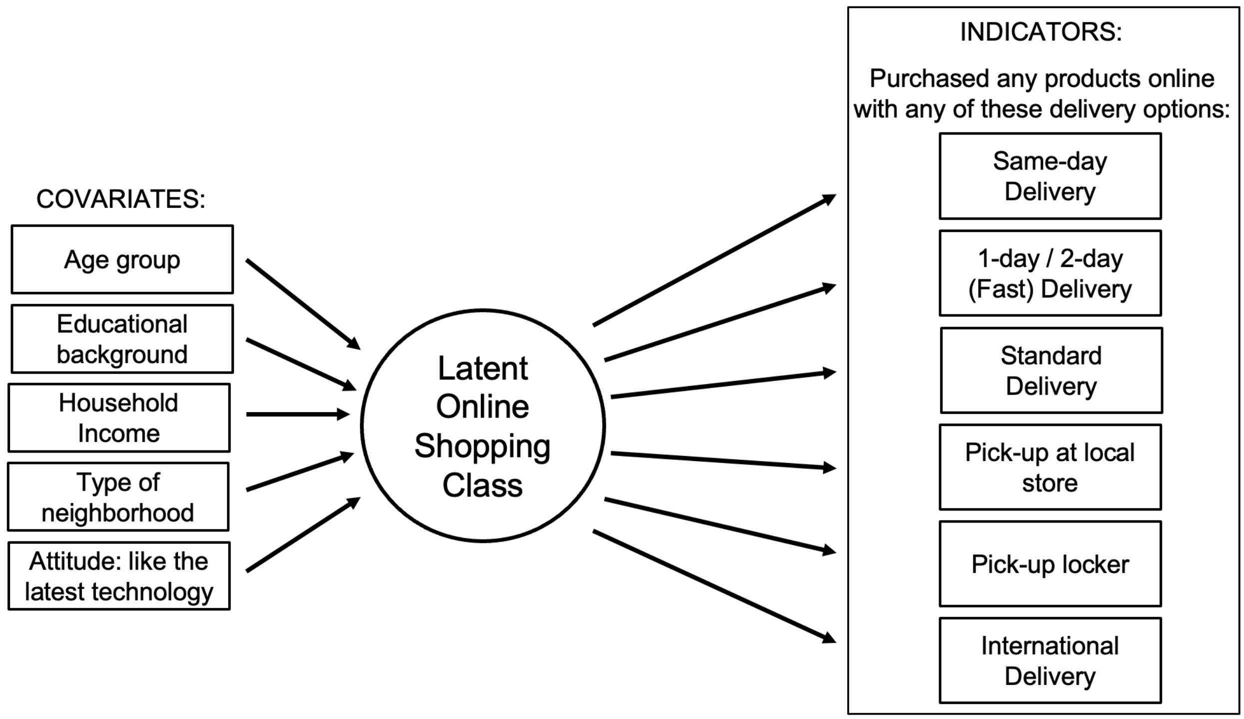

Figure 9. Conceptual Model of Latent Class Cluster Analysis

The latent class model using the poLCA package in R is estimated by maximizing the log-likelihood function with respect to Pr and π_{jrk}, using the expectation-maximization (EM) algorithm (Linzer & Lewis, 2011).

$$\log L = \sum_{i=1}^{N} ln \sum_{r=1}^{R} Pr \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}} \tag{1}$$

Where:
i is individual 1 to N
r is class 1 to R
Pr denotes the mixing proportions of class that provide the weights in the weighted sum of cross-classification tables, with $\sum_r Pr = 1$
j is variable/ indicator 1 to J
k is response to the jth variable, from 1 to K_j (number of possible outcomes)
π_{jrk} denotes outcome probabilities that individuals i on class r.
Y_{ijk} is observed values of the J. $Y_{ijk} = 1$, when respondent i gives the kth response to the jth variable.

Linzer & Lewis (2011) further explain that the LCCA model in R can be selected using several tools. Other than using theoretical reasons, the selection is also more of exploratory nature to find the best fitting or most suitable model by increasing the latent class number one by one. The most widely used criteria to obtain the most parsimonious model are the Bayesian Information Criterion (BIC) and Akaike information criterion (AIC). BIC is usually chosen as the quality of fit measure as it emphasizes a parsimonious model (Nylund et al., 2007) and their relative simplicity (Linzer & Lewis, 2011). Another one is AIC3, that penalizes the parameters three times, which is stricter than AIC but is less strict than BIC (Dziak et al., 2019). AIC3 also has a high-performance rate and is not too overfitting (Dias, 2006). Interpretability was also considered along with the other statistical criteria. Each latent class should be able to be interpreted and applied in practice (Weller et al., 2020). Even though no guideline provides the minimum size of a latent class, Weller et al. (2020) further explain that the size of each latent class should not be too small to make conceptual sense and have higher accuracy (*e.g.*, should not be less than 5% shares of respondents).

