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Investigation of E-Commerce Enabled Freight Demand and Activities in Residential Areas

Deliverable 7 – Final Report

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Forecasting and Trends Office

Florida Department of Transportation

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METRIC CONVERSION CHART

APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yards	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
NOTE: Volumes greater than 1000 L shall be shown in m^3				
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or metric ton)	Mg (or t)
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F−32)/9 or (F−32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	pound force	4.45	newton	N
lbf/in^2	pound force per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS TO SI UNITS

SYMBOL	WHEN YOU KNOW	MULTIPLY BY	TO FIND	SYMBOL
LENGTH				
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
AREA				
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
VOLUME				
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
MASS				
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or t)	mega grams (or metric ton)	1.103	short tons (2000 lb)	T
TEMPERATURE (exact degrees)				
°C	Celsius	1.8C+32	Fahrenheit	°F
ILLUMINATION				
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
FORCE and PRESSURE or STRESS				
N	newton	0.225	pound force	lbf
kPa	kilopascals	0.145	pound force per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380. (Revised March 2003)

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16. Abstract

This report presents a study investigating online shopping activities and the impacts in light of the recent disruptions and changes brought by the COVID-19 pandemic. Three main objectives of the study were: understand online shopping activities and the potential effects on shopping travel; explore how different groups make shopping channel decisions in view of the trade-offs among cost and time attributes; and examine whether and to what extent the shopping travel behavior changed during different stages of the pandemic. For the purpose of this study, a two-wave Web-based survey of Florida residents was conducted in 2021. The survey collected information on personal and household characteristics, shopping behavior, mobility profile and preferences, and a variety of personal attitudes and preferences related to shopping activities. A stated preference (SP) component was also included in the survey that asked the respondents to choose their shopping channel (online vs. in store vs. curbside pickup) in a set of given scenarios.

Various analytical and modeling approaches were used. Model results show that, in general, online shopping complements in-store shopping. The projection that e-commerce will continue to grow post-pandemic may pose transportation challenges, as higher delivery demand might increase and complexify freight logistics operation and passenger travel. The models identified various attitudes that played significant roles in individuals' shopping behavior. These include joy of shopping, technology-savviness, data security concerns, cost consciousness, and green travel preferences, etc. Significant changes in the effects for some of the attitudes during the pandemic were also detected. Delivery cost and delivery time were the most discouraging factors for online shopping for groceries and non-groceries, respectively.

This study provides useful and meaningful insights on individuals' shopping behavior and the impacts on shopping travel. The study results contribute to a better understanding of e-commerce demand and its impacts. The findings would be helpful for transportation planners in framing effective planning and management policies.

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EXECUTIVE SUMMARY

The rise in the use of e-commerce coupled with rapid development in user-centric on-demand delivery services have changed conventional shopping behavior and may be reshaping the supply-chain and logistics industry. Households that traditionally produced "home-based shopping" trips to retail establishments for goods and services are now becoming part of the larger production-consumption link. Within the production-consumption link is the changing modality of e-commerce between curbside pickup and home delivery. However, existing data, tools, and models still follow the traditional paradigm where "freight" activities end at commercial establishments, leaving an increasing gap not only in goods movement analysis, but also in the highway network analysis, at large. The missing components may have great implications in land use planning and community design to provide proper facilities and capacities to accommodate freight demand.

Given the above motivations, this report presents a study investigating online shopping activities and the impacts. Specifically, this study focused on:

- Understand online shopping activities and the potential substitution or complementary effects on in-person shopping as well as the influential factors, including socioeconomic and demographic characteristics, household attributes, land use factors, and attitudes.
- Explore how different groups make trade-offs among time and cost attributes in their shopping channel decisions among online, in store, or curbside pickup.
- Examine whether and to what extent the present stage of the Covid-19 pandemic may have influenced shopping travel behavior.

For the purpose of this study, a two-wave Web-based survey of Florida residents was conducted from February 1 through April 19, 2021 (the first wave), and November 10 through December 13, 2021 (the second wave). The survey collected information on personal and household characteristics, shopping behavior, mobility profile and preferences, and a variety of personal attitudes and preferences related to shopping activities. A stated preference (SP) component was also included in the survey that asked the respondents to choose their shopping channel (online vs. in store vs. curbside pickup) in a set of given scenarios. Various analytical and modeling approaches were used in answering the research questions. The main findings are summarized below.

E-commerce Effects

The shopping travel effects of e-commerce in shopping for various products were estimated using the structural equation modeling approach. Eight different product types were considered: (a) books and electronics (BE); (b) prepared food (PF); (c) grocery (Gr); (d) home, garden, and tools (HGT); (e) clothing, shoes, watches, jewelry (CSWJ); (f) beauty and health (BH); (g) pet supplies (PS); and (h) toy, kids, and baby (TKB). Judging from our analysis using the combined (first and second wave) dataset, the classification of shopped-for products seems to affect the shopping travel effects. Shopping for search goods (like BE and PS) neither increased nor reduced travel, although in-store shopping increased online shopping frequency. Results for experience goods, however, showed that e-commerce complements in-store shopping, especially for products with higher shopping enjoyment. An implication of these effects is that e-commerce by itself cannot be seen as a traffic-mitigation strategy. The projection that e-commerce will continue to grow post-pandemic may pose transportation challenges for planners because higher delivery demand might increase and complexify freight logistics operation and passenger travel in residential areas. While encouraging e-commerce itself may not offer many transportation benefits, we found that individuals with positive attitudes toward specific advantages of online shopping, (i.e., shopping 24/7, finding items in high demand, and having variety of choices) tended to substitute shopping travel with online shopping. That is, fostering positive attitudes toward these aspects has the potential to reduce the complementary effects. Also, there is a potential for e-grocery to replace portions of grocery shopping trips for high income-earning households. It may be expected that, as retail companies competitively seek ways to reduce e-commerce delivery costs and increase their market shares, e-commerce may replace in-store shopping for many Florida residents.

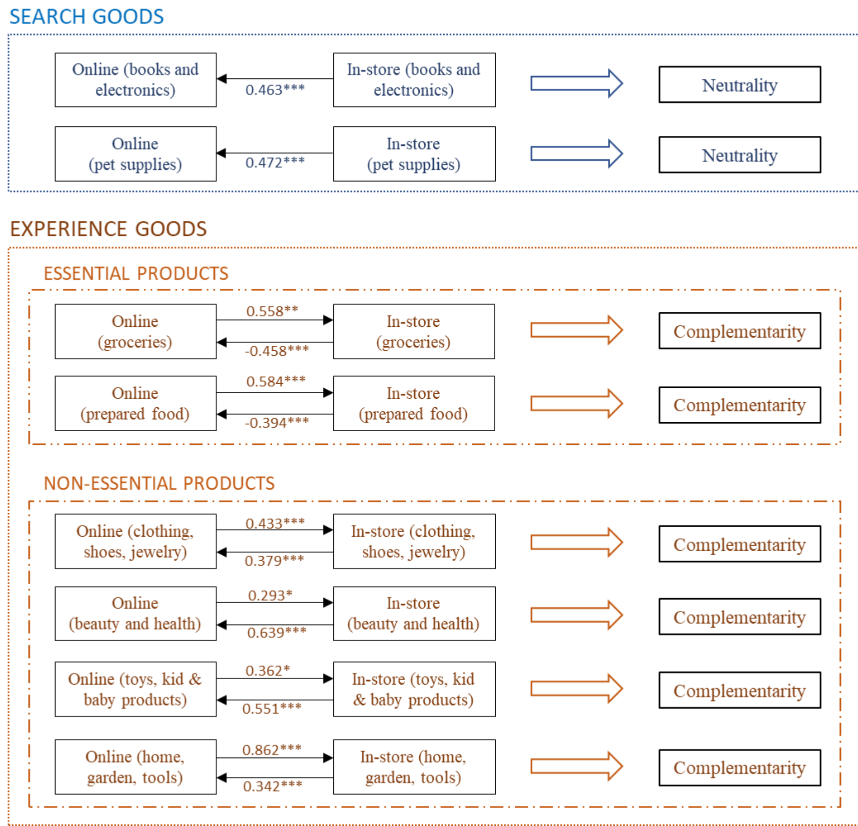

Fig.1 E-commerce effects on shopping travel by product type.

The Role of Attitudes in Travel Effects

Various attitudes had different effects on shopping behavior for different products. Results also differed between waves. Our analysis showed that over time, shoppers' preferences for alternative mobility options **increased**. This suggests that Florida residents became more comfortable using buses, trains, and other shared transportation modes. However, the effect of this change did not necessarily affect the online shopping travel effects for the products similarly because time **reduced** the positive effects of alternative mobility on online shopping frequency for PF, BH, and PS, but not for other product types.

Some effects were also affected over time. The online shopping frequency for BE products **decreased** significantly in the second wave. Also, the positive effect of tech savviness on shopping online for BE products was **weakened** over time.

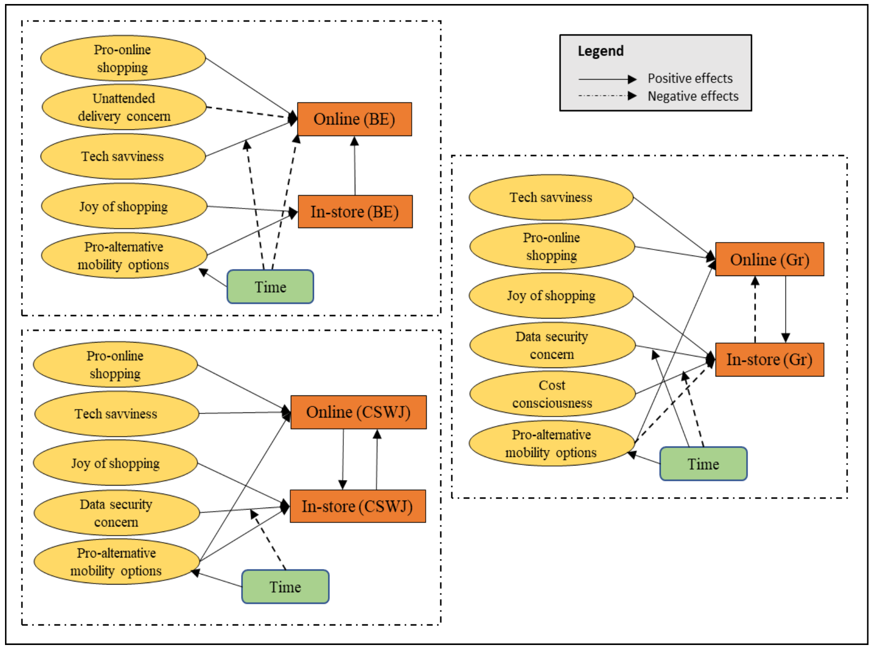

Fig. 2 The role of attitudes in e-commerce effects.

For grocery shopping, analysis for the second wave revealed that online shopping **increased** shopping travel, as opposed to the first wave when online shopping had no significant effect on shopping travel for groceries. Over time, the positive effect of data security concern on in-store grocery shopping was **strengthened**, while the positive effect of cost consciousness on in-store grocery was **weakened**. This suggests that perceived data security risk is strongly linked to in-store shopping.

Unlike grocery shopping, time **weakened** the positive effect of data security on in-store shopping for CSWJ. This indicates that the same attitudes may have significantly different effects on shopping frequency for different products. There were several changes and many other complex interactions between attitudes and the shopping frequencies for other products and between both waves. While it could be said that each product has unique characteristics, our results show that in assessing the travel effects of online shopping, products can be grouped into search, essential experience, and non-essential experience goods because there are important distinctions evident between the product classification and similar effects within the product classification. This not-too-narrow distinction by product type would be useful in travel demand forecasting models and planning processes.

It should also be noted that much of the changes in the effects of attitudes on shopping behavior were not consistent across product types. For some of the models, significant changes in attitudes did not show significant effects on shopping behavior, while insignificant changes in some attitudes caused significant effects. This is indicative of a very complex interplay between and within both the measured and unmeasured causes.

Shopping Channel Choice

Discrete choice experiments with three shopping channels (home delivery, curbside pickup, and in-store) and five time-cost attributes (product price, shopping time, delivery time, delivery cost, and travel time) were constructed and used to understand consumer choices and tradeoffs in both grocery and non-grocery shopping. There were some similarities and differences between grocery and non-grocery shopping during the first and second waves of data collection. For grocery shopping, in-store shopping remained the dominant shopping channel, and delivery cost was the most unpleasant attribute discouraging e-commerce (home delivery and curbside pickup). For non-grocery shopping, however, delivery time and delivery cost were the most unpleasant attributes discouraging e-commerce. Even though the sample distribution between the two waves differed, similar results with regards to the time-cost attributes were found for both waves. This indicates that shoppers have different sensitivity to price and time attributes when shopping for different products (i.e., grocery vs. non-grocery). Delivery time was not a determinant factor in grocery shopping probably because in general it is accomplished within a short time frame rather than a few hours to next day for delivery.

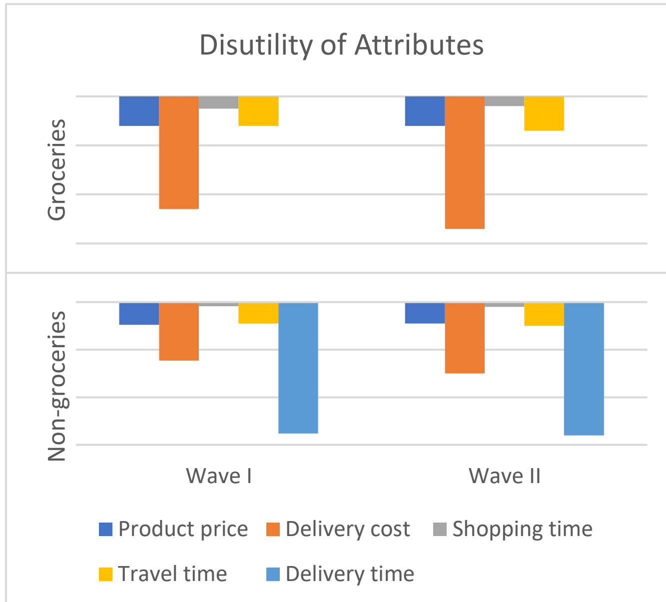

Fig.3 Influential factors on shopping channel choice.

Generally, blacks, workers, students, those 65 years or less tended to prefer the home delivery and curbside pickup alternatives, while Asians, low education, low to middle income-earning households were associated with preference for in-store shopping choice. Also, the preference of high-income individuals was affected by product classification, as they tended to prefer online and curbside pickup alternatives for grocery shopping but in-store shopping for non-grocery items. This suggests that the potential of high-income individuals to substitute in-store shopping with e-commerce is higher in grocery shopping than in non-grocery shopping.

Results on the effects of highly educated individuals and household characteristics were not very clear. Also, there seemed to be some changes in the channel choice preference of some groups across the two waves. For example, in the first wave, Hispanics tended to prefer online shopping and curbside pickup for grocery and non-grocery shopping but tended to prefer in-store shopping during the second wave, especially for non-grocery shopping.

Furthermore, attitudes such as technology savviness, pro-environment attitude, and pro-online shopping were associated with a high tendency to choose home delivery or curbside pickup options, while data security concern, preference for alternative mobility options, and local store purchase were associated with the in-store shopping alternative. Although the results of our structural equation models indicated that those who enjoyed shopping (i.e., recreational shoppers) tended to frequently shop in-store, the results of the choice experiment show that those who enjoyed shopping were likely to choose online shopping and curbside pickup, for both grocery and non-grocery shopping, and during both waves. This suggests that there is a strong potential for recreational shoppers to substitute in-store shopping with online shopping when e-commerce offers competitive options.

Estimation of Delivery Rates

Online shopping frequency is directly indicative of the level of home deliveries and consequently the impacts on traffic. In this regard, household online shopping rates were estimated by product type based on the survey data as a proxy to home delivery rates. The cross-classification approach was used, and random forest models were developed to identify the most influential factors in determining delivery rates by product type. Although the importance of the predictive variables varies slightly by product type, age, having children between 5 and 18 years, education level, and income tend to be among the top three variables affecting online shopping frequency. Also, those with a bachelor's degree or higher (especially middle-aged individuals) tended to receive more deliveries than those with lower education levels.

It is worth noting that the impact of sociodemographic variables on online shopping frequency were not always linear. For example, middle-aged individuals received more grocery deliveries than either young or older individuals. The estimation presents an approximation of delivery rates that could be useful for transportation planners and help to provide more insights into freight planning and management strategies.

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1 INTRODUCTION

The rise of e-commerce and rapid development in user-centric on-demand deliveries have changed the way we shop and receive goods. These societal trends and technological advancements are also reshaping the supply chain and logistics industry. Households that traditionally produced "home-based shopping" trips to retail establishments for goods and services are now becoming part of the larger production-consumption link. Since much of the last-mile deliveries are directed to the end consumers, these households become the new attraction points at the end of the supply chain. However, existing data, tools and models still follow the traditional paradigm where "freight" activities end at commercial establishments. This leaves an increasing gap in goods movement analysis. This missing component may also have great implications in land use planning and community design to provide proper facilities and capacities to accommodate freight demand.

Existing freight demand studies have mostly focused on freight trip generation at commercial establishments, either the production (manufacturer) end or the consumption (retailer) end. Research on household attractions of freight trips has lagged behind. On the other hand, e-commerce has received a fair amount of attention in research, but mainly on the relationships between online shopping activities and shopping trips from a passenger travel perspective.

To fill this knowledge gap, this research aims to advance our understanding in how e-commerce, demographic factors and societal trends drive freight demand and to provide an approach to addressing the last-mile component in the supply chain. To achieve the above goals, the specific objectives were:

1. Capture household level consumptions and attractions of goods and services.
2. Measure the relationships between household and land use attributes and freight trip generation.
3. Recommend approaches to incorporating e-commerce considerations into the FSUTMS and freight demand analysis process.

Residential deliveries enabled by e-commerce and on-demand delivery services have been increasing rapidly. This shift in how consumers receive goods and services has direct impacts on the state and local roadway network. However, our existing data and tools are not able to accurately reflect this trend. This research helps to address the missing residential delivery component and to better reflect the actual freight demand and truck trips in the planning process. This approach will lead to more effective policies, programs, and projects, as well as more context-sensitive land use and community design decisions.

This report is organized into chapters. Chapter 2 – literature review – presents and summarizes past studies, reports, and projects on shopping travel behavior. The review is presented in terms of the factors affecting shopping behavior, the relationship between online shopping and in-store shopping behavior, as well as the modeling approaches that have been used. Chapter 3 describes the survey design and implementation. Chapter 4 – data description – summarizes the aspects of the data. Chapter 5 – methodology – introduces the analytical approaches. Chapters 6 through 8 present the results from three main perspectives: attitudes, purchase frequencies, and channel choice behavior. Chapter 9 – impact assessment – estimates freight demand by delivery rates. Chapter 10 – the last chapter – summarizes the major findings and provides recommendations on shopping demand.

2 LITERATURE REVIEW

Many researchers have studied online shopping behavior and the impacts on in-store shopping. Findings are often mixed and contradictory because of the complexity in determining the impacts of online shopping on in-store shopping and travel (Cao, 2009; Le et al., 2021; Mokhtarian, 2004; Rotem-Mindali & Weltevreden, 2013; Suel & Polak, 2018). Some factors are known to reduce travel, while other factors increase travel and the extent of the impact of these factors in relation to one another largely varies from one study to another. Factors that contribute to the variations in the outcomes of the studies may include the nature of the sample, the methodology or approach used, the definitions of e-shopping (i.e., searching activities, purchasing, and delivery) and e-shoppers (level of frequency of activity-specific e-shopping), the definition of the impacts on in-store shopping, the hypotheses tested, and the goods type considered, etc. With this in mind, this section presents a summary of the literature, with the aim of providing some insights into what has been studied in the field and the contexts of the studies. Factors affecting online shopping, effects of online shopping on in-store shopping, and differences in methodologies and approaches used are presented.

2.1 Factors Affecting Shopping Behavior

The quest to understand and predict the commercial and travel impacts of online shopping adoption has prompted many researchers to investigate the shopping behavior of consumers. A range of factors possibly associated with online and in-store shopping behavior has been explored, alongside the extent to which these factors affect shopping behavior. These factors include socio-demographic characteristics (such as age, gender, income, education, employment, car ownership, and household characteristics), Internet usage and experience, spatial attributes, shopping attitude, shopping basket characteristics, channel and channel alternative characteristics, time of purchase and so on.

2.1.1 Personal and Household Attributes

As regards the influence of age on shopping behavior, there is overwhelming evidence from the literature that younger individuals tend to engage in online shopping more frequently than older individuals (Cao et al., 2012; Crocco et al., 2013; Farag et al., 2006; Irawan & Wirza, 2015; Kedia et al., 2019; Lee et al., 2015; Suel et al., 2015). It has been suggested that because older individuals are often household leaders who have the responsibility to cater for not only themselves but for other members of their households, they tend to make a higher number of shopping trips especially when the products of purchase are large. Other explanations hint at the higher Internet use and tech-savviness of the younger generation. Also, some studies seem to indicate that the negative relationship between age and online shopping may not be necessarily linear. For example, Amaro & Duarte (2013) found that middle-aged individuals between ages 25 and 55, possessing higher levels of education and income were more likely to purchase travel online. Shi et al. (2019) also found a positive relationship between age and online shopping frequency. Although the finding was based on a sample of relatively young individuals, it thus indicates that a negative relationship between age and online shopping frequency does not occur until middle-age (around mid-thirties).

There also exists gender effects on shopping behavior, as many studies have shown that males tend to make more online purchases and females tend to make more shopping trips (Farag et al., 2006; Irawan & Wirza, 2015; Xue et al., 2021). However, some other studies have noted deviating findings such as Lee et al. (2015) and Hoogendoorn-Lanser et al. (2019) that observed no gender effect on online shopping frequency. Meanwhile, Ramirez (2019) found that females tended to make not only more online purchases but more purchases in general (i.e., online and in-store) than men. It has been suggested that the characteristics of product types considered in the studies may have resulted in differing effects by gender. For example, some studies have found that women were more likely to make frequent in-store purchases of clothing, home supplies and daily goods compared to men, while men were likely to make in-store purchases of electronics and sporting goods more frequently than women (Lee et al., 2015; Zhen et al., 2016). Also, Chocarro et al. (2013) observed a gender effect in the choice of the channel in purchasing search goods (books and plane tickets), but not in purchasing experience goods (T-shirts and personal computers). In making food purchases, Kim & Wang (2021) found that males were more likely to receive food deliveries than females. For grocery shopping, gender does not seem to have any significant impact on the choice and frequency of online shopping (Kim & Wang, 2021; Suel et al., 2015). One study however, showed that frequent in-store grocery shoppers tended to be females, and having more females in the household reduced the likelihood to never order groceries online and increased the number of grocery deliveries (Saphores & Xu, 2021).

It has also been found that online shopping is positively affected by level of income and educational attainment both with regards to grocery shopping (Dias et al., 2020; Hagberg & Holmberg, 2017; Saphores & Xu, 2021; Suel et al., 2015) and non-grocery shopping (Cao et al., 2012; Crocco et al., 2013; Farag et al., 2006; Lee et al., 2015; Ramirez, 2019; Swaminathan et al., 1999). However, other studies have found a negative association. For example, Irawan & Wirza (2015) analyzed a dataset collected from 281 respondents residing in mostly urban areas of Indonesia using structural equation modeling and found that level of income and educational attainment had a negative effect on online shopping. Although no explanation was given for this contradictory finding, Indonesia's retail structure and urbanization pattern may have influenced the finding. Likewise, Shi et al. (2019) found that online shopping was reduced with income. However, the study also found that income negatively affected shopping trips, the implication of which may be that high-income earners have higher time pressure and value of time resulting in lower shopping demand generally.

Regarding the effect of employment status on online shopping, it has been found that full-time workers or those who have at least one member part of the working population were more likely to shop online than other employment groups (Lee et al., 2015; Motte-Baumvol et al., 2017), while students and unemployed individuals (including homemakers) were inclined to shop in-store more frequently than full-time workers (Joewono et al., 2019; Saphores & Xu, 2021). With regards to grocery channel choice, however, Suel et al. (2015) found no association between employment status and the choice of online grocery shopping.

Results on the effect of car ownership on shopping behavior have been mixed but may have been influenced by the differing urbanization patterns, retail structures, and the built environmental characteristics of each country or location of study. For example, car ownership was linked with higher online shopping frequency in New Zealand (Kedia et al., 2019) and the Netherlands (Farag et al., 2006), and lower in-store shopping frequency in Indonesia (Irawan & Wirza, 2015; Joewono et al., 2019) and China (Shi et al., 2019). Also, a study conducted in England found that owning cars or vans was negatively associated with the choice of using online grocery shopping (Suel et al., 2015). However, studies conducted in other countries like Sweden and the U.S. have found differing results. Hagberg & Holmberg (2017) showed that car usage increased the frequency of in-store grocery shopping and travel distance to the grocery store in Sweden. Moreover, studies conducted in the U.S. indicate that households with more vehicles tended to make more shopping trips, and individuals who use public transportation and active transportation made lesser shopping trips yet had high online shopping orientation (Dias et al., 2020; Ramirez, 2019; Xue et al., 2021). It should be noted that the relationship between car ownership and shopping behavior in the U.S. may not be applicable for all product types, as households with zero cars were less likely to receive frequent online grocery and meal deliveries (Dias et al., 2020).

Several household characteristics have been found to influence shopping behavior. Some studies have found either a positive association between number of children and the likelihood of online purchase (Chocarro et al., 2013) or a negative relationship between number of children and in-store shopping (Zhen et al., 2016). Similar findings have been demonstrated with regards to grocery shopping (Kim & Wang, 2021; Lo et al., 2021). However, Saphores & Xu (2021) found that having more children under 18 increased the likelihood of never shopping online, and slightly increased the number of grocery deliveries. It has been suggested that the demand on the time for parents to chauffeur their children to various kinds of extra-curricular activities may be a reason for the tendency to shop online for households with children. Another possible explanation is that shoppers often avoid the difficulty in shopping in-store with young children, and thus, prefer to purchase groceries online (Berg & Henriksson, 2020). Regarding family size, some studies have suggested that those with larger household sizes tended to shop online less frequently than smaller households (Kedia et al., 2019; Suel et al., 2015). However, results in Dias et al. (2020) indicated that frequency of both online and in-person shopping episodes increased with household size. Since greater number of items to be purchased increases the likelihood the items would be purchased in a store (Mokhtarian & Tang, 2011), the positive association between household size and in-store shopping trips can be explained by the relative higher quantity of items large households need and purchase. Other household characteristics that have been found to influence shopping behavior are number of productive family members (Irawan & Wirza, 2015), possession of a driver's license (Xue et al., 2021; Zhen et al., 2016) or number of household members with drivers' license (Irawan & Wirza, 2015; Ramirez, 2019).

2.1.2 Internet Experience and Spatial Attributes

Internet experience and frequency of Internet usage increase the likelihood to make online searches and actual purchases (Cao et al., 2012; Farag et al., 2006). The positive association between frequency of Internet usage and online purchase is heightened if the desired item is a search good (Chocarro et al., 2013). Also, Crocco et al. (2013) found that experience with new technologies increases the likelihood to purchase online. Irawan & Wirza (2015) found that Internet experience and fast Internet connection positively affected not only online searching and online buying, but also shopping trips. Unnikrishnan & Figliozzi (2020) found that the amount of time per week spent on desktop, laptop, or smartphone increased the likelihood to spend more money on household deliveries. Thus, these findings show that Internet usage or experience has a positive effect on both online and in-store shopping. Contrastingly, a study conducted by Shi et al. (2019) in China contradicted the consistent results found in the literature. It was found that frequent online purchases were negatively affected by internet experience on PCs. However, it was indicated that the new context of the information era in China had shifted a large percentage of e-retailing sales from being used through PCs to mobile devices, and thus have made the use of PCs unnecessary for online shopping.

The spatial attributes of shoppers also affect shopping behavior. Urban residents were more likely to make more online shopping or have more home deliveries than non-urban residents (Dias et al., 2020; Farag et al., 2006; Hagberg & Holmberg, 2017; Ramirez, 2019; Zhou & Wang, 2014). Urban residents also tended to make more in-store shopping trips and in-person eat-out activities (Dias et al., 2020; Etminani-Ghasrodashti & Hamidi, 2020). This finding seems reasonable since living in areas with high levels of land use diversity, high intersection density, and a well-connected street network increases accessibility to shopping destinations. Thus, urban residents would make more shopping trips.

2.1.3 Shopping Characteristics

Shopping basket characteristics (i.e., the variety or quantity of products) are known to affect shopping behavior and channel preferences (Suel et al., 2015). Books, computer hardware, electronic media, and gifts tended to be purchased online, while groceries and articles of clothing tended to be purchased in-store (Crocco et al., 2013; Lee et al., 2015; Schmid et al., 2016). Furthermore, the greater the number of items to be purchased, the higher the likelihood the items would be purchased in a store (Mokhtarian & Tang, 2011). However, the difficulty in carrying heavy shopping bags may discourage consumers from shopping for a large collection of items in-store (Berg & Henriksson, 2020).

Distance or travel time to store influences shopping behavior but the effects depend on the product type. Long distances to stores seem not to discourage shopping for experience goods in-store (Farag et al., 2006; Lee et al., 2015), but in purchasing a search good such as a book, the value of travel time is much higher than the value of waiting time or delivery time (Hsiao, 2009), thus shoppers would prefer to shop for search goods online (Chocarro et al., 2013). However, travel distance between shoppers' homes and their preferred shopping outlets may increase both in-store and online shopping frequency (Etminani-Ghasrodashti & Hamidi, 2020). Also, an association has been found between in-store shopping and online shopping, but findings seem to be mixed. Zhou & Wang (2014) found that in-store shopping frequency negatively affected online shopping frequency. However, Dias et al. (2020) and Etminani-Ghasrodashti & Hamidi (2020) indicated that in-store shopping itself may lead to online shopping.

People tend to make more shopping trips during weekends rather than on weekdays, while online transactions are mostly conducted on weekdays and appear to decrease from Monday through Sunday (Schmid et al., 2016; Zhou & Wang, 2014). Thus, the day of the week in which shopping is considered may affect the choice of channel. Other factors that have been found to affect online shopping behavior are the channel by which shoppers became aware of the product, searched product information, or tried the product (Cao, 2012), characteristics of a shopping channel and shopping channel alternatives, time of day when purchasing is being considered (Chocarro et al., 2013), pro-exercise attitude (Mokhtarian & Tang, 2011), and frequency of missing attended deliveries (Kedia et al., 2019), etc.

2.1.4 Attitudes toward Shopping

Attitudes toward online shopping and intention to shop online have also been studied extensively. Positive perceptions toward online shopping positively affected online shopping intention and actual online purchasing behavior, while positive perceptions toward in-store shopping increased the propensity to make shopping trips (Amaro & Duarte, 2013; Farag et al., 2006; George, 2004; Irawan & Wirza, 2015).

There is also a range of factors that have been found to affect attitude or serve as antecedents to attitude towards online or in-store shopping. Personal innovativeness was found to affect the attitude and intentions to shop online (Limayem et al., 2000). Internet trustworthiness, which was a bigger concern for consumers than unauthorized use of personal data, significantly affected consumers' attitudes toward Internet purchasing, which in turn affected actual purchasing behavior (George, 2004). Perceived risk concerning credit cards or perceived consequences toward online shopping negatively affected attitude, which in turn affected online purchase intention or actual purchase (Crocco et al., 2013; Hsu et al., 2014; Limayem et al., 2000). Various dimensions of trust (such as trust in the website or trust in the vendor) were found to affect the attitude and perceived risk towards online shopping (Hsu et al., 2014). Furthermore, perception of convenience in placing orders, contacting vendors, and making purchases have been found to affect consumers' shopping behavior, as consumers who were motivated primarily by convenience were more likely to have a favorable perception of online shopping, and thus make more online purchases (Crocco et al., 2013; Mokhtarian & Tang, 2011; Swaminathan et al., 1999).

Those who value recreational shopping preferred to shop in-store (Crocco et al., 2013; Swaminathan et al., 1999) and were likely to be more loyal to a physical store than to an online store (Scarpi et al., 2014). And though the desire for social interaction or to shop for fun motivates consumers in making shopping trips, shopping trips generally result in more actual purchases than online shopping (Lee et al., 2015).

Moreover, recreational shopping may differ by product type. Zhen et al. (2016) found that shopping enjoyment was positively associated with store purchasing frequency for daily goods but negatively associated with store purchasing frequency for electronics. It should be noted, however, that the preference for recreational shopping does not imply preference for driving or active travel modes, as online shoppers tend to prefer active travel modes than in-store shoppers (Lee et al., 2015; Zhou & Wang, 2014).

Furthermore, cost-consciousness and time-consciousness seem to positively affect online shopping and online shopping attitude (Cao et al., 2012; Schmid et al., 2016). However, Zhen et al. (2016) found a negative association between time consciousness and online purchasing frequency for clothing, but not for electronics. Thus, the effect of time-consciousness may also vary by product type.

2.2 Effects of Online Shopping on In-Store Shopping

Research on the travel impacts of Information Communications Technology (ICT) dates to the energy crisis of the 1970s, when transportation researchers and engineers were prompted to seek ways to improve energy savings (Mokhtarian, 1990). ICT was seen as a tool that could be used to substitute travel, and lead to a reduction in traffic congestion, energy, and environmental costs (Mokhtarian, 1990; Tonn & Hemrick, 2004). Transportation researchers sought to classify the direct effects of ICT on personal travel in four main ways: complementarity, substitution, modification, and neutrality (Andreev et al., 2010; Mokhtarian, 1990; Salomon, 1986). A complementarity effect is said to occur when an ICT-based activity encourages or necessitates some location-based activity and thus increases travel, which may not occur otherwise. Substitution effects occur when an ICT-based activity obviates the need or desire to make a location-based activity, and thus reduces or replaces a significant portion of travel. Modification effects occur when ICT does not significantly increase or reduce travel, but modifies travel in terms of trip timing, mode, chaining, and activity sequence. Neutrality effects occur when ICT neither increases, decreases nor modifies travel in any significant way.

Most studies generally categorize the effects of online shopping on in-store shopping by complementarity or substitution effect. While that categorization is necessary, the picture of the effect of specific online shopping activities on specific measures of in-store shopping impacts also needs to be shown. This section begins by presenting the effect of online shopping frequency on in-store shopping frequency. The effects of shopping activity fragmentation and product type were also examined.

2.2.1 Online Shopping Frequency on In-Store Shopping Frequency

Cao (2012) examined the relationship between e-shopping and store shopping for products within the search goods category (i.e., books, CDs, VCDs, videotapes, and album). Data was collected from 540 internet users in the Minneapolis-St. Paul metropolitan area, USA and analyzed using binary logit models. It was suggested from the results that the hybrid shopping process occurring in internet transactions generated shopping trips to traditional stores, thus indicating a **complementarity** effect.

Zhou & Wang (2014) examined the impact of online shopping on personal trips. A large dataset containing 85,663 records, collected from the 2009 National Household Travel Survey (NHTS) in the U.S, was analyzed using the structural equation modeling approach. On the one hand, online shopping frequency had a **complementarity** effect on in-store shopping frequency, but on the other hand, the frequency of in-store shopping showed a **substitution** effect on online shopping. Neither a pure substitution nor pure complementary effect was concluded between online shopping and the frequency of shopping trips. It was also suggested that in-store shopping experience suppresses the desire to shop online.

Hiselius et al. (2015) explored the effect of frequent, regular, and infrequent online shoppers on travel behavior for physical shopping trips (for groceries, other purchases, and the pick-up of goods purchased online) in Sweden. Data was collected from 3,086 respondents in 2011 and 1,390 respondents in 2012 through a questionnaire. There was an indication from the results that the time saved from online shopping was spent on more shopping trips and other trips in general. Thus, online shopping exhibited a **complementarity** effect on physical shopping.

Schmid et al. (2016) explored the choice between online and in-store shopping for experience goods (groceries) and search goods (electronic appliances) in Zurich, Switzerland. 339 respondents provided their information through a one-week travel diary, questionnaire and in a stated choice experiment. An integrated choice and latent variable (ICLV) modeling approach was used. There seemed to be a **substitution** pattern between online shopping and in-store shopping that was mediated via attitudes. However, the statistical significance of the effect could not be validated.

Ding & Lu (2017) investigated the interactions between online shopping, in-store shopping, and other dimensions of activity travel behavior. The data used was a 7-day GPS-based activity travel diary collected from 537 individuals in the Shangdi area of Beijing, China. A structural equation model was used to analyze the data. Results showed that online shopping frequency had a **complementarity** effect on in-store shopping frequency. However, the negative relationship between online buying frequency and the frequency of out-of-home leisure activities indicated some form of **substitution**.

Zhai et al. (2017) examined the interactions between e-shopping and store shopping in the shopping process for search goods (books) and experienced goods (clothing). Data was collected from 952 respondents in California. After deconstructing respondents' shopping process into four stages (product awareness, information search, product trial, and transaction), a binary logit model was used for the analysis. The effect of online shopping on travel behavior was **inconclusive**, but it was suggested that information search and product trial through the internet may help trip reduction, since store buyers could go online to obtain information while already at a store, and therefore complete their cross-channel shopping process with a single trip to the store.

Suel et al. (2018) investigated the effects of online shopping on shopping trips and overall shopping events (including both online and in-store) within the context of grocery shopping. Data were collected from 124 households in Barnet and Enfield, London, and 44 randomly selected households in London from a one-year long longitudinal grocery shopping purchase data. Gap times between recurring grocery shopping occasions were modeled using the Cox proportional hazards model, and a **substitution** effect was shown to exist between online shopping frequency and shopping trip rates.

Zhen et al. (2018) explored the influence of spatial attributes on shopping channel choices at the pre-purchase and purchase stages in the shopping process for both search goods (books) and experience goods (clothing). Data was collected through a survey of 963 adult internet users in Nanjing, China, and analysis was done using trivariate probit models. **Substitution** of store shopping frequency by online shopping frequency was found to occur at the pre-purchase and purchase stages of the shopping process when shop accessibility was low. However, there was a difference in the effect between shopping for books and clothing, implying that product type can moderate the associations between shopping accessibility and online shopping behavior.

Shi et al. (2019) examined the effect of online shopping for four types of products (clothes and shoes, electronics, food and drink, and cosmetics) on shopping trips. Data was collected from 710 respondents in Chengdu, China through structured interviews. Negative binomial regression models were used to investigate the determinants of e-shopping and shopping trip frequency, a linear regression model was developed to identify the determinants of the share of e-shopping, and a binomial logistic regression model was used to identify the determinants of whether e-shopping replaces or generates shopping trips. Results showed that 44% of the respondents claimed that they made fewer shopping trips due to e-shopping, as opposed to 14.9% of respondents who said they increased their shopping trip frequency. This seems to indicate e-shopping frequency may have a **substitution** effect on the frequency of shopping trips. However, the extent of this effect seems moderated by car ownership and high frequency of online purchases.

Ramirez (2019) examined the factors influencing the relationship between online shopping and home-based shopping trips. Survey responses of 16,145 individuals, collected from a database by the 2017 National Household Travel Survey (NHTS), were analyzed using ANOVA tests and negative binomial regression models. A correlation between online shopping and the number of home-based shopping trips was found. And though the correlation was weak, the positive effect that online shopping had on home-based shopping behavior suggests a **complementary** relationship between online shopping and home-based shopping trips.

Hoogendoorn-Lanser et al. (2019) investigated the effect of each of the constituent stages (browsing/orienting, comparing, selecting, and purchasing products) of online shopping for grocery and non-grocery products on personal mobility. Data provided by 833 respondents through a three-day travel diary and questionnaire was analyzed using a multivariate analysis. A **complementarity** effect was found between online shopping frequency and shopping trip distances for non-grocery shopping, but not for grocery shopping. It was suggested that the reason for this difference owes to the routine nature and uncommon product information search associated with grocery shopping.

Kedia et al. (2019) investigated the effect of online shopping on in-store shopping travel considering consumer attitudes towards missing 'attended' deliveries. Data were collected from 355 online surveyed consumers residing in Christchurch, New Zealand. There was no correlation found between the frequency of consumers' in-store shopping and online shopping, indicating a **neutral** effect between online shopping frequency and in-store shopping travel frequency.

Etminani-Ghasrodashti & Hamidi (2020) examined the shopping travel behavior of individuals in Iran through their online and in-store shopping frequency. Structural equation models were used to analyze data collected through a survey of 526 residents of Shiraz, a metropolitan city in Iran. Online shopping frequency showed a **complementarity** effect on in-store shopping frequency. Also, in-store shopping frequency showed a positive and even stronger association with online shopping frequency.

Dias et al. (2020) sought to unravel the effect of non-grocery goods, grocery products, and ready-to-eat meals in the relationships between online and in-person shopping activities. The data used consisted of 705 household responses, derived from the 2017 Puget Sound Regional Household Travel Survey. A multivariate ordered probit model was used for analysis, and it indicated that the relationship between in-person and online shopping activities was complex because there was evidence of **complementarity** effect between the frequency of online and in-store shopping for non-grocery products, and substitution effect between the frequency of online and in-store shopping for grocery products. Results also showed that in-store shopping itself leads to online shopping.

Xi et al. (2020) examined the effects of same-day delivery (SDD) online shopping on local shopping travel to five types of stores (supermarkets, convenience stores, vegetable markets, fruit stores, and restaurants). Data were collected through face-to-face interviews using two structured questionnaires from 1,207 respondents (684 SDD online shopping users and 523 non-users) in Nanjing, China. Cross-sectional analysis and longitudinal approaches were compared, and it was found that the two approaches yielded differing outcomes. Quasi-longitudinal analyses demonstrated that SDD online shopping frequency **substituted** for local store shopping frequency, while cross-sectional analyses showed either a **neutral** or **complementarity** effect existed. It was argued that the longitudinal analysis is a superior approach because it accounts for influences of time-invariant confounding factors, whereas cross-sectional analysis does not. This study, therefore, concluded that online shopping frequency exhibited a substitution effect on local store shopping frequency.

Xue et al. (2021) investigated individuals' online and in-store shopping travel behavior using travel diary data obtained from the 2017 National Household Travel Survey (NHTS) dataset. Data collected were from 129,696 households, including 264,234 individuals aged five and older in the U.S. Using a bidirectional structural equation modeling approach, e-shopping frequency was found to have a **complementarity** effect on shopping trips. However, in-store shopping showed a **substitution** effect on e-shopping.

2.2.2 Constituent Stages of Shopping

Online and in-store shopping processes involve stages that could be fragmented and examined individually. The online shopping process could be decomposed into the browsing/orienting, comparing, selecting, and purchasing stage, or the searching and purchasing stage. Different shopping indicators such as online shopping duration, in-store shopping duration, travel time, and travel distance have all been used to represent, define, and measure these individual stages or fragments.

In examining how online searching frequency affects in-store shopping frequency, Cao et al. (2012) and Irawan & Wirza (2015) found *complementarity* effects. Likewise, online buying frequency tended to yield *complementarity* effects on in-store shopping frequency (Cao et al., 2012; Farag et al., 2006). The complementarity effect of the frequency of online searching and online buying on in-store shopping do not seem equally weighted, as Cao et al. (2012) showed that online searching frequency exhibited a larger complementarity effect on in-store shopping frequency than that exhibited by online buying frequency on in-store shopping frequency. This finding also supports the notion that many shoppers often use the Internet to shop online without the intention to purchase online, or shop online to prepare for in-store shopping. Results in Irawan & Wirza (2015) however showed that online buying frequency would potentially exhibit a *substitution* effect on the number of shopping trips in Indonesia. It should be noted that the usage of the terms "e-shopping" and "online shopping" in Irawan & Wirza (2015) seems to encapsulate online searching and online buying in the introduction and literature review section, but the usage of the term "online shopping" in the results and conclusion sections presumably connotes online buying.

Further fragmentation of the online shopping process that goes beyond online searching and online buying have also been considered. For example, Zhai et al. (2019) fragmented the pre-purchasing process into three stages: product awareness, information search, and product trial stages. It was concluded that the impact of online shopping on individuals' shopping travel is complex since shopping activity fragmentation can induce both *substitution* and *complementarity* effects during the shopping process. Some studies have also fragmented in-store shopping to enable the examination of the effect of online buying on in-store buying (Suel et al., 2015; Zhen et al., 2016). Suel et al. (2015) found a net *substitution* relationship between the frequency of online buying and in-store buying of groceries, while results in Zhen et al. (2016) showed a *complementarity* effect between the frequency of online buying and in-store buying of four types of products: clothing, books, daily goods, and electronics. However, the extent of the complementarity effect found in Zhen et al. (2016) varied by product type, as less frequently purchased products showed a larger effect.

Insights have also been provided on the relationship between shopping duration and shopping behavior (Farag et al., 2006; Lachapelle & Jean-Germain, 2019). Farag et al. (2006) examined the effect of online buying frequency on the duration of shopping activity for daily and non-daily products and found that online buying frequency exhibited a *substitution* effect on the duration of average shopping activity for non-daily products. Though no substitution effect was found between online buying frequency and in-store shopping duration for daily store visits, the substitution effect found for non-daily products seems to indicate that if online buying frequency increases in-store shopping, then frequent online buying would obviate the need and tendency to shop in-store for a long period of time. Lachapelle & Jean-Germain (2019) explored how the duration of Internet use for different purposes affected travel behavior. Results from multinomial logistic regression demonstrated that online shopping duration exhibited a *complementarity* effect on both the frequency and travel time of shopping trips. Also, Hoogendoorn-Lanser et al. (2019) investigated the effect of each of the constituent stages (browsing/orienting, comparing, selecting, and purchasing products) of online shopping for grocery and non-grocery products on shopping trip distance. A *complementarity* effect was found between online shopping frequency and shopping trip distances for non-grocery shopping, but not for grocery shopping. It was suggested that the reason for this difference owes to the routine nature and uncommon product information search associated with grocery shopping.

2.3 Analysis Methodology

2.3.1 Product Type

The differences in the shopping behavior of shoppers across different products have led many researchers to specify the products or product types they considered or intentionally omitted in their studies. Products are often classified into search versus experience goods, daily versus non-daily goods, grocery versus non-grocery products.

Search products are products whose essential qualities can be accurately known prior to purchase, while experience products are those whose qualities can only be ascertained after purchase or during consumption. Products such as books, dried food products, tickets, electronic appliances, digital and media products such as software products, CDs, VCDs and albums are classified as search products, whereas articles of clothing, shoes, fresh food products, perfume, and cars are classified as experienced products (Cao, 2012; Chocarro et al., 2013; Schmid et al., 2016; Zhai et al., 2017, 2019; Zhen et al., 2018). For search products, information regarding the essential attributes of the products is revealed through the information put on the packet or back cover. In the case of experienced products, extrinsic attributes such as the price, brand and referrals are pointers in determining the product quality, and shoppers tend to feel, taste or "experience" the products before purchasing. Furthermore, advertisement, payment and distribution of search goods are mostly done online whereas experience goods are suited for advertisement, payment, and distribution both physically and virtually (Zhai et al., 2019).

Products have also been classified as grocery and non-grocery products. Grocery shopping is routine and necessary involving higher activity frequency and shorter distances to stores. Grocery shopping takes up a larger percentage of the retailing sales, has a minimal recreational value, and more cumbersome logistics operation than non-grocery shopping. Online pre-purchasing fragmentation when conducting grocery shopping is less relevant for additional trip generation (Suel et al., 2018). Substitution effects were found between the frequency of shopping for groceries online and in store (Dias et al., 2020; Suel et al., 2015, 2018). However, results in Hagberg & Holmberg (2017) yielded a complementarity effect. Also, Hoogendoorn-Lanser et al. (2019) found that online shopping frequency exhibited a complementarity effect on shopping trip distance for non-grocery shopping but had no effect on grocery shopping trip distance.

The classification of products into daily or non-daily products is similar to grocery and non-grocery product types, as books, clothes, electronics, and gifts have been classified under non-daily products, while groceries and other sundries have been classified as daily products. Though most products purchased online are non-daily products, there seem to be little difference in their respective effects on in-store shopping, as complementarity effects were found when both product types were purchased online (Cao et al., 2012; Farag et al., 2006). There seems to be contradictory results found in the literature in assessing online grocery and non-grocery product effects on in-store shopping. Other studies have differentiated products in other ways such as clothes and shoes, electronics, food and drink, and cosmetics (Shi et al., 2019), meal delivery versus restaurant eat-out (Dias et al., 2020), daily goods, packaged foods, fruits and vegetables, and catering services (Xi et al., 2020), automotive parts, gifts etc.

2.3.2 Modeling Approaches

The major models that have been used to determine associations between online shopping and travel behavior are regression models, probit models, structural equation models, and hybrid choice models. Known for its simplicity of use, the choice of regression models mostly depends on the nature or structure of the collected data. Multiple linear regression model has been used to predict the frequency of in-store shopping when represented as a continuous variable (Hagberg & Holmberg, 2017). When data were collected as a form of counts and the means of online shopping frequency and in-store shopping frequency were both smaller than their variances, negative binomial regression model have been used (Shi et al., 2019). And as regards the ordinal logistic (OL) regression model, in-store shopping frequency must be represented as an ordinal variable (Farag et al., 2006; Kedia et al., 2019; Ramirez, 2019). It is noteworthy that although studies that employed the regression models in their analysis mostly focused on the effect of online shopping in terms of shopping frequencies, online shopping effect in terms of shopping duration, travel time and distance have also been examined (Farag et al., 2006; Lachapelle & Jean-Germain, 2019).

A few studies have used probit models to analyze the shopping behavior of consumers (Dias et al., 2020; Zhen et al., 2016, 2018). The ordered probit model has been used to measure shopping frequency on an ordinal scale. It assumes there is an underlying latent continuous variable that represents the store shopping frequency of individuals. The latent variable can be expressed as (Zhen et al., 2016):

$$Y^* = B'X + \xi$$

Where β = vector of parameters, X = vector of explanatory variables, and ξ = unobserved error term. Also, the observed variable, $Y = j$ if $\mu_{j-1} < Y^* \leq \mu_j$ where $j = 1,2, \ldots, J$, μ_j represents threshold parameters defined as $\mu_{-1} = -\infty$, $\mu_j = +\infty$, and $\mu_{j-1} < \mu_j$ for all j. For the multivariate probit model, shopping choices are modeled jointly allowing relevant unobserved characteristics to be correlated across the choices (Zhen et al., 2018).

The Structural Equation Modeling (SEM) approach has also been used by several researchers to investigate the relationship between online shopping and travel behavior (Cao et al., 2012; Ding & Lu, 2017; Etminani-Ghasrodashti & Hamidi, 2020; Irawan & Wirza, 2015; Zhou & Wang, 2014). Advantages of the SEM approach over regression models are that it could capture direct, indirect, and total influences of exogenous variables on endogenous variables, influences within the endogenous variables, and allows for reciprocal influence among variables (Ding & Lu, 2017; Etminani-Ghasrodashti & Hamidi, 2020; Irawan & Wirza, 2015). SEM also accommodates latent variables, which can be used as unobserved variables in the model. Conceptually, SEM evaluates structures between measurement models constructed for exogenous or endogenous variables. The structural equation model can be expressed as (Cao et al., 2012):

$$y = By + \Gamma x + \xi$$

Where $y = (M_y * 1)$ column vector of endogenous variables (M_y = number of endogenous variables), $x = (M_x * 1)$ column vector of exogenous variables (M_x = number of exogenous variables), $B = (M_y * M_y)$ matrix of coefficients representing the direct effects of endogenous variables on other endogenous variables, $\Gamma = (M_y * M_x)$ matrix of coefficients representing the direct effects of exogenous variables on endogenous variables, and, $\xi = (M_y * 1)$ column vector of errors. Common indicators for endogenous variables are related to shopping or travel behavior, while indicators for exogenous variables often used are antecedents to shopping behavior, such as socio-demographic characteristics, Internet experience, spatial attributes, shopping accessibility, product type, etc.

Hybrid choice models appear not to have caught a lot of attention in the literature. An example of a hybrid choice model was presented by (Schmid et al., 2016). The model, perhaps the first alternative-specific integrated choice and latent variable (ICLV) modeling approach in the field of shopping behavior, is relevant in addressing how latent variables like attitude and perceptions of people function in a choice process. The concept involves integrating latent variables that have been defined in the structural model with measurable socio-economic variables into random utility-maximization (RUM) models to estimate the coefficients in the structural model. These coefficients are thus used to predict the distribution of attitudes in the population. This method seems to have an advantage in better representing decision processes.

2.3.3 Data Collection Approaches

As regards the nature of the data collected for analysis, the major approach used has been the cross-sectional approach, which involves using surveys, questionnaires, structured interviews, or travel diary to elicit information from respondents about their shopping behavior. However, few studies have employed the longitudinal approach (Suel et al., 2018; Xi et al., 2020). For the sake of comparison between these two approaches, (Xi et al., 2020) examined the effects of same-day delivery (SDD) online shopping on local shopping travel to stores using the quasi-longitudinal analyses and cross-sectional analysis. Differing outcomes were found, as the quasi-longitudinal analyses showed a substitution effect, while the cross-sectional analysis showed a complementarity effect. It was argued that the quasi-longitudinal analysis is a superior approach because it accounts for influences of time-invariant confounding factors, whereas the cross-sectional approach has the intrinsic limitation in addressing time precedence and spurious relationships. Thus, the observed positive associations in cross-sectional analyses may be explained by shopping channel diversification. The major difficulty, however, in using the longitudinal analysis is the expensive and time-consuming nature of the approach.

2.4 Summary of Literature

Progress has been made in the quest to understand the associations between online shopping and in-store shopping but determining whether online shopping exhibits a substitution or complementarity effect on in-store shopping is notably complex. First, a wide range of factors have been found to influence shopping behavior, including socio-demographic characteristics (such as age, gender, income, education, employment, car ownership, and household characteristics), Internet usage and experience, spatial attributes, shopping attitude, shopping basket characteristics, channel and channel alternative characteristics, time of purchase and so on. Second, some fragments of the shopping process, such as product awareness, information search, product trial, purchase, delivery, pick-up, and return have been examined in relation to their effects on in-store shopping. Third, different indicator variables have been used to measure online shopping, and differences in outcomes have been found. For example, the frequency of specific online shopping activities seems to differ from the time spent shopping online in their effect on shopping trips. In-store shopping measurements in terms of frequency, trip length or distance, travel time have also been considered. Fourth, product classifications have been shown to affect shopping behavior. Classifications such as search and experience goods, daily and non-daily goods, grocery and non-grocery products, etc. yield differing effects on shopping behavior. Finally, different methodological approaches for analysis have been used, such as regression models, probit models, structural equation models, and hybrid choice models. Moreover, approaches bordering on the nature of the collected samples, namely cross-sectional and longitudinal approaches, have been shown to yield differing outcomes. Since all these factors yield differing effects and cannot all be considered independently and jointly in a single study, the effect of online shopping on in-store shopping is yet inconclusive.

2.5 Limitations and Knowledge Gaps in Literature

Although much research efforts have been made in exploring and measuring the effect of online shopping on in-store shopping, there are gaps and even recurrent recommendations from previous research works to enhance better understanding of shopping behavior. Because the longitudinal approach is expensive and time-consuming, there is a dearth of studies that have employed the approach in collecting shopping and travel data. However, exploring this approach may be beneficial as the problem of relying on shoppers' stated preference and the tendency of cross-sectional approaches to yield spurious relationships may be avoided. The longitudinal approach may also help to examine the impact of chained trips on in-store shopping impacts. Different performance measures such as frequency, travel distance or travel time alongside specific shopping activity or fragment should be explored, alongside how modal choice (i.e., foot, bicycle, personal car, or public transit), shopping basket characteristics, and time of day or week affect those chained trips.

Also, the impacts of products between different classifications have been compared, but more studies are needed in comparing products within the same classification. The share of switch shoppers, store shoppers, and online shoppers across product types should also be examined (Zhai et al., 2019), with consideration of the shopping impacts of restaurant dine in and take out. Shopping effect by shopping location, Internet use, variety of land use measures and other factors still needs exploration (Etminani-Ghasrodashti & Hamidi, 2020). Moreover, questions on the relationship between the time spent shopping online and shopping in-store are worth considering. Is there extra time saved from online shopping, and how is the extra time spent in relation to total number of trips or total distance spent travelling? All these issues and questions still require a great deal of attention in accurately determining the effect of online shopping on in-store shopping or travel behavior in general.

3 SURVEY DESIGN AND IMPLEMENTATION

3.1 Survey Design

Researchers have widely used stated preference surveys to understand people's behavior, choice, and preferences. The stated preference survey in this study has seven major components, including a) personal and household characteristics, b) purchasing behavior, c) purchasing preferences, d) mobility profile and preferences, e) preference for robot delivery, f) most frequent purchases, and g) choice experiment. This section elaborates on the details of the stated preference experiment design for this study.

3.1.1 Personal and Household Characteristics

The first part of the survey collects information about respondents' socioeconomic and demographic characteristics. This information could be used to better understand the shopping behavior among different groups of respondents. This information will also be used to implement sampling in this survey. The collected information includes age, gender, marital status, education, employment status, ethnicity, home type, household income and size, household members and age group, and home location.

3.1.2 Purchasing Behavior

In this section, respondents were asked to provide information regarding their household shopping activities. Respondents were queried about their household shopping frequency and the expenditure for different types of products for both in-store and online purchases in a thirty-day period. Eight categories of products were presented, including a) books and electronics, b) prepared food, c) grocery, d) home, garden, and tools, e) clothing, shoes, jewelry, watches, f) beauty and health, g) pet supplies, h) toy, kids, and baby. The respondents were also asked to provide the distance traveled for the products they purchased in-store. Considering the potential changes in shopping activities during the COVID-19 pandemic, we also requested participants to provide information about their shift toward online shopping for grocery and non-grocery purchases. Lastly, information about the number of returns initiated by the household in a thirty-day period was requested from the respondents. Three types of returns were incorporated in the question: a) a trip to the post office, b) picked up by a carrier, and c) return to store. This question aims to provide information about the number of trips online shoppers tend to make when returning purchased products.

3.1.3 Purchasing Preferences

People's preferences play a critical role in their decision-making process (Jin et al., 2020; Rahimi et al., 2020); hence it would be essential to capture the respondents' attitudes toward various aspects of shopping. In this regard, multiple statements about shopping preferences were introduced for each of the following aspects to better understand the people's attitude and preference. These questions were presented with a Likert scale format (alternatives: strongly disagree, disagree, indifferent, agree, strongly agree).

- Preferences for shopping methods (e.g., strolling through shopping areas is enjoyable and refreshing, I prefer buying products online because I do not have to carry them).
- Attitude toward local stores (e.g., local stores sell mostly low-quality products, local stores provide personalized services as they know the community and their needs).
- Delivery experience (e.g., I often receive damaged packages from online stores, I do not mind curbside pickup at a store).
- Social interaction (e.g., Shopping in physical stores is too stressful and tiring, because I love meeting people, I often opt to shop in real stores).
- Data security (e.g., I trust online shopping, I have heard much bad news about online shopping scams).

Moreover, a set of statements about the general lifestyle preference for shopping were presented in the survey focusing on the following aspects:

- Cost (e.g., I find it stressful waiting to find sales and special offers before buying products, I always look for the best deals
- Time (e.g., it is a good idea for other people to shop for me since I am often busy, I love to take my time when I shop)
- Convenience (e.g., I like to easily compare multiple products and their prices when shopping, Shopping online is not as convenient as shopping in person)
- Environment (e.g., I do not like too much product packaging because it wastes environmental resources, I do not think about any negative environmental impacts before driving to stores)

The statements in each subsection cover both the positive and negative views toward the concepts, as shown in the examples, and were presented in a randomized format to avoid potential bias.

The respondents were also asked to rate the importance of factors involved in choosing a store or website/application to shop from. The presented factors for in-store purchase include travel time/distance, store crowdedness, price level, other's reviews, store brand, opening and closing hours, on-site parking, and neighborhood safety. On the other hand, the presented factors for online shopping consists of comparing prices, avoid going to stores, shopping 24/7, avoid crowds, having a greater variety of choices, and finding items in high demand. Finally, a list of potential concerns for online shopping was included in the survey, and the respondents were asked to express their level of concern for each aspect.

- Possibilities of inaccurate info on the websites.

- Not being able to try or examine the item.
- Not having the item momentarily (i.e., waiting for it to ship).
- Shipping costs.
- The return processes.
- Privacy of my info.

3.1.4 Mobility Profile and Preferences

The major focus of this section is to acquire information on the respondents' current mobility profile as well as their mobility preferences. This information will help us to understand the connection between people's shopping behavior and their mobility choices.

The mobility profile subsection captures information about the number of available vehicles in the household (owned or leased), and the respondents' level of access to a private car. Considering the potential changes in the mobility profile amid pandemic, the survey also presented questions about trip frequency before and after the COVID 19 pandemic. The presented modes include a) private vehicle, b) transit, c) taxi, ridesourcing, car sharing, and d) walk, bike, scooter and mopeds.

Regarding mobility preferences, respondents were presented with multiple statements about the preference for different mobility options, including transit, shared mobility, and private vehicle, and were asked to select the option that best fits their attitude or personality. These statements covered different aspects of the travelers' attitude toward mobility options such as cost, convenience, reliability, safety, privacy, and time efficiency.

3.1.5 Preference for Robot Delivery

The major focus of this section is to acquire information on the respondents' inclination to receive their grocery or food purchases by a driverless car (robot delivery), as shown in Figure 1. The respondents were also asked to express their opinion about technology and automation, as shown in the following examples using a Liker scale format.

- Attitudes toward technology (e.g., without technology, my life would be boring, I have had too many frustrating experiences while using new technology).
- Attitudes toward automation (e.g., robot delivery would be safer and more reliable than human delivery, I do not like using robotic delivery due to the potential impact on the job market).

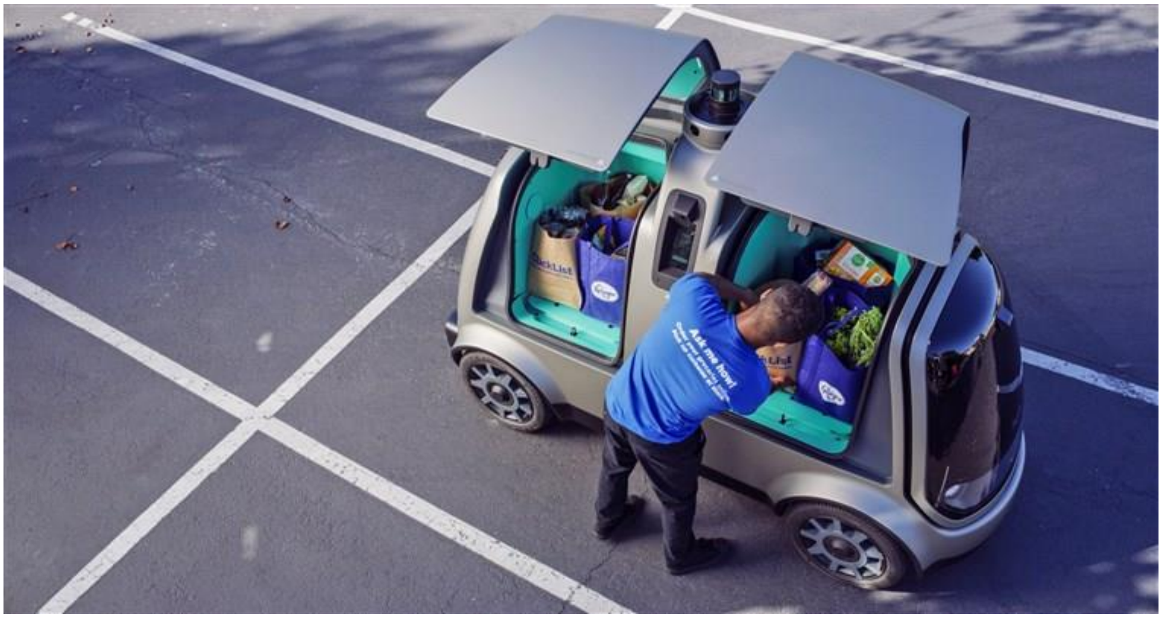


Figure 1. **A prototype driverless car for contactless delivery**

3.1.6 Most Frequent Purchases

The major focus of this section is to collect information about households' most frequent grocery and non-grocery trips. The questions in this section focused on the shopping type (in-store or online), shopping cost and shopping time as well as the delivery time and the delivery cost. For those selecting in-store as their most frequent purchasing method, three additional questions were presented about the mode of travel, travel time, and trip distance.

3.1.7 Choice Experiment

The choice experiment is a quantitative technique for obtaining people's preferences. In this approach, a set of hypothetical scenarios needs to be developed. Respondents will be asked to select their preferred option based on each scenario's attributes. The choice experiment method has been widely used in transportation literature and provided valuable insights for researchers (Azimi et al., 2020; Schmid et al., 2016).

The scenarios in a choice experiment can be described with two components: attributes and levels. Attributes are the variable that defines different alternatives while the levels are the values that describe a specific attribute. After identifying the alternatives and their associated attributes and levels, researchers need to combine these components and create the choice sets. A choice experiment design with a list of all possible choice sets is called the full factorial design. Considering the number of alternatives and attributes, it might not be feasible to present the full factorial design to the respondents and ask them to select their preferred option. For example, considering two alternatives and four attributes, each with three levels, a full factorial design includes (81×80)/2 = 3,240 choice sets.

An alternative approach would be the fractional factorial design, which includes a selected number of choice sets from the full factorial design. The statistical efficiency of a fractional factorial design could be evaluated using D-efficiency criteria, which is a function of the variances and covariances of the parameter estimates. The modified Fedorov algorithm can be used to improve the design by iteratively maximizing the D-efficiency (Carlsson & Martinsson, 2003; Zwerina et al., 2010).

In this study, two sets of choice experiments were presented to the respondents to understand their shopping method preferences. In the first-choice experiments, the respondents were asked to select their preferred grocery shopping method, and the second experiment focused on the non-grocery (durable goods) shopping behavior.

Three different alternatives were introduced to the respondents: in-store purchase, online purchase, and curbside pickup purchase. In the first option, individuals need to travel to a store, experience the products, and decide on buying the products right away. In the online purchase alternative, the respondent needs to search for products online and place the order. The products will be received a few hours or days later, plus (often) an additional delivery cost. In the last alternative, the person needs to place the order online and pick up the products at their convenient time, without the need to wait for the products to be delivered or spend time collecting the items at the store. There may be a delivery cost involved, but often cheaper than the online purchase. These alternatives were described with different attributes, including travel time (travel time to the store), travel cost, delivery time, delivery cost, shopping cost, and shopping time (the time spent in-store or searching online and purchasing the products). Tables 1 and 2 present each alternative’s attributes and levels for grocery and non-grocery shopping scenarios, respectively.

In the survey design, two constraints were added to grocery and non-grocery shopping scenarios to ensure the choice experiment’s rationality. In the first constraint, the travel time for in-store and curbside pickup alternatives was equal, meaning that stores provide both options to the respondents. In the second constraint, the shopping time for online and curbside pickup alternatives was set to be equal. The time to search and place the order online should not be different based on the type of delivery.

Respondents were assigned to different choice experiments for grocery and non-grocery scenarios based on their reported shopping cost in the Purchasing Behavior section. In this regard, three base values were included for the shopping cost (as shown in the tables). The delivery cost was also customized based on these base values.

Table 1. Attributes and Levels for the Grocery Shopping Scenarios

Attribute	Alternatives			Levels
	Home delivery	**Curbside pickup**	**In-store**	
Travel time (min)		✓	✓	-25%, 0, +25% (Base value: 20 min)
Delivery time	✓			6-8 hr., Same day, Next day
Shopping Cost	✓	✓	✓	-10%, 0, 10% (Base values: $50, $100, $200)
Delivery cost	✓			$3, $5, $7 (For shopping cost of $50) $7, $9, $11 (For shopping cost of $100) $11, $13, $15 (For shopping cost of $200)
Delivery cost		✓		$2, $4, $6 (For shopping cost of $50) $6, $8, $10 (For shopping cost of $100) $10, $12, $14 (For shopping cost of $200)
Shopping Time (min)	✓	✓		-20%, - 10%, +5% (Base value: 30 min)
Shopping Time (min)			✓	-10%, 0, 15% (Base value: 30 min)

Table 2. Attributes and Levels for the Non-Grocery Shopping Scenarios

Attribute	Alternatives			Levels
	Home delivery	**Curbside pickup**	**In-store**	
Travel time (min)		✓	✓	-25%, 0, +25% (Base value: 40 min)
Delivery time	✓			Next day, 2-3 days, 1-week
Shopping Cost	✓	✓	✓	-10%, 0, 10% (Base values: $100, $300, $750)
Delivery cost	✓			$0, $3, $5 (For shopping cost of $100) $0, $5, $7 (For shopping cost of $300) $0, $7, $9 (For shopping cost of $750)
Delivery cost		✓		$0, $2, $4 (For shopping cost of $100) $0, $4, $6 (For shopping cost of $300) $0, $6, $8 (For shopping cost of $750)
Shopping Time (min)	✓	✓		-20%, - 10%, +5% (Base value: 45 min)
Shopping Time (min)			✓	-10%, 0, 15% (Base value: 45 min)

	Online	Curbside	In-store
Product price	$45	$55	$50
Ordering time / Shopping time	27 mins	27 mins	35 mins
Delivery time	6-8 hr delivery	-	-
Travel time (both ways)	-	20 mins	20 mins
Delivery cost	$3	$6	-

Which option would you choose?

- ○ Online
- ○ Curbside
- ○ In-store

Figure 2. Example of a choice situation for grocery purchase.

	Online	Curbside	In-store
Product price	$675	$825	$750
Ordering time / Shopping time	41 mins	41 mins	52 mins
Delivery time	Next-day delivery	-	-
Travel time (both ways)	-	40 mins	40 mins
Delivery cost	$0	$8	-

Which option would you choose?

- ○ Online
- ○ Curbside
- ○ In-store

Figure 3. Example of a choice situation for non-grocery purchase.

The choice experiments were designed using a modified Fedorov algorithm (Carlsson and Martinsson, 2003). Twenty-one scenarios were created for each experiment (grocery or non-grocery) and each shopping cost segment (e.g., $100, $300, $750 for the grocery experiment). These scenarios were segmented into three blocks, each with seven situations. In total, the choice experiments consist of sixty-three grocery and sixty-three non-grocery scenarios. The respondents were assigned to only one block for the grocery experiment and one block for the non-grocery experiment based on their reported shopping cost. The assignment of the blocks and the order of scenarios in each block were set to be randomized. Examples of the choice experiment in the survey were shown in Figure 2 and Figure 3.

3.2 Survey Implementation

The survey firm that was chosen and used to implement the survey is Qualtrics. The firm uses its cloud-based survey tool/software to design, distribute, and analyze web-based surveys (Qualtrics, 2021). Qualtrics survey tool has been widely used in academic research due to its advantages over many other tools. Some of its advantages are that it has user-friendly drag-and-drop software interface, a large array of options for presenting questions, advanced conditional logic and branching tools, and the ability to score and evaluate survey questions. It allows fielding surveys with any target audience from among their 90 million panel respondents. Comprehensive profile information of respondents is kept allowing for sourcing of a target population suitable for research and according to the criteria set by the researcher(s). To aid survey completion, panel respondents are rewarded and incentivized through their partners, Rybbon and Tango Card. Qualtrics also allows for collaboration with multiple users on the platform, translating a survey into multiple languages, and monitoring respondents' time spent on survey questions.

A few verification questions and data checking algorithm were implemented in the survey to identify problematic responses, such as speeders, straightliners, or those who were not paying sufficient attention to the questions, etc. This ensured that the responses collected were reliable. Two waves of data collection were conducted. This allowed for the monitoring of potential changes in the wake of the Covid-19 pandemic, better quantification of last-mile demand and higher accuracy of the prediction of shopping behavior in the future.

The first wave of the survey was implemented initially for a soft launch from January 27 to January 31, 2021, to allow the research team to evaluate the survey questions, logic and results. Data collection for the first wave was from February 1 through April 19, 2021. For the second wave, data was collected from November 10 through December 13. Also, the survey was presented to Florida residents (see Appendix A) who were at least 18 years old, and in both English and Spanish.

3.3 Sample Distribution

There were over 11,000 responses recorded in Qualtrics for both waves, including responses from respondents who were ineligible, out-of-state, timed out, unsure about providing their best answers, etc. Some verification questions and data checking algorithms were implemented in the survey to ensure the collection of a high-quality data, as well as to identify and categorize problematic responses as speeders, straight-liners, or inattentive respondents. The target was 1,000 high-quality responses for each wave. With the survey estimated to be completed in approximately 25 mins, responses completed in less than 12.5 mins were excluded as "speeders", responses with only one line of an alternative in any set of attitudinal questions were truncated and excluded as "straight-liners", and respondents who incorrectly answered any of the verification questions were also truncated and excluded as "inattentives". The excluded low-quality data was further screened manually.

Although screening the dataset manually was tedious and inefficient, it was helpful to detect other ways to spot suspicious or unreliable responses unique to the dataset collected. Some of the criteria that influenced removal of responses from the low-quality data are as follows (see Appendix B for examples):

- multiple attitudinal responses speed-lined in a block
- two-way straight-lining on three or more attitudinal questions in a block (e.g., tending to select "agree" and "strongly agree")
- speeders less than 600s (including responses with logically consistent responses)
- numerical errors (e.g., number of children living in household > total household size)
- implausible patterns for selecting purchasing cost by product type
- incompatibility between purchasing frequency and purchasing cost or distance to the store (e.g., selecting "never" in purchasing some product types through a channel, and yet selecting different purchase costs through that same channel)
- other suspicious responses (e.g., sum of return frequencies "in the past month" >= 20)

The detection of patterns of unreliable responses also served as a precursor in writing an algorithm to clean the fuller datasets. The high-quality data were added to the remaining usable low-quality dataset kept after the manual screening, the data combination of which were cleaned using Python. Also, duplicate pairs based on IP Address, and socio-demographic characteristics were removed. The final datasets for the first and second wave were 2,257 and 1,747 responses, respectively.

Table 3 shows the comparison of stratification between the study sample and the 2015- 2019 ACS 5-Year Data Profile for the state of Florida (US Census Bureau, 2019). It should be noted that the US Census data for education level data is only available for people aged 25 and above, while the data for race, ethnicity, and income level have no age specification. The sample distribution among demographic groups generally follows the Census distribution profile, except for some categories, like those with less than a high school degree, and those from households earning $150,000 or more. The slight under-sampling of these groups can be attributed to the difficulty in concomitantly reaching the quotas for all the strata, considering the limitations of time and cost. The discrepancy for gender owes to the low response rate and quality of males as compared to females. However, the sample size is large enough to deal with these discrepancies without materially biasing estimates.

Table 3. Sampling Characteristics for Both Waves

Group	Variable	Sample (2257N)	Sample (1747N)	2015-2019 ACS for Florida (%)
Sex	Male	36.8	35.9	48.4
	Female	63.2	64.1	51.6
Age group	Gen Z (18-24 years)	7	12.3	6.1 (20-24)
	Millennials (25-40 years)	36	30.5	25.1 (25-44)
	Gen X (41-56 years)	25.9	25.9	13.1 (45-54)
	Younger boomers (57-66 years)	12.2	15.5	13.2 (55-64)
	Older boomers (67-75 years)	14.9	12.2	11.1 (65-74)
	Silent generation (76-99 years)	4	3.5	9 (75+)
Racial group	White	77.1	71.7	77.5
	Black or African American	13.9	18.2	14.5
	Asian	2.7	2.7	3.5
	Others	6.2	7.3	4.5
Ethnicity	Hispanic or Latino (of any race)	22.5	22.8	25.6
	Not Hispanic or Latino	77.5	77.2	74.4
Household income	Less than $15,000	11.6	13.7	10.8
	$15,000 - $24,999	10.9	11.9	9.9
	$25,000 - $34,999	11.7	16.3	10.3
	$35,000 - $49,999	15.2	16.5	13.9
	$50,000 - $74,999	19.5	19.1	18.3
	$75,000 - $99,999	11.7	11.3	12.4
	$100,000 - $149,999	13.2	8.3	13.1
	$150,000 or more	6.2	2.8	11.3
Educational attainment	Less than high school	2.4	3.4	11.8
	High school graduate	20.2	29.6	28.6
	Some college but no degree	25.4	23.2	19.9
	Associate degree (2-year)	14.3	13.5	9.8
	Bachelor's degree (4-year)	24.5	21	18.9
	Grad/post-grad/professional degree	13.1	9.4	11
Marital status	Single (Never married)	33	39.2	28.3 (F), 35 (M)
	Married	46.1	39.5	44.3 (F), 48.5(M)
	Divorced/Separated	15.6	15.6	17.1 (F), 13.2 (M)
	Widowed	5.4	5.7	10.3 (F), 3.2 (M)
Employment status	Full-time (35+ hours/week, paid)	35.9	35.3	58.8 (in labor force)
	Part-time (< 35 hours/week, paid)	8.7	10.9	
	Self-employed	8.7	7.7	
	Student/unpaid volunteer/intern	4.1	4.2	41.2 (not in labor force)
	Homemaker	7.6	6.8	
	Retired	23.2	21.8	
	Not currently employed	11.7	13.4	

4 SHOPPING PATTERNS

Survey respondents were asked about their household's shopping behavior "in the past month." In other words, the data for the first wave reflected shopping patterns during the months of January to March 2021. Note that this was when a state of emergency was still in place (which expired June 26), social distance measures were still in play (restrictions were lifted July 1), and vaccines gradually became available to certain segments of the population in Florida. We refer to this period as the early transition phase to normalcy – businesses and schools were not fully back to pre-pandemic operations, and telecommunications still played a significant role in people's daily activities.

For the second wave, shopping patterns are reflected for the months of October to November 2021. Widespread vaccination marks this period, as almost 200 million Americans had been fully vaccinated around the middle of October, compared to the beginning of February when less than eight million Americans had been fully vaccinated (Mathieu et al., 2021). It could be conjectured that shoppers had become more comfortable in returning to their normal shopping patterns or at least formed more stable shopping patterns than the preceding months.

This section provides a detailed shopping pattern analysis focusing on the weighted data obtained through the first wave of data collection, and a comparison between the first and the second wave. Specifically, we describe general shopping patterns (purchase frequency, expenditure, and shopping trip distance by product type), shopping patterns and attitudes by the sociodemographic variables (such as age, gender, and income), and attitudes between online and in-store shoppers. All the hundreds of graphs that were created will not be presented for the sake of space and relevance. Thus, the few graphs presented were selected for their higher relevance and to be somewhat representative examples of the trends between the two waves.

4.1 Purchase Frequency

First Wave

Figure 4 shows that in-store shopping frequency slightly exceeded online shopping frequency in general, except for books and electronics. People tended to shop online more often for clothes, shoes, jewelry, and beauty & health than other products. In-store shopping for groceries and prepared food was the dominant mode for most people – about 94% of the respondents made at least one grocery shopping trip in the past month, while only 43% made online purchases for groceries.

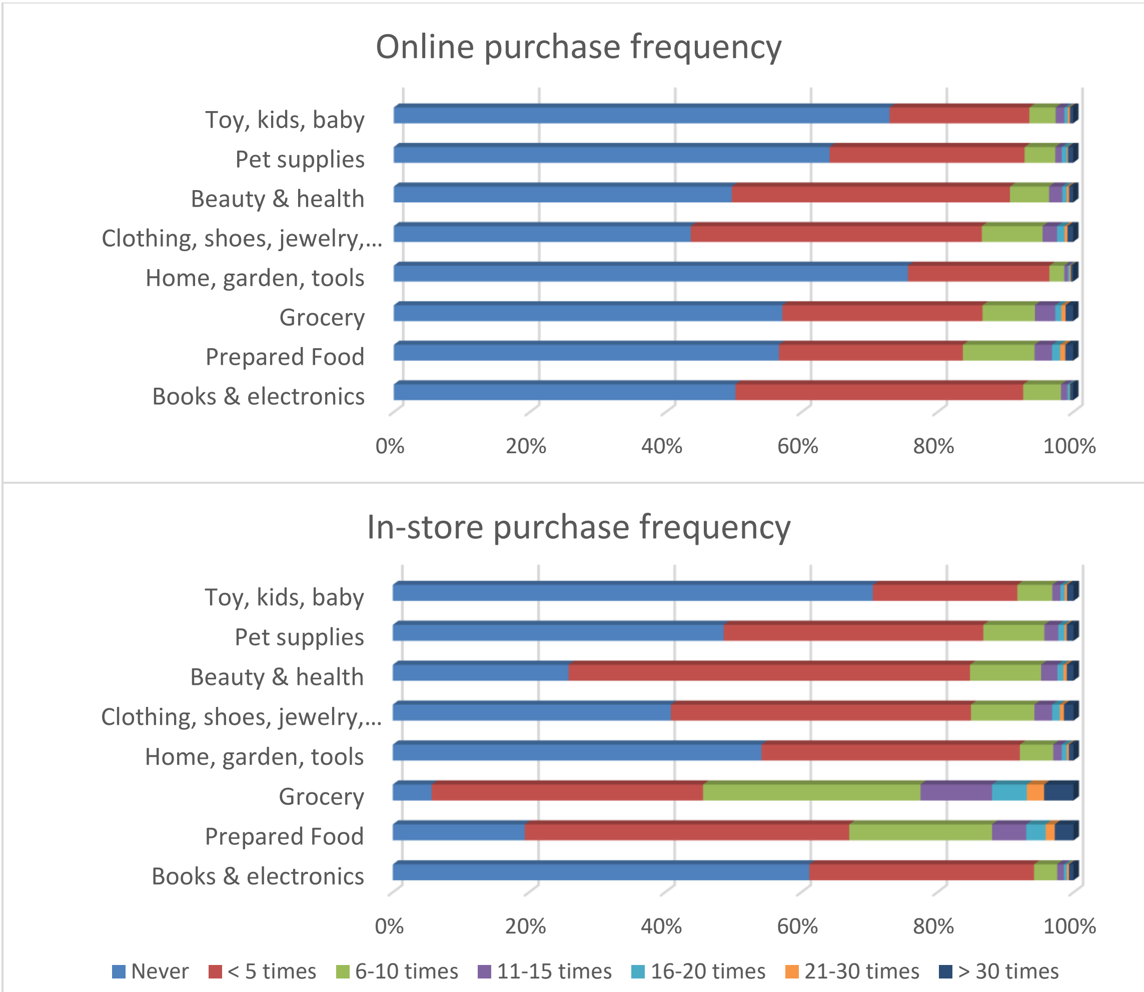


Figure 4. Online and in-store purchase frequency by product type in the past month.

To further understand how purchase frequency may differ by demographic attributes, crosstabulations were produced for purchase frequency by age, gender, and income. Figures 5 through 7 present the shopping frequency by age, gender, and income. In terms of age, older adults (age 55 and above) showed significantly less shopping frequency than other age groups both online and in-store for all product types, as shown in Figure a in the Appendix. Across the categories, about 50% to 85% of those aged 55 and above had not made one purchase in the past month. The only exception is perhaps in-store grocery shopping.

Looking at shopping frequency by gender, females had higher shopping frequency both online and in-store for "clothing, shoes, jewelry, watches", "beauty & health", and "toys, kid, baby" compared to males, while males were more likely to shop for "home, garden, and tools". The gender differences were more prevalent for online purchases, especially for clothing, shoes, jewelry, and beauty and health. Interestingly, income does not seem to affect in-store shopping frequency, but positively affected online shopping frequency for all product types. Those with household income of $100,000 or more made significantly more online purchases than the other individuals.

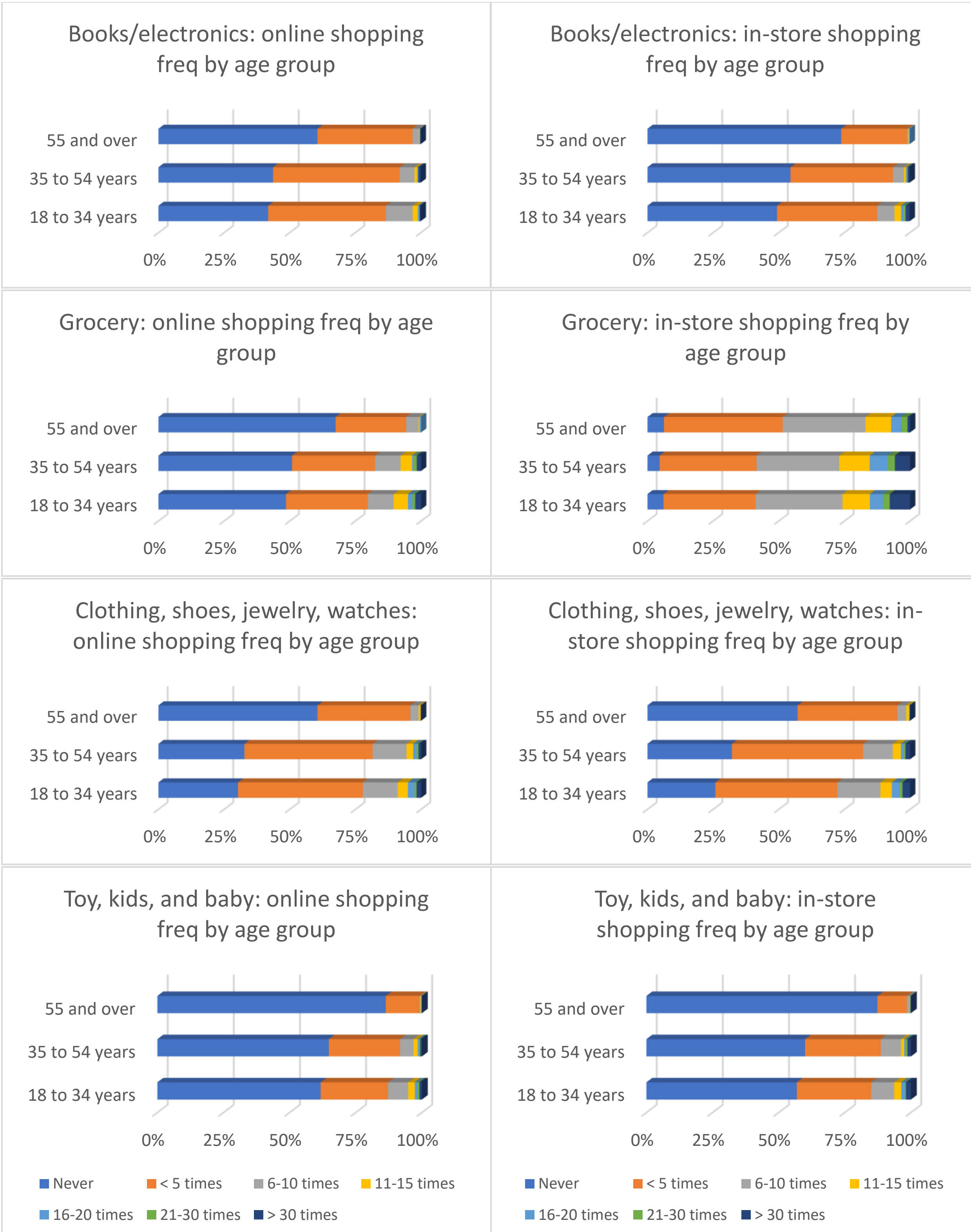


Figure 5. Shopping frequency by age group for selected product types.