The indicators of the LCCA model in this study are the frequency of using six delivery options for online purchases that reported as count variables by survey respondents. The number of deliveries for online shopping using each delivery option is classified to be the LCCA indicator. The classification considered the mean, median, and percentile value of responses for each delivery option in with and without 0 value cases in the dataset (see

Table *3*). The delivery frequency is classified into three frequencies: Frequency 1 is zero-frequency, or no online purchases were made by the respondents, Frequency 2 is low-frequency for those who made one to three online purchases per month using any delivery options, and Frequency 3 is high-frequency for those who had more than three online purchases in a month between March and April 2020.

The five covariates used in the LCCA model are based on the exploratory data analysis results, which are: age group, educational background, household income, type of neighborhood, and attitudes toward technology (*e.g.,* if a respondent likes to be among the first people to have the latest technology). After identifying the recommended number of classes using goodness-of-fit statistics, these covariates are added to the model to explain the sociodemographic of each latent class. This study uses the "poLCA" package from R for LCCA estimation. The summary of indicators and covariates used in the model can be seen in **Table 4** and **Table 5**.

Table 4. Summary of Indicators

Variables	Response Scale	Final Scale
Same-day delivery	Any integer	1. 0 purchase 2. 1-3 purchases 3. More than 3 purchases
Fast delivery	Any integer	1. 0 purchase 2. 1-3 purchases 3. More than 3 purchases
Standard delivery	Any integer	1. 0 purchase 2. 1-3 purchases 3. More than 3 purchases
Local pickup	Any integer	1. 0 purchase 2. 1-3 purchases 3. More than 3 purchases
Locker pickup	Any integer	1. 0 purchase 2. 1-3 purchases 3. More than 3 purchases
International delivery	Any integer	1. 0 purchase 2. 1-3 purchases 3. More than 3 purchases

Table 5. Summary of Covariates

Variables	Question/ Statement	Variable Type	Response Scale	Final Scale
Age	In what year were you born?	Count Variable	Year in 4-digit format (*e.g.,* 1975)	1 : age 18-34 2 : age 35-54 3 : age 55+
Educational Background	What is your educational background?	Categorical Variable	1. Some Grade/ High School 2. Completed High School/ GED 3. Some College/ Technical School 4. Bachelor's Degree 5. Graduate Degree 6. Professional Degree	1. Some Grade/ High School 2. Completed High School/ GED 3. Some College/ Technical School 4. Bachelor's Degree 5. Graduate Degree 6. Professional Degree
Attitudinal Factor: Like to be among the first people to have the latest technology	Factor scored based on self-reported level of agreement of respondents' conformity to the attitudinal statements	Categorical Variable	1. Strongly disagree 2. Somewhat disagree 3. Neither agree nor disagree 4. Somewhat agree 5. Strongly agree	1. Strongly disagree 2. Somewhat disagree 3. Neither agree nor disagree 4. Somewhat agree 5. Strongly agree
Household Income	Please check the category that contains your approximate 2019 annual household income before taxes. Remember, by "household" we mean "people who live together and share at least some financial resources". *(Housemates/ roommates are usually not considered members of the same household).*	Categorical Variable	1. Less than $25K 2. $25K - $50K 3. $50K - $75K 4. $75K - $100K 5. $100K - $150K 6. $150K or more	1. Less than $25K 2. $25K - $50K 3. $50K - $75K 4. $75K - $100K 5. $100K - $150K 6. $150K or more
Type of Neighborhood	How would you characterize the area where you currently live?	Categorical Variable	1. Urban part of a city/region 2. Suburban part of a city/region 3. Small town 4. Rural area	1. Urban 2. Suburban 3. Small town 4. Rural area

5. Results and Discussion

5.1 Binomial Logistic Regression Results

The results of the binary logistic regression model estimation for each delivery option are shown in **Table 6**. The negative sign of an estimated coefficient denotes that a variable is negatively associated with the use of a delivery option, while a positive coefficient denotes the contrary. Cells with the "-" sign mean that the effect of the explanatory variable was found to be not significant for the model for that delivery option and therefore removed from the final model specification for parsimony. The p-value of 0.1 is used as the threshold to select the highly significant variables that influence the use of each delivery option. The results are distinguished into four groups: personal attributes, household attributes, ownership attributes, and the frequency of revealed preference.

The results show that the male variable is statistically significant in the model for every delivery option, even though they are only positively correlated and more likely to use *same-day* delivery, *locker pickup*, and *international* delivery. Age variable negatively influences the use of *same-day* delivery, *fast* delivery, and *local pickup.* In addition, our previous analyses (Silaen et al., 2022) using the same survey data showed that books, clothing, medicine, and restaurant delivery were commodities that female e-shoppers would likely buy compared to their male counterparts. Silaen et al. (2022) found that the age variable only has a positive correlation with the frequency of buying medicine online.

The education level increases the likelihood of using *fast* delivery, *standard* delivery, and *local pickup*, while the student status positively affects the use of *same-day* delivery, *locker pickup*, and *international* delivery. People who do not work are less likely to use *same-day* delivery, and those who have part-time jobs like to use the *locker pickup* option. The agreement with the attitudinal statement measuring the degree by which the respondent likes to be among the first people to have the latest technology is found to be a good predictor of e-shopping adoption for every delivery option, more than the attitudinal statements measuring how much the respondent likes to try new things or likes driving. Owning devices and having fast internet services increase the likelihood of e-shopping using almost every delivery option.