Figure 6. Purchase frequency by gender for selected product categories.

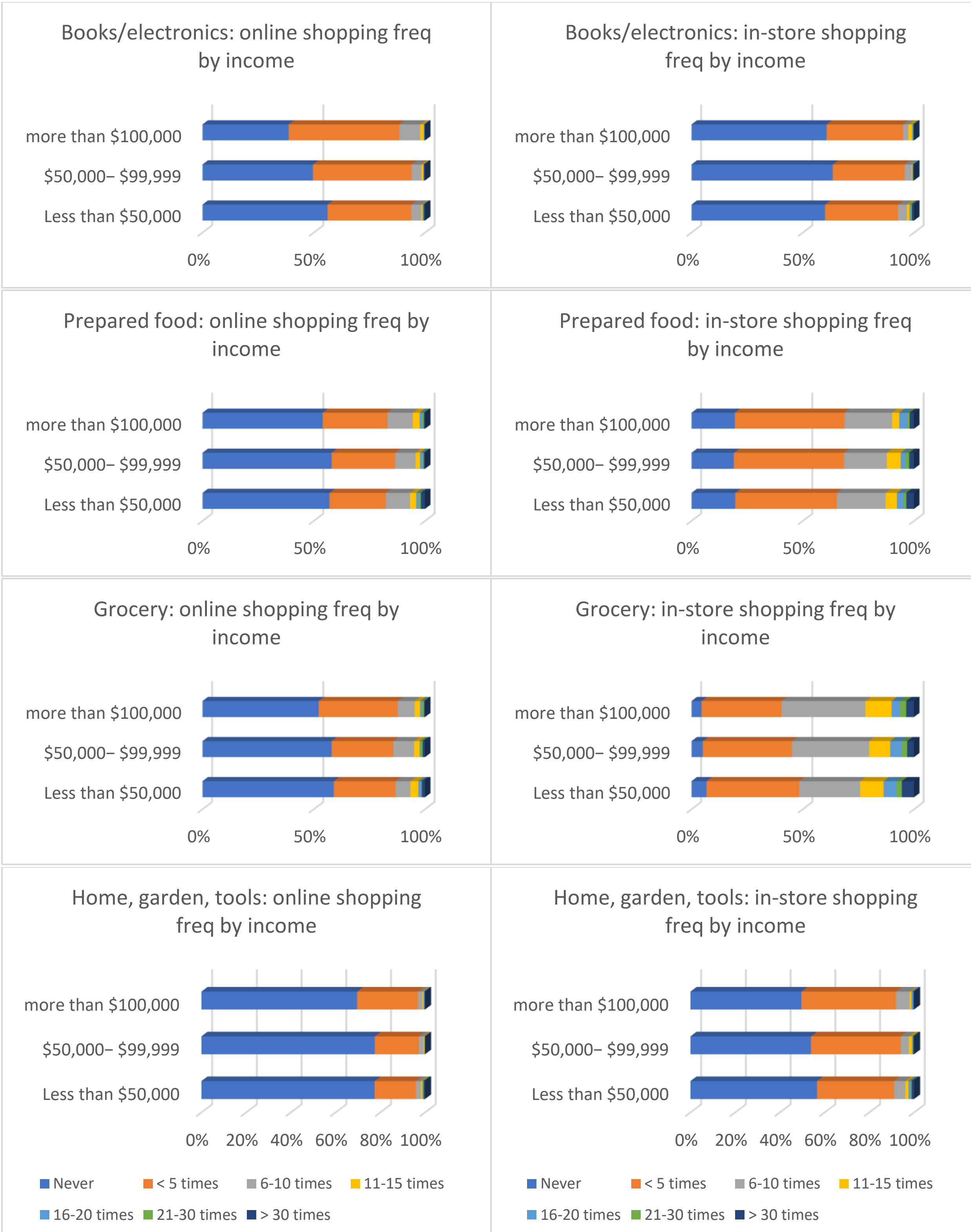


Figure 7. Shopping frequency by income for the first four product types.

Second Wave

Figure 8 shows that, generally, the purchase patterns between the first and second wave were similar. However, small changes are noticeable for some product types. Regarding online purchase patterns, the higher levels for the online purchase frequencies in shopping for CSWJ and TKB appear to be slightly larger during the second wave. This suggests that Floridians shopped more frequently online for CSWJ and TKB, over time. The reverse was the case for BE, however, as more than 50% never shopped online during the first wave but less than 50% did so during the second wave. For in-store shopping, the patterns suggest that in-store shopping frequency had increased for all the product types, especially for Gr and CSWJ.

Figure 8. Purchase frequencies for wave I (left) vs. wave II (right), weighted data

4.2 Purchase Expenditure

Figure 9 presents online and in-store purchase expenditure by product type. It shows similar patterns of monthly expenditures for online and in-store purchases. Grocery shopping showed the highest monthly expenditure for both online and in-store purchases among the eight product types, while the lowest amount of money was spent on "beauty and health" products.

When one compares the amount of money spent online versus that spent in-store, shoppers spent slightly more money for the same product categories online than in-store, except for grocery items. This is an interesting finding given that people made slightly less frequent online purchases than in-store. While information relating to the quantity or number of items purchased was not collected in this study and might have shed some light on this finding, the higher purchase cost spent online may be related to shipping cost, delivery fees, or higher product price.

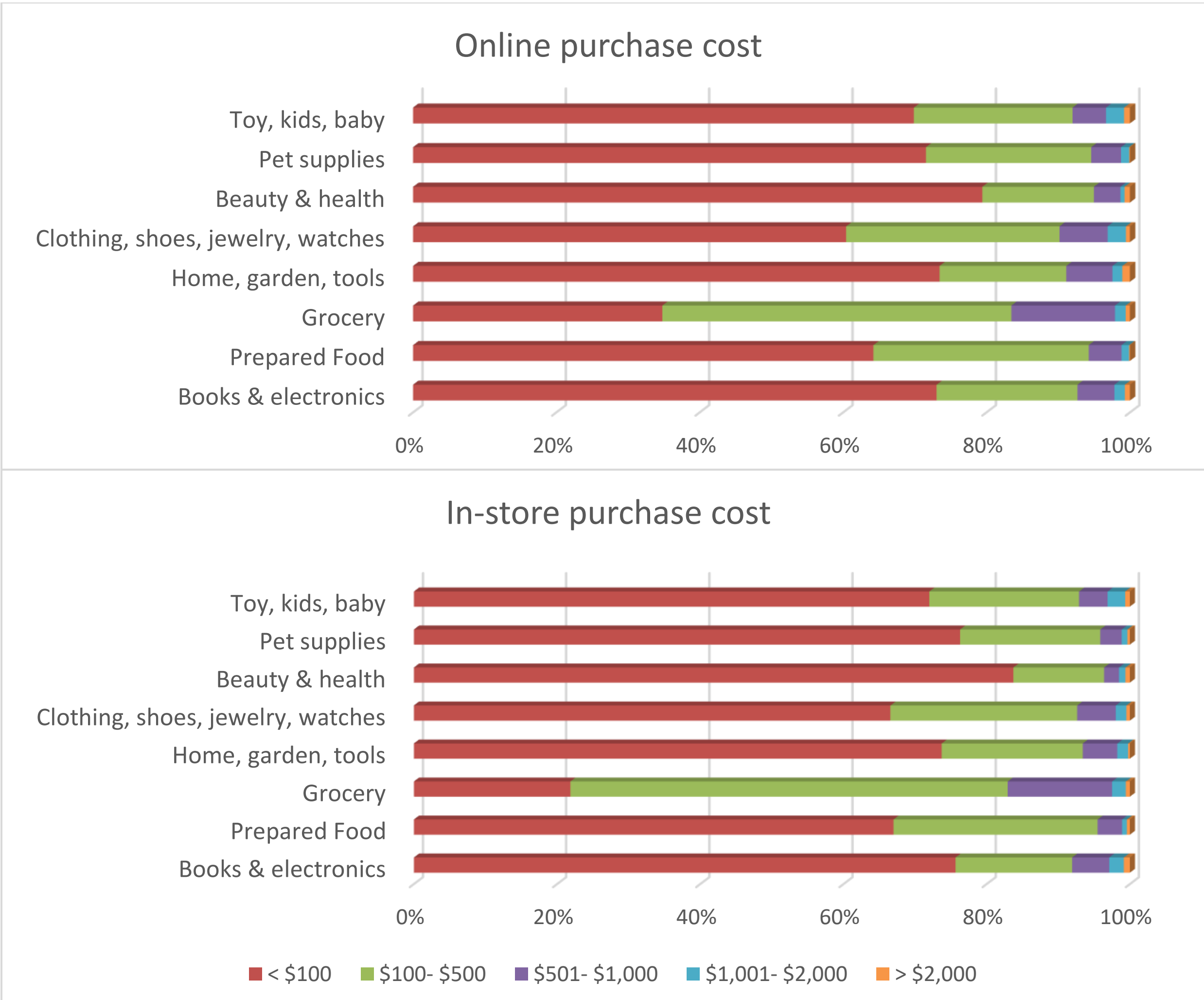


Figure 9. Online and in-store purchase expenditure by product type.

Again, further breakdown of purchase expenditure by demographic attributes was presented in figures 10 through 12. It shows that, like purchase frequency, age negatively affected online and in-store purchase expenditure for all product types, except for grocery purchase in stores, where young adults seemed to spend less than other age groups. Interestingly, males spent more money than females in both online and in-store shopping for all product types, including the product categories for which females made higher purchase frequency (that is, "clothing, shoes, jewelry, watches"; "beauty and health"; and "toys, kids and baby"). Online and in-store shopping expenditure by income showed similar patterns for all product types. In general, those with higher income ($100,000 or more) tended to spend more than other individuals both online and in store.

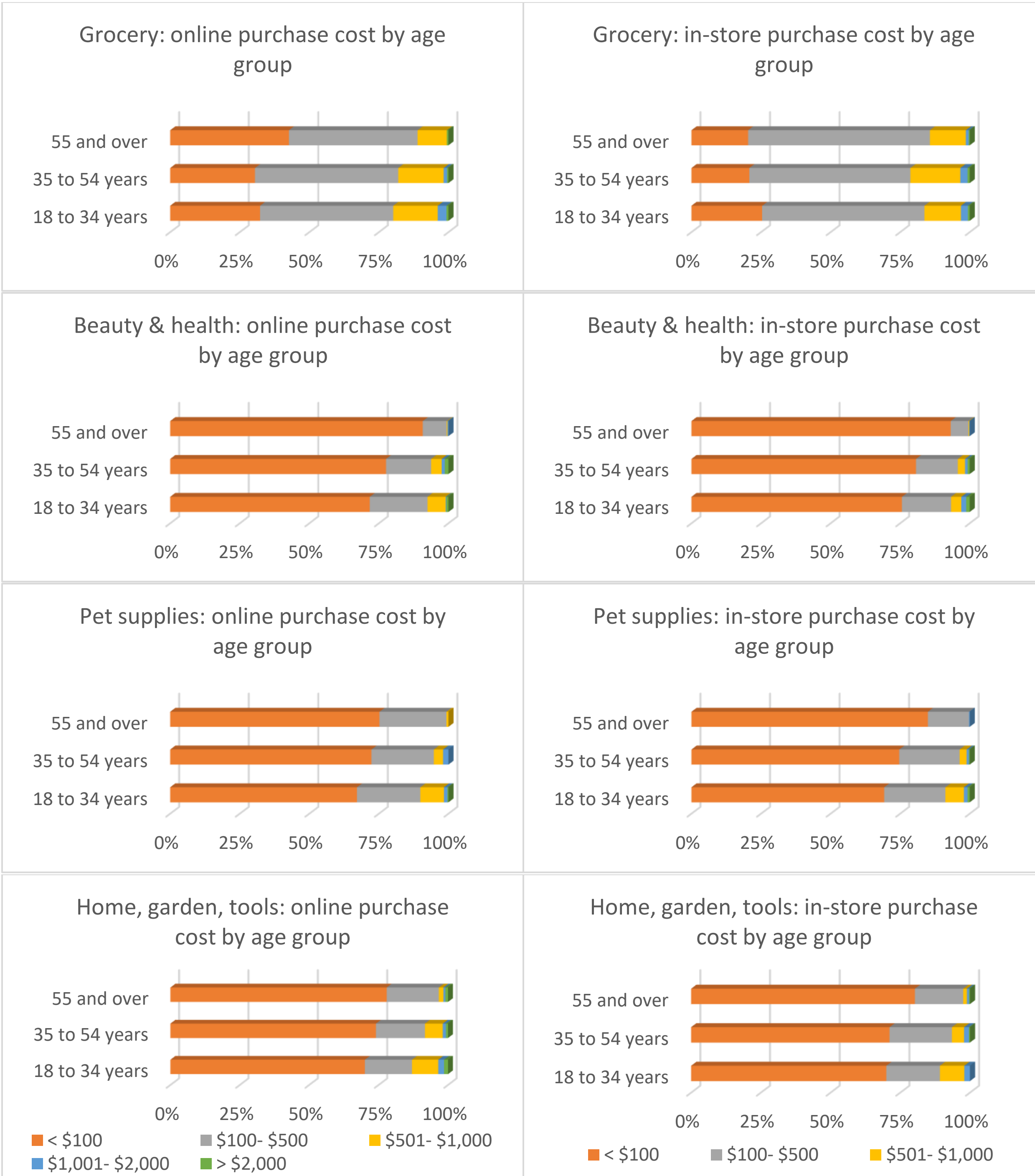


Figure 10. Purchase expenditure by age group for selected product categories.

Figure 11. Purchase expenditure by gender for selected product categories.

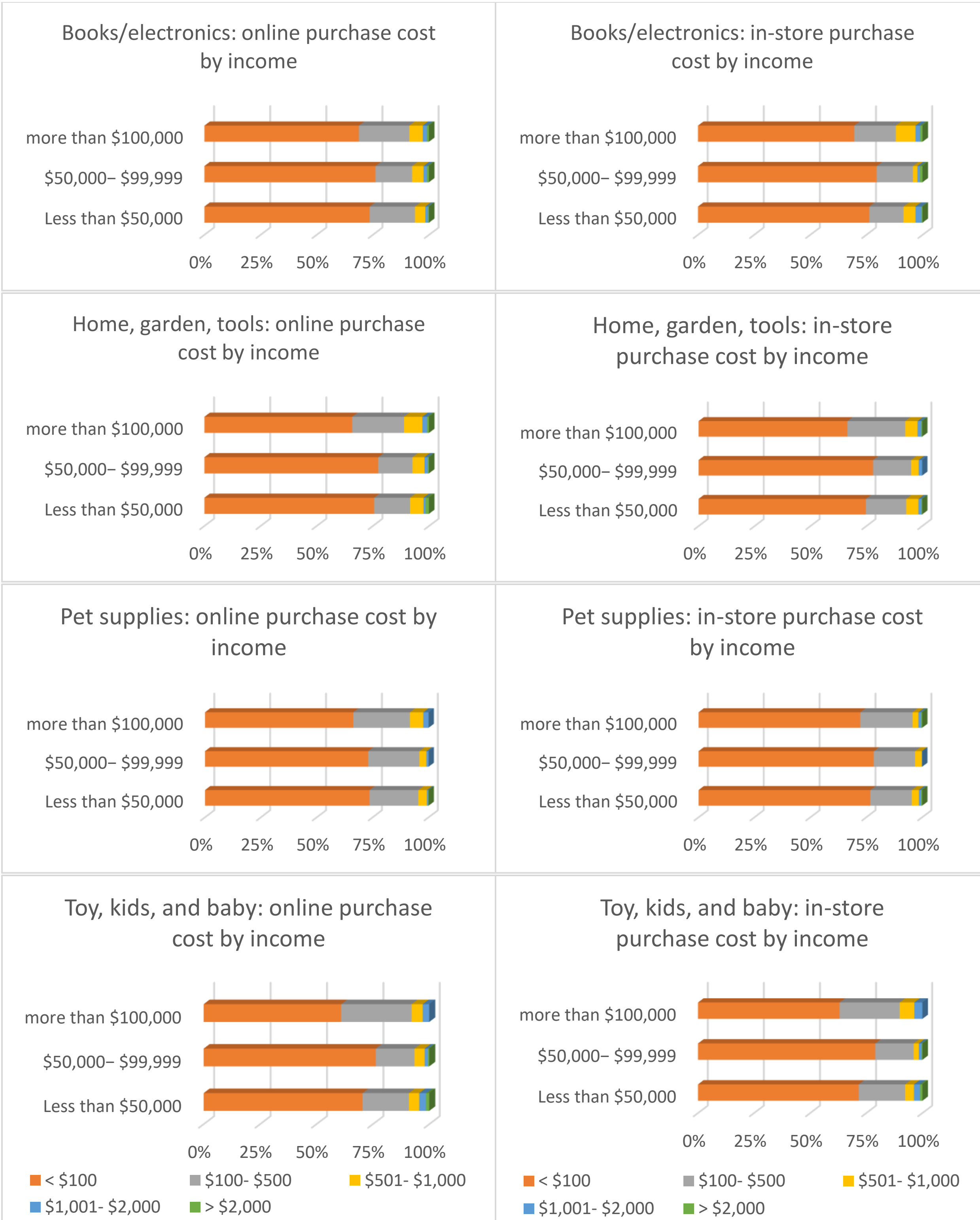


Figure 12. Purchase cost by income for selected product types.

Second wave

The patterns for shopping expenditure were consistent with that of the purchase frequencies. Shoppers spent similar amounts or slightly more in shopping online or in-store during the second wave (see Figure 13). These patterns are in line with the US statistics that indicate a relatively higher growth in in-store shopping sales in 2021 (Forbes, 2022; U.S. Census Bureau, 2022).

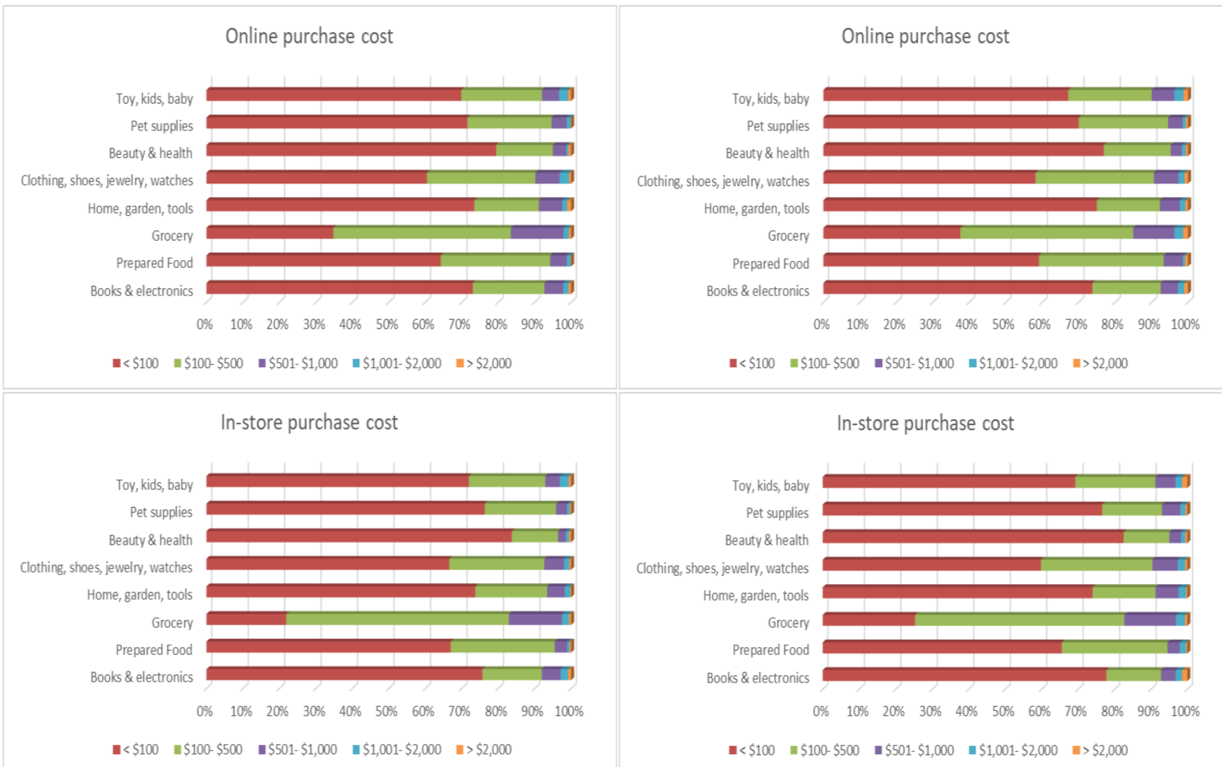


Figure 13. Shopping expenditure for wave I (left) vs. wave II (right), weighted data

4.3 Travel Distance to Store

For those who made shopping trips to the store for a specific product type, the respondents were also asked how long they usually travel to the stores. Figure 14 showed that people were more willing to travel further for "clothing, shoes, jewelry, watches", followed by "toy, kids, baby", and "books & electronics". While grocery and prepared food purchases were more likely to be within shorter distances – more than 85% of these purchases were within 10 miles.

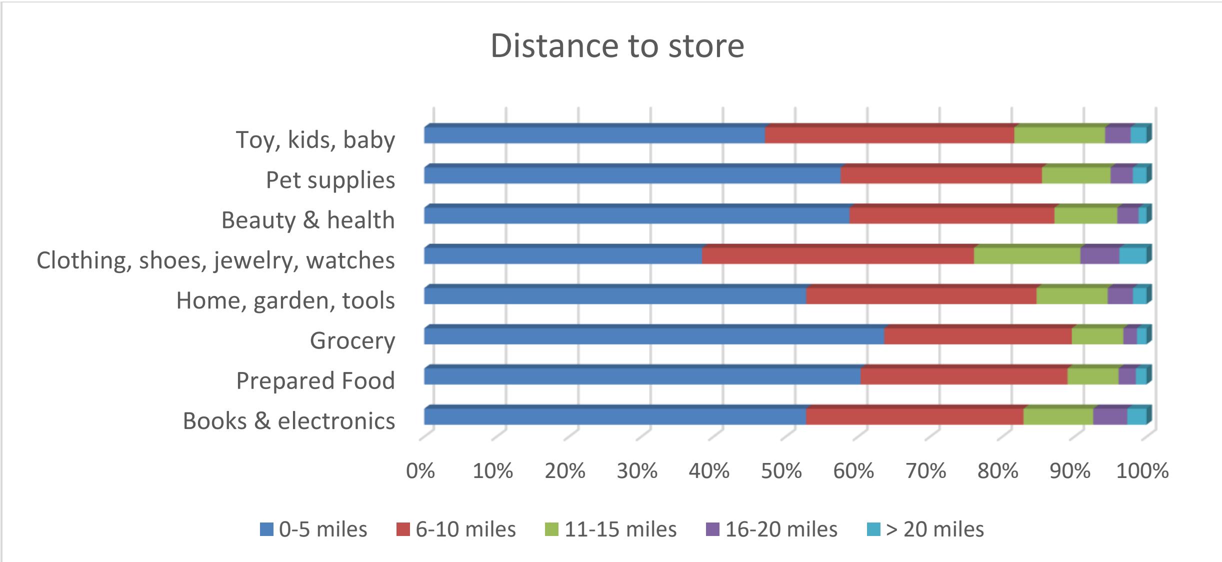


Figure 14. Distance to store by product type.

Age negatively affected travel distance to the store for all product categories, as shown in figure 15. However, one exception to this negative association between age and travel distance to store is traveling to purchase "home, garden, tools", for which middle-aged individuals traveled longer than the younger and older groups.

Like travel distance to the store by age group, shopping for "home, garden, and tools" deviated from the patterns. From figures 16 and 17, females traveled farther to the store for all product types than males, but not necessarily for "home, garden, and tools", for which there was no significant difference by gender. Income did not seem to affect shopping distance to store, except for "clothing, shoes, jewelry, watches", where high income individuals traveled further for these purchases.

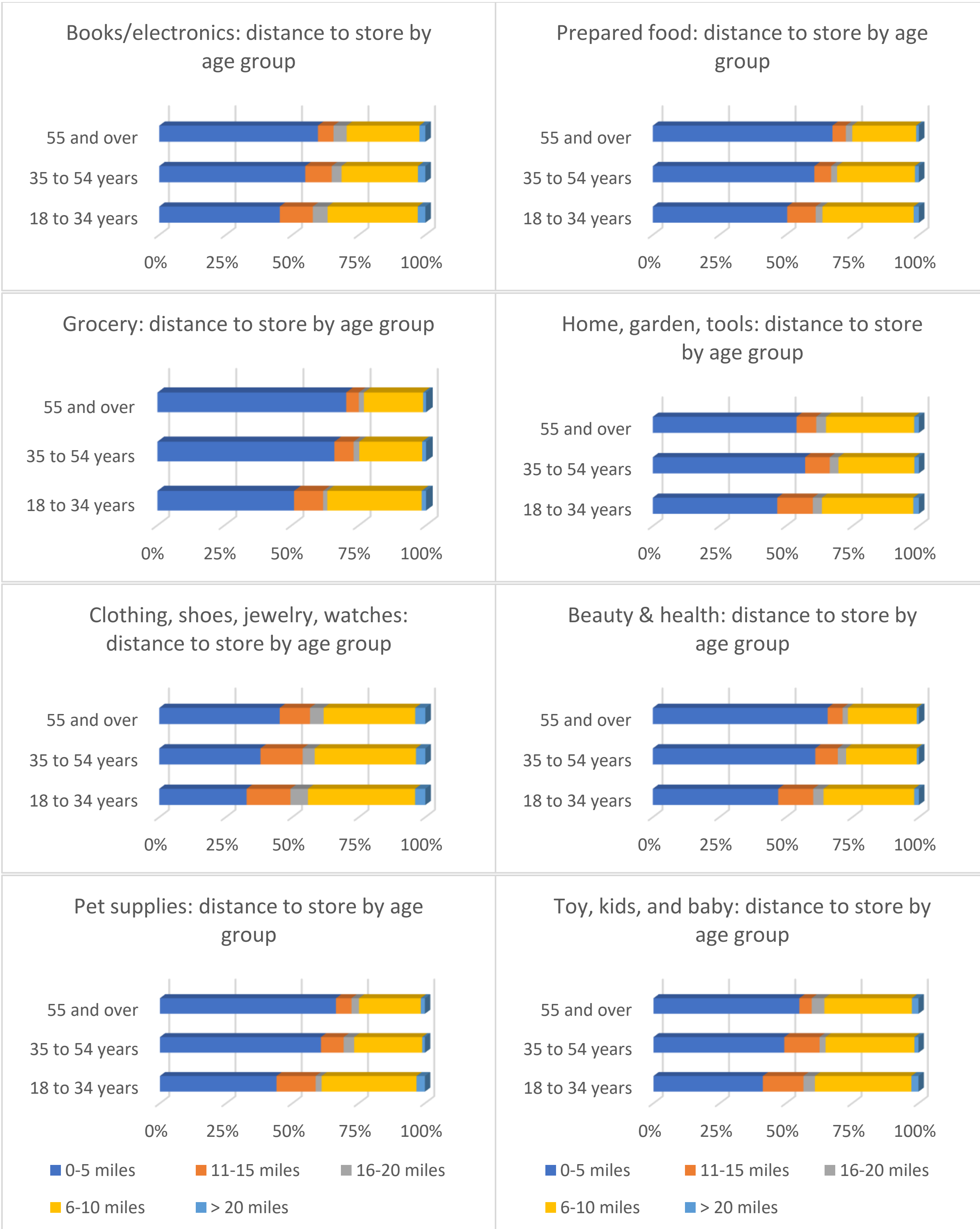


Figure 15. Distance to store by age group for product types.

Figure 16. Travel distance to store by gender.

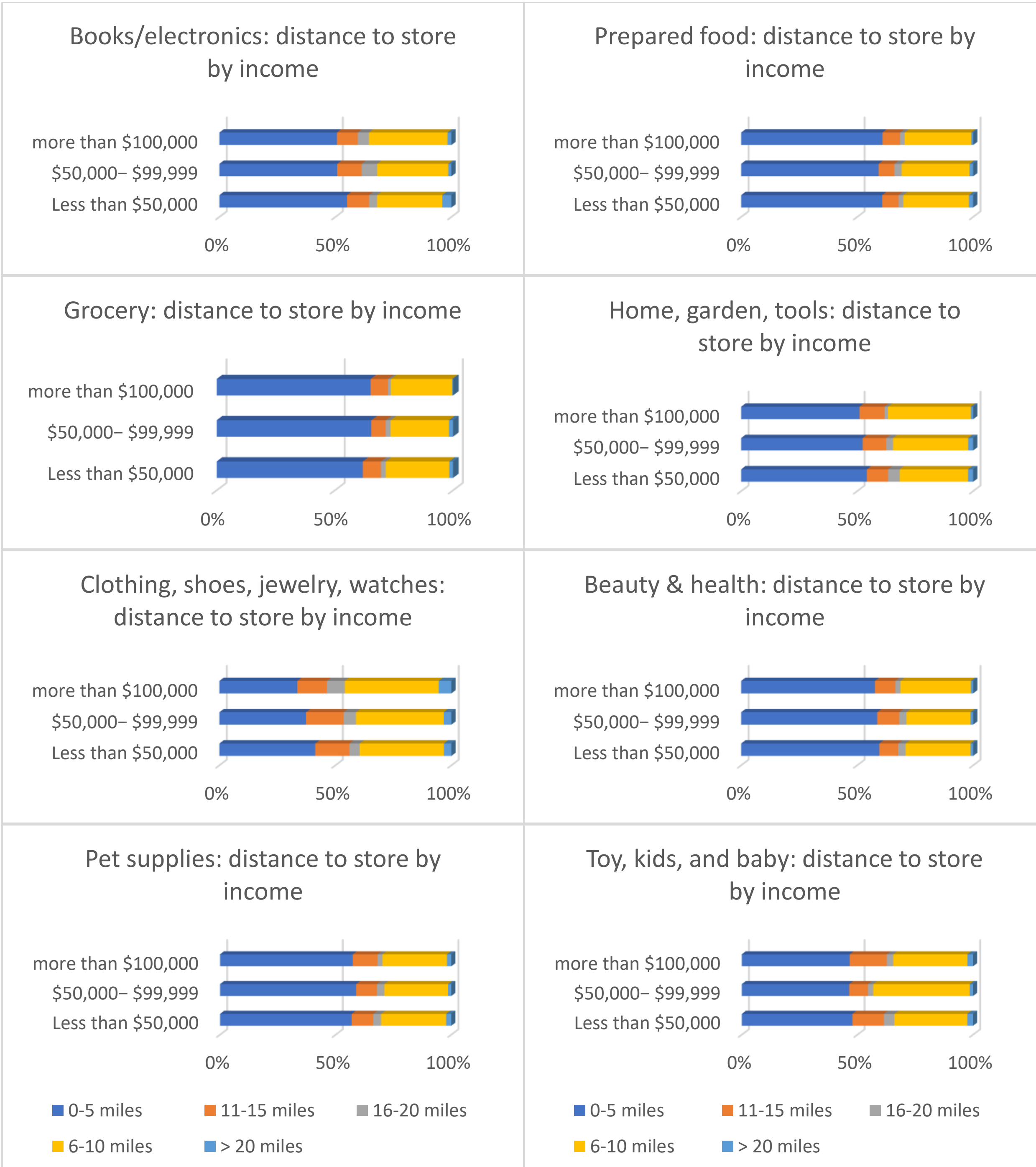


Figure 17. Travel distance to store by income.

Second Wave

Home-to-store travel distance seems not to have become necessarily higher for most product types during the second wave, as shown in Figure 18. Perhaps, shoppers stuck to their shopping destinations and tended not to explore stores relatively farther than usual.

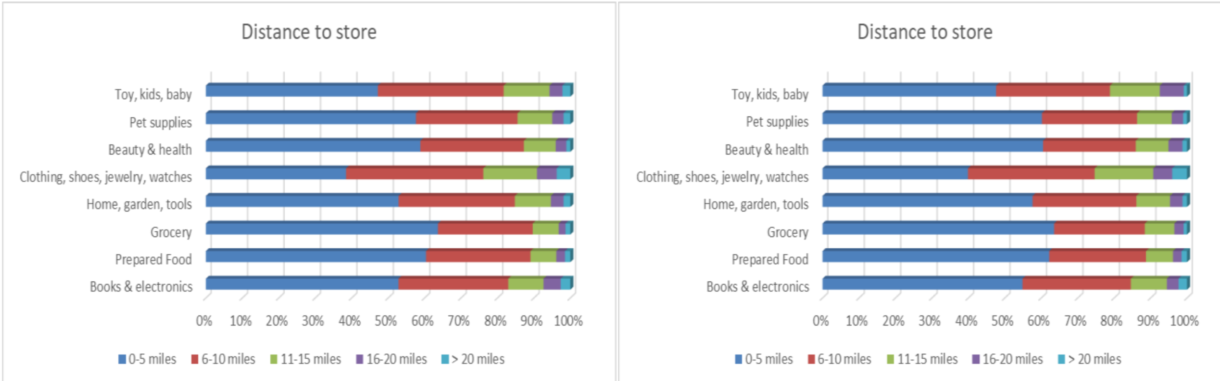


Figure 18. Home-to-store travel distance for wave I (left) vs. wave II (right), weighted data

4.4 Attitudes by SED Variables

Generally, the attitudes had by Florida residents did not change much from wave I to wave II. From the exploration of the patterns by SED variables, however, there are a few differences that are more noticeable, and are worth mentioning.

4.4.1 Tech Savviness

Compared to the first wave, Figure 19 indicates that more people encountered many frustrating experiences with using new technology, especially middle-aged, older adults, and females.

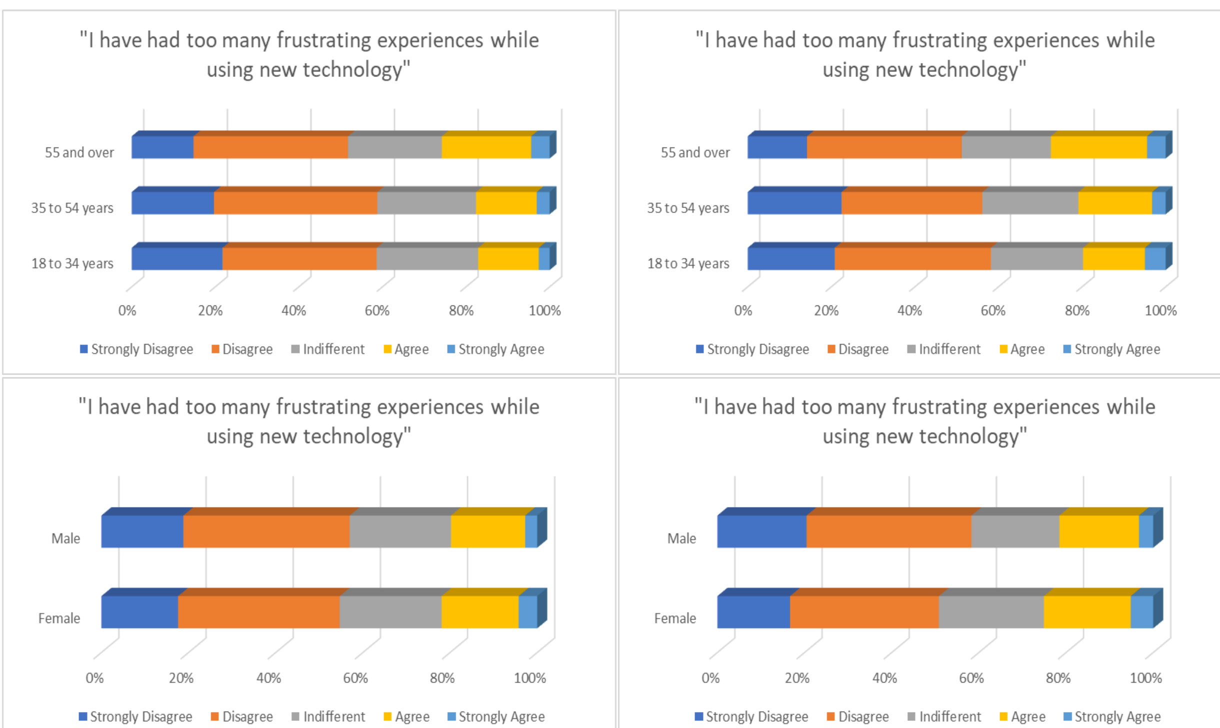


Figure 19. Differences in tech savviness for wave I (left) vs. wave II (right)

4.4.2 Data Security Concerns

From Figure 20, it appears younger individuals had become slightly more likely to think "too much personal information is required for online purchase". Less noticeable changes were seen for gender and income.

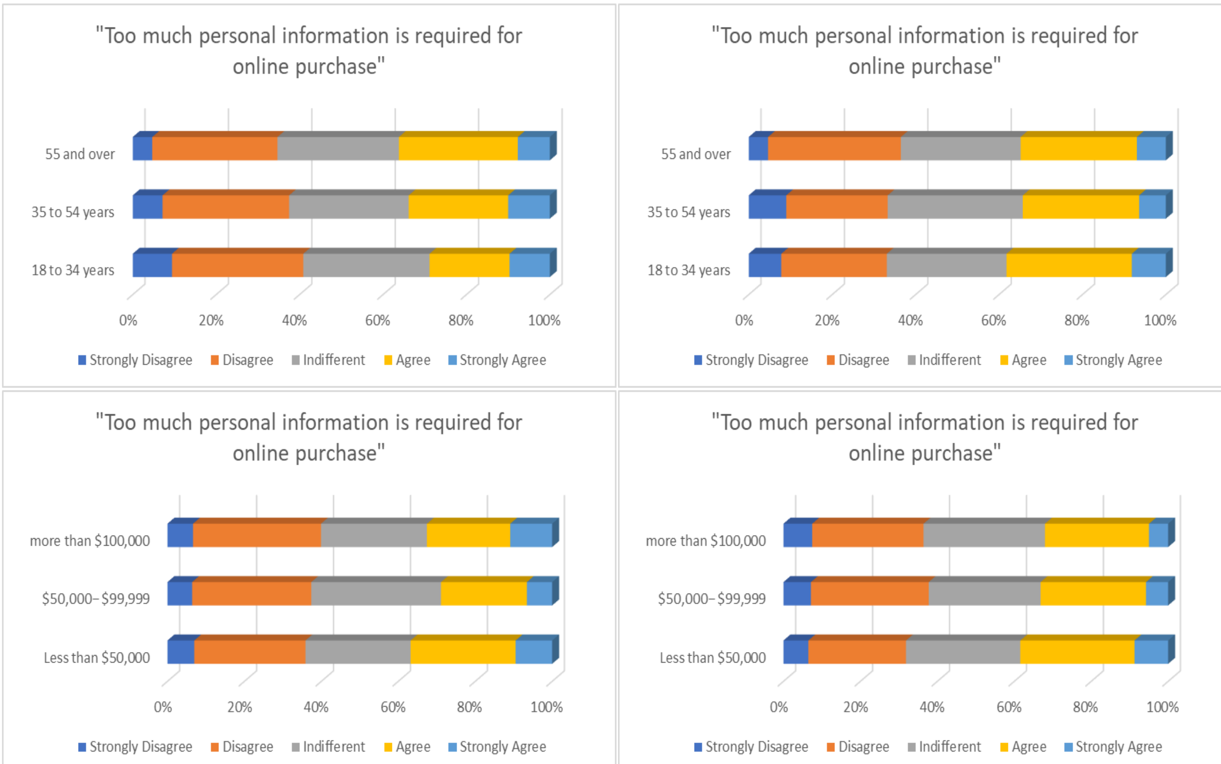


Figure 20. Differences in data concerns: wave I (left) vs. wave II (right)

4.4.3 Environment

Attitudes regarding the cost to be paid in order to preserve the environment changed slightly. Figure 21 shows that over time, more people (except perhaps, younger ones) disagreed that raising the price of gas to reduce air pollution makes sense.

4.4.4 Alternative Mobility

Figure 22 shows that the desire not to share rides with strangers slightly declined over time, though the patterns by age, gender, and income were similar. This decline may be attributed to the lessening concerns regarding contracting the Covid-19 from strangers.

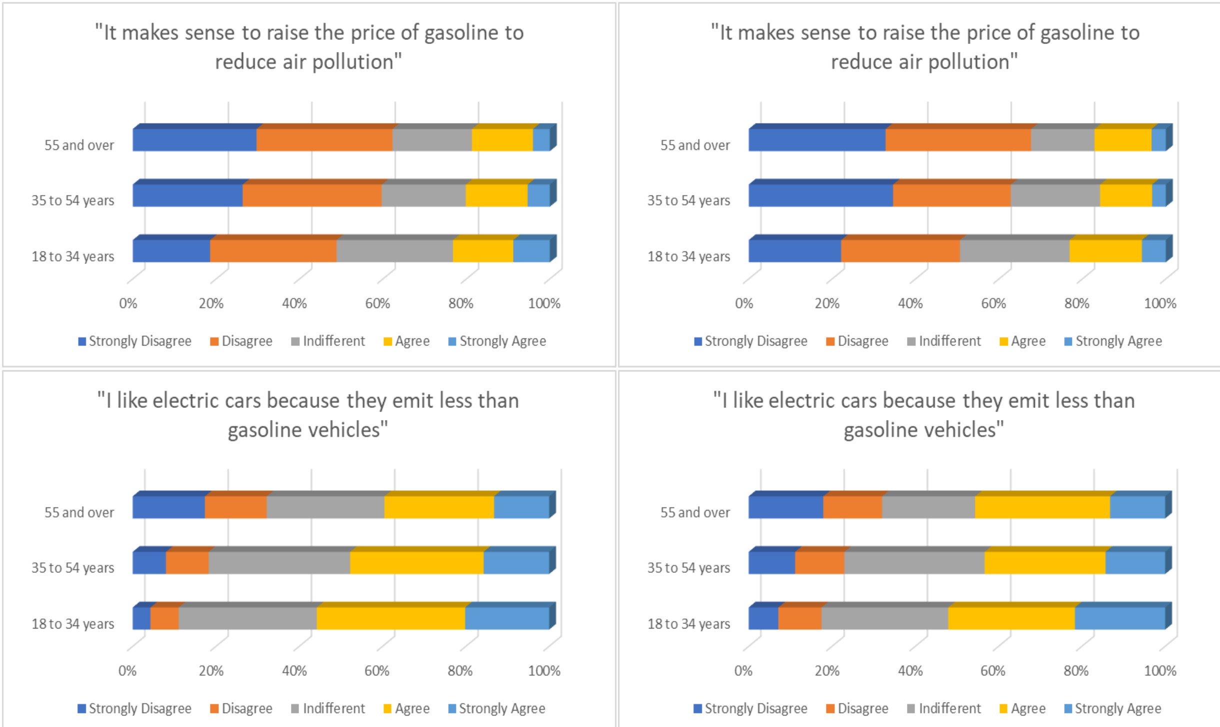


Figure 21. Differences in pro-environment attitude for wave I (left) vs. wave II (right)

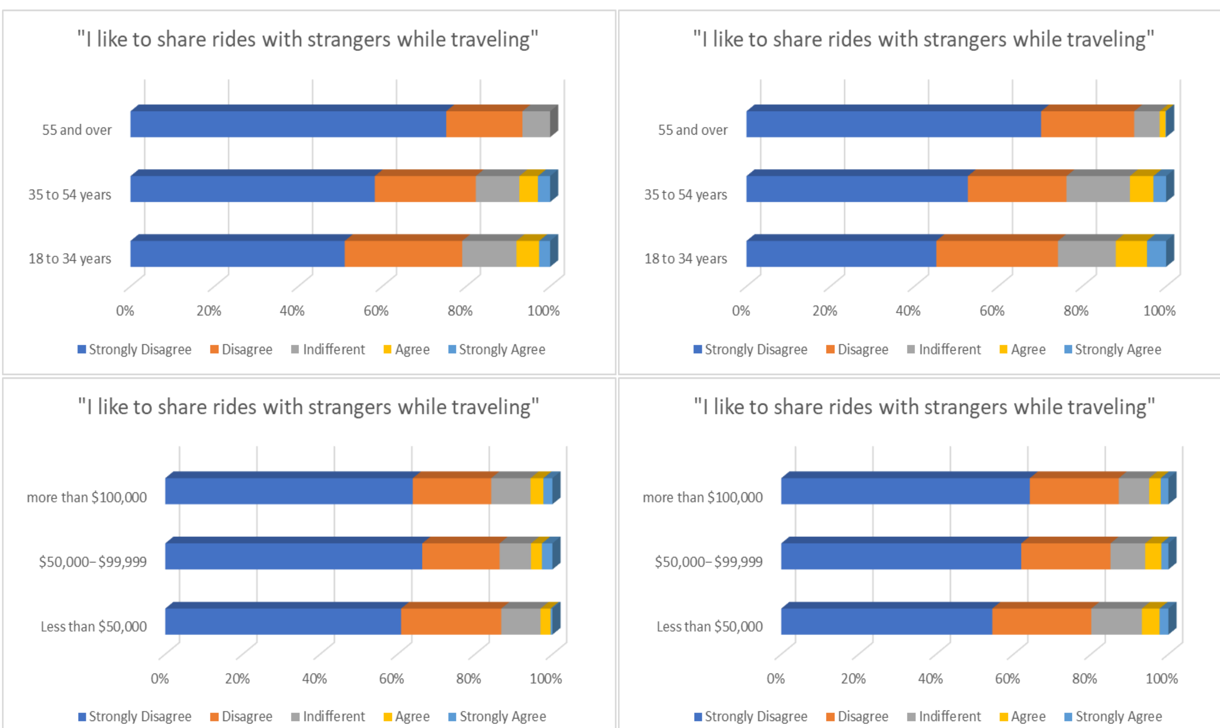


Figure 22. Differences in alternative mobility preference for wave I (left) vs. wave II (right)

4.5 Summary of Shopping Patterns

Interesting patterns of shopping behavior during the early transition phase of COVID-19 can be observed from the survey data. First and foremost, despite the trend of going digital for many other essential activities (e.g., teleworking, e-banking, online education, telemedicine, etc.), grocery and prepared-food shopping were likely to remain in stores – 94% did in-store shopping for groceries. Even when strict social distancing orders were still in place back in April 2020, more than 90% of respondents went to stores for grocery shopping (although with less frequency) and only 10% of new customers adopted online grocery shopping, based on an earlier survey conducted by the authors. This is probably due to the need to examine and pick the products in person to ensure freshness and quality of the goods. Online shopping may be suitable for some types of groceries, as more than 40% of people shopped online for groceries, it is unlikely to replace physical visits to stores for groceries.

Among other product categories, books and electronics were much more likely to be bought online. The monthly expenditures for online and in-store shopping were similar across the product categories. Moreover, older adults (age 55 and above) shopped less frequently and spent less both online and in store and were more likely to choose nearby stores compared to other age groups. Women showed higher shopping frequency for clothing, shoes, jewelry, and beauty and health products, especially online, although men spent more money than women across all product types. Interestingly, income did not affect in-store shopping frequency, but high-income individuals ($100,000 or more) seemed to shop more often online and spent more money both online and in stores. Also, shopping patterns between the first and second wave suggest little changes in the residents' shopping behavior. However, in-store shopping frequency for Gr and CSWJ had become higher in the second wave, especially for those less than 34 years and older than 55 years.

Attitudinal patterns also showed general consistency between the two waves; only the ones with more noticeable differences were presented. Specifically, slightly more females and older adults (35+) seemed to experience more frustrations with technologies, more younger individuals (34 or younger) expressed concerns about putting too much personal information for online purchase, less people agreed with raising gasoline prices to reduce air pollution except for younger adults, and the desire not to share rides with strangers decreased slightly in the second wave.

5 ATTITUDES OF ONLINE AND IN-STORE SHOPPERS

As mentioned in section 3 of this report, the survey included several sets of questions that cover various aspects of consumers' attitudes toward channel choice, technology and automation, social interaction, data security, cost consciousness, time consciousness, convenience, and the environment, etc. This section presents the main findings on respondents' attitudes and potential association with their online shopping behavior. We compared the attitudes of those who did online shopping at least once "in the past month" (online and switch shoppers) and those who did not shop online at all (in-store shoppers). For the purpose of this analysis, the former is referred to as online shoppers, and the latter referred to as in-store shoppers in this paper. Note that all analysis were based on the weighted dataset.

5.1 Technology and Automation

Respondents' attitudes in this category includes their experience and usage of technology and attitudes toward automation. Figure 23 displays some of the questions asked.

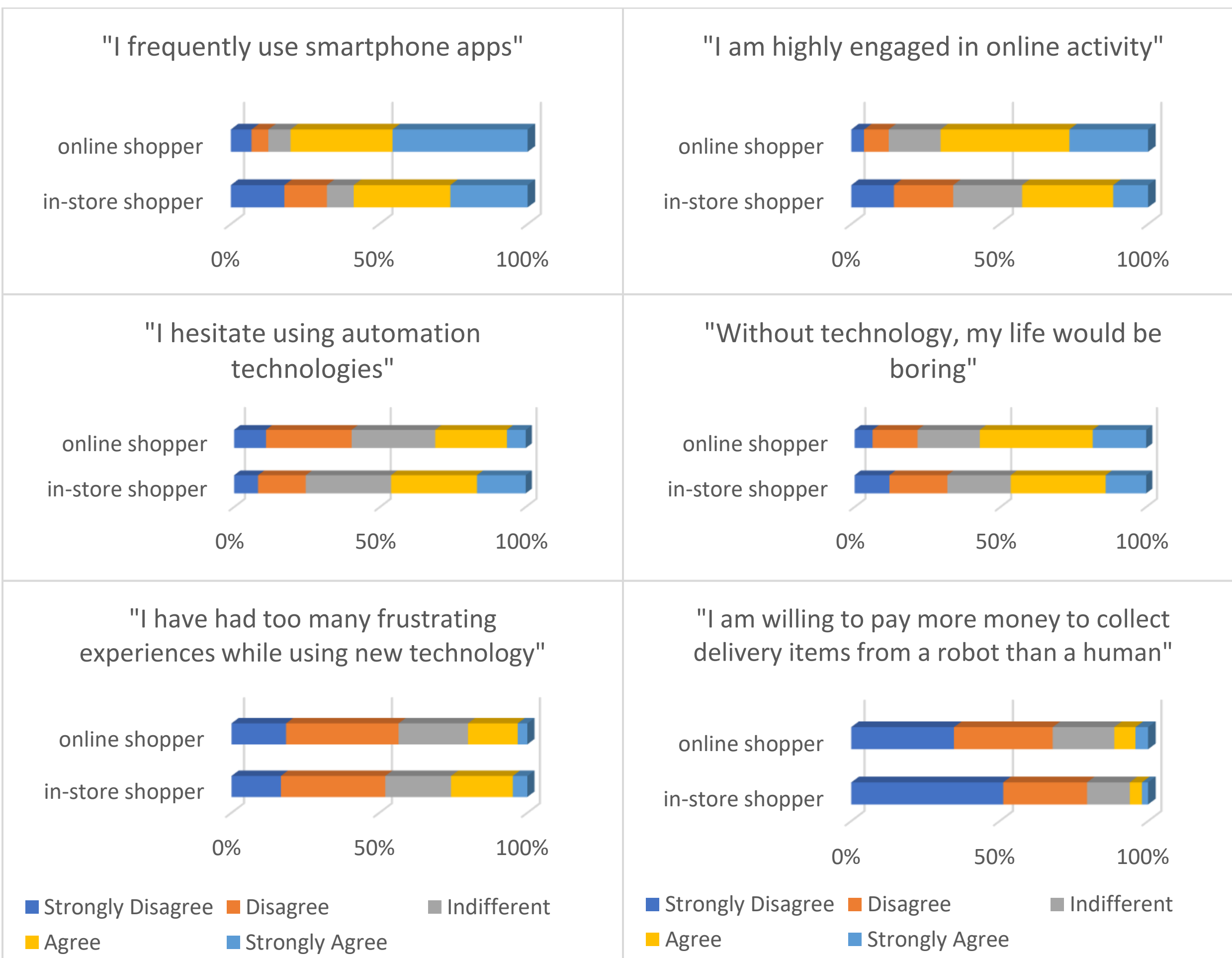


Figure 23. Attitudes toward technology and automation.

The results showed that in-store shoppers were less involved in the use of phone apps or the internet and have less favorable attitudes towards robots and automation technologies, as compared to online shoppers. There were wider differences observed in current technology usage than their past negative experiences ("had too many frustrating experiences while using new technology"). Looking into personal attributes, income did not necessarily affect the attitudes toward technology, but younger groups (54 years or younger) showed much higher usage of smartphone apps and the Internet and less frustrating experiences with using new technology.

5.2 Shopping Method and Social Interaction

Figure 24 shows the attitudes toward shopping method and social interaction. It shows that more online shoppers agreed that shopping in physical stores was "too stressful and tiring", while more in-store shoppers found shopping online inconvenient or did not fit their lifestyles. In-store shoppers were also more willing to drive to the store even in bad weather. Interestingly, both groups were equally likely to agree that "strolling through shopping areas is enjoyable and refreshing". In terms of social interaction attitudes, most people liked shopping without interacting with anyone for both online and in-store shoppers, but more so for online shoppers. In-store shoppers were more influenced by the prospect of meeting people in their choice to shop in a physical store. Being able to talk to someone before making a purchase decision did not seem to affect shopping method.

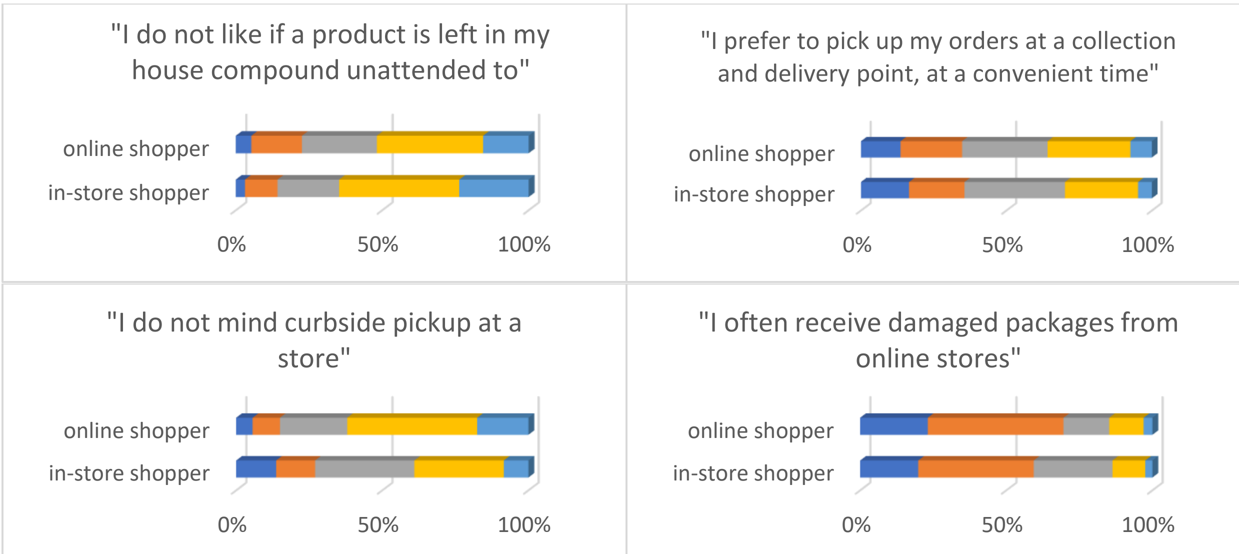
In terms of demographic attributes, older respondents (age 55 or above) tended to love meeting people in stores, were less likely to prefer uncommunicative shopping, and were less likely to find in-store shopping stressful or tiring. Surprisingly, females were more likely to find shopping in real stores stressful than males, and were less likely to choose physical stores because they love meeting people, and were less likely to find it important to talk to someone before making their final purchase decision. Again, income was not associated with attitudes toward shopping method and social interactions.

Figure 24. Attitudes toward shopping method and social interaction.

5.3 Delivery Experience and Local Stores

And as shown in Figure 25, there is no difference in how often both groups received damaged packages, although in-store shoppers tended to not like unattended delivery left in their homes or curbside pickup at a store. As regards attitudes toward local stores, most people liked purchasing from local stores because they know the people behind the business for both groups, and even more so for online shoppers. The two groups did not show significant differences in other attitudes toward local stores.

Younger respondents were more likely to not mind curbside pickup and to collect items at a collection and delivery point. Income and gender did not affect preferences for curbside and delivery point pickups, or attitudes toward local stores.



buisness

Figure 25. Attitudes toward delivery experience and local store.

5.4 Data Security Concerns

Figure 26 showed that people generally trusted online shopping, although in-store shoppers were relatively less likely to trust online shopping and online stores' websites and tended to be more concerned about putting in their personal information online, including debit and credit card information, perhaps an indication of their privacy concerns or fear of being swindled.

Older respondents (age 55 or above) were more likely to agree that too much information was required for online purchase and were more concerned about putting their debit or credit card information online. However, they were just as trusting of online shopping as the younger respondents. Gender and income did not seem to affect attitudes toward online data security concerns, although high income people were more likely to trust online shopping.

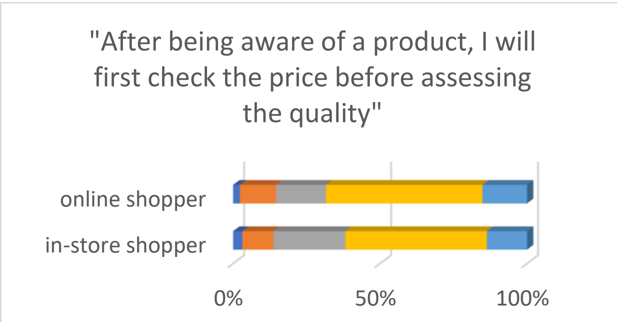
Figure 26. Attitudes toward data security.

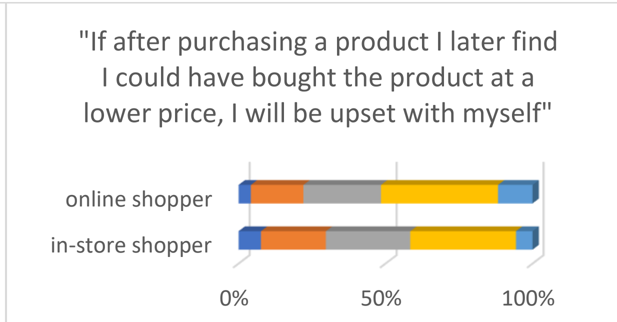
5.5 Cost Consciousness and Time-Consciousness

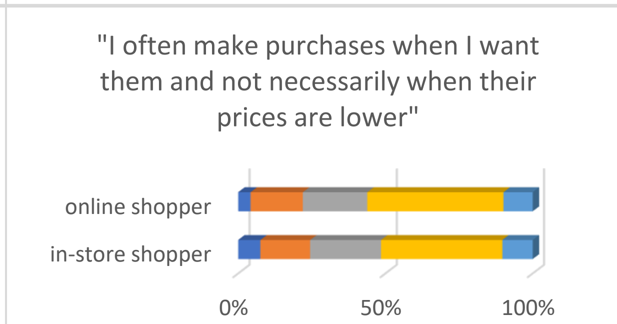
From Figure 27, respondents were generally price conscious, but that depended on how strongly the shopper wanted the product. Online shoppers were more likely to "first check the price before assessing the quality" of a product; on the other hand, they were slightly more likely to "find it stressful waiting to find sales and special offers" and "make purchases when I want them and not necessarily when their prices are lower." Younger respondents (54 or younger) tended to be more cost conscious but more likely to find it more stressful waiting for sales and special offers than older counterparts. Males did not tend to wait for sales and special offers and were slightly less price conscious than females. Income did not seem to affect cost consciousness.

Online shoppers seemed to be more time conscious than in-store shoppers when choosing whether to shop online or in store. They also liked to take their time and shop multiple times before making their final purchase, which was probably an advantage of online shopping, in that more varieties of products are made available, and one can easily compare multiple products at one time. Online shoppers were also more likely to have other people shop for them due to their busy schedules.

Younger respondents (age 54 or younger) were slightly more time-conscious with regards to shopping than older respondents. Older respondents overwhelmingly did not want others to shop for them. Males were less likely to take their time when they shop and tend to head straight to where the products are without wasting time. Lower income individuals were slightly less likely to prefer other people shopping for them, and more likely to prefer to take their time shopping.







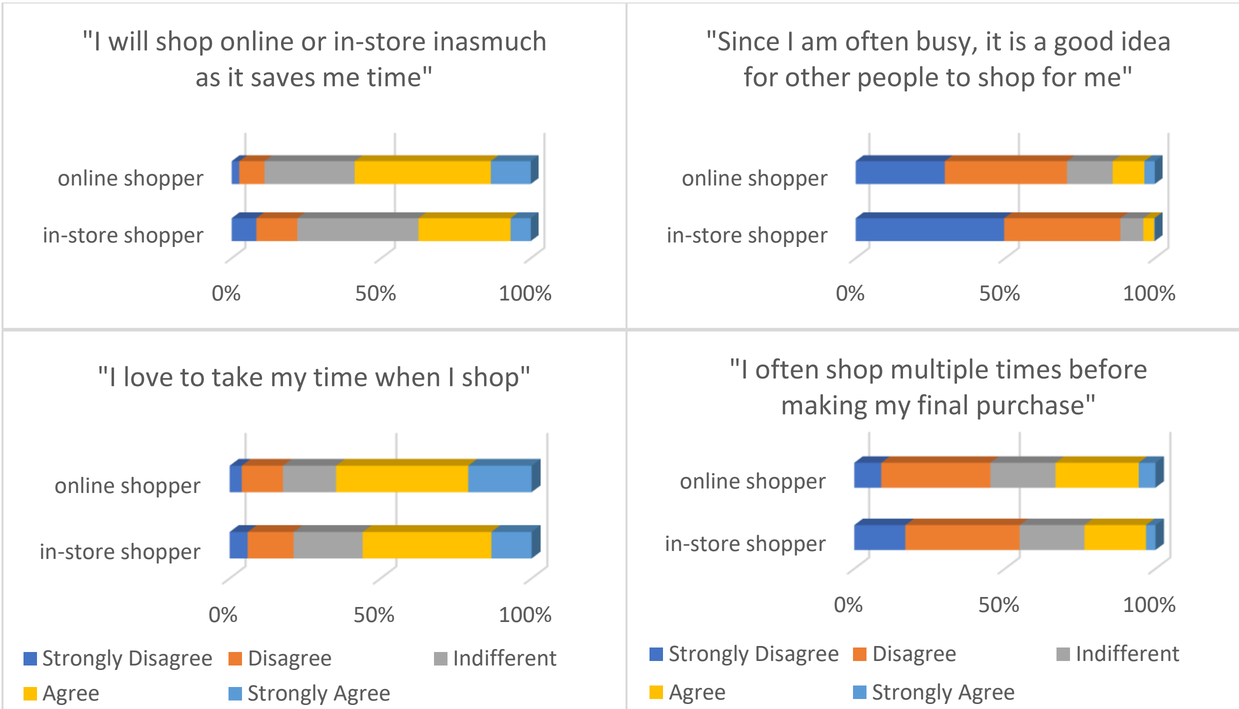
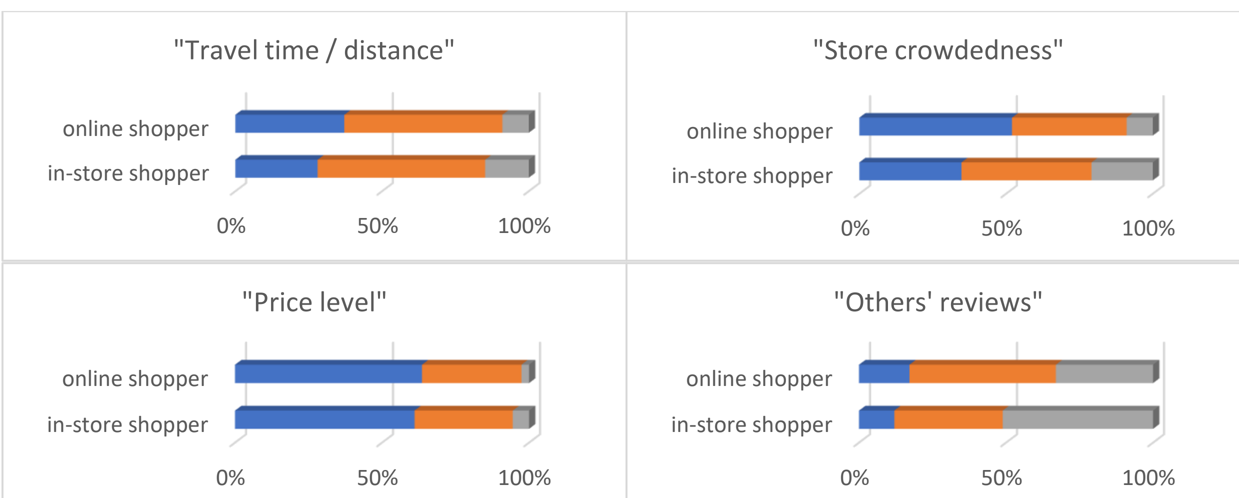


Figure 27. Attitudes toward cost-consciousness and time-consciousness.

5.6 Factors Affecting Store Choice

Respondents were asked about the level of importance of eight factors in their choice of shopping at a particular store (see Figure 28). The price level, safety of the neighborhood, and availability of on-site parking were the most important factors while the store brand and others' reviews were the least important factors to both online and in-store shoppers. A major difference between online and in-store shoppers is that in-store shoppers are less concerned about store crowdedness.



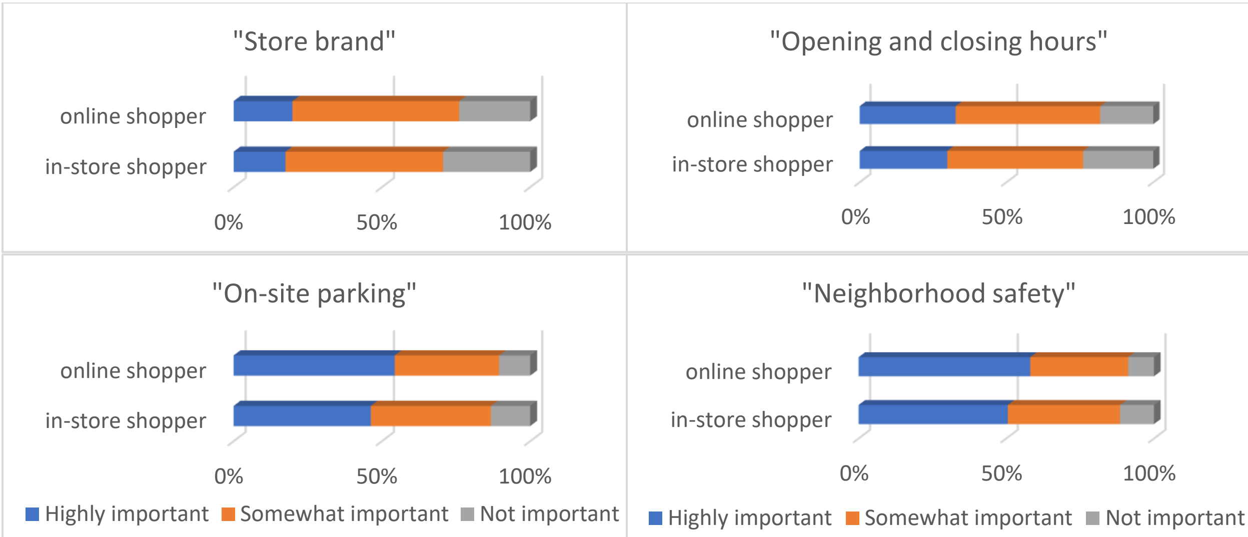
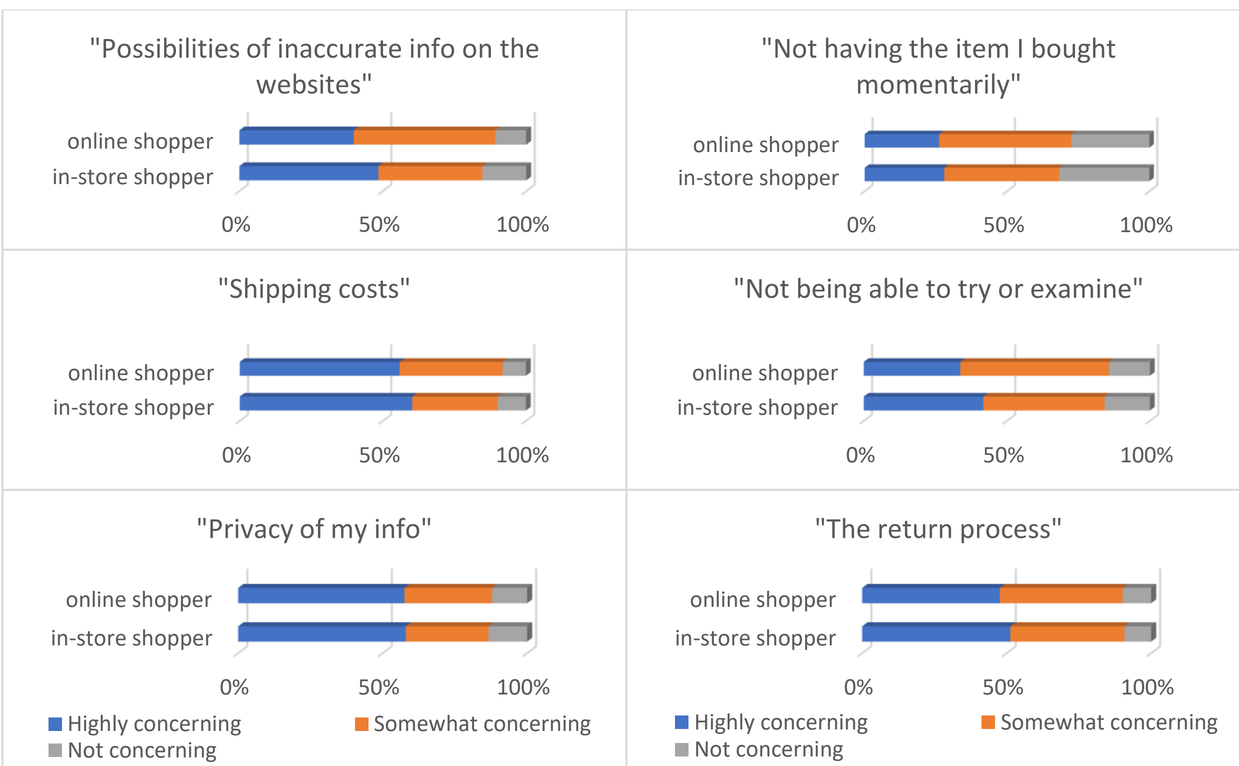


Figure 28. Ratings of factors affecting store choices.

5.7 Factors Influencing Online Shopping

Respondents were presented with six concerning and six appealing factors for online shopping and asked to rate them from highly concerning to not concerning, and from highly appealing to not appealing. Figure 29 displays respondents' rating of the factors. Among the six concerning factors, privacy, shipping cost and return process were the top three concerns. Not having the item bought momentarily was the least concerning compared to other factors.



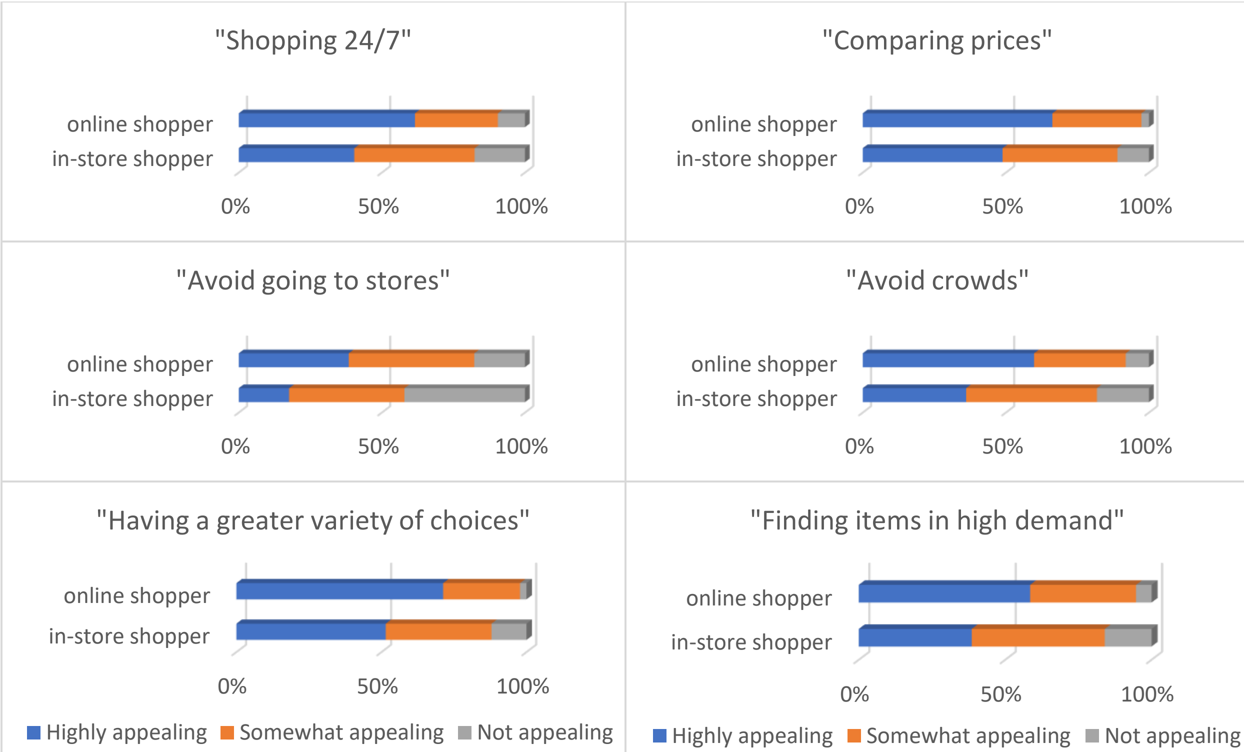


Figure 29. Ratings of concerning and appealing factors for online shopping.

Between online shopper and in-store shopper, the latter were relatively more likely to be concerned about inaccurate information on the website, and not being able to examine the products. Among the six appealing factors of online shopping, having a greater variety of choices, being able to compare prices were the top two factors, followed by avoiding crowds, being able to shop 24/7, and finding items in high demand. "Avoid going to stores" was the least appealing factor for both online and in-store shoppers. In general, in-store shoppers were less likely to find any of the factors highly appealing compared to online shoppers.

5.8 Summary of Attitudes

In investigating attitudes that may influence people's shopping behavior, the first wave of the survey revealed that online shoppers tended to be those who used phone apps and the Internet more frequently, had positive attitudes toward technology, found online shopping more convenient, more likely to feel stressed from physical shopping, did not necessarily like talking to or meeting people in stores, trusted online shopping websites, and more time conscious. They also liked to take their time and shop multiple times before making their final purchase, which were probably an advantage of online shopping, in that more varieties of products are made available, and one can easily compare multiple products at one time. Online shoppers were also more likely to have other people shop for them due to their busy schedules.

In-store shoppers were less likely to like unattended deliveries. Their dissatisfaction for unattended deliveries may be owing to concerns about products being stolen or tampered with, considering that we found that dislike for unattended deliveries is negatively associated with household income. Also, in-store shoppers were less likely to prefer curbside pickup or collecting items at a delivery point. While curbside pickup removes concerns about shipping costs and return process, concerns about privacy of personal information remain. Other possible reasons could be that in-store shoppers tended to like meeting and communicating with people while shopping, or it may stem from their concerns about the possibility of inaccurate information and the inability to examine products.

Looking at concerning and appealing features of online shopping, it seems that in-store and online shoppers had similar opinions, with privacy, shipping cost, and return process being the top three concerns, and having a greater variety of choices, being able to compare prices being the top two benefits. However, in-store shoppers were more likely to be concerned of the concerning factors and less likely to find any of the beneficial features highly appealing compared to online shoppers.

Interestingly, income was not associated with individual's attitudes toward technology, shopping method, social interactions, local stores, delivery preferences, data security, and price consciousness. The only difference is that high income individuals were more likely to trust online shopping, while lower income individuals were slightly less likely to prefer other people shopping for them, and more likely to prefer to take their time shopping.

Older respondents (age 55 or above) showed less usage of technology, tended to love meeting people in stores, were less likely to prefer uncommunicative shopping, and were less likely to find in-store shopping stressful or tiring. They overwhelmingly did not want others to shop for them. They were more likely to agree that too much information was required for online purchase and were more concerned about putting their debit or credit card information online. However, they were just as trusting of online shopping as the younger respondents. Younger respondents tended to be more time-conscious and cost-conscious but more likely to find it more stressful waiting for sales and special offers.

Surprisingly, females were more likely to find shopping in stores stressful than males and were less likely to choose physical stores because they love meeting people, and were less likely to find it important to talk to someone before making their final purchase decision. Males were less likely to take their time when they shop and tend to head straight to where the products are without wasting time.

6 ANALYTICAL FRAMEWORK

6.1 Structural Equation Modeling (SEM)

SEM is widely used in the literature on shopping travel behavior (Cao et al., 2012; Ding & Lu, 2017; Etminani-Ghasrodashti & Hamidi, 2020; Farag et al., 2007; Xue et al., 2021). Its preference over other statistical methods is based on its capability to estimate several endogenous variables at the same time and include latent (unobserved) variables in the model structure (Bollen, 1989). SEM can also model both direct and indirect effects on multiple variables. A variable is said to exhibit a direct effect on another when such effect is unmediated by a third variable, while an indirect effect involves the mediation of one or more variables with another, namely, the mediating variable (or mediator) (Brown, 1997). An indirect effect is estimated as the product of the path coefficients for all the direct effects that make up the indirect effect, while the total effect is the sum of the direct and indirect effects. For mediation to occur, the exogenous variable must have a significant effect on the potential mediating variable, and the mediating variable, in turn, must have a significant effect on the endogenous variable. SEM consists of two main components: the "structural" and the measurement components. The "structural" model associates the causal relationships between a set of exogenous variables and endogenous variables, while the measurement model relates the latent variables (which cannot be directly measured) with their observed measures (which can be directly measured). The formulation of the structural component of a SEM with exogenous, mediating, and endogenous variables can be expressed as follows (Bollen, 1989; Hoyle, 2012):

$$y = By + \Gamma x + \xi \quad (1)$$

where,

$y = (M_y * 1)$ column vector of endogenous variables and M_y = number of endogenous variables,
$x = (M_x * 1)$ column vector of exogenous variables and M_x = number of exogenous variables,
$B = (M_y * M_y)$ matrix of coefficients representing the direct effects within endogenous variables,
$\Gamma = (M_y * M_x)$ matrix of coefficients representing the direct effects of exogenous on endogenous variables, and
$\xi = (M_y * 1)$ column vector of errors.

In presence of latent variables (i.e., attitudinal factors), the SEM quantifies them based on a series of observed variables (i.e., attitudinal statements). This is usually referred to as the "measurement model" and is formulated as:

$$Q = \Pi Z + \zeta \quad (2)$$

where,

Q = v × 1 vector of latent attitudinal factors, a subset of endogenous variables y,
Z = w × 1 vector observed attitude such as the response in Likert scale,
Π = v × w matrix of coefficients of the regression effect of Z on Q, and
ζ = v × 1 vector of error terms.

6.1.1 SEM Concept

In this study, we conceptualized a non-recursive model (i.e., a bi-directional model with feedback loops) for each of the product types to adequately model and examine the complex interrelationships between the variables. From Figure 30, the endogenous variables (that is, online purchase frequency and store purchase frequency) were expected to have significant direct reciprocal effects with each other. We assume the presence of mutual causal effects between both endogenous variables by specifying their covariances. The expectation of reciprocal effects between the endogenous variables stems from the cross-sectional nature of the survey design, that is, the variables were measured once and simultaneously, without any temporal priority unlike longitudinal (panel) designs. Also, informed by the literature, it was expected that socio-demographic, household attributes, return pattern, and attitudes have a significant impact on the endogenous variables. Thus, exogenous variables such as age, gender, income, education, ethnicity, race, marital status, employment status, house type, household size, number of children, number of older adults, members with driver's license, vehicle ownership, and return pattern were modeled as exogenous variables that affect shopping behavior. These exogenous variables were also expected to affect people's attitudes, which in turn, affect shopping behavior. Hence, in addition to the frequency of online and in-store shopping, our model considers latent attitudes as endogenous variables. In order words, the latent attitudes can be predicted by exogenous variables after being measured in a measurement equation.

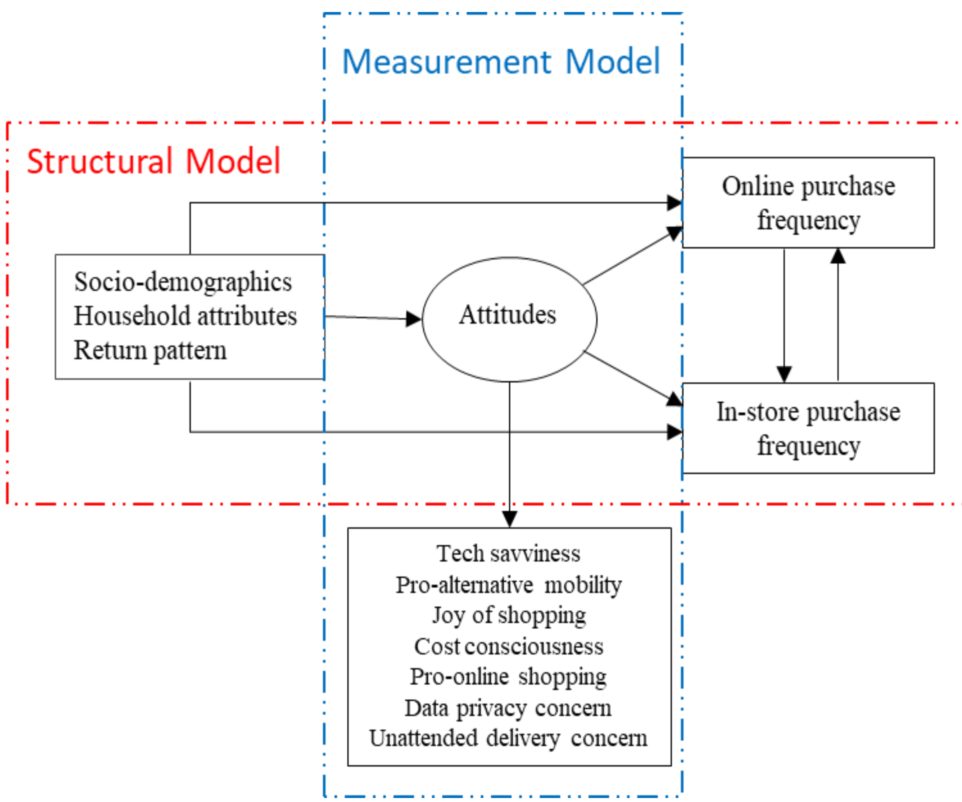


Figure 30. The conceptual SEM model structure.

6.1.2 Moderated Mediation

The model concept presented in the previous section is sufficient to examine people's shopping behavior and attitudes at one point of time and was applied to both the first and the second waves of data, respectively. However, to appropriately identify whether and how people's shopping behavior and attitudes may have changed over time, proper statistical measures need to be introduced. In this regard, a "time" variable is added in the SEM model, and moderation effects of time were introduced through interaction effects between "time" and individual attitudinal indicators, as shown in Figure 31. The "time" variable is defined as a dummy variable indicating whether the data were collected in the first or the second wave. In the moderated mediation model, it is anticipated that any significant attitudinal changes that may have impacted consumers' shopping behavior would be captured through the interaction effects between the "time" variable and the individual attitude indicators. This model will help identify how consumers' attitudes may have changed along the timeline of the pandemic, as well as to identify how those changes may have influenced their shopping decisions to purchase online or in store.

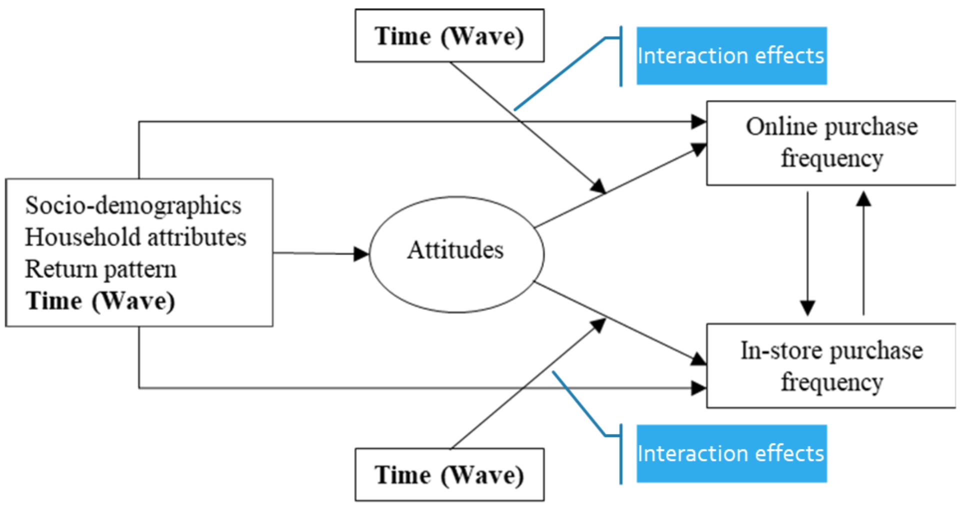


Figure 31. The conceptual SEM model with a time moderator.