Household income is found to affect the likelihood of using all delivery options, except *locker pickup* and *international* delivery. Those with higher incomes are more likely to use every delivery option. People in suburban areas are positively correlated with the use of *fast* delivery and negatively associated with the use of *locker pickup* and *international* delivery. Households with kids and members with health risks also increase the likelihood to engage in e-shopping.

The frequency of revealed variables is the frequency of respondents doing certain activities during the COVID-19 pandemic, which were measured on a Likert-type scale (from never to doing five or more times a week). Of four activities, the grocery visit activity during the early phase of COVID-19 pandemic was found to be the only not significant variable in the model, except for the *same-day* delivery option.

To conclude, the logistic regression results support the exploratory data analyses results where the five variables of age, educational background, household income, type of neighborhood, and attitudinal variable measuring the degree the respondent likes to be among the first people to have the latest technology have a strong impact on e-shopping frequency. Some other variables that may increase the likelihood of someone shopping online using certain delivery options are student status, employment, and frequencies of doing certain activities during the COVID-19 pandemic.

Table 6. Model estimation results for binary logit model for the adoption of various delivery options.

** N = 8,381 observations (significance levels: '***' <0.001, '**' <0.01, '*' <0.05, '' <0.1)*

Variable	Delivery Type: Any Delivery	Same-day Delivery	Fast Delivery	Standard Delivery	Local Pickup	Locker Pickup	International Delivery
Personal Attributes							
Age	-	-0.004*	-0.009***	-	-0.006***	-	-
Gender (Female)							
Male	-0.343***	0.257***	-0.262***	-0.274***	-0.157**	0.215*	0.145*
Other	-	0.869 *	-	-	-	-	0.705*
Race (White)	-	-	0.245**	0.166*	0.183*	-	-
Education Level (Some Grade/ High School)							
Completed High School/ GED	-	-	-	-	-	-0.532	-
Some College/ Technical School	-	-	0.644***	-	-	-	-
Bachelor's Degree	0.469*	-	0.669***	0.365*	-	-	-
Graduate Degree	0.641**	-	0.927***	0.421*	-	-	-
Professional Degree	0.588	-	0.740**	0.381	0.458	-	-
Student Status (Not a student)							
Full-time student	-	0.295**	-	-	-	-	0.237*
Part-time student	-	-	-	-	-	0.488**	-
Taking online courses	-	0.446***	-	-	-	0.503*	0.285*
Employment							
Full-time	-	-	-0.158**	-	-		-
Part-time	-	0.172*		-	-	0.403***	-
Home Maker	-	-0.302*		-	-		-
No Work		-0.151					
Attitudes: Like to among the first people to have the latest technology (Strongly disagree)							
Somewhat disagree	-	-	0.169*	0.235**	-	-	-
Neither agree nor disagree	-	0.295**	-	0.157*	-	-	0.202
Somewhat agree	0.378**	0.440***	0.264**	-	-	0.593**	0.324**
Strongly agree	-	0.731***		-	-	0.857***	-
Attitudes: Like new things (Strongly disagree)							
Somewhat disagree	-	-	-	0.276	-	-	-
Neither agree nor disagree	-	-	-	-	-	-	-
Somewhat agree	-	-	-	0.373**	-	-	-
Strongly agree	-	-	-	0.349*	-	-	-

Variable	Any Delivery	Same-day Delivery	Fast Delivery	Standard Delivery	Local Pickup	Locker Pickup	International Delivery
	Delivery Type						
Attitudes: Like driving (Strongly disagree)							
Somewhat disagree	-	-	-	-	0.413*	-	-
Neither agree nor disagree	-	-	-	-	0.373*	-	-
Somewhat agree	-	-	-	-	0.392*	-	-
Strongly agree	-	-	-	-	0.518**	-	-
Household Attributes							
Neighborhood (Urban)							
Suburban	-	-	0.138 *	-	-	-0.416	-0.160*
Small Town	-	-	-	-	-	-	-
Rural	-	-	0.270	-	-	-	0.299
HH Income (< $25K)							
$25K - $50K	-	0.204	0.205*	-	-	-	-
$50K - $75K	-	0.213	0.334***	0.196*	0.348**	-	-
$75K - $100K	0.454**	0.380**	0.557***	-	0.370**	-	-
$100K - $150K	0.405**	0.263*	0.452***	0.306***	0.391***	-	-
> $150K	0.310	0.415***	0.692***	0.342***	0.293*	-	-
HH Size	-0.175*	-	-	-0.068**	-	-	-
HH # of children	0.245**	0.105***	0.08*	-	0.096***	0.11**	-
HH # of adults	0.137*	-	-	-	0.08**	-	-
HH # with health risk	-	-	-	0.089***	-	-	0.167***
HH # with licenses	-	-0.072*	-	0.061*	-	-	-0.089*
Ownership Attributes							
Own car	-	-	0.346***	0.238*	0.499***	-	0.160
Household Car	-	-0.205*	0.229**	0.389***	0.210**	-0.333*	0.172
Have no access to cars	-	-	0.004**	0.280*	-0.299	-	-
Own smartphone	0.449**	-	0.517**	-	-	-	0.420*
Own laptop	-	-	0.166*	-	0.221**	-	0.200*
Own desktop computer	-0.240**	0.180**	0.264***	-	0.158*	0.216*	-
Own tablet	0.235**	0.122	0.379***	-	0.209***	0.245*	0.228**
Own smartwatch	0.300**	0.282***	0.564***	0.160**	-	0.267**	-
Own fast internet	0.473**	-	-	0.481***	-	-0.341	0.286*
Frequency of Revealed Preference							
Visit grocery store during pandemic 2020 (Never)							
Less than once a month	-	-0.388**	-	-	-	-	-
1-3 times a month	-	-0.508***	-	-	-	-	-
1-2 times a week	-	-0.682***	-	-	-	-	-
3-4 times a week	-	-0.460**	-	-	-	-	-