6.1.3 SEM Estimation

Various estimators have been employed to estimate SEMs depending on the nature of the data and the assumption of conditions, such as multivariate normality, number of categories, asymmetry of thresholds, sample size, missing data proportion, missing data mechanism, etc. For example, Maximum Likelihood performs best when the data type is a continuous data with at least five levels, while Diagonally Weighted Least Squares and Unweighted Least Squares are preferred and more commonly used for ordered categorical data with three to five levels (Savalei, 2020; Xia & Yang, 2019). Since many past travel behavior studies have used data with five or more levels, the maximum likelihood estimator has been the most popular method (Cao et al., 2012; Ding & Lu, 2017; Etminani-Ghasrodashti & Hamidi, 2020; Irawan & Wirza, 2015; Xue et al., 2021; Zhou & Wang, 2014). Although the endogenous variables (shopping frequencies) in this study have more than five variables, our data violates the assumption of multivariate normality and has data missingness that fits the missing-at-random criterion. Thus, corrections were made using the robust full information maximum likelihood (Gie Yong & Pearce, 2013; Jia & Wu, 2019).

6.1.4 SEM Implementation

The analysis was performed using the lavaan package in R (Rosseel, 2012). All the exogenous variables coded as dummy variables to allow for higher specificity in the representation of categorical variables (e.g., race, house type, marital or employment status, etc.) and the interpretation of the results. Starting with the first model, which contained only the path between the attitudes and the endogenous variables, variables were added one after the other. This was done to ensure the statistical significance of the included variables and the effects of the additions on the overall model fit. Links that were significantly less fit for the model were excluded and were reintroduced for evaluation after other significant links have been retained. The covariances between the endogenous variables were defined to ensure that both variables, which may result from the presence of mutual causal effects, do not have similar unmeasured causes. The final models were retained if their model fit indices met the acceptable thresholds, that is, root mean square error of approximation (RMSEA) < 0.06, comparative fit index (CFI) and tucker-lewis index (TLI) > 0.950 (Savalei, 2020; Xia & Yang, 2019).

In the case of the moderated mediation analysis, a new variable, *time*, was created such that the observations for Wave I was coded as 0, and Wave II as 1. Time was treated as an exogenous variable to be included in the model after the other significant variables have been retained. The interactions of the moderator and the moderated variables were estimated using the product-indicator approach, which involves multiplying the moderator with each indicator of the latent attitudes. This approach was chosen because latent factor scores (from the latent attitudes) cannot be multiplied to calculate a product term. Before the latent interaction variables were created, the indicators were centered to ensure the product terms are uncorrelated with the lower-order terms. The interaction variables were created using the residual centering product indicator strategy, which involves the regression of the product indicators on the first-order indicators from which they were calculated and then using the residual of each product indicator as an indicator of the latent interaction (Schoemann & Jorgensen, 2021).

Each of the new variables was included one after the other and the significant variables were retained in the model. Insignificant variables were removed one after the other, while other variables and the model fit were re-assessed until no insignificant variables were retained and the model met acceptable thresholds. It should be noted that the cutoff values for the model fit indices for the moderated mediation analysis were slightly relaxed to accommodate the impact of the moderating variables.

6.2 Mixed Logit Modeling (MIXL)

6.2.1 Theoretical and Empirical Basis

The use of logit models to analyze the discrete choice experiment are common in shopping and travel behavior studies (Abou-Zeid, 2021; Grashuis et al., 2020; Maltese et al., 2021). Logit models are based on random utility theory, which states that an individual will choose, from a set of available alternatives, the alternative that maximizes their utility. The utility U that decision maker n in choice situation s will choose alternative j can be represented as (Hensher et al., 2015):

$$U_{nsj} = V_{nsj} + \varepsilon_{nsj} \tag{3}$$

where V_{nsj} is the observed or modeled portion of the utility, and ε_{nsj} is the error (unobserved) portion of the true utility. The observed portion V is often represented as a function of k variables, x_{nsjk}, with associated weights or coefficients, β, such that:

$$V_{nsj} = \sum_{k=1}^{k} \beta_k \, x_{nsjk} \tag{4}$$

where x_{nsjk} is a vector of k attributes describing alternative j and covariates relating to the decision maker's personal characteristics or context.

The appropriate choice of a logit model depends on the assumptions surrounding the distribution of the error portion. For the multinomial logit (MNL) model, the error term is assumed to be independently and identically distributed (IID). That is, the unobserved effects have equal distributions ("identically distributed"), and no covariances or correlations between them ("independently distributed). Since this study uses panel data (i.e., one with multiple observations for each individual), the IID assumptions are violated. Moreover, the assumption of equal distributions of the unobserved effects implies that all the decision makers have the same marginal utilities for the parameters (the cost and time variables). The mixed logit (MIXL) model, however, overcomes this challenge by assuming that the unobserved component is randomly distributed with some density $f(\varepsilon_{nsj})$; and allowing for taste heterogeneity among the decision makers. The probability function for the MIXL can be summarized as:

$$\text{Prob}\left(choice_{ns} = j \middle| x_{nsj}, z_n, v_n\right) = \frac{\exp\,(V_{nsj})}{\sum_{j=1}^{Jns} \exp\,(V_{nsj})} \tag{5}$$

where,

$$V_{nsj} = \sum_{k=1}^{k} \beta_{\boldsymbol{n}k} \, x_{nsjk} \tag{6}$$

$$\beta_{\boldsymbol{n}} = \beta + \Delta z_n + \Gamma v_n \tag{7}$$

z_n is a set of P of the decision maker n affecting the mean of the taste parameters, while v_n is a vector of K random variables with zero means and covariances. The separate utilities are linked together by summing up the probabilities for the three alternatives to be equal to one. Since changes in the independent variables and probabilities are non-linear, the maximum likelihood estimation method is used.

6.2.2 MIXL Implementation

Model implementation of a mixed logit model often begins with estimating the random parameters with the MNL framework. This is done to allow for the assessment of the estimated random parameters before the inclusion of the explanatory variables. Although it is usually assumed that the estimated random parameters would follow a normal distribution, when negative effects are not generated for at least one of the random parameters, alternative distributions are appropriate. In order to constrain the random parameters such that only negative values are generated, a zero-bounded triangular distribution was used. Also, 1000 Halton draws was also used, given the complexity of estimating the log-likelihood functions within random parameter frameworks (Abou-Zeid, 2021)

For the MIXL, the socio-economic and demographic (SED) characteristics were coded as dummy variables, while the indicators for the attitudes were used to create regression factors. Like for the SEM, a forward stepwise approach, whereby the explanatory variables were added to the model one after the other, and only the variables significant at the 95% confidence level were retained. Two models were created for each of the grocery and non-grocery discrete choice experiments: the base and heterogenous models. In the base model, the explanatory variables only in their first order term were included. In the heterogenous model, interaction terms between the time and cost variables and the explanatory variables were created and included in the model. The McFadden R-square was used to determine the performance of the models.

7 SHOPPING FREQUENCY ANALYSIS

This section presents the SEM model results analyzing consumers' shopping frequency decisions, focusing on the interactions between online and in-store shopping frequencies and the determinant factors. The SEM models were applied to the first wave and second wave of the data, respectively. It should be noted that the differences observed in the model results for the two waves cannot be automatically attributed to changes in shopping behavior, as there are other factors in play that may affect the model performance and results, such as the composition and size of the sub samples, the variances within each set of data, etc. For this reason, the SEM model with time as a moderating factor was applied to the combined dataset as discussed in the methodology section.

The following sections present the model results for each product type, grouped by search goods, essential experience goods, and non-essential experience goods. Each section starts with a detailed examination of model results for the first wave, focusing on interpreting the effects of individual attitudes and their impacts on shopping frequencies. Then, to avoid unnecessary repetition, each section focuses on the behavioral changes between the two waves by analyzing the time-moderated model based on the combined data.

7.1 Attitudinal Factors

As each SEM model identifies the latent attitudinal factors that played significant roles in the shopping frequency decisions for each product type, there are common attitudinal factors among the models. To avoid repetitive discussions, this section introduces all the latent attitudinal factors that have been derived from the measurement portion of the SEM models through confirmative factor analysis (CFA).

The list of derived factors as well as the contributing attitudinal indicators are presented in Table 4. It also shows the loading factors and the z-value for the estimates. The first factor (F1) indicates technology engagement and frequent online use. The second factor (F2) expresses the preference for alternative mobility options. Factor three (F3) measures enjoyment for shopping at physical stores. The fourth factor (F4) describes individual's trust issues and privacy concerns toward online transactions. Factor five (F5) relates to the attitudes towards the benefits of online shopping. The sixth factor (F6) captures concern about unattended delivery. Finally, factor seven (F7) represents shoppers' sensitivity to product prices. The following sub-sections present the results of the direct and indirect effects for the models representing each product type.

Table 4. Derived Latent Attitudes

Factor	Indicator	Estimate	z-value
F1: Tech savviness	I frequently use smartphone apps	1	na
	I am highly engaged in online activity	0.884	13.524
	Without technology, my life would be boring	0.735	19.792
F2: Pro-alternative mobility options	I like using public transportation to help in reducing traffic congestion	1	na
	I regularly ride public transportation to save money	1.095	21.281
	I cannot afford a private vehicle and prefer using alternative modes	0.839	14.952
	I like to share rides with strangers while traveling	0.669	12.862
F3: Joy of shopping	Strolling through shopping areas is enjoyable and refreshing	1	na
	I sometimes use shopping as an excuse to leave my house or place of work	1.41	8.631
	I love to take my time when I shop	1.197	8.858
F4: Data security or privacy concern	Too much personal information is required for online purchase	1	na
	I have heard much bad news about online shopping scams	0.858	18.817
	I am concerned about putting my debit or credit card information online	1.194	20.3
F5: Pro-online shopping	Shopping 24/7	1	na
	Having a greater variety of choices	1.164	17.376
	Finding items in high demand	1.203	9.555
F6: Unattended delivery concern	I do not like missing an attended delivery	1	na
	I do not like when a product is left in my house compound unattended to	1.343	8.508
F7: Cost consciousness	I first check the price before assessing the quality	1	na
	I always look for the best deals	0.62	14.202
	I become upset if I find lower price after purchasing a product	0.872	13.638
	I like to easily compare multiple products and their prices when shopping	1.072	12.766
	Price level is important in choosing a store to shop from	0.999	11.477

7.2 Search Goods

7.2.1 Books and Electronics (BE)

7.2.1.1 Model Results for First Wave for Books and Electronics

Table 5 and Table 6 present the model results for Books and Electronics products. Table 5 shows the interactions between online and in-store shopping frequency (the endogenous variables), and the impacts of the exogenous variables (attitudinal factors and socioeconomic and demographic attributes) on the shopping frequencies. Table 6 shows the effects of the socioeconomic and demographic variables on attitudes. The path diagram showing the interactions among the variables can be seen in Figure 32.

Table 5 shows that online shopping does not have a significant effect on in-store shopping for books and electronics, while in-store shopping positively influences online shopping frequency. That is, traveling to purchase books and electronics in-store increases the tendency to purchase online. However, shopping online does not in-turn affect in-store shopping frequency. One possible reason could be that those who travel to the store do so to experience the books or electronics but return to use the Internet or store websites to find better deals or options at a lower price or at other stores. Thus, online shopping increases shoppers' options, but does not necessarily discourage them from traveling to the store.

The neutrality effect found seems to be at odds with Cao (2012), that suggested online shopping exhibited a complementarity effect on in-store shopping. Unlike our study, Cao (2012) focused on potential shopping behavior with and without Internet availability, and no causal inferences were made. Moreover, the search goods considered in Cao (2012) included CDs, DVDs and videotapes, whose usage has been largely replaced by streaming services on electronic appliances.

Looking at the influence of attitudes, pro-online shopping and tech savviness showed direct positive effects on online shopping, similar to previous studies (Cao et al., 2012; Farag et al., 2006, 2007). Moreover, those who did not like unattended delivery were discouraged from shopping online. This may be due to the nature of products like electronics, which are often expensive and can be stolen easily if not personally delivered to the buyer. Also, those who loved shopping for pleasure, and who preferred alternative mobility options were more predisposed to in-store shopping. Many past studies have suggested that the desire to experience products and interact with shop assistants when shopping is important to those who enjoy shopping (Cao et al., 2012; Crocco et al., 2013; Farag et al., 2007; Maat & Konings, 2018; Zhen et al., 2016). Regarding pro-alternative mobility options, a recent study (Xue et al., 2021) showed that transit users compared to private drivers were more inclined to make their purchases at online stores. However, shopping for search goods may be different as electronics would tend to be stolen more than clothing or groceries. Moreover, those who preferred alternative mobility options may be relatively low income-earners or those more sensitive to cost, who were more concerned about having expensive items stolen or not delivered.

Our analysis also showed that Baby boomers tended to shop less frequently in-store. While there is overwhelming evidence in the literature that the younger generations tend to shop more frequently online (Cao et al., 2012; Crocco et al., 2013; Farag et al., 2006; Irawan & Wirza, 2015; Lee et al., 2015; Unnikrishnan & Figliozzi, 2020), their increase in in-store shopping for books and electronics suggest product type affects this shopping behavior. Females shopped less frequently in-store than males. Although males are known to make more online purchases, compared to females who make more shopping trips (Crocco et al., 2013; Farag et al., 2006). Some studies have indicated that males tend to make in-store purchases of electronics more frequently than women (Zhen et al., 2016). We also found that those with lower levels of education (i.e., having a high school degree or less) tended to shop less online (Cao et al., 2012; Lee et al., 2015; Ramirez, 2019; Xue et al., 2021).

Table 5. SEM results for Books and Electronics Shopping Frequencies

	Online purchase frequency			In-store purchase frequency		
	Direct	Indirect	Total	Direct	Indirect	Total
Endogenous variables						
Online purchase frequency	0	0	0	-0.042	0	0
In-store purchase frequency	0.561***	0	0.561	0	0	0
Attitudes						
Pro-alternative mobility	0	0.134	0.134	0.239***	0	0.239
Joy of shopping	0	0.076	0.076	0.135***	0	0.135
Pro-online shopping	0.260**	0	0.260	0	0	0
Technology savvy	0.071**	0	0.071	0	0	0
Unattended delivery concern	-0.529***	0	-0.529	0	0	0
Gender						
Female	0	-0.051	-0.051	-0.112**	-0.008	-0.120
Generation						
Gen Z	0	0.062	0.062	0	0.082	0.082
Younger boomers	0	-0.223	-0.223	-0.176**	-0.036	-0.212
Older boomers	0	-0.195	-0.195	-0.212***	-0.047	-0.259
Ethnicity						
Hispanic	0	0.024	0.024	0	0.013	0.013
Race						
White	0	-0.096	-0.096	-0.112*	-0.036	-0.148
Income						
Less than $15k	0	-0.059	-0.059	-0.165*	0.059	-0.106
Between $25k & $35k	-0.103*	0	-0.103	0	0	0
Between $35k & $50k	0	-0.020	-0.020	0	0	0
Between $50k & $75k	0	-0.056	-0.056	-0.099**	0	-0.099
Between $100k & $150k	0	0.090	0.090	0	0	0
Education						
Less than high sch	-0.322**	0	-0.322	0	0	0
High sch grad	-0.087*	-0.016	-0.103	0	0	0
Some college	0	0.012	0.012	0	0	0
Associate	0	0.008	0.008	0	0.014	0.014
Post-grad	0	0.109	0.109	0	0.028	0.028
Marital status						
Single	0	0.008	0.008	0	0	0
Employment						
Homemaker	0	-0.076	-0.076	-0.168**	0.032	-0.136
Retired	0	-0.055	-0.055	0	-0.028	-0.028
House type						

Table 5, Continued

	Online purchase frequency			In-store purchase frequency		
	Direct	Indirect	Total	Direct	Indirect	Total
Detached single	0	0.067	0.067	0	0	0
Townhouse	0	0.010	0.010	0	0.018	0.018
Apt, 2-4 units	0	0.045	0.045	0	0.080	0.080
Household characteristics						
Owned vehicles: 0	0	0.093	0.093	0	0.165	0.165
Owned vehicles: 1	0	0.016	0.016	0	0.028	0.028
Owned vehicles: 3 or more	0	0.014	0.014	0	0	0
Mmbrs wth drivr's licnse: 0	-0.180**	0.041	-0.139	0	0.074	0.074
Mmbrs wth drivr's licnse: 1	0	0.006	0.006	0	0.011	0.011
Mmbrs aged 65 plus: 0	0	0.014	0.014	0	0	0
Mmbrs aged 65 plus: 2 or more	0.088*	0	0.088	0	0	0
Children less than 5 years: 0	0	-0.036	-0.036	0	-0.015	-0.015
Children less than 5 years: 1	0	-0.022	-0.022	0	0	0
Children btw 5 & 18 years: 0	0	-0.126	-0.126	-0.155**	-0.026	-0.181
Product return pattern						
Return frequency	0.102*	0.129	0.231	0.191**	0.039	0.230

Note: * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.
Goodness of fit indices (robust estimation): CFI = 0.959, TLI = 0.952, RMSEA = 0.016, SRMR = 0.020

Interestingly, those from households where no member has a driver's license make less online purchases. It seems their lack of accessibility to driving and preference for alternative mobility options neither discouraged them from shopping in-store nor encouraged them to shop online. Again, this effect may be related to their household income level or residential location. Also, the past behavior of those who have made at least one return in the past month positively affected their shopping in-general, more so that they tend to prefer alternative mobility options and value recreational shopping.

There are some variables that did not have significant direct effects but had significant indirect effects on the shopping frequencies. For example, preference for alternative mobility options and joy of shopping showed positive indirect effects on online shopping. That is, for those who prefer alternative mobility and enjoy shopping, their in-store shopping experience increases their tendency to purchase books and electronics online. Also, females' lower tendency to shop both online and in-store shopping is mediated by their negative attitude toward alternative mobility options, and positive attitude toward recreational shopping and online shopping.

Table 6 shows that Gen Zers' preference for alternative mobility option and their tech savviness led to positive effects on both online and in-store shopping. Baby boomers were disinclined toward shopping in-general.

Table 6. Attitudes for Books and Electronics

	Pro-alternative mobility	Joy of shopping	Pro-online shopping	Tech savviness	Unattended delivery concerns
Gender - Female	-0.127**	0.163***	0.064**	-	-
Generation					
Gen Z	0.344***	-	-	0.222**	-
Younger boomers	-0.150***	-0.088*	-	-0.280**	0.159**
Older boomers	-0.149**	-	-0.122***	-0.251*	-
Race - White	-0.107*	-0.078*	-0.048*	-	-
Ethnicity - Hispanic or Latino	-	0.096*	0.065**	-	-
Income					
Less than $15k	0.182**	0.116*	-	-	-
Between $35k & $50k	-	-	-0.077**	-	-
Between $100k & $150k	-	-	-	-	-0.170**
Education					
High sch grad	-	-	-	-0.228***	-
Some college	-	-	0.045*	-	-
Associate degree	-	0.106*	-	-	-
Post-graduate degree	0.118*	-	-	-	-0.177***
Employment					
Homemaker	-	0.236***	-	-	-
Retired	-0.116**	-	-	-0.552***	-
Marital status					
Single	-	-	-	0.109*	-
House type					
Detached single house	-	-	-	-	-0.127**
Apt, 2-4 units	0.262***	0.129*	-	-	-
Townhouse, row house	-	0.134*	-	-	-
Household Characteristics					
Owned vehicles: 0	0.691***	-	-	-	-
Owned vehicles: 1	0.118**	-	-	-	-
Owned vehicles: 3 or more	-	-	0.054*	-	-
Mmbrs wth drivr’s licnse: 0	0.309**	-	-	-	-
Mmbrs wth drivr's licnse: 1	-	0.082*	-	-	-
Mmbrs aged 65 plus: 0	-	-	-	0.194**	-
Children less than 5 yrs: 0	-	-0.110*	-	-0.386**	-
Children less than 5 yrs: 1	-	-	-	-0.309*	-
Children btw 5 & 18 yrs: 0	-0.110**	-	-0.063**	-0.106*	-
Product return pattern					
Return frequency	0.105**	0.102**	-	-	-

Note: * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.

It is also worth noting that Gen Zers tend to be students in need of books or sophisticated electronics to help them in their classes or navigate the increasingly tech-oriented work environment. Thus, their higher need predisposes them to more purchases in-general. Baby boomers' indirect (negative) effects on both online and in-store shopping, on the other hand, are mediated through their low technology savviness, negative attitude for alternative mobility options, recreational shopping, and online shopping. Hispanics and whites have opposing attitudes. Hispanics tend to enjoy shopping and online shopping while whites do not, leading to differing indirect effects on shopping behavior. Hence, Hispanics' positive effects on online and in-store shopping, and whites' negative effects are mediated by the effects of these attitudes.

Judging from the total effects, our analysis also showed that low- to middle-income earners tended to shop less frequently online. Unconcern for unattended delivery mediated the effects of those whose households make between $100k and $150k, suggesting that they tend to live in high-income neighborhoods where the stealing delivery items is less of a concern than those living in other neighborhoods. This explanation seems somewhat confirmed by the result of those living in a detached single house, who tend to shop online mediating by their unconcern for unattended delivery.

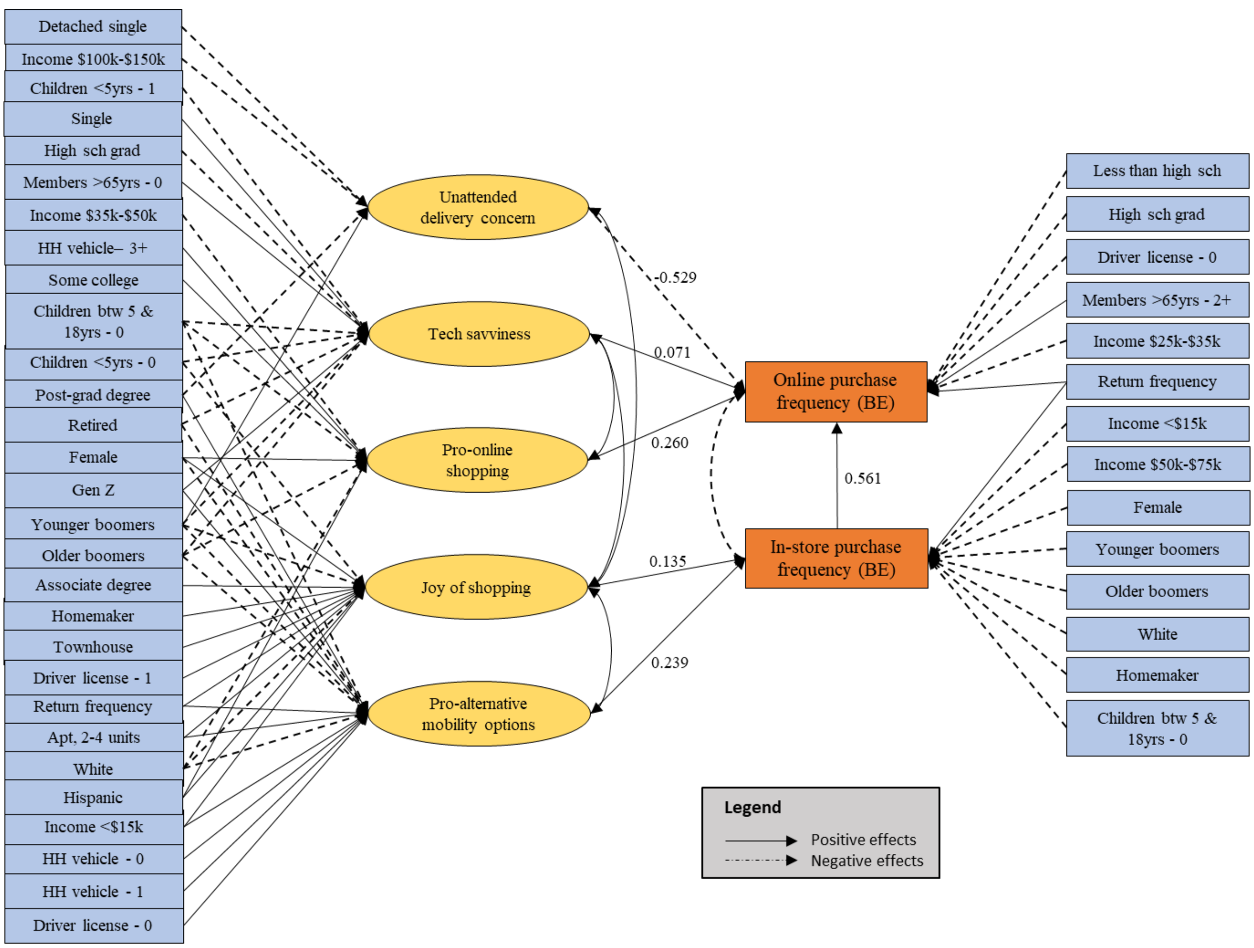


Figure 32. Path diagram for books and electronics

Those with moderate to higher degrees tended to have attitudes that positively influenced books and electronics purchase in general. It seems having a master's degree or higher means using sophisticated and expensive electronics for school or work and might be positively affecting the desire to visit stores and evaluate goods before purchase. Also, singles and those who do not have any senior member in their household tend to have attitudes that lead to purchasing books and electronics online. The negative effects of those with no children (i.e., less than five years old or between 5 and 18 years old) on both online and in-store books and electronics purchase were mediated by negative attitudes toward alternative mobility, shopping enjoyment, online shopping, and technology savviness.

7.2.1.2 Time-Moderated SEM Model for Books and Electronics

The results of the first wave, second wave, and combined dataset were summarized in Table 7. Unlike the first wave that did not show a significant effect of online shopping on in-store shopping, online shopping was found to exhibit a positive effect on in-store shopping, while in-store shopping did not significantly increase online shopping frequency in the second wave. That is, shopping online for books and electronics increased the tendency to make frequent trips to the stores. This result is consistent with Cao (2012), where a complementarity effect was suggested. Also, the impact of attitudes on shopping behavior indicates consistent results between the first and the second wave. However, those who preferred alternative mobility options were more likely to engage in both online and in-store and online shopping, while those concerned about unattended delivery were not discouraged from shopping online during the second wave.

Table 7. Summary of Differences in Results for BE Across Waves

Books and Electronics						
	1st wave		2nd wave		Combined	
	Online	In-store	Online	In-store	Online	In-store
Online		neutral		positive		neutral
In-store	positive		neutral		positive	
Pro-alternative mobility		positive	positive	positive		positive
Joy of shopping		positive		positive		positive
Pro-online shopping	positive		positive		positive	
Tech savviness	positive		positive		positive	
Unattended delivery concerns	negative				negative	

Results from the moderation analysis (see Table 8) showed that the more shoppers were "highly engaged in online activity" ("tech_2" - an indicator for tech savviness), the less they shopped online for books and electronics, over time. This indicates that time significantly **weakened** the positive effect of tech savviness on shopping online for books and electronics. Results also showed that shoppers in general significantly **reduced** their online shopping frequency for books and electronics over time. This goes along with the intuition that the increase in vaccination rates over time increased online shoppers' willingness to make frequent shopping trips.

Another interesting finding is that time **enhanced** shoppers' preferences for alternative mobility options. This suggests that the reduction in Covid-19 safety concerns due to widespread vaccination significantly increased shoppers' comfort with and preference for riding with people in buses, trains, and other shared transportation modes. However, higher preference for alternative mobility would have encouraged not only more online shopping but more in-store shopping since this group are strongly predisposed to shopping frequently in-store, as the results for the first wave of this study demonstrates. Thus, this line of reasoning alongside the weakening effect of time on tech savviness, significantly lower online frequency, and a positive effect of online shopping on in-store shopping all point to a stronger complementarity effect over time.

Table 8. Moderation Analysis Results for BE

	Online purchase frequency	In-store purchase frequency	Pro-alternative mobility	Joy of shopping	Pro-online shopping	Tech savviness	Unattended delivery concern
Endogenous variables							
Online purchase frequency	-	0.093	-	-	-	-	-
In-store purchase frequency	0.463***	-	-	-	-	-	-
Attitudes							
Pro-alternative mobility	-	0.268***	-	-	-	-	-
Joy of shopping	-	0.130***	-	-	-	-	-
Pro-online shopping	0.219***	-	-	-	-	-	-
Technology savvy	0.050**	-	-	-	-	-	-
Unattended delivery concern	-0.456**	-	-	-	-	-	-
Time-related variables							
Time	-0.072**	-	0.064*	-	-	-	-
Time*tech_2	-0.041*	-	-	-	-	-	-

Note: * significant at $p < 0.1$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.
Goodness of fit indices (robust estimation): CFI = 0.953, TLI = 0.944, RMSEA = 0.017, SRMR = 0.018

7.2.2 Pet Supplies (PS)

7.2.2.1 Model Results for First Wave for Pet Supplies

Similar to the results on the relationship between online and in-store shopping for books and electronics, Table 9 shows that online shopping for pet supplies had a neutral effect on its in-store shopping, and in-store shopping positively influences online shopping for pet supplies. Shoppers who have pets and frequently purchase pet supplies also rely on online shopping for their purchases. And though the results on the impact of attitudes on shopping behavior did not contradict that of books and electronics, they were not the same. For pet supplies, those who are cost conscious and enjoy shopping for pleasure tend to be unwilling to shop online. Those who prefer alternative mobility tend to shop online, while data security concerns encourage in-store shopping. These differences in findings may be related to the higher shopping frequency necessary in shopping for pet supplies compared to books and electronics.

Table 9. SEM Results for Pet Supplies

	Online purchase frequency			In-store purchase frequency		
	Direct	Indirect	Total	Direct	Indirect	Total
Endogenous variables						
Online purchase frequency	0	0	0	-0.146	0	0
In-store purchase frequency	0.429***	0	0.429	0	0	0
Attitudes						
Pro-alternative mobility	0.171**	0	0.171	0	0	0
Joy of shopping	-0.078**	0.037	-0.041	0.086**	0	0.086
Pro-online shopping	0.289***	0	0.289	0	0	0
Data security concern	0	0.045	0.045	0.104**	0	0.104
Cost consciousness	-0.149**	0	-0.149	0	0	0
Generation						
Gen Z (aged 18-24)	0	0.292	0.292	0.431***	0	0.431
Millennials (aged 25-40)	0	0.235	0.235	0.387***	-0.013	0.374
Gen X (aged 41-56)	0	0.189	0.189	0.288***	0	0.288
Boomers I (aged 67-75)	0	-0.072	-0.072	-0.139*	-0.011	-0.15
Silent generation (aged 76-99)	0	-0.153	-0.153	-0.225**	0	-0.225
Race						
White	0	-0.019	-0.019	0	-0.029	-0.029
Asian	0	-0.177	-0.177	-0.413***	0	-0.413
Income						
Less than $15k	-0.138*	0.064	-0.074	0	0	0
Between $15k & $25k	0	0.036	0.036	0	0	0
Between $35k & $50k	0	-0.02	-0.02	0	0	0
Between $50k & $75k	0	-0.07	-0.07	-0.142**	-0.01	-0.152
$150k or more	0	0.023	0.023	0	0	0
Education						
High sch grad	-0.105**	0	-0.105	0	0	0
Associate	0	-0.03	-0.03	0	0.015	0.015
Post-grad	0	0.029	0.029	0	0	0
Employment						
Full-time employed	0.117**	-0.006	0.111	0	-0.013	-0.013
Part-time employed	0.223**	-0.074	0.149	-0.173*	0	-0.173
Homemaker	0	-0.038	-0.038	0	0.028	0.028
House type						
Detached single	0	0.071	0.071	0.165**	0	0.165
Townhouse	0	-0.008	-0.008	0	0.017	0.017
Apt, 2-4 units	0	0.048	0.048	0	0.031	0.031
Household characteristics						
Household size: 1	0	-0.092	-0.092	-0.214**	0	-0.214
Mmbrs wth drivr's licnse: 0	0	0.122	0.122	0	0.02	0.02
Mmbrs wth drivr's licnse: 2	0.104**	0	0.104	0	0	0
Children less than 5 years: 0	0	0.112	0.112	0.245**	-0.014	0.231
Children btw 5 & 18 years: 0	0	-0.074	-0.074	-0.127*	0	-0.127
Children btw 5 & 18 years: 1	0	0.013	0.013	0	0	0
Mmbrs aged 65 plus: 0	-0.085*	-0.023	-0.108	0	0	0
Mmbrs aged 65 plus: 1	0	0.059	0.059	0.137*	0	0.137
Product Return frequency	0	0.005	0.005	0	0.01	0.01

Note: * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.

Goodness of fit indices (robust estimation): CFI = 0.959, TLI = 0.952, RMSEA = 0.015, SRMR = 0.021

The result also shows that the younger generation (Gen Zers, Millennials and Gen Xers) tend to shop in-store for pet supplies, while the older ones tend not to shop in-store frequently. These seem to contradict results of past studies that indicate that age and online shopping are positively related (Cao et al., 2012; Crocco et al., 2013; Farag et al., 2006; Irawan & Wirza, 2015; Kedia et al., 2019; Lee et al., 2015; Unnikrishnan & Figliozzi, 2020). However, the indirect effects (shown in Table 10) suggest that younger individuals' tendency to prefer alternative mobility predisposes them to shopping online, while the older adults tend to shop less frequently for pet supplies in general, since pet ownership is less prevalent among older adults and larger households (American Veterinary Medical Association, 2018). Income does not seem to affect shopping behavior for pet supplies, but those who live in detached houses tend to shop more frequently in-store. Moreover, low income and low educated individuals were less likely to shop for pet supplies in-store. Those who were employed tended to purchase pet supplies more often online and less frequently in-store.

Table 10. Direct Effects on Mediators for Pet Supplies

	Pro-alternative mobility	Joy of shopping	Pro-online shopping	Data security concern	Cost consciousness
Generation					
Gen Z	0.718***	-	-	-	0.105*
Millennials	0.434***	-	0.052*	-0.124**	0.100**
Gen X	0.290***	-	0.056*	-	-
Older boomers	-	-0.132*	-0.139***	-	-0.153***
Silent generation	-	-	-0.255***	-	-0.118*
Race - White	-0.103*	-0.145**	-	-0.155***	-
Income					
Less than $15k	0.374	-	-	-	-
Between $15k & $25k	0.211	-	-	-	-
Between $35k & $50k	-	-	-0.069**	-	-
Between $50k & $75k	-	-0.113*	-	-	0.094**
$150k or more	-	-	0.081*	-	-
Education					
Associate degree	-0.134**	0.169**	-	-	-
Post-graduate degree	0.170**	-	-	-	-
Employment					
Full-time employed	-	-	-	-0.126**	-
Homemaker	-0.142*	0.323***	-	-	-
House type					
Apt, 2-4 units	0.291***	0.190**	-	0.140*	-
Townhouse, row house	-	0.196**	-	-	-
Household Characteristics					
Mmbrs wth drivr's licnse: 0	0.667***	-	-	0.188**	-
Mmbrs aged 65 plus: 0	-0.134*	-	-	-	-
Children less than 5 years: 0	-	-0.166**	-	-	-
Children btw 5 & 18 years: 0	-0.117*	-	-	-	-
Children btw 5 & 18 years: 1	-	-	0.045*	-	-
Product return pattern					
Return frequency	0.141**	0.122**	-	-	0.095**

Note: * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.

Results on the impact of household characteristics on shopping behavior for pet supplies are mixed. Those who live alone tended to purchase pet supplies in-store less frequently than larger households though statistics indicate smaller households tend to own pets more than larger households (American Veterinary Medical Association, 2018). Not having children in a household also yielded mixed results, as those who have no children less than five years tended to shop more online while those with no children between 5 and 18 years tended to shop less online. Also, making returns did not affect the shopping behavior for pet supplies. The path diagram showing the interactions among the variables can be seen in Figure 33.

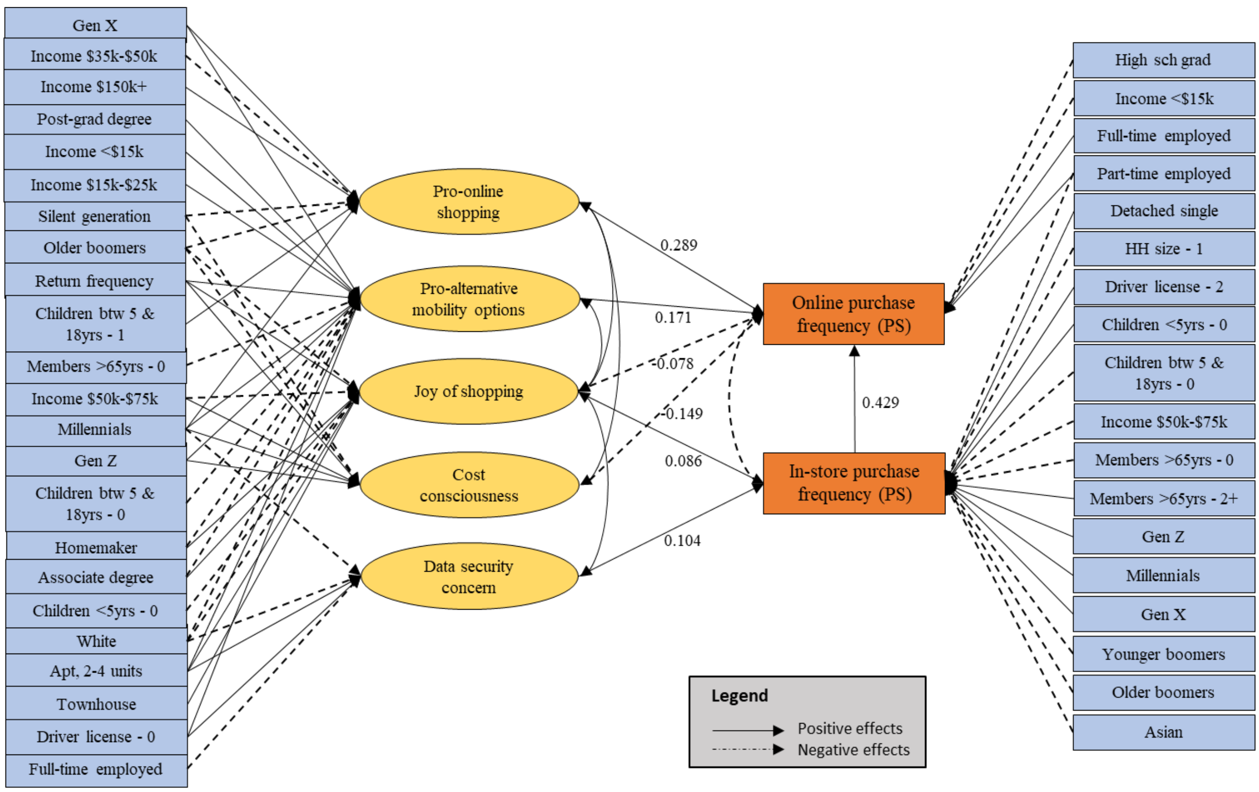


Figure 33. Path diagram for pet supplies

7.2.2.2 Time-Moderated SEM Model for Pet Supplies

Like the results found for books and electronics, the second wave of the analysis for pet supplies reveal in-store shopping increased as online shopping increased (see Table 11). This result is different from the first wave which revealed a neutral effect between online and in-store shopping. Regarding attitudes, several changes to the results between waves are revealed. Preference for alternative mobility options positively affected in-store shopping in the second wave, an effect that was not significant in the first wave. Also, recreational, and cost-conscious shoppers were no longer discouraged from shopping online during the second wave. While the positive effect of tech savviness was significant, positive attitude toward online shopping was no longer significant in the second wave. The effects of data security concern were consistent, as the attitude encouraged in-store shopping in the first wave and discouraged online shopping in the second wave.

Table 11. Summary of Differences in Results for PS across Waves

Pet supplies						
	1st wave		2nd wave		Combined	
	Online	In-store	Online	In-store	Online	In-store
Online		neutral		positive		neutral
In-store	positive		positive		positive	
Pro-alternative mobility	positive		positive	positive	positive	positive
Joy of shopping	negative	positive		positive		positive
Pro-online shopping	positive					
Data security/privacy concerns		positive	negative		negative	
Tech savviness			positive			
Cost consciousness	negative					

Table 12. Moderation Analysis Results for PS

Pet supplies	Online purchase frequency	In-store purchase frequency	Pro-alternative mobility
Endogenous variables			
Online purchase frequency	-	-0.266	-
In-store purchase frequency	0.472***	-	-
Attitudes			
Pro-alternative mobility	0.157***	0.170**	-
Joy of shopping	-	0.199*	-
Data security concern	-0.104**	-	-
Time-related variables			
Time	-	-	0.087**
Time*mobility_3	-0.081*	-	-

Note: for simplicity, the effects of the exogenous variables were not presented
CFI = 0.941, TLI = 0.929, RMSEA = 0.023, SRMR = 0.020

The moderation analysis results, shown in Table 12, reveal that time negatively affected the effect of those who "regularly ride public transportation to save money" (mobility_3 – an indicator pro-alternative mobility) on online purchase frequency. That is, time *weakened* the positive effect of pro-alternative mobility on online shopping for pet supplies. It was also found that time positively affected consumers' pro-alternative mobility preference. This means as Covid-19 safety concerns declined, those who preferred alternative mobility for financial reasons slightly reduced the frequency of their online purchase, while those who preferred alternative mobility for other reasons also made frequent in-store purchases. This line of reasoning alongside the complementarity effect of online on in-store shopping during the second wave may be indicative of a stronger complementarity effect over time.

7.2.3 Summary for Search Goods

From our analysis on the relationship between online and in-store shopping for search goods (books/electronics and pet supplies, respectively), we found that online shopping had a neutral effect on in-store shopping, but those who frequently shopped in-store shopping tended to frequently shop online. There were differences in the impact of attitudes affecting both products respectively. In shopping for books and electronics, pro-online shopping attitude and technology savviness encouraged online shopping, preference toward alternative mobility and recreational shopping encouraged in-store shopping, and unattended delivery concern discouraged online shopping. For pet supplies, however, cost consciousness and the joy of shopping discouraged online shopping, while data security concern predisposed shoppers to the physical store. These differences can be somewhat attributed to the difference in the frequency of shopping for each of these two product types, and the characteristics of the shoppers. These results show that, even within the search goods classification, distinct product characteristics can have differing consumer characteristics, and thus differing effects on online or in-store shopping behavior.

7.3 Essential Experience Goods

7.3.1 Groceries (Gr)

7.3.1.1 Model Results for First Wave for Groceries

In this subsection, the model results for grocery shopping are presented. Table 13 shows the interactions between the online and in-store purchase frequencies, and the influences of the attitudes and personal and household attributes. Table 14 shows the direct effects of the exogenous variables on the attitudes.

From Table 13, the bi-directional relationship between online and in-store purchase frequencies shows that in-store shopping negatively affected online shopping frequency, while online shopping had a neutral effect on in-store shopping. In order words, those who made their grocery purchases in-store were less likely to shop online for groceries, but those who made grocery purchases online tended not to reduce their in-store grocery shopping. Our finding that online shopping did not discourage in-store shopping for groceries has been demonstrated by Hand et al. (2009). It seems that e-grocery merely provides an alternative that may be exploited when circumstances warrant. Although this finding deviates from most of the past studies that often suggested substitution effects for grocery shopping, and as has been extensively discussed in the literature review section of this paper, most of them often made no causal assumptions in their analyses, had unrepresentative samples of e-grocery users, or used ambiguous definitions of substitution effects. And again, our results agree with Dias et al. (2020), which was conducted in the U.S.

Table 13. SEM Results for Grocery Shopping

Groceries		Endogenous variables					
		Online purchase frequency			In-store purchase frequency		
		Direct	Indirect	Total	Direct	Indirect	Total
Shopping behavior	Online purchase frequency	-	-0.014	-0.014	0.026	-	0.026
	In-store purchase frequency	-0.528***	0.007	-0.521	-	-0.014	-0.014
Attitudes	Tech savviness	0.089**	-0.001	0.088	-	0.002	0.002
	Pro-alternative mobility options	0.514***	-0.007	0.507	-	0.013	0.013
	Joy of Shopping	-	-0.097	-0.097	0.187***	-0.003	0.184
	Cost consciousness	-	-0.164	-0.164	0.315***	-0.004	0.311
	Pro-online shopping	0.408***	-0.006	0.402	-	0.01	0.01
Sex	Female	-	-0.053	-0.053	-	0.03	0.03
Generation	Younger boomers (aged 57 to 66)	-0.177***	-0.052	-0.229	-0.159**	-0.006	-0.165
	Older boomers (aged 67 to 75)	-	-0.161	-0.161	-	-0.044	-0.044
Household income	HH income: $15k or less	-	0.15	0.15	-	0.03	0.03
	HH income: $50k to $75k	-	-0.015	-0.015	-	0.005	0.005
	HH income: $75k to $100k	-	0.015	0.015	-	-0.029	-0.029
Education	Less than high school degree	0.116**	0.016	0.132	-	0.003	0.003
	Associate degree	-	-0.057	-0.057	-	0.022	0.022
Employment	Homemaker	-	-0.037	-0.037	-	0.07	0.07
	Retired	-0.253***	0.035	-0.218	-0.299***	-0.052	-0.351
Household characteristics	Apt, 2-4 units	-	0.127	0.127	-	0.035	0.035
	Townhouse/rowhouse	-	-0.016	-0.016	-	0.03	0.03
	HH size: 1	-0.172**	0.144	-0.028	-0.312***	-0.001	-0.313
	Have children aged 4 or less: 0	-	-0.105	-0.105	0.203**	-0.028	0.175
	HH members aged 65 plus: 0	-	0.017	0.017	-	-	-
	HH members with driver's license: 0	-0.310***	0.301	-0.009	-	-	-
Product return pattern	Return frequency	0.276***	-0.043	0.233	0.174**	0.063	0.237

Note: * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.
Goodness of fit indices (robust estimation): CFI = 0.958, TLI = 0.951, RMSEA = 0.018, SRMR = 0.025

Attitudes were found to significantly impact grocery shopping behavior. Tech savviness, pro-alternative mobility, and pro-online shopping attitudes had direct positive effects on online shopping frequency. It indicates that individuals who valued the benefits of online shopping (shopping 24/7, having a great variety of choices and finding items in high demand), were familiar with technology (i.e., often use smartphone applications or the internet), or preferred alternative transportation modes (i.e., transit, shared mobility, etc.) showed a higher inclination toward online shopping for grocery items. These findings are consistent with previous studies' that found that tech-savviness or internet usage tended to increase trust in using online shopping and actual online purchase (Cao et al., 2012; Farag et al., 2006, 2007). Regarding pro-alternative mobility, a recent study (Xue et al., 2021) has also shown that transit users compared to private drivers were more inclined to make their purchases online due to limitations caused by time, distance, and weather.

On the other hand, people who loved wandering through shopping areas or saw shopping as a form of recreational activity (joy of shopping) were more inclined to shop at physical stores. Several past studies have confirmed that the inclination toward recreational shopping was fundamental to in-store shoppers, most of whom tended to prefer handling, taking a closer look at products, and interacting with shop assistants when shopping (Crocco et al., 2013; Farag et al., 2007; Maat & Konings, 2018; Zhen et al., 2016). Also, cost-consciousness was found to positively affect in-store grocery shopping frequency, suggesting that these individuals probably preferred in-store shopping as a better alternative that provided better prices. In this regard, shipping and delivery costs associated with online shopping might be factors discouraging them from shopping online. Our result on cost consciousness seems to contradict (Zhen et al., 2016), that found no correlation between cost consciousness and online shopping frequency for daily goods (groceries). However, the limitation of the study population to only one adult Internet-using member from each household in Nanjing, China, might have over-represented household leaders, who tend to be wealthier and less price conscious than others. Furthermore, a recent report found that those who were price sensitive tended to not shift toward e-grocery (U.S. Online Grocery Report, 2021).

Looking into the impact of socio-economic and demographic variables, younger baby boomers (i.e., those between 57 and 66 years) and retired individuals showed negative impacts toward both online and in-store grocery shopping frequency. Since these are older individuals who tend to not have dependent children, shopping in general (both online and in-store) is expected to be relatively low. Moreover, Table 14 shows that younger boomers tended to be less tech savvy or pro-alternative mobility which further discouraged them from making frequent grocery shopping online.

It is also intuitive that respondents who made at least one return in the past month tended to be frequent shoppers in general, while single-member households shopped less frequently in general, since they would not need as much grocery items as larger households. People without pre-schoolers less than five years were more likely to shop at physical stores, probably because those without pre-schoolers can travel to the store at any time and do not face the challenge of monitoring their kids frolicking around at the grocery store or having to look for a family member to stay with the kids at home while they are away at the grocery store. Furthermore, the mediating effects indicate that they tended to have a negative tendency toward tech savviness and joy of shopping, which increased their likelihood to shop in stores.

Table 14. Direct Effects on Mediating Attitudes for Grocery Shopping

		Endogenous variables				
		Tech savviness	Pro-alternative mobility	Joy of shopping	Cost consciousness	Pro-online shopping
Sex	Female	-	-0.128***	0.170***	-	0.070***
Generation	Younger boomers (aged 57-66)	-0.331***	-0.213***	-	-	-
	Older boomers (aged 67-75)	-0.267**	-0.216***	-	-0.126***	-0.122***
Household income	HH Income $15k or less	-	0.323***	0.140***	-	-
	HH Income $50k-$75k	-0.144**	-	-0.083*	0.065**	-
	HH Income $75k-$100k	-	-	-	-0.093***	-
Education	Less than high school	0.203***	-	-	-	-
	Associate degree	-	-0.088**	0.128***	-	-
Employment	Homemaker	-	-	0.240***	0.082*	-
	Retired	-0.627***	-0.134***	-0.095**	-0.091**	-0.062**
Household characteristics	Apt, 2-4 units	-	0.283***	0.169***	-	-
	Townhouse	-	-	0.164***	-	-
	HH size: 1	-	-	-	-	-0.052*
	Children less than 5 years: 0	-0.136**	-	-0.134***	-	-
	Members aged 65 plus: 0	0.198***	-	-	-	-
	Members with driver's license: 0	-	0.586***	-	-	-
Product return pattern	Return frequency	-	0.130***	0.107***	0.118***	0.039*

Note: * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.

Although it is baffling to find that people with less than a high school degree had a higher inclination toward online shopping, crosstabulation reveals that about 93% of them were younger generations (Gen X or younger) and less than 10% of them have full-time or part-time jobs, suggesting that they are relatively young individuals who would tend to fill up their higher free time with frequent Internet or technology usage. The results from the mediating attitudes also indicate that lower educated people were more interested in using technology and the internet, and eventually tended to shop online more frequently.

There are some variables in the grocery shopping model that did not have significant direct effects, but had significant indirect effects on shopping frequency. For example, females had a negative indirect impact on online shopping and a positive indirect impact on in-store shopping through three mediating variables, namely, pro-alternative mobility options, joy of shopping, and pro-online shopping. Females were less likely to prefer alternative mobility options and had a positive attitude toward online shopping, indicating their propensity toward online shopping. Nevertheless, their shopping enjoyment suggests that they tended to shop more at the physical store for grocery items. Like females, homemakers tended to shop more in-store and less online

(Saphores & Xu, 2021)

Our results for income indicate that attitudes change as the household income level rises. For instance, individuals from lower-income households (making less than $15k per year) had positive attitudes toward alternative mobility options and tended to enjoy shopping at the physical store. However, middle-class households earning between $50k and $75k were less tech-savvy and tended to not enjoy shopping, while upper middle-class households earning between $75k and $100k tended to be less cost conscious than other income groups. These differing attitudes explain indirect effects of lower-income earners who tended to shop both online and in-store, middle-income earners who were more likely to shop less frequently online, and the higher income earners who showed higher propensity toward online shopping.

Although older boomers (aged 67-75) did not have significant direct effect on grocery shopping behavior, their low tech savviness and cost consciousness, and less preferences for alternative mobility options and online shopping cumulatively reduced their shopping behavior in general. Individuals with an associate degree were less enthusiastic about using alternative mobility options, which acted as a mediating factor that indirectly discouraged them from shopping online. And their tendency to enjoy shopping indirectly increased their in-store shopping behavior. Homemakers tended to be cost conscious people who very much enjoy shopping and were indirectly more likely to shop in-store and less likely to shop online. Individuals from households with no older people (aged 65 and older) were likely to be more tech-savvy, which affected their positive indirect effect on online shopping.

The path diagram for the grocery shopping model showing the associations between the variables can be seen in Figure 34.

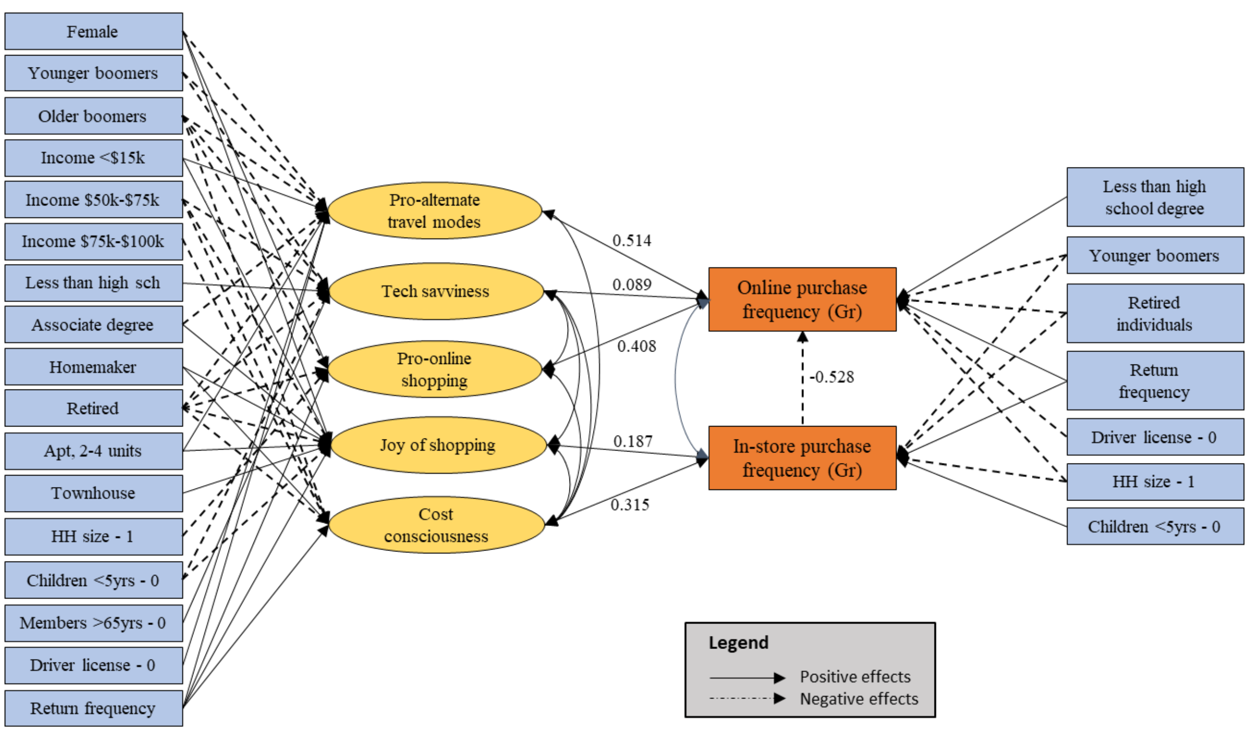


Figure 34. Path diagram for grocery shopping

7.3.1.2 Time-Moderated SEM Model for Groceries

Again, similar to the results found for search goods (books/electronics and pet supplies, respectively), the second wave of the analysis for grocery shopping reveal those who frequently shopped online tended also to shop frequently in-store, as opposed to the first wave when online shopping did not have a significant effect on in-store shopping (see Table 15). There are two main differences in the attitudinal effects. Data security concern seems to have encouraged more in-store shopping over time, while cost consciousness seems to not encourage in-store shopping during the second wave.

Table 15. Summary of Differences in Results for Grocery Shopping across Waves

Groceries						
	1st wave		2nd wave		Combined	
	Online	In-store	Online	In-store	Online	In-store
Online		neutral		positive		positive
In-store	negative		negative		negative	
Pro-alternative mobility	positive		positive		positive	negative
Joy of shopping		positive		positive		positive
Pro-online shopping	positive		positive		positive	
Data security/privacy concerns				positive		positive
Tech savviness	positive		positive		positive	
Cost consciousness		positive				positive

Table 16. Moderation Analysis Results for Grocery Shopping

Groceries	Online purchase frequency	In-store purchase frequency	Pro-alternative mobility
Endogenous variables			
Online purchase frequency	-	0.558**	-
In-store purchase frequency	-0.458***	-	-
Attitudes			
Pro-alternative mobility	0.343***	-0.300***	-
Joy of shopping	-	0.301***	-
Pro-online shopping	0.390***	-	-
Data security concern	-	0.137*	-
Technology savvy	0.142***	-	-
Cost consciousness	-	0.200**	-
Time-related variables			
Time	-	-	0.060*
Time*store_3	-	-0.244**	-
Time*security_1	-	0.084*	-

Note: for simplicity, the effects of the exogenous variables were not presented
CFI = 0.941, TLI = 0.932, RMSEA = 0.018, SRMR = 0.020

Table 16 shows the results for the moderation analysis results and reveals three important findings. First, those who think "too much personal information is required for online purchase" (security_1 – an indicator for data security concern) tended to increase the frequency of their in-store purchase, over time. In order words, time *strengthened* the positive effect of data security concern on in-store grocery shopping. This finding is consistent with differences in the effects of data security concern effects between the waves. Second, those who claimed that "price level is an important factor in choosing a store to shop from" (store_3 – an indicator for cost consciousness) tended to shop less frequently online for groceries, with time. This is also consistent with the differences found in the effects of cost consciousness on in-store grocery shopping for the waves. Thus, time *reduced* the positive effect of cost consciousness on in-store grocery shopping. Third, and lastly, time positively affected pro-alternative mobility. While the moderation analysis reveals important findings, it does not necessarily inform why online shopping showed a complementarity effect on in-store shopping in the second wave, considering that the moderating effect of time with cost consciousness is stronger on in-store shopping than with data security concern. However, we conclude that the complementarity effect found is not unrelated to the time factor within the Covid-19 pandemic context.

7.3.2 Prepared Food (PF)

7.3.2.1 Model Results for First Wave for Prepared Food

Table 17 shows the results of the estimated influences of the explanatory variables on the endogenous variables, and Table 18 shows the effects through the mediating factors for prepared food. Because the results for the grocery shopping behavior was presented in detail in the previous section, and to avoid unnecessary repetition, only the findings that substantially differ from that of the grocery shopping will be expatiated on.

The results of the interaction between online and in-store purchase frequencies for prepared food reveal that purchasing prepared food online increased the tendency to purchase in-store, but purchasing food in-store had no effect on purchasing food online. Thus, online shopping complemented in-store shopping for prepared food. The effects of attitudes such as tech savviness, pro-alternative mobility options, joy of shopping, and pro-online shopping on shopping frequencies for prepared food were quite similar to the results found for groceries. Cost consciousness, however, did not significantly affect shopping behavior for prepared food.

Unlike the results for grocery shopping that did not find significant influences of the younger generations (Gen Zers and Millennials), direct positive effects were found between millennials and online shopping frequency for prepared food. Also, the high tech savviness and preference for alternative mobility of the younger generation mediated their frequent online shopping tendency. Whites tended not to frequently buy prepared food in general. Also, those who had graduate or professional degrees tended to shop more frequently online and in-store, mediated by their preference for alternative mobility options.

Table 17. SEM Results for Prepared Food Shopping

Prepared Food		Endogenous variables					
		Online			In-store		
		Direct	Indirect	Total	Direct	Indirect	Total
Shopping behavior	Online purchase frequency	-	-0.007	-0.007	0.204**	-0.001	0.203
	In-store purchase frequency	-0.036	-	-0.036	-	-0.007	-0.007
Attitudes	Tech-savvy	0.115***	-0.001	0.114	-	0.023	0.023
	Pro-alternative mobility	0.587***	-0.004	0.583	-	0.119	0.119
	Shopping enjoyment	-	-0.007	-0.007	0.205***	-0.001	0.204
	Pro-online shopping	0.429***	-0.003	0.426	-	0.087	0.087
Sex	Female	-	-0.05	-0.05	-	0.022	0.022
Generation	Gen Z (18 to 24)	-	0.282	0.282	-	0.058	0.058
	Millennials (25-40)	0.099*	0.12	0.219	-	0.045	0.045
	Younger boomers (57-66)	-	-0.102	-0.102	-0.279***	-0.021	-0.3
	Older boomers (67-75)	-	-0.163	-0.163	-0.411***	-0.052	-0.463
Ethnicity	White	-0.172**	-0.078	-0.25	-	-0.068	-0.068
Household income	HH income: $15k or less	-	0.107	0.107	-	0.047	0.047
	HH income: $100k-$150k	-	0.018	0.018	-	0.004	0.004
	HH income: $150k +	-	0.007	0.007	-0.224**	0.031	-0.193
Education	Some college	-	0.012	0.012	0.159**	0.002	0.161
	Associate degree	-	-0.001	-0.001	-	0.024	0.024
	Graduate	-	0.073	0.073	-	0.015	0.015
Employment	Homemaker	-	0.008	0.008	-0.267***	0.047	-0.22
Marital status	Married	-	-0.015	-0.015	-	-0.003	-0.003
House type	Apt, 2-4 units	-	0.139	0.139	-	0.054	0.054
	Townhouse	-	-0.001	-0.001	-	0.028	0.028
Household characteristics	HH size: 1	-	-0.069	-0.069	-0.153**	-0.014	-0.167
	HH size: 2	-	-0.041	-0.041	-	-0.008	-0.008
	No of children less than 5 years: 0	-	0.001	0.001	-	-0.024	-0.024
	No of children aged 5 to 18: 1	0.197**	0.064	0.261	-	0.053	0.053
	No of children aged 5 to 18: 2	-	0.143	0.143	-0.467**	0.029	-0.438
	No of children aged 5 to 18: 2 plus	-	-0.018	-0.018	0.492**	-0.004	0.488
	No of members aged 65 plus: 0	-	0.053	0.053	0.143**	0.011	0.154
	No of members with driver's license: 0	-0.335***	0.177	-0.158	-	-0.032	-0.032
	No of members with driver's license: 1	-	-0.001	-0.001	-	0.018	0.018
Vehicle ownership	No of vehicles: 0	-0.290*	0.434	0.144	-	0.029	0.029
	No of vehicles: 1	-	0.075	0.075	-0.103*	0.015	-0.088
Product return pattern	Return frequency	0.143**	0.057	0.2	0.120*	0.062	0.182

Note: * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.
Goodness of fit indices (robust estimation): CFI = 0.957, TLI = 0.950, RMSEA = 0.017, SRMR = 0.020

Table 18. Direct Effects on Mediating Attitudes for Prepared Food

		Endogenous variables			
		Tech savviness	Pro-alternative mobility	Shopping enjoyment	Pro-online shopping
		Direct	Direct	Direct	Direct
Sex	Female	-	-0.130***	0.158***	0.063***
Generation	Gen Z (age 18-24)	0.405***	0.405***	-	-
	Millennials (age 25-40)	0.283***	0.151***	-	-
	Younger boomers (age 57-66)	-0.306***	-0.133***	-	-
	Older boomers (age 67-75)	-0.390***	-0.159***	-0.094**	-0.096***
Ethnicity	White	-	-0.099**	-0.084**	-0.052**
Household income	HH Income: $15k or less	-	0.185***	0.125***	-
	HH Income $35k-$50k	-	-	-	-0.072***
	HH Income $100k-$150k	0.157**	-	-	-
	HH Income $150k or more	-	-	0.145**	-
Education	High school graduate	-0.228***	-	-	-
	Some college	-	-	-	0.041*
	Associate degree	-	-	0.116***	-
	Graduate degree	-	0.126***	-	-
Employment	Homemaker	-	-	0.223***	-
Marital status	Married	-0.135***	-	-	-
House type	Apt, 2-4 units	-	0.240***	0.125**	-
	Townhouse	-	-	0.136***	-
Household characteristics	HH size: 1	-0.280***	-	-	-0.099***
	HH size: 2	-0.132***	-	-	-0.061***
	No of children less than 5 years: 0	-	-	-0.118***	-
	No of children aged 5 to 18: 1	-	0.112**	-	-
	No of children aged 5 to 18: 2	-	0.217***	-	-
	No of members aged 65 plus: 0	0.324***	-	-	0.050**
	No of members with driver's license: 0	-	0.300***	-	-
	No of members with driver's license: 1	-	-	0.086***	-
Vehicle ownership	No of vehicles: 0	-	0.742***	-	-
	No of vehicles: 1	-	0.122***	-	-
Product return pattern	Return frequency	-	0.109***	0.104***	-

Note: * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.

Interestingly, higher income people who made more than $150k or more per year were less likely to shop at the physical store, probably because of time constraints. Looking at the mediating effects, their tendency to enjoy shopping increased their propensity to shop in-store and slightly moderated their low propensity to buy food in-store.

Homemakers tended not to frequently buy food in-store, though they enjoyed shopping for leisure. Those living alone or with one person tended to not frequently buy prepared food in general. The effects on the number of children between 5 and 18 years were not consistent, just as one previous study found mixed results in relation to the effect of the number of children under 18 years (Saphores & Xu, 2021). Although we specified the age range of the children to capture the characteristics of children who are not overly dependent on their parents (unlike pre-schoolers), it is speculated that the characteristics of children within this age range are not homogenous enough to give consistent results. Interestingly and somewhat similar to the results for grocery shopping, lack of private vehicles in the home or having members who do not have a driver's license were linked with reduced tendency to buy food online. However, their strong preference for alternative mobility options moderated this tendency, and judging by the indirect effect, increased their tendency to shop online. The path diagram showing the interactions among the variables can be seen in Figure 35.

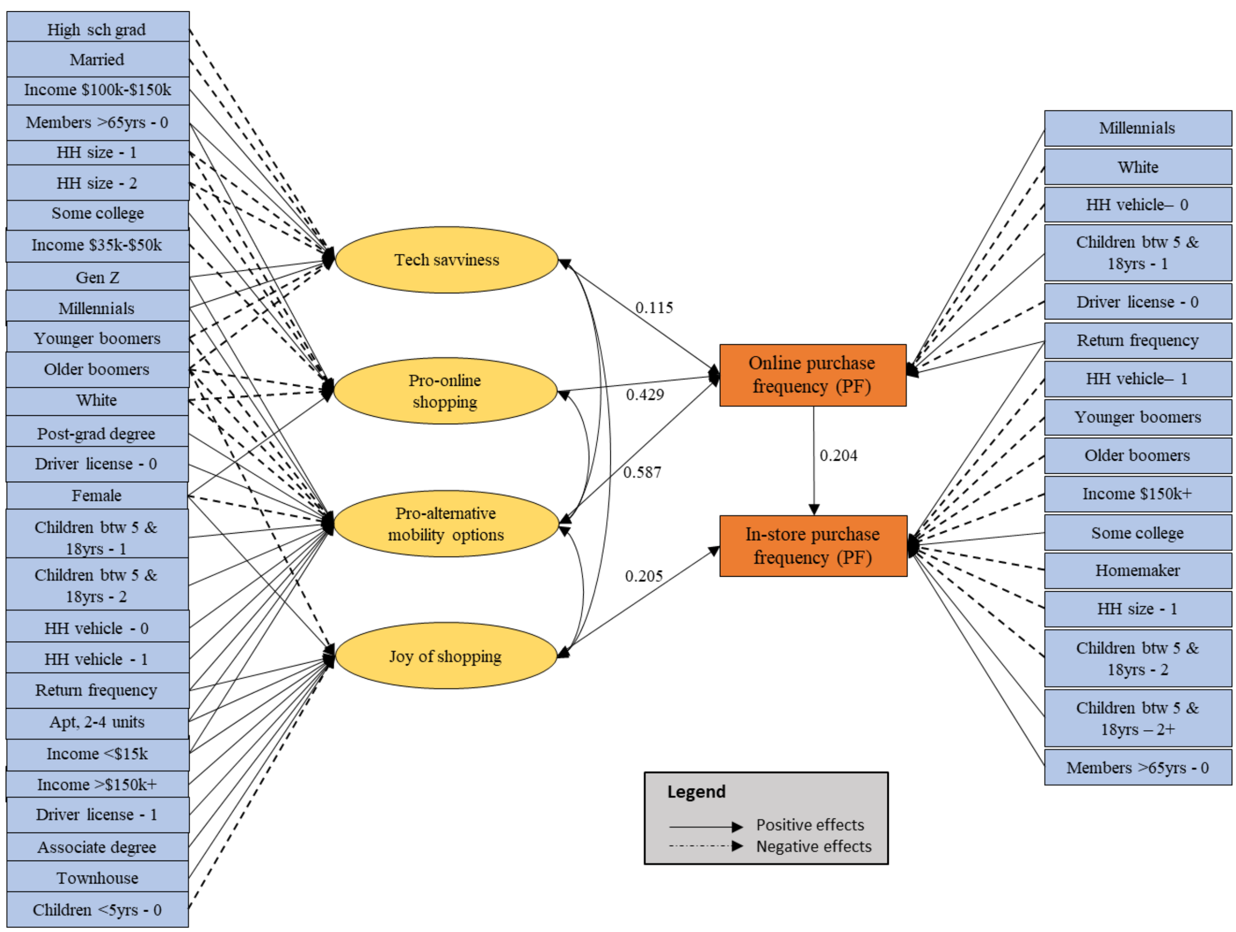


Figure 35 . Path diagram for prepared food

7.3.2.2 Time-Moderated SEM Model for Prepared Food

From Table 19, the results for prepared food seem quite consistent except the impact of in-store shopping on online shopping. In-store shopping had a neutral effect on online shopping during the first wave, while a negative effect was found during the second wave. It is suggested that the re-opening of restaurants for in-person dine in may have discouraged in-store shoppers from purchasing online. While the attitudinal effects are similar over the two waves, the moderation analysis reveals strengthening and weakening effects of time.

Table 19. Summary of Differences in Results for Prepared Food across Waves

Prepared Food						
	1st wave		2nd wave		Combined	
	Online	In-store	Online	In-store	Online	In-store
Online		positive		positive		positive
In-store	neutral		negative		negative	
Pro-alternative mobility	positive		positive		positive	
Joy of shopping		positive		positive		positive
Pro-online shopping	positive		positive		positive	
Tech savviness	positive		positive		positive	

From Table 20, those who "regularly ride public transportation to save money" (mobility_3 – an indicator pro-alternative mobility) shopped online less frequently, over time. This means, time *weakened* the positive effect of pro-alternative mobility on online shopping for prepared food. This result is similarly found when shopping for pet supplies. Also, those who claimed that "without technology, my life would be boring" (tech_3 – an indicator for tech savviness) tended to shop online more frequently than those who are generally tech savvy, over time. In order words, time *strengthened* the positive effect of tech savviness on online shopping for prepared food. Like the results found in the moderation analyses of other products, time positively affected pro-alternative mobility. While moderating effects were found, changes were not strong enough to reduce the significance of the positive effects on shopping behavior.

Table 20. Moderation Analysis Results for Prepared Food

Prepared food	Online purchase frequency	In-store purchase frequency	Pro-alternative mobility
Endogenous variables			
Online purchase frequency	-	0.584***	-
In-store purchase frequency	-0.394***	-	-
Attitudes			
Pro-alternative mobility	0.331***	-	-
Joy of shopping	-	0.428**	-
Pro-online shopping	0.521***	-	-
Technology savvy	0.181***	-	-
Time-related variables			
Time	-	-	0.069**
Time*tech_3	0.095*	-	-
Time*mobility_3	-0.076*	-	-

Note: for simplicity, the effects of the exogenous variables were not presented
CFI = 0.943, TLI = 0.933, RMSEA = 0.020, SRMR = 0.021

7.3.3 Summary for Essential Experience Goods

We have examined how online and in-store shopping (for groceries and prepared food, respectively) are interacting with each other, the SED characteristics and return pattern affect shopping behavior, and the attitudes mediate the effects. We found that online grocery shopping had no significant effect on in-store grocery shopping trips, but those who frequently shopped in-store tended to shop less frequently online. This suggests that online shopping is not substituting travel, and the use of in-store grocery shopping obviates the need for most shoppers to use online grocery retail stores. For prepared food, online shopping complemented in-store shopping, but in-store shopping did not significantly affect online shopping.

Among the seven attitudes included in our model, five of them were significant for groceries, while four were for prepared food. Similar effects were seen for both product types, as individuals who were tech savvy, preferred alternative mobility options, and were pro-online shopping were likely to shop more frequently online, while those who enjoyed in-store shopping tended to make more in-store shopping frequencies. In grocery shopping, however, cost-consciousness encouraged shopping trips to the grocery store. While in-store shopping remains the dominant mode of food and grocery shopping and the reasons are mostly attributable to the joy of shopping in-store and the high cost of online grocery shopping, online shopping tends to substitute travel for some high income-earning households (for both groceries and prepared food). Thus, as retail companies compete to accommodate e-grocery, the resulting lower cost of online shopping might attract cost-conscious individuals in replacing their shopping trips with e-grocery.

7.4 Non-Essential Experience Goods

7.4.1 Clothing, Shoes, Watches, Jewelry (CSWJ)

7.4.1.1 Model Results for First Wave for Clothing, Shoes, Watches, Jewelry

The results of the effects of various factors on the shopping frequencies are presented in Table 21. From the interactions between the endogenous variables, Positive effects were found between online and in-store shopping behavior for CSWJ in both directions of influence, though the effect of online shopping on in-store shopping frequency was larger than its reverse direction of influence. This finding is generally consistent with some studies that found online shopping frequency to exhibit a positive effect on in-store shopping frequency for non-daily or non-grocery products (Cao et al., 2012; Dias et al., 2020), and other studies that demonstrated that in-store shopping also increased online shopping in general (Ding & Lu, 2017; Etminani-Ghasrodashti & Hamidi, 2020; Farag et al., 2007). The results indicate that online shopping did not replace in-store visits for CSWJ. Individuals who often shopped online for these products were likely to also make more shopping trips. Regarding the reverse effects from in-store to online shopping, a possible explanation might be that in-store shoppers may have purchased some items in the store, become attracted by some other items, and then gone back to use the Internet or store websites to find better alternatives, or similar products at a lower price or to purchase items online when stores are closed (Ding & Lu, 2017).

Table 21. Effects on Online and In-Store Shopping Behavior for CSWJ

	Online purchase frequency			In-store purchase frequency		
	Direct	Indirect	Total	Direct	Indirect	Total
Endogenous variables						
Online purchase frequency	0	0.658	0.658	0.852***	0.561	1.413
In-store purchase frequency	0.466***	0.307	0.773	0	0.658	0.658
Attitudes						
Pro-alternative mobility	0.120*	0.079	0.199	0	0.17	0.17
Joy of shopping	0	0.124	0.124	0.160***	0.105	0.265
Pro-online shopping	0.409***	0	0.409	-0.348**	0.349	0.001
Technology savviness	0.040*	0.026	0.066	0	0.057	0.057
Privacy and security concerns	0	0.124	0.124	0.160***	0.105	0.265
Unattended delivery concerns	-0.297***	-0.196	-0.493	0	-0.42	-0.42
Gender - Female	0	0.068	0.068	0	0.058	0.058
Generation						
Gen Z (aged 18-24)	0	0.324	0.324	0.267**	0.276	0.543
Millennials (aged 25-40)	0.088**	0.091	0.179	0	0.132	0.132
Younger boomers (aged 57-66)	0	-0.093	-0.093	0	-0.079	-0.079
Older boomers (aged 67-75)	0	-0.182	-0.182	-0.144***	-0.108	-0.252
Ethnicity - Hispanic	0	0.053	0.053	0	0.056	0.056
Race						
White	0	-0.048	-0.048	0	-0.057	-0.057
Black	0.185**	0.147	0.332	0	0.283	0.283
Income						
Less than $15k	0	0.018	0.018	0	0.039	0.039
Between $35k & $50k	0	-0.03	-0.03	0	0	0
Between $100k & $150k	0	0.083	0.083	0	0.071	0.071
Education						
High sch grad	0	-0.012	-0.012	0	-0.01	-0.01
Associate degree	0	0.014	0.014	0	0.029	0.029
Bachelor’s degree	0	0	0	-0.101**	0	-0.101
Post-grad degree	0	-0.01	-0.01	-0.132**	-0.009	-0.141
Marital status						
Divorced/separated	0	-0.012	-0.012	0	-0.027	-0.027
Employment						
Full-time employed	0.107**	0.055	0.162	0	0.119	0.119
Homemaker	0	0.032	0.032	0	0.068	0.068
Unemployed	0	-0.069	-0.069	0	-0.059	-0.059
Retired	0	-0.066	-0.066	0	-0.056	-0.056
House type						

Table 21, Continued

	Online purchase frequency			In-store purchase frequency		
	Direct	Indirect	Total	Direct	Indirect	Total
Detached single	0	0.052	0.052	0	0.044	0.044
Townhouse	0	0.018	0.018	0	0.039	0.039
Apt, 2-4 units	0	0.097	0.097	0	0.136	0.136
Household characteristics						
Household size: 1	-0.119***	-0.078	-0.197	0	-0.168	-0.168
Household size: 3	0	0.021	0.021	0	0	0
Household size: 4	0	0.024	0.024	0	0.021	0.021
Members aged 65 plus: 0	0	0.011	0.011	0	0.009	0.009
Owned vehicles: 0	0	0.136	0.136	0	0.116	0.116
Owned vehicles: 2	0	-0.016	-0.016	0	-0.014	-0.014
Owned vehicles: 3 or more	0	0.022	0.022	0	0	0
Members with driver's license: 0	0	0.077	0.077	0	0.095	0.095
Members with driver's license: 3 plus	0	-0.022	-0.022	0	-0.019	-0.019
Children less than 5 years: 0	0	-0.015	-0.015	0	-0.033	-0.033
Children less than 5 years: 2	0	0.016	0.016	0	0.014	0.014
Product return pattern						
Return frequency	0.198***	0.164	0.362	0	0.326	0.326

Note: * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.
Goodness of fit indices (robust estimation): CFI = 0.957, TLI = 0.951, RMSEA = 0.016, SRMR = 0.021

In view of the impacts of the latent attitudes on shopping frequency, we found that those who preferred to use alternative mobility options (e.g., public transport) had a higher tendency to make their purchases online. Although mobility preferences tended to differ by study location or country, our finding agrees with the study conducted by Ramirez (2019) which showed that public transportation commuters in the U.S. were more likely than others to make frequent online purchases. As expected, a positive direct effect was observed from technology savviness to online shopping frequency, which complies with overall findings in the literature (Cao et al., 2012; Farag et al., 2006). A similar positive direct effect was observed in "pro-online shopping" attitude, indicating that these amenities of online shopping (i.e., "shopping 24/7", "finding items in high demand", and "having a greater variety of choices") contributed to the decision to shop online for those who found these features attractive. As expected, pro-online shopping attitude also reflects a direct negative impact on in-store shopping frequency, but it was almost cancelled out by the positive indirect effects mediated through online shopping frequency.

The results show that those who enjoyed shopping tended to shop more frequently in-store (Cao et al., 2012; Crocco et al., 2013; Swaminathan et al., 1999), which indicates that there are certain elements in physical shopping that cannot be replaced by online shopping, especially for those who are not under any time pressure. Similarly, concerns about data privacy and security during online transactions tended to increase in-store shopping frequency, but with no direct (negative) effect on online shopping. This might indicate that privacy and security concern was not a determinant factor in discouraging online shopping, people still shop online for some of their needs even in the presence of such concerns. Past studies, however, have reported negative effects of perceived risk (and its antecedents) in using the Internet for online shopping (Crocco et al., 2013; George, 2004; Hsu et al., 2014). This may be a unique finding of this study suggesting that the COVID-19 experience may have neutralized the negative concerns on data privacy and online security. Similar to findings in the literature (Kedia et al. 2019), our model showed that those who had a negative attitude toward unattended deliveries were likely to make less frequent online purchases for CSWJ products.

Looking at the direct effects of the exogenous variables, millennials tended to shop more frequently online for CSWJ products, while Gen-Z showed a direct positive effect on in-store shopping frequency. Older baby boomers were less likely to shop in-store, and younger baby boomers did not show preferences to any shopping alternatives. While overwhelming evidence in the literature suggests that younger generations tended to shop more frequently online (Cao et al., 2012; Crocco et al., 2013; Farag et al., 2006; Irawan & Wirza, 2015; Lee et al., 2015; Unnikrishnan & Figliozzi, 2020), Gen Zers' frequent in-store shopping for CSWJ may owe to the fact that they are less likely to be working full-time and would tend to have lower time-pressure than the Millennial generation. The tendency of older adults to generally drive less to avoid complex driving situations, busy traffic conditions and night driving, alongside their reduced desire to make new purchases in general may explain their negative effect on in-store shopping frequency. We also found that blacks or African Americans tended to shop more frequently online than other racial groups, which is not at odds with past studies that suggested that, in shopping for food or groceries, blacks tended to be oriented towards online shopping than other groups. (Kim & Wang, 2021).

Our model also indicates a direct negative impact of one-person households on online shopping frequency, which consequently results in an indirect negative impact on in-store shopping. This might be reasonable in the sense that living alone reduces shopping needs in general. In addition, one can see that those who experienced at least one product return in the past month were more likely to shop online, probably due to the free-return policy implemented by many online shops. Since shoppers are not usually penalized for returning purchased items, customers can risk buying multiple items they like, test or experience them, keep the ones they like and easily return the rest. And in turn, they go online and purchase more items.

There are a number of variables in the model (Table 21) that did not have significant direct effects on shopping frequency, but had significant indirect effects mediated through attitudes, e.g., gender, income, education, employment, marital status, house type, and household characteristics. Homemakers' shopping behavior was mostly affected by their joy of shopping. Less concern for unattended delivery was associated with highly educated individuals, those from wealthy households, and those living in detached single houses, which increased their tendency for online shopping. Household characteristics contributed to varying attitudes, which in turn influenced their shopping frequencies.

Mediating Effects for CSWJ

Table 22 shows the direct effects of the exogenous variables on the latent attitudes, which in turn influenced individuals' shopping behavior. It is observed that the effect of gender on shopping behavior was mediated by various attitudes. Females tended to enjoy shopping, value the benefits of online shopping (i.e., shopping 24/7, having more choices and finding items in high demand), not prefer alternative mobility options, and have less concern about unattended delivery. The positive relationships between female and pro-online shopping and joy of shopping suggest that females shopped more frequently both online and in-store than males, but due to different underlying reasons. Females' negative attitude toward alternative mobility options may be moderating their online shopping frequency, and their lesser concern toward unattended delivery may be encouraging more online shopping. Thus, the results suggest that female had indirect positive effects on both online and in-store shopping for CSWJ products, which is supported by the literature (Ramirez, 2019).

Gen Z and Millennials were alike in their preference for alternative mobility options and technology savviness, but Millennials tended to have less data security concerns. Baby boomers' lower technology savviness might have predisposed them to less online shopping. Our analysis also indicates that those living in households with income level lower than $15k tended to enjoy shopping more, while those with higher income levels (between $100k and $150k) tended to be more tech savvy and not as much concerned about unattended delivery compared to other income groups. These led to higher in-store shopping frequency for the low-income groups and higher online shopping frequency for the higher income groups, albeit both groups showed positive indirect effects on both online and in-store shopping frequency due to the complementary effects between the two. On the other hand, individuals with low-to-medium income ($35k to $50k) were less likely to be pro-online shopping, which resulted in negative indirect impacts on both online and in-store shopping frequencies.

Regarding the impact of education on shopping behavior for CSWJ, the direct effects showed that those with at least a bachelor's degree tended to shop less frequently in-store. The indirect effect of education through different attitudes revealed that as education level increased, both online and in-store shopping frequencies increased. In addition, our results indicate that those with lower levels of education (i.e., having an associate degree or less) tended to shop online less frequently compared to in-store shopping, while those with a post-graduate degree showed the opposite effects (less in-store purchases compared to online purchases). These findings are consistent with the literature (Cao et al., 2012; Lee et al., 2015; Ramirez, 2019; Xue et al., 2021). This could be attributed to the low tech-savviness of individuals with lower level of education (i.e., high school graduates) and post-graduate degree holders' less concern for unattended delivery.

Table 22. Direct Effects on Mediators for CSWJ

	Pro-alternative mobility	Joy of shopping	Pro-online shopping	Tech savviness	Data security concerns	Unattended delivery concerns
Gender						
Female	-0.120**	0.167***	0.077***	-	-	-0.080*
Generation						
Gen Z	0.455***	-	-	0.404***	-	-
Millennials	0.162***	-	-	0.245***	-0.127**	-
Younger boomers	-	-	-	-0.211*	-	0.160***
Older boomers	-	-	-0.135***	-0.226*	-	-
Race						
White	-	-0.101**	-0.053*	-	-0.113**	-
Black	0.129*	-	-	-	-	-
Ethnicity						
Hispanic or Latino	-	0.119**	0.066**	-	0.090*	-
Income						
Less than $15k	-	0.148**	-	-	-	-
Between $35k & $50k	-	-	-0.074**	-	-	-
Between $100k & $150k	-	-	-	0.049*	-	-0.148**
Education						
High school graduate	-	-	-	-0.179**	-	-
Associate degree	-	0.111*	-	-	-	-
Post-graduate degree	-	-	-	-	-	-0.186***
Employment						
Full-time employed	-	-	-	-	-0.122**	-
Unemployed	-	-	-	-	-	0.141**
Homemaker	-	0.257***	-	-	-	-
Retired	-0.161***	-	-	-0.512***	-	-
Marital status						
Divorced or separated	-	-	-	-	-0.101*	-
House type						
Detached single house	-	-	-	-	-	-0.105**
Apt, 2-4 units	0.283***	0.159 **	-	-	0.174**	-
Townhouse, row house	-	0.147**	-	-	-	-
Household characteristics						
Household size: 3	-	-	0.052*	-	-	-
Household size: 4	0.121*	-	-	-	-	-
Children less than 5 years: 0	-	-0.124**	-	-	-	-
Children less than 5 years: 2	-	-	-	0.244*	-	-
Members with driver's license: 0	0.270**	-	-	-	0.185 **	-
Members with driver's license: 3 plus	-0.113**	-	-	-	-	-
Members aged 65 plus: 0	-	-	-	0.162*	-	-
No of vehicles: 0	0.683***	-	-	-	-	-
No of vehicles: 2	-0.080*	-	-	-	-	-
No of vehicles: 3 plus	-	-	0.054*	-	-	-
Product return pattern						
Return frequency	0.103*	0.110**	-	-	-	-

Note: * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.