Variable	Delivery Type: Any Delivery	Same-day Delivery	Fast Delivery	Standard Delivery	Local Pickup	Locker Pickup	International Delivery
5 or more times a week	-	-0.451*	-	0.385*	-	-	-
Order groceries online during pandemic 2020 (Never)							
Less than once a month	0.993***	0.765***	0.504***	0.406***	0.896***	0.585***	-
1-3 times a month	1.671***	1.364***	0.828***	0.454***	1.36***	0.752***	-
1-2 times a week	1.770***	1.749***	0.915***	0.498***	1.572***	1.077***	-
3-4 times a week	0.885*	2.563***	1.102***	0.560***	1.677***	1.587***	-
5 or more times a week	-	2.222***	0.961***	0.620**	1.777***	1.586***	-
Pickup at restaurant during pandemic 2020 (Never)							
Less than once a month	0.188	-	0.152*	0.298***	0.531***	-	0.297**
1-3 times a month	0.475***	-	0.210**	0.381**	0.710***	-	0.271**
1-2 times a week	0.467***	-	0.258***	0.529***	0.805***	0.410**	0.497***
3-4 times a week	0.562*	-	0.286*	0.390**	0.832***	0.667**	0.658***
5 or more times a week	0.907	-	0.721**	-	0.933***	0.630*	0.754***
Have restaurant delivery during pandemic 2020 (Never)							
Less than once a month	0.747***	0.517***	0.386***	0.241**	-	0.472**	0.335***
1-3 times a month	1.253***	0.622***	0.530***	0.268***	-	0.395**	0.406***
1-2 times a week	1.214***	0.882***	0.635***	0.314***	-	0.316*	0.468***
3-4 times a week	1.694***	0.948***	0.490***	0.356**	-	-	0.504***
5 or more times a week	1.220***	0.846***	0.868***	-	-	-	0.641**
Model Summary							
% users of each service	81.2	25.1	54.0	56.5	30.2	8.9	17.0
Log Likelihood	-2320.0	-3632.8	-4954.1	-5363.8	-4301.0	-1812.7	-3517.4
Log Likelihood of Market Share model	-2860.2	-4711.6	-5779.9	-5735.1	-5137.9	-2493.0	-3803.7
K	52	40	61	67	47	53	44
Rho squared	0.19	0.23	0.14	0.06	0.16	0.27	0.08
Adjusted Rho squared	0.17	0.22	0.13	0.05	0.15	0.25	0.06

5.2 Latent Class Analysis Results

The latent class model was conducted through multiple trials and an iterative process of increasing the number of classes one at a time in R. Then, the appropriate number of latent classes was assessed based on the fit criteria and interpretability. **Table 7** provides the fit criteria for each solution of the 2-class, 3-class, and 4-class models. The four-class model could be the best solution from this table as it has the lowest AIC, BIC, and AIC3 values compared to the other models. In addition to statistical fit, the interpretability of each latent class was also considered (Nylund et al., 2007). In the 4-class solution, two out of four classes look very similar in most delivery option patterns, which will raise critical issues in result interpretation and application. For this reason, the three-class latent solution is chosen to be the best LCCA model. From a total of 8,593 observations used in this study, Class 1 has 4,357 members (50.7%), Class 2 has 3712 members (43.2%), and Class 1 has 524 members (6.1%).