In terms of employment, full-time workers tended to shop online more frequently since pressure on their time would be higher for them compared to non-workers. It also appears that nonworkers (i.e., homemakers, retired, and currently unemployed) were more likely to have attitudes that lead to more in-store shopping and less online shopping for CSWJ products. For example, homemakers tended to enjoy shopping; retired individuals tended to be less tech savvy and not prefer alternative mobility options, while unemployed individuals were more likely to be concerned about unattended delivery. Figure 36 shows the path diagram for the CSWJ model.

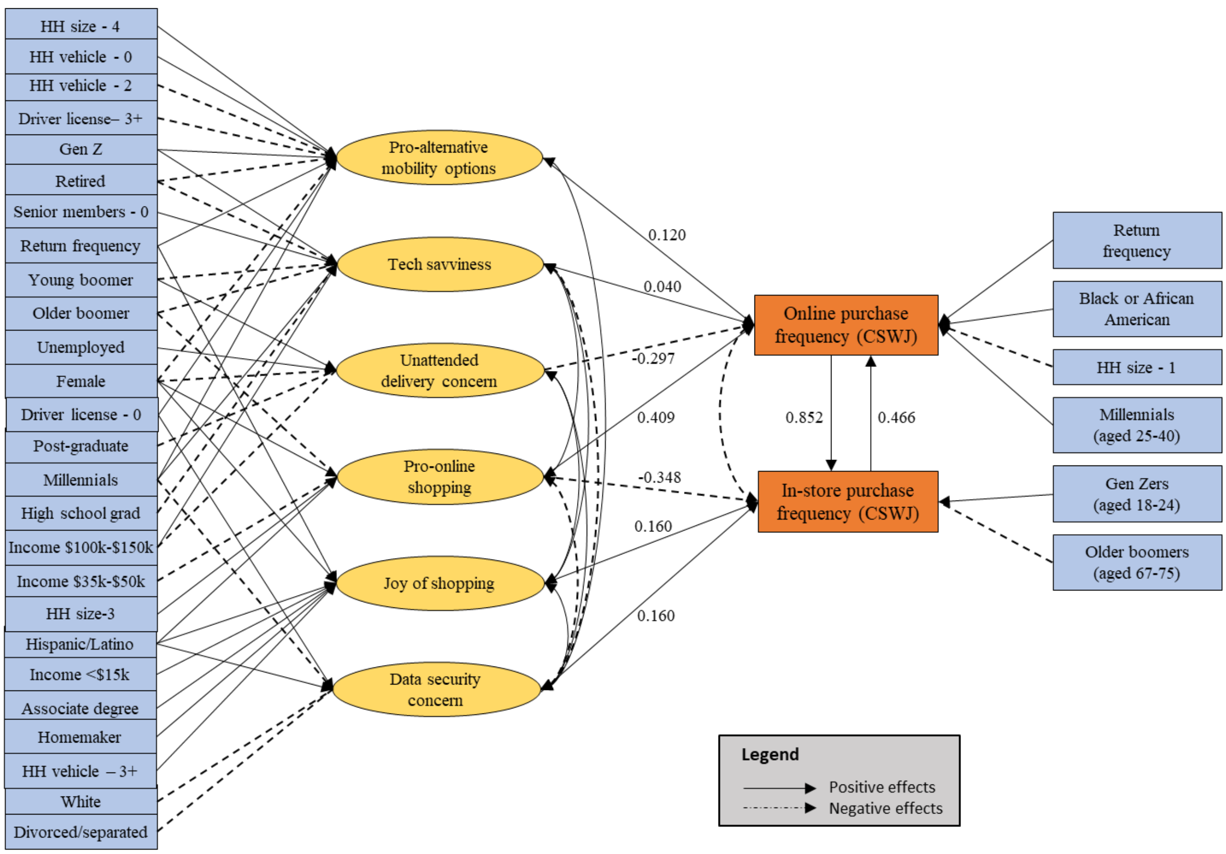


Figure 36. Path diagram for CSWJ

7.4.1.2 Time-Moderated SEM Model for Clothing, Shoes, Watches, Jewelry

Table 23 showed no changes in the relationship between online and in-store shopping for both waves. This does not mean there were no changes to these shopping behavior interactions, it means, however, that the effects of the changes were not strong enough to cause the formerly positive effects to become insignificant or negative. Moreover, it is also possible that the complementarity effects became stronger over time. And while it is possible it is difficult to determine the magnitude of the effect of these changes, the effects of the attitudes on the shopping behavior for both waves may help shed some light.

There were several changes to the impact of attitudes on online and in-store shopping between both waves. Preference for alternative mobility options, that positively affected only online shopping in the first wave, did not have significant effect on online shopping, but had significant positive effects on in-store shopping. This suggests there was a shift in shopping behavior from online shopping to in-store shopping for those who prefer using alternative mobility options. Contrastingly, those who had data security concerns were no longer predisposed to shopping in-store during the second wave. Also, tech savviness no longer encouraged frequent online shopping, while favorable attitude toward online shopping no longer discouraged in-store shopping during the second wave. In addition, concern about unattended delivery was no longer positive relative to online shopping. The change in the effect of those concerned about unattended delivery may be related to the re-opening of non-essential stores over time, as some of those who may have had those concerns in the first wave would have had the opportunity to go to the store to purchase their clothing items or accessories.

Table 23. Summary of Differences in Results for CSWJ across Waves

Clothing, shoes, watches, jewelry						
	1st wave		2nd wave		Combined	
	Online	In-store	Online	In-store	Online	In-store
Online		positive		positive		positive
In-store	positive		positive		positive	
Pro-alternative mobility	positive			positive	positive	positive
Joy of shopping		positive		positive		positive
Pro-online shopping	positive	negative	positive		positive	
Data security/privacy concerns		positive				positive
Tech savviness	positive				positive	
Unattended delivery concerns	negative					

Table 24. Moderation Analysis Results for CSWJ

CSWJ	Online purchase frequency	In-store purchase frequency	Pro-alternative mobility
Endogenous variables			
Online purchase frequency	-	0.433***	-
In-store purchase frequency	0.379***	-	-
Attitudes			
Pro-alternative mobility	0.084*	0.240***	-
Joy of shopping	-	0.197***	-
Pro-online shopping	0.392***	-	-
Data security concern	-	0.091**	-
Technology savvy	0.060**	-	-
Time-related variables			
Time	-	-	0.064*
Time*security_4	-	-0.039*	-

Note: for simplicity, the effects of the exogenous variables were not presented
CFI = 0.938, TLI = 0.929, RMSEA = 0.018, SRMR = 0.021

Table 24 demonstrates that those who tended to "have heard much bad news about online shopping scams" (security_4 – an indicator for data security concern) tended to shop in a store less frequently over time. In this regard, it could be said that time *weakened* the positive effect of data security on in-store shopping for CSWJ. Also, time positively affected the preference for alternative mobility options. While there were complex interactions in place in the model, the biggest change apparently was the shift from the positive effect of those who preferred alternative mobility on online shopping to in-store shopping.

7.4.2 BH, TKB, and HGT

7.4.2.1 Model Results for First Wave for BH, TKB, and HGT

To facilitate easy comparison between CSWJ and the other experienced goods, only the direct effects of the significant factors on the endogenous variables are presented. Table 25 shows the the interactions between the endogenous variables for the four product types. The model fit indices for each product type, shown in Table 26, indicate that the models perform reasonably well. Like CSWJ, the results for TKB indicate positive effects between online and in-store shopping frequency in both directions, though the effect of in-store shopping on online shopping frequency was weaker. For BH and HGT, online shopping had positive effects on in-store shopping frequency, but no effects were found in the reverse direction.

Table 25. Interactions between Endogenous Variables for Non-Essential Experience Goods

			Endogenous	
			Online	In-store
Exogenous variables	Clothing, shoes, watches, jewelry (CSWJ)	Online		0.852***
		In-store	0.466***	
	Beauty and health products (BH)	Online		0.252**
		In-store	0.061	
	Toys, kid, and baby supplies (TKB)	Online		0.460***
		In-store	0.188*	
	Home, garden, and tools (HGT)	Online		0.678***
		In-store	-0.067	

Note: * significant at $p < 0.01$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.

Table 26. Model Fit Indices for Non-Essential Experience Goods

	CSWJ	BH	TKB	HGT
User Model versus Baseline Model:				
Robust Comparative Fit Index (CFI)	0.957	0.959	0.969	0.961
Robust Tucker-Lewis Index (TLI)	0.951	0.952	0.963	0.954
Robust RMSEA	0.016	0.017	0.016	0.016
90% confidence interval – lower	0.014	0.014	0.013	0.014
90% confidence interval – upper	0.017	0.019	0.019	0.018
Standardized Root Mean Square Residual (SRMR)	0.021	0.021	0.019	0.02

The results indicate that online shopping did not replace in-store visits for experience goods. The literature suggested that these shoppers might use online shopping to not only make purchases but to also prepare for physical shopping purposes – e.g., find out where and when to shop or experience their products before purchase (Farag et al., 2007). It should be noted that, unlike previous studies (Ding & Lu, 2017; Etminani-Ghasrodashti & Hamidi, 2020; Farag et al., 2007), no effect was found on online shopping frequency from in-store shopping for BH and HGT products.

Explanatory Factors

There are some factors that affect the shopping behavior in shopping for most or all the product types (see Table 27). Those who prefer alternative mobility options and have positive attitude toward online shopping tend to shop frequently online, while those who value recreational shopping and have data privacy concerns tend to shop more frequently in stores. Also, full time employment predisposed shoppers to shopping frequently online, except when shopping for BH. Being a baby boomer or older negatively affected in-store shopping, but were not significant in affecting online shopping.

While it could be said that there was a general consistency in the shopping behavior among the four product types, shopping behavior differed in some cases. For example, technology savviness and concerns for unattended delivery influenced the shopping behavior for CSWJ products only and did not show significant effects (at 95% CI) for other product types. Moreover, female showed a positive direct effect on online shopping frequency for BH products only. There were only indirect effects between being a female and shopping (online and in-store) for CSWJ, as females tended to have attitudes that are linked with more shopping in general. Although there are no apparent contradictions in the results relating to household characteristics, it is difficult to draw reasonable conclusions from the findings on household characteristics.

Also, online versus in-store shopping frequency differed for some products, as the descriptive statistics show that online and in-store shopping frequencies for CSWJ were similar, but the in-store shopping frequency for BH products was higher than its online shopping. For visualization and comparison purposes, see Figures 37-39 for the path diagrams for BH, TKB, and HGT, respectively.

Table 27. Model Results of Online and In-Store Shopping Frequency for Non-Essential Experience Goods

	CSWJ		BH		TKB		HGT	
	Online	In-store	Online	In-store	Online	In-store	Online	In-store
Attitudes								
Pro-alternative mobility	0.120*	-	0.283***	-	0.186**	-	0.311***	-
Pro-online shopping	0.409***	-0.348**	0.242***	-	0.145**	-	0.231***	-
Tech savviness	0.040*	-	-	-	-	-	-	-
Joy of shopping	-	0.160***	-	0.148***	-	0.157***	-	0.080**
Data security concerns	-	0.160***	-	0.167***	-	-	-	0.083**
Unattended delivery concerns	-0.297***	-	-	-	-		-	-

Table 27, Continued

	CSWJ		BH		TKB		HGT	
	Online	In-store	Online	In-store	Online	In-store	Online	In-store
Gender								
Female	-	-	0.123**	-	-	-	-	-
Generation								
Gen Z	-	0.267**	-	-	-	-	-	-
Millennials	0.088**	-	0.152**	-	-	-	-	-
Gen X	-	-	-	-	-	-	-0.102**	-
Younger boomers	-	-	-	-0.146**	-	-0.122**	-	-
Older boomers	-	-0.144***	-	-0.235***	-	-0.130***	-	-0.154***
Silent generation	-	-	-	-0.228**	-	-	-	-0.223***
Race								
Black	0.185**	-	0.177*	0.253***	-	-	-	-
Income								
Between $35k & $50k	-	-	-	-	-	-	-	0.117*
Between $50k & $75k	-	-	-	-	-	-	-0.098***	-
Education								
Less than high sch	-	-	-	-	-	0.403*	-	-
High sch grad	-	-	-0.170***	-	-0.096*	-	-	-
Associate	-	-	-	-	-0.105**	-	-	-
Bachelors	-	-0.101**	-	-	-	-0.066*	-	-
Post-grad	-	-0.132**	-	-	-	-	-	-
Employment								
Full-time employed	0.107**	-	-	-	0.105**	-	0.119**	-
Retired	-	-	-0.084*	-	-	-	-	-
House type								
Detached single	-	-	-	-	-	-	0.082*	0.108*
Apt, 5 or more units	-	-	-	-	-	-	-	-0.113*
Household characteristics								
Household size: 1	-0.119***	-	-	-0.111*	-0.139***	-	-	-
Children less than 5 years: 0	-	-	-	-	-0.542***	-0.388***	-	-
Children less than 5 years: 2	-	-	-	-	-	-	-	-0.181*
Children btw 5 & 18 years: 0	-	-	-0.139**	-0.198**	-0.285***	-0.242***	-0.110**	-
Children btw 5 & 18 years: 1	-	-	-	-0.178*	-	-	-	-
Members aged 65 plus: 0	-	-	-	-	-0.073*	-	-	-
Members aged 65 plus: 1	-	-	-	-	-	-	-	-0.095*
Owned vehicles: 0	-	-	-	-	-	-	-0.343**	-
Owned vehicles: 1	-	-	-	-	0.121**	-	-	-
Members with driver's license: 0	-	-	-0.265**	-	-	-	-	-
Product return pattern								
Return frequency	0.198***	-	0.269***	0.132**	0.103*	0.096*	0.197***	-

Notes: a. empty cells mean insignificant coefficients at $p \geq 0.05$: paths were excluded from model
b. * significant at $p < 0.05$; ** significant at $p < 0.01$; *** significant at $p < 0.001$.

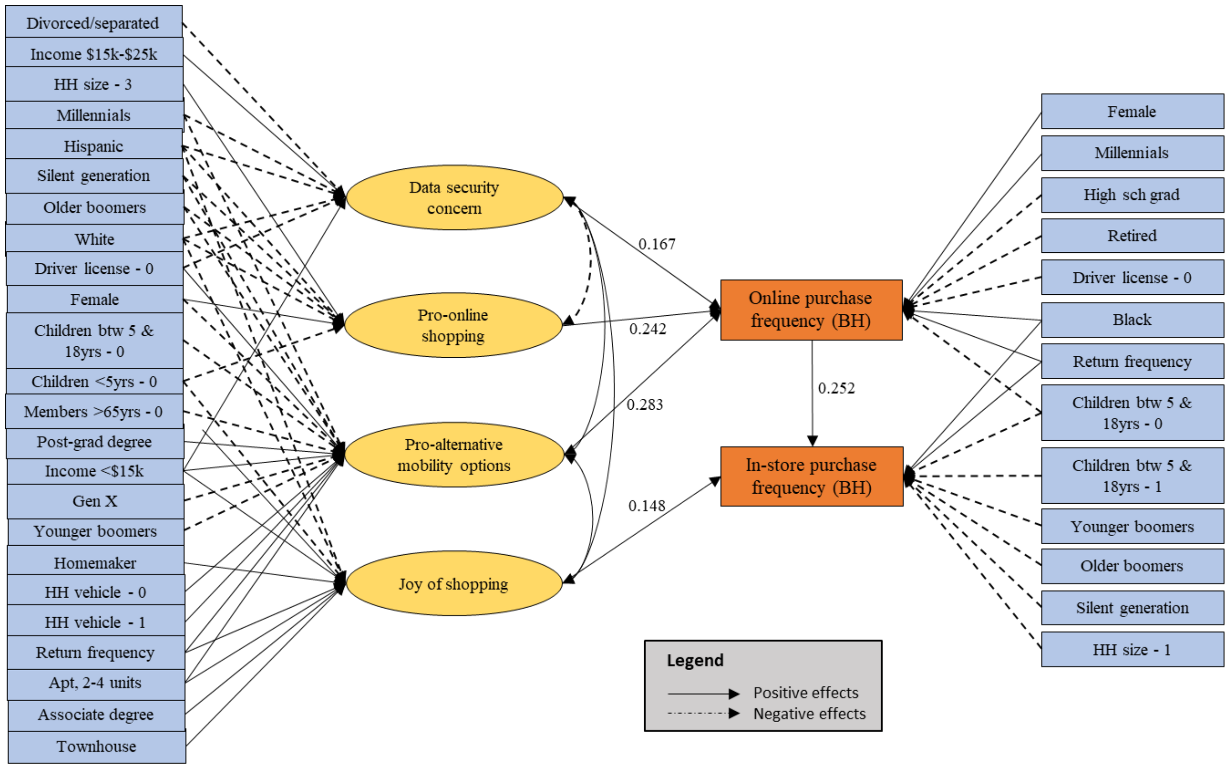


Figure 37. Path diagram for beauty and health products

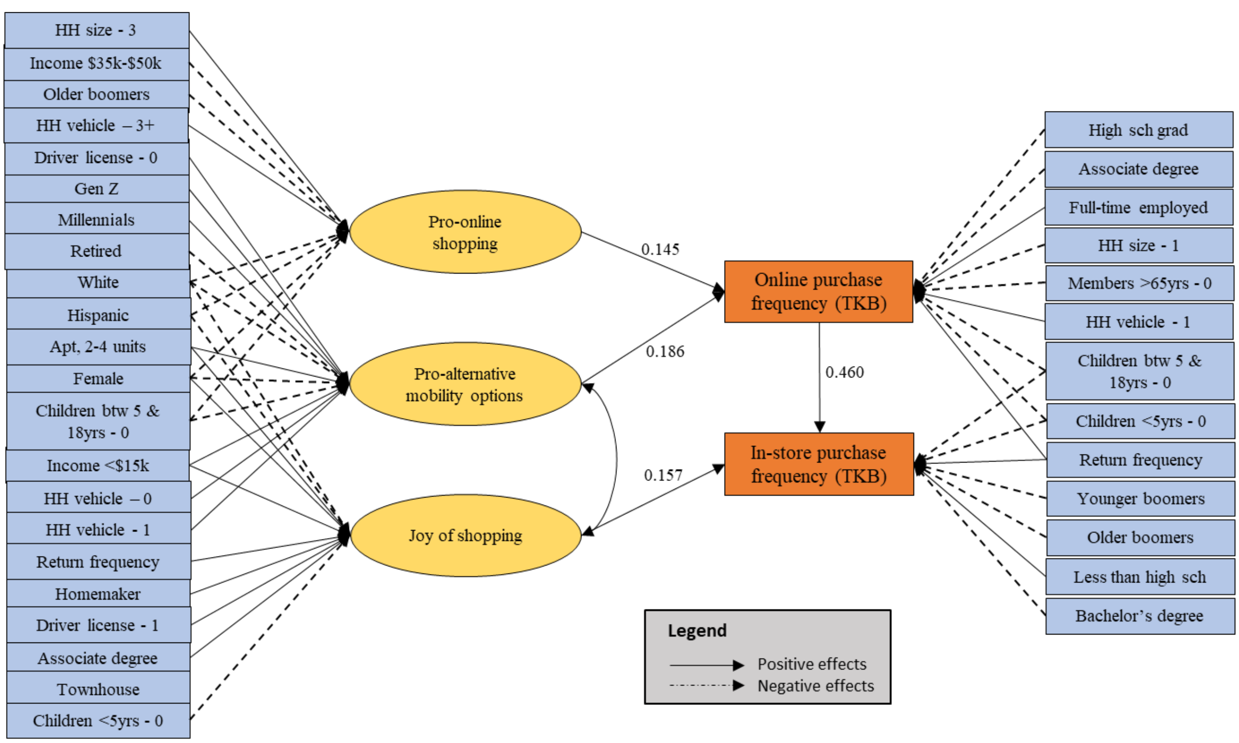


Figure 38. Path diagram for toys, kid and baby products

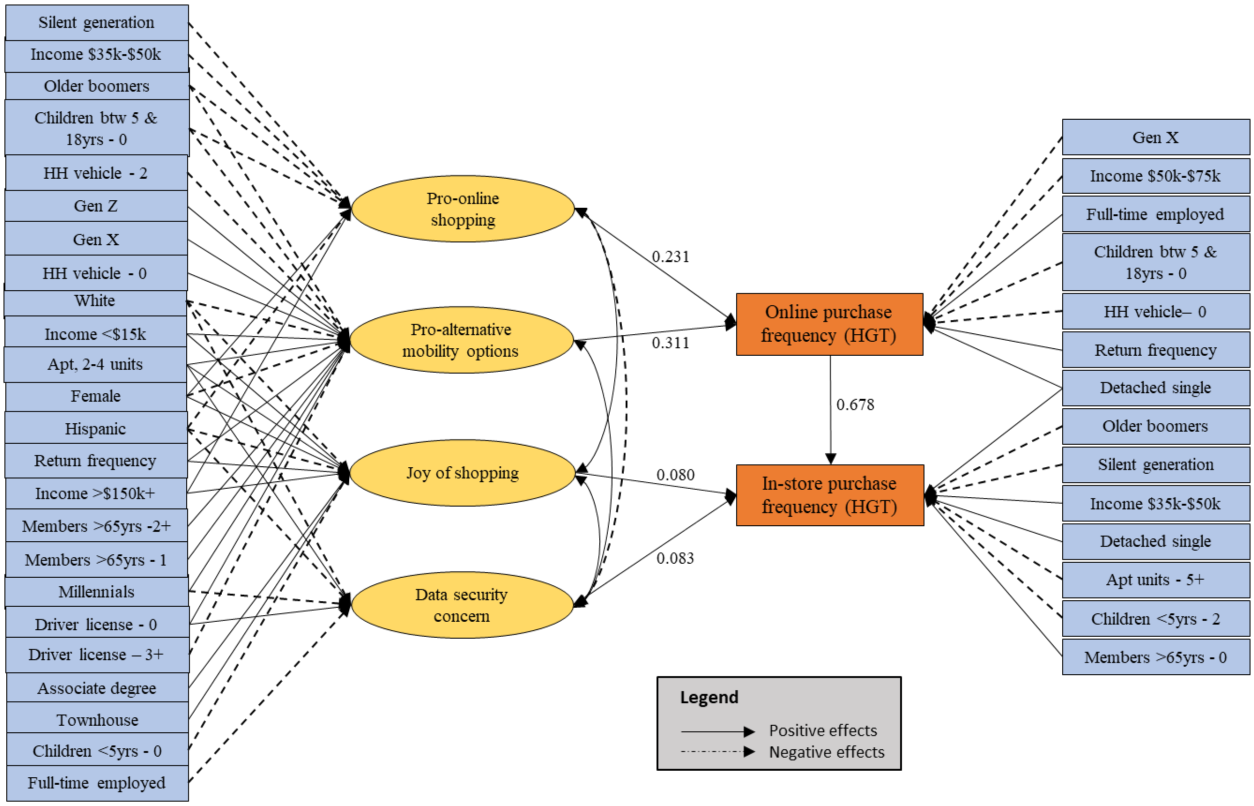


Figure 39. Path diagram for home, garden, and tools

7.4.2.2 Time-Moderated SEM Models for BH, TKB, and HGT

Beauty and Health Products

Like the results for CSWJ, there were no changes in the relationship between online and in-store shopping for both waves, as shown in Table 28.

Table 28. Summary of Differences in Results for BH across Waves

Beauty and health						
	1st wave		2nd wave		Combined	
	Online	In-store	Online	In-store	Online	In-store
Online		positive		positive		positive
In-store	neutral		neutral		positive	
Pro-alternative mobility	positive		positive		positive	
Joy of shopping		positive		positive		positive
Pro-online shopping	positive		positive		positive	
Data security/privacy concerns		positive	negative	positive	negative	positive
Tech savviness			positive			

However, the effects of tech savviness and data security concern on online shopping changed. During the second wave, data security concern discouraged online shopping, while tech savviness encouraged online shopping. These are complex effects, whose cumulative effects on online shopping are difficult to determine.

Table 29. Moderation Analysis Results for BH

Beauty and health	Online purchase frequency	In-store purchase frequency	Pro-alternative mobility	Joy of shopping	Data security concern
Endogenous variables					
Online purchase frequency	-	0.293*	-	-	-
In-store purchase frequency	0.639***	-	-	-	-
Attitudes					
Pro-alternative mobility	0.168***	-	-	-	-
Joy of shopping	-	0.075**	-	-	-
Pro-online shopping	0.206*	-	-	-	-
Data security concern	-0.170***	0.144***	-	-	-
Time-related variables					
Time	-	-	0.075**	-0.052*	0.069*
Time*mobility_8	-0.058*	-	-	-	-
Time*security_5	-0.053*	-	-	-	-

Note: for simplicity, the effects of the exogenous variables were not presented
CFI = 0.949, TLI = 0.940, RMSEA = 0.020, SRMR = 0.020

The model for the moderation analysis revealed some moderating effects. Table 29 shows that those who tended to "like to share rides with strangers while traveling" (mobility_8 – an indicator for pro-alternative mobility) tended to engage in less frequent online shopping, with time. It could be then said that time weakened the positive effect of pro-alternative mobility on online purchase frequency. Time also strengthened the negative effect of data security concern on online purchase frequency, as those who tended to be "concerned about putting my debit or credit card information online" (security_5 – an indicator for data security concern) tended to engage in even less frequent online shopping, with time. Interestingly, it was found that time positively affected pro-alternative mobility and data security concern, but negatively affected the joy of shopping. However, the significant change in the joy of shopping did not change its positive effect on in-store shopping.

TKB and HGT

TKB and HGT are products whose models had relatively many changes between their first and second waves, as shown in Tables 31 and 32, respectively. There are some similarities between the two product types. First, in the first wave, in-store shopping increased as online shopping did, while online shopping did not significantly increase or reduce as in-store shopping did. In the second wave, however, online shopping did not have significant effects on in-store shopping, while in-store shopping had positive effects on online shopping. Also, when the datasets were combined for the moderation analysis, the relationship between online and in-store shopping showed positive-positive effects. Second, pro-alternative mobility had insignificant effects on in-store shopping in the first wave but had positive (significant) effects in the second wave, suggesting a shift from online shopping toward in-store shopping for this attitude. Third, the impact of those with favorable attitude toward online shopping was insignificant in affecting online shopping during the second wave, though it positively affected online shopping in the first wave, Fourth, the formerly positive effect of data security concern on in-store shopping were insignificant during the second wave. Fifth, the moderation analysis for both models showed that the impact of *time* only affected (positively) preference toward alternative mobility options (see Tables 32 and 33).

Table 30. Summary of Differences in Results for TKB across Waves

Toys, kids, and baby						
	1st wave		2nd wave		Combined	
	Online	In-store	Online	In-store	Online	In-store
Online		positive		neutral		positive
In-store	neutral		positive		positive	
Pro-alternative mobility	positive			positive		positive
Joy of shopping		positive	negative	positive		positive
Pro-online shopping	positive			positive	positive	
Data security/privacy concerns		positive				
Tech savviness			positive			

Table 31. Summary of Differences in Results for HGT across Waves

Home, garden, tools						
	1st wave		2nd wave		Combined	
	Online	In-store	Online	In-store	Online	In-store
Online		positive		neutral		positive
In-store	neutral		positive		positive	
Pro-alternative mobility	positive		positive	positive	positive	
Joy of shopping		positive		positive		positive
Pro-online shopping	positive				positive	
Data security/privacy concerns		positive	negative		negative	positive
Tech savviness				positive		

These results are baffling considering that the formerly-found complementarity effects of online shopping on in-store shopping had become insignificant in the second wave, contrary to the effects of the attitudes that seem to point to a shift away from online shopping and more toward in-store shopping. This may be showing a potential for a shift away from online-to-instore complementarity effects, and toward neutrality. However, like other non-essential experience goods, the models for the combined dataset indicate a positive-positive effects between online and in-store shopping frequency.

Table 32. Moderation Analysis Results for TKB

Toy, kids, and baby	Online purchase frequency	In-store purchase frequency	Pro-alternative mobility
Endogenous variables			
Online purchase frequency	-	0.362*	-
In-store purchase frequency	0.551***	-	-
Attitudes			
Pro-alternative mobility	-	0.171***	-
Joy of shopping	-	0.131***	-
Pro-online shopping	0.149***	-	-
Time-related variables			
Time	-	-	0.074**

Note: for simplicity, the effects of the exogenous variables were not presented
CFI = 0.960, TLI = 0.951, RMSEA = 0.018, SRMR = 0.018

Table 33. Moderation Analysis Results for HGT

Home, garden, tools	Online purchase frequency	In-store purchase frequency	Pro-alternative mobility
Endogenous variables			
Online purchase frequency	-	0.862***	-
In-store purchase frequency	0.342***	-	-
Attitudes			
Pro-alternative mobility	0.176***	-	-
Joy of shopping	-	0.070***	-
Pro-online shopping	0.113**	-	-
Data security concern	-0.059**	0.099***	-
Time-related variables			
Time	-	-	0.071**

Note: for simplicity, the effects of the exogenous variables were not presented
CFI = 0.951, TLI = 0.942, RMSEA = 0.017, SRMR = 0.019

7.4.3 Summary for Non-Essential Experience Goods

This section examined the online and in-store shopping behavior in shopping for experience goods, namely: a) clothing, shoes, watches, and jewelry (CSWJ); b) beauty and health products (BH); c) toys, kid, and baby supplies (TKB); and d) home, garden, and tools (HGT). The influences of the endogenous variables on one another indicate that forms of complementarity effects were occurring in shopping for each of the product types. Specifically, there were positive-positive effects between the online and in-store shopping for CSWJ and TKB (see Figure 40). BH and HGT showed in-store shopping increased as online shopping increased, but in-store shopping had neutral effects on online shopping. This suggests that shopping behavior does not always yield reverse complementary effects for all types of experience goods. While the explanatory factors of shopping behavior across the product types are somewhat consistent, there were major distinctions in the findings. These distinctions suggest that the common use of "clothing" to represent experience goods in measuring travel and shopping behavior does not capture some important distinctions among different types of experience goods.

7.5 Summary for Shopping Frequency Analysis

Figure 40 presents the summary results of online and in-store shopping interactions for each product type. Shopping for search goods (like BE and PS) neither increased nor reduced travel, although in-store shopping increased online shopping frequency. Results for experience goods, however, showed that e-commerce complements in-store shopping, especially for products with higher shopping enjoyment. An implication from these effects is that e-commerce by itself cannot be seen as a traffic-mitigation strategy. The projection that e-commerce will continue to grow post-pandemic may pose transportation challenges for planners, as higher delivery demand might increase and complexify freight logistics operation and passenger travel.

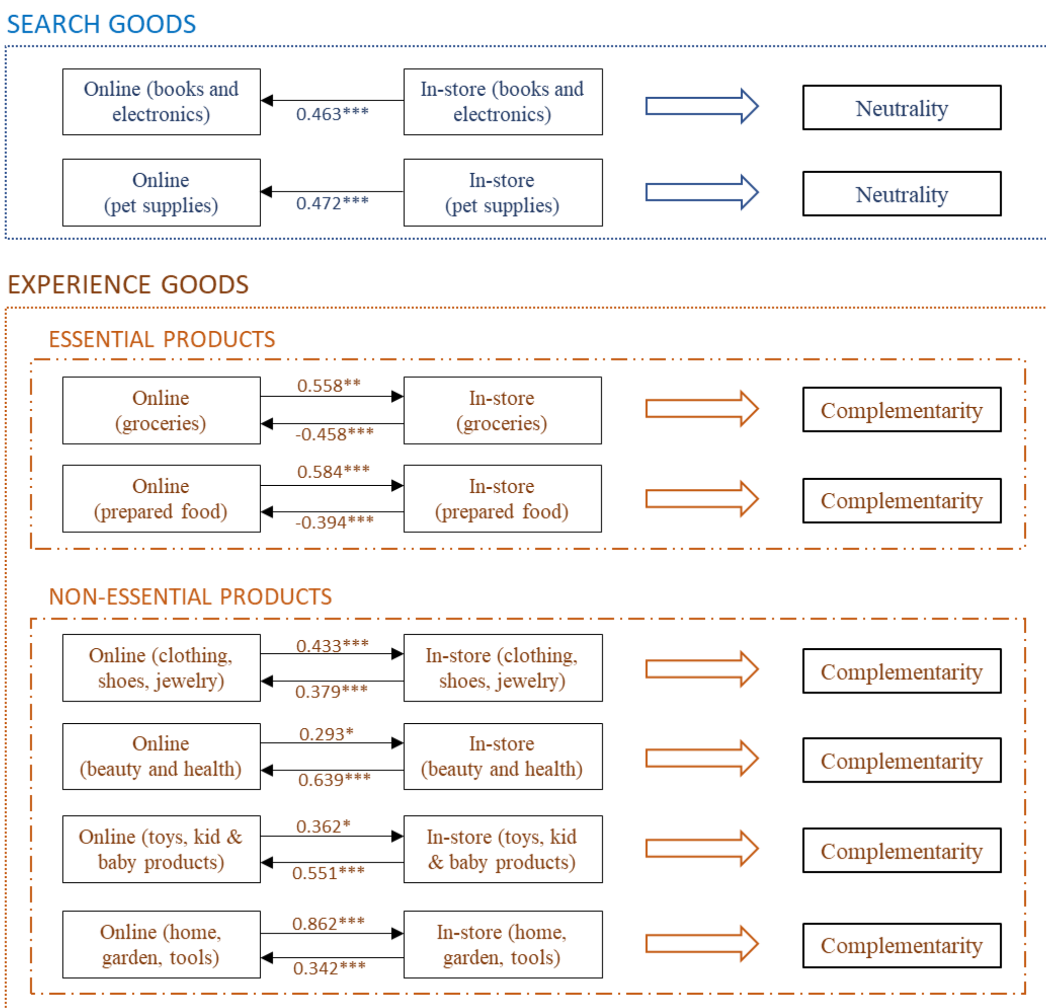


Figure 40. Online and in-store shopping interactions by product classification for Wave II

For the moderation analysis, differences in results for the SEMs between the first and second wave prompted the development of moderation analyses to determine how time may be moderating the effects of attitudes on the changing shopping behavior. The results of the SEMs for the first, second wave, and moderation analyses were summarized and presented, results for comparative evaluation. Table 34 summarizes the effects of attitudes on shopping frequency as well as the time moderation effects for each product type.

Table 34. Summary of Time Moderation Effects

	BE		PS		Gr		PF		CSWJ		BH		TKB		HGT	
	On-line	In-store	On-line	In-store	On-line	In-store	On-line	In-store	On-line	In-store	On-line	In-store	On-line	In-store	On-line	In-store
Attitudes																
Pro-alternative mobility		+	+	+	+	-	+		+	+	+			+	+	
Joy of shopping		+		+		+		+		+		+		+		+
Pro-online shopping	+				+		+		+		+		+		+	
Data security concern			-			+				+	-	+			-	+
Tech savviness	+				+		+		+							
Cost consciousness						+										
Unattended delivery concern	-															
Moderation Effects																
Time	-															
Time*tech savviness	-						+									
Time*pro-alternative mobility			-				-				-					
Time*data security						+				-	-					
Time*cost consciousness						-										

Note: + indicates a positive effect, - indicates a negative effect
time also had a positive effect on pro-alternative mobility

It can be seen that much of the changes in the effects of attitudes on shopping behavior were not consistent across product types. For some of the models, significant changes in attitudes did not show significant effects on shopping behavior, while insignificant changes in some attitudes caused significant effects. This is indicative of a very complex interplay between and within both the measured and unmeasured causes. However, there were general patterns in the results that are worth mentioning as discussed in the previous sections. For example, the effects of tech savviness on online shopping for books and electronics reduced over time but strengthened for the purchase of prepared food online. The positive effects of data security concerns for shopping groceries in-store further strengthen during later stages of the pandemic as our daily activities gradually transition back to normal.

8 SHOPPING CHANNEL CHOICE MODELING

8.1 Grocery Shopping

8.1.1 Wave I

Two mixed logit models were developed for the grocery shopping choice experiment. The first model identified the time and cost attributes (product price, delivery cost, shopping time, delivery time, and travel time) that had significant random effects, and the individual-specific characteristics with significant main effects. The second model (heterogeneous model) includes significant interaction effects between the random parameters and the individual-specific characteristics. The first model determines the preferences of different groups in their grocery shopping channel choice, while the second model identifies the potential sources of heterogeneity or the sensitivity of different groups to the cost and time attributes. The following two subsections describe the estimated results of the two models.

8.1.1.1 Base model (main effects)

Table 35 presents the results of the base model. The values inside the parentheses represent z-value for the corresponding variable and the variables that were not significant at the 95% significance level were not considered. The goodness-of-fit values of this model, as measured by McFadden's pseudo-R-square indicate satisfactory model fit. Product price, delivery cost, shopping time, and travel time showed statistically significant mean and standard deviation, indicating the existence of taste heterogeneity. Also, the negative values indicate disutility, that is, the higher a random parameter is associated with a channel choice the more the decision maker tends to opt for the alternative choices. The reference category used was in-store shopping, meaning that significant negative coefficients indicate preference for in-store shopping, while positive values indicate preference for the other alternative being considered.

In view of the socioeconomic and demographic variables, the results showed that females and Hispanics tend to prefer to purchase their groceries online and at the curbside compared to traveling for in-store grocery shopping. Blacks or African Americans tended to prefer curbside pickup. Younger generations between 18 and 56 years (Gen Z, Millennials, and Gen X) showed a positive tendency toward online shopping and curbside pickup than in-store shopping, and their preference for online shopping was higher than for curbside pickup. The younger generations' preferences for alternative channel choices can be attributed to their tech savviness. Interestingly, younger boomers (aged 57-66) preferred online to in-store shopping. Boomers' preference for online shopping may also be due to their tech-savvy. According to Pew Research Center, 85% of baby boomers use the Internet, and 68% of them own a smartphone (Pew Research, 2019). In relation to income, low- to middle-income earning households (earning up to $75k) tended to prefer in-store shopping. This finding is consistent with the existing literature (Farag et al., 2006). We also found that lower educated individuals (high school graduate or less) preferred in-store shopping, while those with an associate degree preferred online shopping. Past studies have shown the similar results (Saphores & Xu, 2021).

The relationship between employment status and channel choice preference indicates that those employed full-time preferred alternative shopping channels to in-store shopping, and with higher preference for online shopping than curbside pickup. Part-time workers and students also showed a positive tendency toward online shopping. The restricted schedule of work for workers puts more pressure on their time and might be influencing their preference for online shopping. Students usually have less access to personal vehicles; hence, they have restricted mobility. This might be a reason behind their preference. Moreover, existing literature suggests that students shop at the physical store less frequently (Cao et al., 2012).

Turning to the impacts of household characteristics, those living in larger households (three or more members) preferred online shopping and curbside pickup. This finding seems contradictory with the existing literature, as Fabusuyi et al. (2020) noted that online purchase frequency decreases as household size increases. A potential reason could be that larger households had multiple children of different ages and older members. Farag et al. (2007b) showed that singles made less online purchases than households with two or more members. As expected, households with no children aged 5-18 were less likely to prefer curbside pickup to in-store shopping. Since household members without children are expected to be less time-pressured, it is likely that such households are more inclined to in-store shopping. Likewise, households with no senior members preferred in-store shopping to online shopping. As expected, households with no member having a driver's license preferred online shopping and curbside pickup, probably due to their vehicle inaccessibility, as compared with those with full access to their vehicles who tended to prefer in-store shopping to other shopping channel alternatives.

Looking at attitudes, concern for data privacy/security, preference for alternative mobility options, and preference to make purchases at a local store predisposed individuals toward in-store shopping. It is quite intuitive that those who had concern about putting personal and credit or debit card information online and people who liked to shop at the local store were less likely to purchase things online and curbside. Interestingly, individuals who preferred alternative mobility option to mitigate traffic congestion as well as to save money had lower likelihood of shopping online and curbside.

Expectedly, technology savviness, pro-environment, and positive attitude for online shopping (such as opportunity to shop at any time, variety of choices etc.) encouraged individuals to shop online. However, people with concern toward unattended delivery were inclined to choose online shopping and curbside pickup. Surprisingly, those who enjoyed shopping for pleasure in-store (recreational shoppers) were also likely to choose online shopping and curbside pickup. Regarding the distance to store from home location, those living close to the store (within five miles) tended to prefer purchasing their groceries in-store.

Table 35. Results of Mixed Logit Base Model

	Variables	Parameter	Std Dev
Random parameters	Product price	-0.12 (-39.41)	0.12 (39.41)
	Delivery cost	-0.46 (-32.79)	0.46 (32.79)
	Shopping time	-0.05 (-6.56)	0.05 (6.56)
	Travel time	-0.12 (-19.25)	0.12 (19.25)
Attributes	**Variables (Main effects)**	**Online**	**Curbside**
Constant		-1.93 (-6.38)	0.72 (2.81)
Gender	Female	0.38 (4.02)	0.33 (3.68)
Ethnicity	Hispanic	0.31 (2.88)	0.37 (3.55)
	Black		0.36 (2.98)
Generations	Gen Z (age 18-24)	1.16 (4.43)	0.87 (3.49)
	Millennials (age 25-40)	1.39 (6.77)	1.03 (5.51)
	Gen X (age 41-56)	1.17 (5.72)	0.86 (4.70)
	Younger boomers (57-66)	1.01 (4.80)	
HH Income	$15k to $25k	-0.35 (-2.30)	
	$25k to $35k		-0.33 (-2.45)
	$35k to $50k	-0.47 (-3.64)	-0.31 (-2.54)
	$50k to $75k	-0.32 (-2.61)	-0.32 (-2.71)
Education	Less than high school	-1.89 (-5.43)	-1.72 (-5.35)
	High school graduate	-0.46 (-3.76)	
	Associate degree	0.32 (2.61)	
Employment	Full time	0.84 (7.45)	0.43 (4.15)
	Part time	0.66 (4.03)	
	Student	0.70 (3.13)	
HH Size	Three	0.81 (6.25)	0.46 (3.60)
	Four	1.08 (7.01)	0.70 (4.67)
	Five or more	0.55 (2.84)	0.80 (4.34)
Children age 5-18	None		-0.28 (-2.39)
Members aged 65 plus	None	-0.50 (-3.76)	
Members with driver's lic.	None	0.66 (3.63)	0.53 (3.05)
Number of vehicles own	One	0.32 (3.17)	
	Three or more	-0.27 (-2.05)	-0.31 (-2.34)
Vehicle accessibility	0 percent		-0.58 (-3.30)
	100 percent	-0.44 (-2.92)	-0.35 (-2.45)
Attitudes	Data security concern	-0.51 (-9.02)	-0.16 (-2.96)
	Technology savviness	0.43 (6.89)	0.38 (6.52)
	Pro-alternative mobility	-0.44 (-8.03)	-0.16 (-2.98)
	Pro-environmental	0.24 (4.36)	0.15 (2.81)
	Local store preference	-0.20 (-3.47)	-0.13 (-2.30)
	Joy of shopping	0.75 (13.56)	0.47 (9.07)
	Unattended delivery concern	0.14 (2.41)	0.19 (3.53)
	Pro-online shopping	0.34 (5.69)	
Store distance	0 to 5 miles	-0.71 (-7.89)	-0.56 (-6.50)
Log-Likelihood		-5,974.7	
McFadden R^2		0.29842	
Likelihood ratio test: chi-square		5,082.8 (p-value = < 2.22e-16)	

Note: online, curbside, and in-store shopping choice frequencies are 22%, 22%, and 56% respectively

8.1.1.2 Heterogeneous model (interaction effects)

To further explore the effects of the random parameters (product price, delivery cost, shopping time, and travel time), various attitudes, socio-demographic characteristics, and household attributes were tested as interaction variables, representing potential sources of heterogeneity.