Table 7. Fit criteria for each class solution

Model	Log-Likelihood	Residual degrees of freedom	BIC	ABIC	AIC	AIC3	Likelihood Ratio (Gsq)	Smallest class count (n)	Smallest class size (%)
2-class	-36198.49	684	72795.56	72655.74	72484.98	72528.98	2956.912	2,827	32.9
3-class	-35488.1	652	71664.66	71423.15	71128.2	71204.2	2165.939	524	6.1
4-class	-35168.2	620	71314.75	70971.54	70552.41	70660.41	1567.406	309	3.6

Figure 10. The output of the three-class latent solution by delivery option and response classification

Figure 10 shows the three-class latent solution by delivery option and frequency classification. Class 1 or *Occasional Shoppers* are respondents who shopped not very frequently; some made 1-3 or more than three online purchases in a month, while others made no online purchases. *Occasional Shoppers* prefer *fast* and *standard* delivery compared to the other delivery options. This class has the largest share of respondents as about half of the respondents belong to Class 1. Class 2 or *Non-Shoppers* are people who made very few or no online purchases, which mainly fall into the zero-frequency category. Class 2 has the second largest share of respondents, which accounts for 43.2% of the sample. Class 3 or *Super Shoppers* represents frequent shoppers who made frequent online purchases in a month. This class has the least share of respondents, with only 6,1% of respondents belonging to this group.

I analyzed the demographic features of each class of the defined three-class solution by featuring the variables as covariates in the LCCA model. The membership model and shares of covariates in each latent class can be seen in **Table 8** and **Table 9**, respectively. The membership model helps to demonstrate the effects of a covariate on the respondents' affinity with either *Non-Shoppers* or *Super Shoppers*. The *Occasional Shoppers* class acted as the neutral category and a class that was compared to the other two classes.

The results show that people in the age group 55+ compared to the age group 18-34 are more likely to be in the *Non-Shoppers* class than the *Occasional Shoppers*. The same tendency can also be found in the age group 35-54 but with a lower magnitude. Compared to the age group 18-34, respondents in the age group 55+ are less likely to be in the *Super Shoppers* class than the *Occasional Shoppers* class. The results align with the tendency of young people that are more eager to use online shopping and various delivery options compared to elders. Respondents with more education are less likely to belong to the *Non-Shoppers* class than the *Occasional Shoppers* class. Lower-income respondents are less likely to belong to the *Super Shoppers* class than the *Occasional Shoppers* class.

People who reported positive attitudes toward technology, who stated they somewhat agree or strongly agree that they like to be among the first people who have the latest technology, are less likely to be in the *Non-Shoppers* class than the *Occasional Shoppers* compared to those who reported negative attitudes. This tendency is even clearer when comparing the *Super Shoppers* and the *Occasional Shoppers*, where people with positive attitudes are more likely to belong to the *Super Shoppers* class.

As for household income, a clear gradual increase of magnitude can be seen in **Table 8**, indicating that people with higher income will be less likely to belong to the *Non-Shoppers* class compared to the *Occasional Shoppers* class. This tendency, however, is not very clear when compared to the *Super Shoppers*, as the results did not show significant coefficients with a p-value less than 0.05.

The type of neighborhood indicates a very interesting result. Compared to people who live in urban areas, those who do not live there are more likely to belong to the *Non-Shoppers* class or the *Super Shoppers* class. Therefore, those who do live in urban areas are more likely to be *Occasional Shoppers*.

Table 8. Membership model (N=8,593 respondents)

	Class 2 (Non-Shoppers) compared to Class 1 (Occasional Shoppers)		Class 3 (Super Shoppers) compared to Class 1 (Occasional Shoppers)	
	Coefficient	**P-value**	**Coefficient**	**P-value**
(Intercept)	2.618	0.000	-1.567	0.008
Covariates				
Age group				
Compared to 18-34				
35-54	0.271	0.002	-0.101	0.432
55+	1.097	0.000	-1.576	0.000
Educational Background *Compared to Some Grade/ High School*				
Completed High School/ GED	-0.714	0.022	-1.312	0.003
Some College/ Technical School	-1.464	0.000	-1.885	0.000
Bachelor's Degree	-1.627	0.000	-1.543	0.000
Graduate Degree	-1.905	0.000	-0.903	0.036
Professional Degree	-1.754	0.000	-0.435	0.340
Like to be among the first people who have the latest technology				
Compared to Strongly disagree				
Somewhat disagree	-0.548	0.000	0.107	0.821
Neither agree nor disagree	-0.605	0.000	0.681	0.113
Somewhat agree	-0.974	0.000	1.712	0.000
Strongly agree	-0.706	0.000	2.649	0.000
Income				
Compared to < $25K				
$25K-$50K	-0.620	0.000	0.038	0.896
$50K-75K	-0.916	0.000	0.113	0.691
$75K-100K	-1.195	0.000	0.421	0.145
$100K-$150K	-1.517	0.000	-0.010	0.972
> $150K	-1.901	0.000	-0.490	0.110
Neighborhood type				
Compared to Urban				
Suburban	-0.212	0.007	-1.036	0.000
Small Town	-0.401	0.025	-0.908	0.013
Rural	-0.135	0.521	-0.045	0.906

Table 9 provides the shares of respondents by covariates in each latent class. Among the 8,593 observations, half of the respondents are *Occasional Shoppers*, about 43% are *Non-Shoppers*, and only 6% are *Super Shoppers*. The results show that the age group 35-54 is the dominant group in both the *Occasional Shoppers* (40%) and *Super Shoppers* (50%) class, while respondents in the age group 55+ makes up the largest group of *Non-Shoppers* (41%). *Super Shoppers* has the largest share of respondents who have a minimum of bachelor's degree with more than 70% of respondents in this class having this level of education, followed by *Occasional Shoppers* (62%) and *Non-Shoppers* (42%).

Most *Super Shoppers* are respondents who have positive attitudes toward technology as more than 80% of respondents belong to this class, while only 26% of *Non-Shoppers* have this attitude. *Occasional Shoppers* have a quite even distribution of respondents who have positive and negative attitudes toward technology. Most *Occasional Shoppers* and *Super Shoppers* are part of higher income groups, while the *Non-Shoppers* class is dominated by lower-income respondents who have less than $50K annual income.

The shares of the respondents by the type of neighborhood are significantly different by class. *Super Shoppers* is dominated by people who live in urban areas (64%), followed by those who live in suburban areas (30%), while the remaining shares belong to those who live in either small towns or rural areas. *Occasional Shoppers* and *Non-Shoppers* have a similar pattern of shares, with the largest group of respondents living in suburban areas, followed by urban areas, small towns, and rural areas.

Table 9. Shares of Covariates by Class (N=8,593 respondents)

Covariates	Class 1 Occasional Shoppers	Class 2 Non-Shoppers	Class 3 Super Shoppers
Population	50.7%	43.2%	6.1%
Age group			
18-34	35.6%	29.5%	46.3%
35-54	40.5%	29.7%	50.2%
55+	23.9%	40.8%	3.5%
Education level			
Some Grade/ High School	0.7%	3.8%	2.9%
Completed High School/ GED	8.4%	21.0%	9.5%
Some College/ Technical School	28.0%	33.2%	15.2%
Bachelor's Degree	38.2%	29.1%	30.4%
Graduate Degree	20.0%	10.6%	28.1%
Professional Degree	4.6%	2.4%	13.8%
Like to be among the first people to have the latest technology			
Strongly disagree	10.4%	22.7%	1.8%
Somewhat disagree	23.2%	25.0%	4.7%
Neither agree nor disagree	25.3%	26.1%	10.3%
Somewhat agree	28.8%	17.3%	36.1%
Strongly agree	12.3%	9.0%	47.1%
HH Income			
< $25K	7.0%	23.1%	6.2%
$25K - $50K	15.6%	25.6%	13.3%
$50K - $75K	16.3%	17.2%	17.8%
$75K - $100K	15.1%	11.5%	21.6%
$100K - $150K	25.2%	14.7%	24.7%
> $150K	20.9%	7.8%	16.5%
Type of Neighborhood			
Urban	31.1%	36.1%	64.0%
Suburban	62.0%	56.0%	30.8%
Small Town	4.5%	4.4%	2.3%
Rural	2.5%	3.5%	2.9%

6. Conclusions

The e-shopping demand increased sharply in the early phase of the COVID-19 pandemic or early 2020. Some studies suspected that the COVID-19 restrictions, lockdown, and fear of contracting the COVID-19 virus encouraged people to shift to and adopt e-shopping. Using the Spring 2020 COVID-19 Mobility Study data with a total of 8,593 respondents, the study conducted exploratory data analysis to define the e-shopping patterns using different types of delivery options during the early phase of the COVID-19 pandemic, estimated binary logistic regression models to identify variables that impacted the use of various delivery services for online purchases, and used latent class cluster analysis to identify subgroups within respondents that share certain characteristics in using various shipping options.

The exploratory data analysis results show that *fast* and *standard* delivery options are the most popular services. The average number of purchases of both delivery options is about two purchases per respondent a month, while other delivery options have less than one purchase per respondent on average. When not including the zero value cases (*i.e.*, respondents who made no purchases with each delivery option), *fast* and *same-day* delivery have the highest average purchases or about four purchases per respondent in a month and other delivery options have the average of three or fewer monthly purchases per respondent.

Variables that positively correlated with online shopping behavior during the early phase of the COVID-19 pandemic were age group, educational background, household income, type of neighborhood where respondents live, and attitudes towards technology - like to be among the first people to have the latest technology. The correlations between e-shopping and age and education level can mostly be found in all delivery options, especially *fast* and *same-day* delivery for respondents within the age group 35-54 and *standard* delivery for those within the age group 55+. Attitudes towards technology are remarkably correlated with the use of all delivery options.

The most popular delivery options in urban areas are *same-day*, *local pickup*, and *locker pickup*. People in suburban areas are more likely to use *fast* delivery, while those in small towns and rural areas commonly use *fast* and *standard* delivery options. Another variable that is greatly associated with e-shopping frequency is household income. The data shows that the average online purchases tend to be higher among the higher-income respondents in almost every delivery option, except *locker* pickup and *international* delivery. Although the higher income group has the highest average purchases in every shipping option, *fast* delivery is found to be the most popular one. Lower-income groups commonly use *standard* or *fast* delivery options. Car accessibility is also associated with shipping choices, especially for the *local pickup* option. This is reasonable as people need to go to nearby local stores and pick up their orders in person, and access to cars would make this task a little bit easier.

The binomial logistic regression results support the previous exploratory data analysis. The results also show that student status, employment, and frequencies of certain activities during the early phase of the COVID-19 pandemic strongly impact e-shopping frequency. However, these variables only affect the likelihood of using specific delivery options and only a few categories within those variables that are statistically significant.

The latent class cluster analysis estimation results present three subgroups or latent classes of the Spring 2020 survey respondents. Class 1 (50.7% of the sample) is composed of *Occasional Shoppers*, consisting of respondents who made infrequent purchases and preferred to use *fast* and *standard* delivery options. Class 2 (43.2%) or *Non-Shoppers* is a group of people who made few online purchases or did not purchase online and were mainly part of the zero-frequency group.

Lastly, Class 3 (6.1%), the *Super Shoppers*, made frequent online purchases or more than three purchases in a month using any delivery option.

Super Shoppers and *Occasional Shoppers* are more likely found among respondents in the age group 35-54 and those who have a bachelor's degree or higher education. *Non-Shoppers* are more commonly found among respondents of age 55+ and those who do not have a bachelor's degree. Respondents who reported positive attitudes toward technology are mostly part of *Super Shoppers*, and those who reported negative attitudes are more likely part of *Non-Shoppers* class. *Occasional Shoppers* have an almost equal share of respondents who have positive and negative attitudes toward technology. *Super Shoppers* are more likely to live in urban areas, while *Occasional Shoppers* and *Non-Shoppers* are more likely to live in suburban areas.

The results of these three analyses indicate that e-shopping and various delivery services might only have been used and benefited certain groups of people during the early phase of the COVID-19 pandemic. For example, younger people made frequent online purchases with any shipping options. Older people are more likely to be *Non-Shoppers* who made no online purchases or only use the *standard* delivery option when they made a few online purchases. Some shipping options (*e.g.*, *same-d*ay delivery service or crowdshipping) require their customers to have access to the internet and skills to use it to register their emails and make orders through delivery apps. These requirements may be challenging for some people with lower digital literacy (*e.g.*, older people), and thus the *standard* delivery option may seem more appealing. The tendency of younger people buying more online than older people before the COVID-19 pandemic was already found in the literature. The results of this study confirm that the same tendency still occurred during the early phase of the COVID-19 pandemic.

Some delivery options (*same-day*, *local pickup*, and *locker pickup*) are more likely to be used by people who live in urban areas, as these services are more common and available in high-density areas. People in suburban areas generally prefer *fast* delivery, and those who live in small towns and rural areas typically use *standard* delivery. One of the reasons potentially because *same-day*, *local pickup*, and *locker pickup* options are less available in non-urbanized areas. For example, a package cannot be delivered on the same day to a customer living in a small town located far away from sellers or stores. The low access to *local* or *locker pickup* also may force customers to use the only available ones (*i.e.*, *fast* or *standard* delivery).

Based on the literature review, delivery to pickup points only had few enthusiasts before the COVID-19 pandemic (*e.g.*, only 10% of e-shoppers in Germany used this service) (Iwan et al., 2016). This study found that the number of users of delivery to pickup points during the early phase of the COVID-19 pandemic was not that small. The average delivery to pickup points (*i.e.*, *local* and *locker pickup*) is about the same as the *standard* delivery with about three monthly purchases. The survey data in this study also showed that the number of observations that used *local pickup* was higher than the *same-day* delivery option during this period. Deliveries to pickup points are most likely requested by Super Shoppers, who are likely part of younger, wealthier groups with higher education and who live in urban areas. The same tendency can also be found before the COVID-19 pandemic when delivery to pickup points was usually requested by people who lived in urban areas and had higher income.

The differences in accessibility to certain delivery options are linked to the different access to buy certain commodities (that require special treatment, *e.g.*, food) or receive orders as quickly as customers who live in urban areas. Such differences already existed before the COVID-19 pandemic, but they became an even bigger issue during unprecedented challenges like the COVID-19 pandemic, where restrictions and lockdowns were mandated.

This study has some limitations on the data. The Spring 2020 COVID-19 Mobility Study survey data lack definite or clear questions regarding why respondents engaged in e-shopping and preferred to use certain delivery options over the other available ones. Some respondents may have chosen not to engage in e-shopping during the early phase of the COVID-19 pandemic because of personal reasons or different attitudes towards the COVID-19 pandemic, or things that were not directly related to their income or education level. This lack of information can be misleading to some extent. However, many things still can be learned from the available survey data and the analysis results, as discussed in the earlier sections. To avoid this issue, this study recommends the inclusion of specific survey questions related to online shopping behavior in future e-shopping surveys (*i.e*., the reason for engaging in e-shopping or for choosing certain delivery options over the other available ones). Moreover, comprehensive research on delivery options and types of commodities after COVID-19 in different parts of the world would be an interesting research to analyze the e-shopping behavior and demand even better. This would help the government to prepare the freight systems and its citizens for other challenges in the future.

7. The implication of Accessibility to E-commerce and Delivery Services

The result that shows e-commerce and various delivery services are used mainly by and only benefitted some group of people indicates the existence of inequality in accessing e-commerce and different delivery options. For instance, the results conclude that younger people with higher digital literacy are more likely to shop online and use various delivery options than older people. This result is consistent with prior studies that indicate access to smartphones, fast internet, and the skill to use communication-based technologies affect the adoption of e-commerce.

Figliozzi and Unnikrishnan (2021) stated that the growing e-shopping demand during the pandemic existed, along with the increasing expectations of more accessible, affordable, and convenient delivery services. Crowdshipping for *same-day* delivery is one example of a creative way to provide a more effortless shopping experience. This service presents a clear barrier for some customers without access to the internet and those who struggle to use recent technology. Customers who desire to get the most out of their experience with crowdshipping need this accessibility and a general understanding of the process of getting started, such as downloading the app, registering an email, and signing up to begin using the service. Punel et al. (2018) discovered that crowdshipping users found the system was complex. Therefore, government assistance can help make e-shopping and various delivery services widely accessible through policy interventions to educate and improve digital literacy as well as getting access to affordable smartphone devices and internet access with subsidies to low-income people and elders. This assistance will help disadvantaged groups prepare themselves under challenging circumstances such as a pandemic or other events where in-person shopping is less feasible and desirable.

Access to home deliveries is also associated with the use of e-commerce (Figliozzi and Unnikrishnan, 2021). The results of this study confirm prior studies about the effects of built-environment variables on online shopping behavior. The *Super Shoppers* who use all kinds of delivery services, including *local* and *locker pickups*, are mostly people who live in urban areas. Punel et al. (2018) and Mladenow (2016) found that crowdshipping preferences depend on the location where the customers live. They further explained that dense and residential areas appear to be the ideal location to develop crowdshipping services, as places that are located far away may lack the “crowd” to implement crowdshipping services. A similar pattern can also be seen for same-day delivery services, where implementation of such service could be hard to carry out when the customers live far away in rural areas, far from the stores or sellers. Thus, crowdshpipping and *same-day* delivery services are more common and available for those who live in urban areas.

Some e-retailers may not have physical stores and shops, which means the products should be delivered at home or other appointed destinations, like offices, next door, or pickup points. Besides post offices, curbside and locker pickup are some other services that are more likely to benefit people living in urban areas because private companies that provide these services would usually operate them in the densest areas of the city's employment and transit network (Keeling et al., 2021). Jaller and Pahwa (2021) added that pickup points and crowdsourced vehicles offer a shorter delivery time with competitive costs regardless of customer density. Thus, more pickup points in low-density areas offer the possibility to have a faster delivery time for people living in those areas.

The locker and curbside pickup options are very special during the pandemic and helpful in reducing COVID-19 exposure as both services reduce the possible interactions between customers and workers (*e.g.*, delivery men or drivers). However, it is unfortunate that such services are not available for people who live in less dense areas as the COVID-19 pandemic impacts everyone, including those who do not live in urban areas. Thus, this study also supports Keeling et al. (2021) suggestion of allocating more parcel locker systems outside urban areas to improve spatial equity and serve a much greater population, especially during unprecedented challenges like the COVID-19 pandemic.

Access to home deliveries and e-commerce are also not distant from the income variable. This study confirmed previous studies about the tendency of wealthier people would be more likely to benefit from e-commerce and various delivery services. The results show that *Super Shoppers* and *Occasional Shoppers* are mostly part of the higher income groups, while lower-income people are more common in the *Non-Shoppers* class. Figliozzi and Unnikrishnan (2021) explained how household income that links to some personal and household attributes (*i.e.*, internet access, device ownership, household income, and education level) eventually affect the use of e-commerce. Nguyen et al. (2019) also concluded that customers put the greatest weight on delivery fees before other things in evaluating a delivery service. Thus, customers would choose to or not to shop online and what delivery services they would use depending on their income.

Lower-income people are generally the most affected group by the negative environmental impact of e-commerce growth. The reason is that most factories or logistic/distribution centers are located in peripheral areas where lower-income people usually live (to get affordable housing and reduce costs). Thus, the increased traffic, noise, and air pollution would more plausibly affect them. Meanwhile, higher-income people are not impacted by these externalities as those people are more likely to live in urban or suburban areas that use e-commerce the most.

To conclude, the study suggests that policymakers maintain fairness in accessibility to online shopping and various delivery options through several programs or policy interventions. For example, the government can provide education to improve digital literacy and work with private companies to make *locker* and *local pickups* more available to communities in non-urbanized areas and ensure the infrastructure allows all delivery services to be completed in those areas. Government actions and interventions are crucial in maintaining fair access to e-commerce and various delivery services to all groups of people with different socio-demographic and economic backgrounds. Moreover, special attention should be paid to reduce externalities that only affect specific communities near factory locations and distribution centers. In addition, the government needs to work with private companies to expand the delivery networks to reach customers who have low income and education levels and do not live in urban areas, especially to prepare them for unexpected and unprecedented challenges like the COVID-19 pandemic.

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