Tables 36 and 37 present the estimated results of the model with interaction effects. This model was found to be better fitted than the base model in terms of the McFadden's pseudo-R-square and the likelihood ratio, indicating that the inclusion of the interaction effects (heterogeneity) improved the model performance.

Table 36. Main Effects for the Heterogenous Model (Grocery Shopping)

	Variables	**Parameter**	**Std Dev.**
Random parameters	Product price	-0.23 (-23.85)	0.23 (23.85)
	Delivery cost	-0.75 (-28.41)	0.75 (28.41)
	Shopping time	-0.05 (-6.61)	0.05 (6.61)
	Travel time	-0.17 (-18.22)	0.17 (18.22)
	Variables (Main effects)	**Online**	**Curbside**
Constant		-3.60 (-10.03)	-0.19 (-0.70)
Gender	Female	1.30 (2.81)	
Ethnicity	Hispanic	0.56 (4.45)	0.59 (4.48)
	Black	0.55 (2.74)	0.65 (3.52)
Generations	Gen Z	3.53 (4.04)	-1.00 (-2.16)
	Millennials	2.77 (4.62)	
	Gen X	2.74 (4.20)	
	Younger boomers	2.57 (2.71)	-0.95 (-2.30)
HH Income	$35k to $50k	-0.50 (-3.49)	
Education	Less than high school	-3.91 (-3.91)	-3.96 (-4.24)
Employment	Full-time worker	1.02 (7.55)	0.63 (5.06)
HH Size	Three members	0.81 (5.77)	0.62 (4.44)
	Four members	1.13 (7.02)	1.01 (6.44)
	Five or more members		0.96 (5.25)
Members aged 65 plus	None	-0.65 (-4.44)	-0.33 (-2.27)
Member with driver's license	None	0.49 (2.21)	0.50 (2.50)
Number of vehicles owned	One	0.32 (2.75)	
	Three or more	-1.86 (-3.02)	-0.39 (-2.69)
Vehicle accessibility	No access	0.52 (3.09)	
Attitudes	Data security concern	-0.33 (-2.28)	
	Technology savviness		0.46 (6.86)
	Pro-alternative mobility	-0.32 (-2.33)	
	Local store preference	-0.31 (-4.54)	-0.21 (-2.93)
	Joy of shopping	0.88 (13.29)	0.60 (9.75)
	Unattended delivery concern	0.19 (2.89)	0.30 (4.47)
	Pro-online shopping	0.44 (6.39)	
Store distance	Within 0 to 5 miles		-0.87 (-6.66)

Table 37. Interaction Effects for the Heterogenous Model (Grocery Shopping)

Interaction effects				
	Variables	**Product price**	**Delivery cost**	**Travel time**
Gender	Female		0.08 (3.19)	0.06 (2.71)
Ethnicity	Hispanic	0.02 (4.20)		
	White		0.05 (2.88)	
	Asian	0.03 (2.11)	0.15 (4.55)	
Generations	Gen Z		0.47 (9.57)	0.22 (5.50)
	Millennials		0.34 (10.52)	0.13 (4.77)
	Gen X	0.03 (4.98)	0.37 (10.50)	0.16 (5.15)
	Younger boomers	0.04 (3.42)	0.26 (4.73)	0.14 (3.01)
HH Income	Less than $15k		0.08 (3.87)	0.03 (3.50)
	$35k to $50k	0.02 (2.33)		
	$100k to $150k		0.03 (2.28)	
Education	Less than high school		0.24 (2.36)	
	High school grad	0.10 (8.81)		
	Some college	0.10 (8.50)	0.04 (2.82)	
	Associate	0.09 (8.31)	0.05 (3.38)	
	Bachelor	0.07 (6.95)		
	Graduate	0.07 (6.46)		
Employment	Part-time worker		0.08 (4.75)	
	Student			-0.02 (-2.08)
	Homemaker		-0.08 (-3.75)	
	Retired		0.10 (4.53)	
House type	Detached single house		0.03 (3.19)	
HH Size	One		0.06 (3.67)	
Number of vehicles own	Three or more			-0.08 (-2.84)
Vehicle accessibility	No access	0.05 (5.22)		
	Always	0.03 (4.07)		
Attitudes	Data security concern	0.01 (2.64)	-0.04 (-2.84)	
	Technology savviness			-0.03 (-2.28)
	Pro-environmental	-0.01 (-3.61)		
	Local store preference	-0.01 (-3.36)		
	Unattended delivery concern	0.01 (3.23)		
	Pro-online shopping	-0.01 (-3.26)		
Store distance	0 to 5 miles	-0.05 (-7.82)		0.07 (3.16)
	5 to 10 miles	-0.04 (-5.18)	-0.04 (-2.60)	
	10 to 15 miles			0.03 (2.81)
	20 miles or more	0.04 (2.68)		
Log-Likelihood		-5,484.9		
McFadden R^2		0.35594		
Likelihood ratio test: chi-square		6,062.4 (p-value = < 2.22e-16)		

As shown in Table 36, the coefficients of the main effects in the heterogenous model are quite similar to that of the base model. The results of the interaction effects showed that females, and very low-income earners (less than $15k) are sensitive to delivery cost and travel time. Since females tend to prefer online shopping (in the main effects), traveling long distances seem to have discouraged them from preferring in-store shopping. People with less than a high school degree are highly sensitive to delivery cost, which may explain their preference for in-store shopping.

From Table 37, individuals who are concerned about the security or privacy of their data online are less sensitive to delivery cost, and more sensitive to product price. Reducing the price of a grocery item and adding it to its delivery cost may encourage this group (those concerned about their data security online) to use online shopping. Also, those who are concerned about deliveries being left in their compounds are also sensitive to product price. Shopping within five miles of one's home location is associated with high sensitivity to product price, but less sensitive to travel time. This suggests that this group have more time and are not discouraged from traveling to stores at farther distances to save money on a grocery purchase.

8.1.2 Wave II

Comparing the results of the second wave of this study (as shown in Table 38) with that of the first wave suggests that some preferences changed while some other group preferences did not. Like the first wave, significant levels of individual sensitivities to the random parameters exist. The younger generations (from Gen Zers to younger boomers) preferred online shopping, and females preferred curbside pickup to in-store shopping. Also, high income earners, individuals who have children, those who have no members with a driver's license, and those without full access to a vehicle tended to prefer online shopping. Furthermore, attitudes related to tech savviness, alternative mobility option, the environment, recreational shopping, and online shopping did not change consumers' shopping channel preferences over time. However, there are some differences that may be indicative of a change in group preferences over time. For example, cost consciousness discouraged online shopping in the second wave. Also, the in-store shopping preference by those with data security concern and local store preference were not significant in the second wave. It is likely that privacy concerns regarding their personal information online might have been mitigated by the high adoption rate of online shopping. Regarding cost consciousness, it seems health concerns have diminished so much that the benefit of purchasing online cannot compensate for the extra expenditure online purchases entail.

There are also some socio-demographic differences between the first and second wave. Those without a high school degree were more likely to prefer in-store during the first wave, but during the second wave tended to prefer online shopping, while high school graduate and bachelor's degree holders tended to prefer in-store shopping. The result relating to the in-store preference of those without a high school degree may be related to the age composition, as they tend to be mostly young individuals. Another seemingly contradictory finding is the online shopping preference retired individuals have. While the first wave of this study (and the literature) indicates that workers preferred online shopping, it is possible that Covid-19 safety concerns still linger among the older population, who may have formed a new online shopping habit.

Table 38. Grocery Shopping for Wave II

	Variables	Parameter	Standard deviation
Random parameters	Product price	-0.12 (-32.82)	0.12 (32.82)
	Delivery cost	-0.54 (-29.38)	0.54 (29.38)
	Shopping time	-0.04 (-4.38)	0.04 (4.38)
	Travel time	-0.14 (-18.75)	0.14 (18.75)
Attributes	**Variables (Main effects)**	**Online**	**Curbside**
Constant		-2.32 (-6.60)	0.78 (2.59)
Gender	Female		0.41 (3.82)
Race	Asian	-0.71 (-2.11)	-0.94 (-3.15)
Generation	Gen Z (aged 18-24)	2.09 (6.58)	1.08 (3.71)
	Millennials (aged 25-40)	2.14 (8.18)	1.32 (5.45)
	Gen X (aged 41-56)	1.82 (7.26)	1.11 (4.93)
	Younger boomers (aged 57-66)	0.65 (3.02)	
HH Income	$15k to $25k		-0.55 (-3.17)
	$150k or more	1.05 (3.69)	1.15 (4.08)
Education	Less than high school	0.80 (2.74)	
	High school graduate	-0.45 (-3.55)	-0.49 (-3.93)
	Bachelor's degree	-0.33 (-2.36)	-0.32 (-2.49)
Employment	Homemaker		-0.44 (-2.24)
	Retired	0.77 (4.02)	
	Unemployed		-0.50 (-3.00)
House type	Detached single	0.56 (5.01)	0.37 (3.44)
Marital status	Single	0.40 (3.19)	0.43 (3.39)
Children < 5 years	None	-0.39 (-2.43)	-0.43 (-2.68)
Children aged 5-18	None	-0.62 (-5.04)	-0.40 (-3.45)
Members aged 65 plus	Two or more	-0.59 (-3.25)	
Member with driver's license	Three or more	-0.62 (-4.27)	-0.35 (-2.64)
No. of vehicles owned	None	0.83 (3.89)	
Vehicle accessibility	0 percent	2.10 (5.26)	
	20 percent	1.46 (3.15)	1.09 (2.22)
	40 percent	1.17 (2.96)	
	80 percent	0.74 (3.68)	0.85 (4.27)
Attitudes	Cost consciousness	-0.21 (-2.97)	0.19 (2.75)
	Technology savviness	0.65 (8.55)	0.36 (5.10)
	Pro-alternative mobility	-0.20 (-3.24)	-0.31 (-5.20)
	Pro-environmental	0.44 (6.64)	0.17 (2.65)
	Joy of shopping	0.85 (13.33)	0.62 (10.19)
	Pro-online shopping	1.02 (12.24)	0.48 (6.29)
Log-Likelihood		-4,451.4	
McFadden R^2		0.31734	
Likelihood ratio test: chi-square		4,138.5 (p-value = < 2.22e-16)	

Note: online, curbside, and in-store shopping choice frequencies are 21%, 19%, and 60% respectively

8.2 Non-Grocery Shopping

8.2.1 Wave I

8.2.1.1 Base model (main effects only)

Table 39 presents the results of the base model. The five cost and time variables (random parameters) had statistically significant means and standard deviations, indicating the presence of taste heterogeneity. Our findings show that females tended to prefer curbside pickup over in-store shopping. This result is surprising considering that females, though are often willing to travel long distances for non-grocery shopping, tend to like window shopping (or recreational shopping). However, females disproportionate Covid-19 safety concern may have increased the disutility of traveling to shop in-store. Gen Zers and Millennials had a positive tendency toward online shopping and curbside pickup than in-store shopping. The tech savviness and relatively low income of the younger generations may explain their preferences for alternative shopping channels. Also, Gen X preferred curbside pickup to in-store shopping. Since Gen X tend to be full-time workers, in-store shopping may overly strain their time, and curbside pickup may be preferred. This explanation may also be applied to full-time workers and students, who prefer alternative shopping channels.

While it is intuitive that low-income earning households (lower than $50k) and low-educated individuals were more inclined to prefer in-store shopping to other channel choices, it is quite interesting to find that those from high-income earning households (earning more than $150k) also tended to prefer in-store shopping. It should be noted, however, that realism was enforced to reduce the bias of high-income earners in their choices. Thus, this finding may be an indication that high-income earners would travel to shop in-store if the items to be purchased are equally as expensive to them as it is to low-income earners. Expectedly, post-graduate degree holders tended to prefer alternative channel choices.

Regarding the impacts of household characteristics on channel preference, those in households with no children aged 5-18 or senior members were more likely to prefer in-store shopping. This finding is not at odds with past findings that have shown that household size has a positive association with shopping online (Chocarro et al., 2013), or a negative association with physical shopping (Zhen et al., 2016). Furthermore, those with one vehicle preferred in-store shopping, while those without full access to the vehicle(s) in the household preferred online shopping and curbside pickup to in-store shopping. This finding confirms the efficiency hypothesis that low accessibility to stores tend to increase the propensity to buy online (Motte-Baumvol et al., 2017).

Looking at how attitudes after the choice of a shopping channel, our analysis indicates that the concern for privacy/security of one's data online, and preference for alternative mobility options were linked with preference to shop in-store. It is intuitive that those who have data security concern would prefer in-store shopping, but the relationship between preference for alternative mobility options and preference to shop in-store contradicts past findings that transit users tend to make frequent online purchases (Farag et al., 2006; Ramirez, 2019; Xue et al., 2021). While the reason for this finding is obscure, those who prefer alternative mobility options may mostly consist of people who have no vehicles or do not have the financial means to own a vehicle and would prefer in-store shopping to save money. As expected, technology savviness, being pro-environment, and positive attitude toward online shopping are all associated with the preference to shop online. Unexpectedly, those who enjoy shopping for pleasure tend to prefer alternative channels, indicating the potential to attract more recreational shoppers into adopting online shopping.

Table 39. Results of Mixed Logit Base Model

	Variables	**Parameter**	**Std Dev**
Random parameters	Product price	-0.095 (-46.864)	0.09 (46.86)
	Delivery cost	-0.246 (-18.009)	0.25 (18.01)
	Shopping time	-0.018 (-3.837)	0.02 (3.84)
	Delivery time	-0.553 (-10.140)	0.55 (10.14)
	Travel time	-0.090 (-28.238)	0.09 (28.24)
Attributes	**Variables (Main effects)**	**Online**	**Curbside**
Constant		-2.312 (-10.071)	-0.47 (-3.46)
Gender	Female		0.213 (2.706)
Ethnicity	Hispanic	0.335 (3.110)	0.200 (2.081)
	Asian	-1.062 (-3.941)	
	Black		0.420 (3.914)
Generation	Gen Z (aged 18-24)	0.676 (3.160)	1.131 (5.825)
	Millennials (aged 25-40)	0.614 (4.163)	0.543 (4.289)
	Gen X (aged 41-56)		0.485 (3.888)
Income	Less than $15k	-0.399 (-2.625)	
	$35k to $50k	-0.551 (-4.602)	-0.234 (-2.217)
	$150k or more	-0.442 (-2.425)	-0.447 (-2.757)
Education	Less than high school	-1.686 (-5.109)	-0.835 (-3.402)
	High school graduate	-0.463 (-4.149)	-0.220 (-2.246)
	Graduate	0.500 (3.833)	0.284 (2.384)
Employment	Full-time worker	0.295 (2.970)	0.472 (5.427)
	Student	0.728 (3.118)	0.501 (2.261)
Children aged 5-18	None	-0.215 (-2.193)	-0.346 (-3.954)
Members aged 65 plus	None	-0.333 (-2.778)	-0.519 (-5.211)
No. of vehicles owned	One		-0.201 (-2.598)
Vehicle accessibility	60 percent (often)	0.657 (2.652)	0.754 (3.200)
Attitudes	Data security concern	-0.765 (-13.784)	-0.272 (-5.677)
	Technology savvy	0.221 (3.748)	0.265 (5.020)
	Pro-alternative mobility	-0.414 (-8.387)	
	Pro-environment	0.113 (2.245)	
	Local store preference		-0.131 (-2.658)
	Joy of shopping	0.843 (16.100)	0.467 (10.035)
	Pro-online shopping	0.555 (9.769)	0.272 (5.884)
Log-Likelihood		-6,564.7	
McFadden R^2		0.30363	
Likelihood ratio test: chi-square		5,724.7 (p-value = < 2.22e-16)	

Note: online, curbside, and in-store shopping choice frequencies are 33%, 30%, and 36% respectively

8.2.1.2 Heterogeneous model (interaction effects)

The heterogenous model was developed to further identify the sensitivity of different groups to the cost and time variables. Tables 40 and 41 present the estimated results of the model with the main and interaction effects, respectively. The higher McFadden's pseudo-R-square value and the likelihood ratio indicate improved model performance compared to the base model. A holistic view of the heterogenous model suggests few groups are sensitive to delivery time, (i.e., whites and having a child). Those with larger household sizes (four or more) are sensitive to the delivery cost. Since results in the base model and in the literature suggest household size is positively associated with online shopping, the relatively large basket size of their purchase may have increased their sensitivity to the delivery cost. Cost-conscious individuals are slightly less sensitive to travel time, suggesting their willingness to visit physical stores to save money. Recreational shoppers are slightly less sensitive to product price, which may mean reducing the price of a product to be compensated for other time and delivery variables may encourage recreational shoppers to shop online. Those who prefer alternative mobility options tend to be less sensitive to product price, delivery cost, shopping time, and delivery time.

Table 40. Main Effects for the Heterogenous Model for Non-Grocery Shopping

	Variables	**Parameter**	**Std Dev**
Random parameters	Product price	-0.252 (-31.145)	0.252 (31.145)
	Delivery cost	-0.858 (-17.965)	0.858 (17.965)
	Shopping time	-0.064 (-5.346)	0.064 (5.346)
	Delivery time	-1.770 (-17.756)	1.770 (17.756)
	Travel time	-0.129 (-22.761)	0.129 (22.761)
	Main effects	**Online**	**Curbside**
Constant		-0.527 (-1.440)	-0.497 (-2.741)
Gender	Female	0.307 (2.592)	0.345 (3.462)
Ethnicity	Hispanic	0.376 (2.776)	0.282 (2.417)
	Asian	-2.350 (-4.957)	
	Black	3.389 (4.927)	0.497 (3.207)
Generation	Gen Z (aged 18-24)	0.819 (3.269)	1.347 (6.191)
	Millennials (aged 25-40)	1.853 (3.743)	0.673 (4.261)
	Gen X (aged 41-56)	0.555 (2.662)	0.870 (4.996)
HH Income	$35k to $50k	-0.599 (-3.909)	-0.363 (-2.729)
	$150k or more	-0.587 (-2.537)	-0.728 (-3.711)
Education	Less than high school	-2.301 (-5.518)	-0.975 (-3.314)
	High school grad	-0.755 (-4.969)	
	Graduate	1.877 (2.698)	
Employment	Full-time workers		0.494 (4.442)
Children aged 5-18	None		-0.550 (-4.428)
Members aged 65 plus	None	-0.588 (-3.220)	-0.765 (-5.398)
No. of vehicles owned	One	-0.210 (-1.410)	-0.421 (-3.641)
Vehicle accessibility	60 percent (often)		0.731 (2.629)
Attitudes	Data security concern	-0.972 (-13.419)	-0.301 (-5.387)
	Technology savvy	0.355 (4.617)	0.337 (5.271)
	Local store preference	-0.212 (-2.361)	-0.327 (-3.943)
	Joy of shopping	1.120 (16.001)	0.552 (9.230)
	Pro-online shopping	0.774 (10.442)	0.338 (5.861)

Table 41. Interaction Effects for the Heterogenous Model for Non-Grocery Shopping

Interaction Effects						
	Variables	Product price	Delivery cost	Shopping time	Delivery time	Travel time
Race and ethnicity	Hispanic	0.011 (3.566)				
	White	0.064 (13.603)	0.303 (6.800)		0.726 (7.119)	0.064 (9.156)
	Black	0.084 (15.733)	0.330 (5.885)			0.118 (6.755)
	Asian	0.055 (5.335)	0.310 (2.699)			
Generation	Millennials					0.024 (2.094)
	Gen X			0.037 (2.849)		
HH Income	$15k to $25k	0.025 (4.797)	0.085 (2.125)			
	$50k to $75k	0.022 (6.268)				
	$75 to $100k	0.019 (5.403)				
	$100k to $150k	0.019 (5.164)				
Education	High school grad	0.048 (10.803)				
	Some college	0.030 (7.039)				0.014 (4.176)
	Associate	0.034 (8.007)				
	Bachelor	0.023 (6.013)				
	Graduate					0.040 (2.342)
Employment	Full-time workers	0.020 (6.153)				
	Part-time workers			0.044 (2.820)		
	Homemakers	0.031 (4.900)	-0.223 (-4.522)			
	Retired	0.023 (4.255)				
House type	Detached single		0.073 (2.609)			0.010 (3.417)
HH Size	Four		0.171 (5.039)			
	Five or more		0.184 (4.403)			
Children <5	None				0.247 (3.587)	
Children 5-18	None		0.167 (5.015)			0.028 (2.616)
Members aged 65 plus	None		0.125 (3.645)			
Mmbrs with driver's lic.	None	0.039 (10.286)				
No. of vehicles	None	0.026 (4.006)				
	One		0.135 (4.151)			
Vehicle accessibility	No access (0%)	0.009 (2.506)		0.011 (2.652)		0.014 (3.432)
	Always (100%)			0.040 (3.333)		
Attitudes	Technology savvy	-0.015 (-10.693)			-0.164 (-5.161)	
	Pro-alternative mobility	-0.017 (-13.090)	-0.069 (-5.091)	-0.013 (-2.596)	-0.156 (-5.207)	
	Cost consciousness					-0.007 (-3.026)
	Joy of shopping	-0.005 (-3.600)				
Log-Likelihood		-5,894.5				
McFadden R^2		0.37473				
Likelihood ratio test: chi-square		7,065.2 (p-value = < 2.22e-16)				

8.2.2 Wave II

Similar to the grocery shopping SP results where similarities and differences were found between the first and the second wave, results of the second wave of this study suggest that some preferences changed while some did not. Table 42 indicates the presence of taste heterogeneity, or significant levels of individual sensitivities to the random parameters. Like the first wave for the non-grocery SP results, the younger generations generally preferred online shopping and curbside pickup to in-store shopping, while low- to middle-income earners, those with lower degrees and those currently unemployed or working part-time were more likely to prefer in-store shopping. Also, having only one vehicle or not having full access to the vehicle(s) in a household predisposed shoppers to online shopping. Likewise, attitudes related to data security concern, tech savviness, alternative mobility option, the environment, recreational shopping, and online shopping did not change consumers' shopping channel preferences over time.

Turning to the differences by socio-demographic factors, females preferred online shopping to in-store shopping unlike the first wave when their preference was not significant, while Hispanics' preference seemed to have changed from alternative shopping channels to in-store shopping. The reasons for this are unclear. Regarding attitudes, those who are cost conscious or who prefer purchasing at a local store preferred curbside pickup over in-store shopping in the second wave. Also, unattended delivery concern predisposed consumers to in-store shopping preference, unlike the first wave where it was not significant. It is speculated that curbside pickup is beginning to attract more consumers, especially those who initially preferred in-store shopping (e.g., cost conscious individuals). Shoppers may be gradually harnessing the benefits of curbside pickup, especially its price and time-saving advantage over online shopping and in-store shopping, respectively. For unattended delivery, concerns seem to have grown back and affected shopping behavior since most people no longer worked remotely or stayed home for long as much as the early months of 2021.

Table 42. Non-Grocery Shopping for Wave II

	Variables	Parameter	Standard deviation
Random parameters	Product price	-0.09 (-39.79)	0.09 (39.79)
	Delivery cost	-0.30 (-18.30)	0.30 (18.30)
	Shopping time	-0.02 (-3.44)	0.02 (3.44)
	Delivery time	-0.56 (-9.02)	0.56 (9.02)
	Travel time	-0.10 (-26.38)	0.10 (26.38)
Attributes	**Variables (Main effects)**	**Online**	**Curbside**
Constant		-3.03 (-9.81)	-0.88 (-4.19)
Gender	Female	0.36 (3.53)	
Race/ethnicity	Hispanic	-0.28 (-2.28)	
	White		-0.30 (-3.02)
Generation	Gen Z (aged 18-24)	1.25 (5.97)	0.82 (4.29)
	Millennials (aged 25-40)	0.60 (3.42)	0.64 (4.25)
	Gen X (aged 41-56)	0.54 (3.32)	0.42 (3.02)
	Younger boomers (aged 57-66)	0.95 (5.82)	
Income	$15k to $25k	-0.55 (-3.38)	-0.50 (-3.60)
	$35k to $50k	-0.27 (-1.94)	-0.37 (-3.02)
Education	High school graduate	-0.34 (-3.00)	-0.22 (-2.13)
	Some college	-0.58 (-4.69)	
House type	Detached single	0.50 (4.40)	0.28 (2.80)
	Townhouse	0.81 (4.11)	0.67 (3.64)
Employment	Part-time worker	-0.39 (-2.34)	
	Unemployed	-0.44 (-2.79)	-0.28 (-1.98)
Marital status	Divorced/separated	-0.52 (-3.70)	
Children < 5 years	None	0.95 (2.37)	
Children aged 5-18	None	-0.31 (-2.64)	
Member with driver's license	None	-1.17 (-5.17)	
	One	0.26 (2.19)	0.26 (2.53)
No. of vehicles owned	One	0.65 (2.53)	
	Two	-0.26 (-2.39)	
Vehicle accessibility	60 percent (often)	0.74 (2.34)	
Attitudes	Cost consciousness		0.13 (2.10)
	Data security concern	-0.20 (-2.89)	-0.13 (-2.16)
	Technology savvy	0.41 (5.76)	0.25 (3.77)
	Pro-alternative mobility	-0.18 (-2.93)	-0.13 (-2.55)
	Pro-environment	0.34 (5.78)	0.37 (6.67)
	Local store preference		0.14 (2.77)
	Joy of shopping	0.81 (13.31)	0.39 (7.36)
	Unattended delivery concern	-0.25 (-4.15)	
	Pro-online shopping	0.77 (10.07)	0.38 (6.07)
Log-Likelihood		-5,170.4	
McFadden R^2		0.30387	
Likelihood ratio test: chi-square		4,513.9 (p-value = < 2.22e-16)	

Note: online, curbside, and in-store shopping choice frequencies are 32%, 26%, and 41% respectively

8.3 Channel Choice Summary

Results on how different groups make tradeoffs between attributes in their choice of a channel have been presented. There are some similarities and differences between grocery and non-grocery shopping, as well as the first and second wave of data collection. During both waves, delivery cost remained the most unpleasant attribute discouraging grocery shopping, while delivery time (followed by delivery cost) had the highest disutility for non-grocery shopping. Generally, blacks tended to prefer online and curbside pickup, while Asians tended to prefer in-store shopping. Those 65 years or less tended to prefer online and curbside pickup to in-store shopping. In addition, having a high school graduate degree or less, living in low to middle income-earning households are associated with preference for in-store shopping. Product type seems to affect the preference of high-income individuals, as they preferred online and curbside pickup for grocery shopping but preferred traveling to the store when shopping for non-grocery items. Workers and students preferred online shopping and home delivery. In the first wave for grocery and non-grocery shopping, Hispanics tended to prefer online shopping and curbside pickup. However, Hispanics' preference changed during the second wave, as they tend to prefer in-store shopping, especially for non-grocery shopping. Also, results on the effects of highly educated individuals, and household characteristics were not very clear.

The effect of attitudes on shopping channel preference were mostly intuitive. Technology savviness, pro-environment attitude, and pro-online shopping were associated with a preference to shop online or opt for curbside pickup, while data security concern, preference for alternative mobility options, and local store purchase led to in-store shopping preferences. Interestingly, those who enjoyed shopping (i.e., recreational shoppers) were likely to choose online shopping and curbside pickup, both between the product types, and during the two waves. Concerns toward unattended delivery differed by product type and by the wave of data collection. Our analysis also sought to understand the levels of sensitivity of the groups to the time-cost attributes. This section has reported the determinants of shopping channel choice, explanations supporting the results, and the potential changes that could occur among the groups in their shopping channel choice.

9 IMPACT ASSESSMENT

This section aims to provide more insights into the traffic implication of the growing e-commerce adoption in residential areas. Having conducted extensive analyses on the determinants of shopping behavior, the objective of this section is to estimate the total monthly delivery rates for specific products based on critical socio-demographic variables.

9.1 Freight Demand and Trip Generation

Within the business-to-business supply chain logistics in freight transportation, the generation of demand (e.g., tons) and generation of traffic (e.g., truck trips) are often treated as two separate concepts because of their weak correspondence. Unlike passenger transportation, where passenger trips and vehicle trips have fairly tight correspondence (i.e., 1 to 1.2 passengers per vehicle), the generation of freight trips are based on logistical decisions influenced primarily by shipment sizes. The relationship between freight demand and traffic can be represented using economic order quantity (EOQ) model from the inventory theory (Holguín-Veras et al., 2011):

$$Q = \sqrt{\frac{2KD}{h}} = \sqrt{\frac{2(setup\ cost)(demand\ per\ unit\ time)}{inventory\ cost}} \tag{1}$$

$$T = \sqrt{\frac{2K}{hD}} = \sqrt{\frac{2(setup\ cost)}{(inventory\ cost)(demand\ per\ unit\ time)}} \tag{2}$$

$$f = \frac{1}{T}\sqrt{\frac{hD}{2K}} = \sqrt{\frac{(inventory\ cost)(demand\ per\ unit\ time)}{2(setup\ cost)}} \tag{3}$$

where
Q is the optimal order quantity (i.e., shipment size)
T is the optimal time between orders
f is the optimal frequency

Freight trip generation is the number of vehicles required to transport shipment size Q multiplied by the delivery frequency f. This indicates that an increase in shipment size due to an increase in demand does not generate a proportional increase in freight trips. It has been suggested that a small company may generate more traffic than a large company because of the smaller shipment sizes it handles (Bastida & Holguín-Veras, 2009).

Also, in the business-to-consumer environment (i.e., the last-mile delivery segment), estimation of trips is complex. Factors affecting last-mile delivery are associated with the level of consumer service (time windows, lead time, etc.), delivery type (e.g., attended vs. unattended delivery), geographical area (density, pooling of goods), type of delivery vehicles, etc. (Gevaers et al., 2014). Also, various optimization models have been adopted for parcel delivery activities (Perboli & Rosano, 2019). Moreover, some food delivery platforms like Door Dash now provide delivery services for grocery and other product types. Thus, our aim is to quantify consumer demand, and not the traffic or trips generated due to the demand.

9.2 Cross-classification Analysis

While demand and traffic in freight transportation are separate concepts, studies have sought to estimate freight demand. Freight delivery rate, for example, has been explored by a study (Alho & de Abreu e Silva, 2016) that compared three estimation methods, including multiple classification analysis (MCA), partition method, and generalized linear model. MCA was advocated for the simplicity of its application, interpretation alongside its practical benefits.

MCA is a cross-classification technique that assumes delivery rates as a function of data stratification. Large sample sizes are required, and the total number of strata used must "fit" the sample size. That is, the total number of strata must not be too large to accommodate enough sample sizes in each stratum and should not be too small that too much information is lost. Thus, this study uses the cross-classification method to develop delivery rates.

9.2.1 Variables Considered

During the period of the first wave of data collection, attitudes and behavior may be unstable since the cumulative number of fully vaccinated Americans were still relatively low. For instance, as of Feb 1, 2021, less than 8 million Americans have been fully vaccinated (Mathieu et al., 2021). However, during the second wave of data collection, almost 200 million Americans had been fully vaccinated (as of mid-October 2021) suggesting that consumers may have returned to their normal shopping behavior or have formed more stable shopping patterns. Thus, only the data for the second wave of the survey was used to develop the delivery rates.

The selected dependent variables for the eight product types were the online shopping frequencies (for each product), which were used as proxies for the *number of monthly deliveries received per household*. Nine independent variables (IVs) were selected to estimate online shopping frequency, including age group, gender, income, education, race (white), worker (full-time, part-time, or self-employed), number of vehicles, number of children less than 5 years old, and number of children between 5 and 18 years old. Other socio-economic and attitudinal variables were excluded because of their impractical value in developing trip rates for the eight product types. Table 43 shows the unweighted and weighted sample distribution for the IVs.

Online shopping frequencies were aggregated in strata and rounded to the nearest peak within each category. For example, online shopping frequency of "6-10 times" per month was assumed to equal 8 deliveries per month. Also, categories with small sizes were combined with the nearest ones for better representation, as shown in Table 44.

Table 43. Sample Distribution of Key Demographic Variables before and after Weighting

Variables	Categories	Unweighted sample	Percent	Weighted sample	Percent
Age group	18-30	388	22.2	3,243,500	19.4
	31-44	484	27.7	4,235,700	25.3
	45-64	535	30.6	5,355,100	32.0
	65 or more	340	19.5	3,889,700	23.3
Gender	Male	628	35.9	8,523,200	51.0
	Female	1119	64.1	8,200,800	49.0
Income	Less than $25,000	448	25.6	3,756,000	22.5
	$25,000 - $49,999	573	32.8	4,577,100	27.4
	$50,000 - $99,999	532	30.5	5,146,600	30.8
	$100,000 or more	194	11.1	3,244,300	19.4
Education	High school grad or less	576	33.0	6,466,700	38.7
	Some college or associate degree	640	36.6	5,204,900	31.1
	Bachelor's degree or higher	531	30.4	5,052,400	30.2
Race	White	1253	71.7	12,536,500	75.0
	Black	318	18.2	2,644,100	15.8
	Asian	48	2.7	430,900	2.6
	Other races	128	7.3	1,112,500	6.7
Employed	Yes	940	53.8	8,987,900	53.7
	No	807	46.2	7,736,100	46.3
Children less than 5 years old	None	1524	87.2	14,896,300	89.1
	At least one	223	12.8	1,827,700	10.9
Children between 5 and 18 years old	None	1258	72.0	12,275,000	73.4
	One	291	16.7	2,708,500	16.2
	Two or more	198	11.3	1,740,500	10.4
Number of vehicles	None	127	7.3	1,115,900	6.7
	One	758	43.4	7,030,700	42.0
	Two	608	34.8	5,944,500	35.5
	Three or more	253	14.5	2,632,900	15.7
	Total	1,747		16,724,000	

Table 44. Categorization of Online Shopping Frequencies by Product Type

Product type	Characteristics	Categories						
		Never	< 5 times	6-10 times	11-15 times	16-20 times	21-30 times	> 30 times
Prepared food	Distribution (%)	57.7	26.7	8.8	2.5	1.7	2.6	
	Approx. deliv. rate	0	3	8	13	18	30	
Groceries	Distribution (%)	55.9	29.6	8.7	2.3	3.6		
	Approx. deliv. rate	0	3	8	13	20		
Clothing, shoes, watches, jewelry	Distribution (%)	37.2	46.5	10.5	2.8	2.9		
	Approx. deliv. rate	0	3	8	13	20		
Beauty and health	Distribution (%)	50	40.5	5.9	1.8	1.8		
	Approx. deliv. rate	0	3	8	13	20		
Toys, kid and baby	Distribution (%)	67.7	24.1	5.7	1.5	1		
	Approx. deliv. rate	0	3	8	13	20		
Books and electronics	Distribution (%)	56	37.5	4.8	1.7			
	Approx. deliv. rate	0	3	8	15			
Home, garden, tools	Distribution (%)	74.1	22.1	2.1	1.7			
	Approx. deliv. rate	0	3	8	15			
Pet supplies	Distribution (%)	63.2	28.8	5.5	2.6			
	Approx. deliv. rate	0	3	8	15			

9.2.2 Feature Selection

The selection of critical independent variables is important in developing a cross-classification matrix. Linear regression and random forests are popular methods used for variable selection. Linear regression being a parametric method assumes multivariate normality and homoscedasticity, among others. Random forest, on the other hand, has some similarity with the cross-classification method in that it assumes no distributional relationship (non-parametric) in the data. Thus, the random forest is more appropriate for this study.

Random forests are among the most popular machine learning models used for variable selection due to their efficiency, accuracy and robustness for both classification and regression problems. A random forest is a collection of many binary decision trees, each of which is built based on the random selection of a subset of explanatory variables (Genuer et al., 2010). The measure upon which the optimal condition is chosen is called impurity (or variance, for regression trees). The ranking of features is based on how much each feature reduces impurity in a tree. A drawback of using random forests is that its impurity-based ranking makes feature selection biased towards variables with more categories and correlated features. Thus, to ensure less biased variable ranking, correlations are checked to remove strongly correlated variables, while variables were categorized to at most four categories.

9.2.3 Other Considerations

The cross-classification matrix for each product contains the average delivery rates for each cell. However, several factors were put into consideration in estimating delivery rates. First, online shopping frequencies may fluctuate by seasons, similar to the seasonal fluctuations with regards to total retail sales, as shown in Figure 41. Monthly seasonal factors for retail sales differ slightly for various product types. For example, clothing and clothing accessories stores have more varying seasonal factors than furniture and home furnishing stores. It should be recalled that the data was collected on shopping behavior for mostly the month of October and early November. Since October sales have seasonal factors close to 1.00 for most of the product types considered in this study, it is assumed that the estimated delivery rates based on the survey data are representative of average monthly estimates.

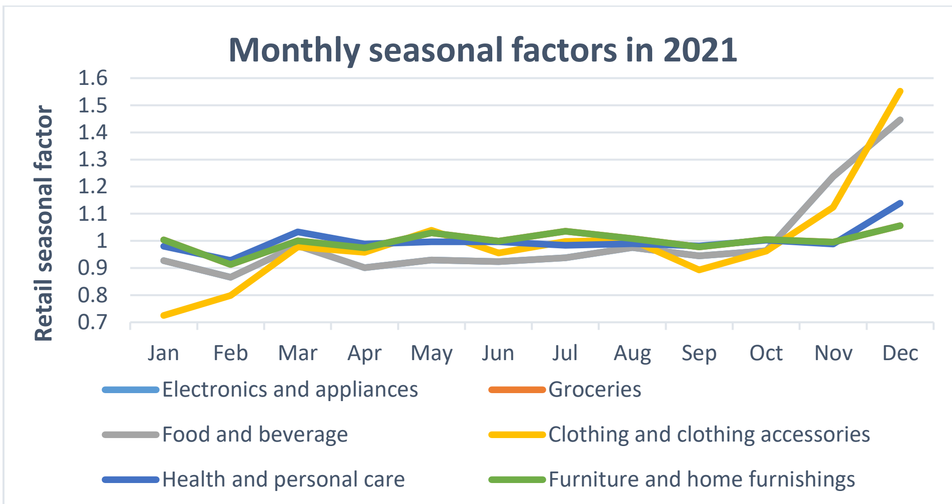


Figure 41. Seasonal factors for total retail sales at six different stores

(Data source: U.S. Census Bureau, 2021**)**

It is necessary to point out that the online shopping frequencies (dependent variables) collected were household variables, while the socio-demographic variables used to develop the matrix are most individual variables (e.g., age, gender, etc.) aside income. Thus, cell values in the classification matrix for delivery rates per household were divided by corresponding cells in the cross-classification matrix for the average number of adults in a household. This ensured that individual delivery rates, as opposed to household delivery rates, were estimated.

9.3 Results

A total of nine IVs were included in the models used for variable selection. Table 45 shows the ranking of the IVs for each product type. Age group was among the top three variables for each product type. Education or income level were one of the top three features for six products. The number of children in a household is very important in the online purchase of toys, kid, and baby products, while gender is featured as the second most important variable in the online purchase of beauty and health products. Regarding online shopping for pet supplies, race and employment status were among the top three variables.

Only the top three variables were used to estimate the delivery rates. The next sub-section presents the graphs for the delivery rates of each product, while the cross-classification tables (matrices) can be found in the Appendix section of this deliverable. It should be noted that cell values containing less than five observations were excluded from the matrix and bar graphs.

Table 45. Variable Ranking by Product Type Based on Random Forest Model

Rank	BE	Gr	PF	CSWJ	BH	HGT	PS	TKB
1	Age group	Age group	Age group	Age group	Age group	Age group	Worker	Chldn_5-18
2	Education	Education	Education	Income	Gender	Education	Age group	Chldn<5
3	Income	Chldn_5-18	Chldn_5-18	Chldn_5-18	Income	Income	Race	Age group
4	No of veh	Income	Income	Education	Education	Chldn_5-18	Education	No of veh
5	Chldn_5-18	Gender	No of veh	No of veh	Chldn_5-18	No of veh	Income	Education
6	Gender	No of veh	Gender	Race	Worker	Gender	Chldn_5-18	Income
7	Worker	Worker	Worker	Gender	No of veh	Worker	No of veh	Gender
8	Race	Race	Race	Worker	Race	Chldn<5	Gender	Worker
9	Chldn<5	Chldn<5	Chldn<5	Chldn<5	Chldn<5	Race	Chldn<5	Race

Table 46 to Table 53 present the results of the estimated online shopping frequency for each product type.

9.3.1 Books and Electronics (BE)

Table 46 shows the delivery rates for BE by age group, education, and income. Delivery rates for BE seem to increase by educational level. Those with a bachelor's degree between the ages of 31-45 years made the highest number of deliveries for BE - almost six deliveries per month. Also, young and middle-aged individuals (aged 18-45) slightly received more deliveries for BE on average than older ones. Income and deliveries for BE seem to be positively related among young to middle-aged individuals, although this may not be so for older individuals.

Table 46. Delivery Rates for Books and Electronics

Age group	Educational level	Income			
		Less than $25,000	$25,000 - $49,999	$50,000 - $99,999	$100,000 or more
18-30	High school graduate or less	0.82	0.52	0.98	0.90
	Some college or associate degree	0.72	1.14	1.13	1.75
	Bachelor's degree or higher	0.79	1.15	1.64	1.30
31-45	High school graduate or less	0.44	0.69	0.92	N/A
	Some college or associate degree	0.74	0.86	1.00	1.42
	Bachelor's degree or higher	1.12	1.35	1.62	1.53
46-64	High school graduate or less	0.43	0.48	0.54	N/A
	Some college or associate degree	1.02	0.69	0.65	0.84
	Bachelor's degree or higher	0.80	0.83	0.77	0.80
65 or more	High school graduate or less	0.56	0.31	0.55	0.26
	Some college or associate degree	1.06	0.74	0.65	0.33
	Bachelor's degree or higher	1.38	0.89	0.94	0.55

N/A: unreliable delivery rates due to insufficient data

9.3.2 Groceries (Gr)

Table 47 shows the delivery rates for groceries by age group, education and living with children between 5 and 18 years old.

Table 47. Delivery Rates for Groceries

Age group	Educational level	Living with children aged 5-18		
		None	One	Two or more
18-30	High school graduate or less	1.31	0.51	1.71
	Some college or associate degree	1.23	1.21	2.62
	Bachelor's degree or higher	2.03	1.96	N/A
31-45	High school graduate or less	1.08	1.47	1.55
	Some college or associate degree	1.90	1.44	1.87
	Bachelor's degree or higher	1.25	1.82	3.34
46-64	High school graduate or less	1.04	1.37	1.97
	Some college or associate degree	1.11	1.51	1.58
	Bachelor's degree or higher	0.59	1.69	1.13
65 or more	High school graduate or less	0.47	N/A	N/A
	Some college or associate degree	0.89	N/A	N/A
	Bachelor's degree or higher	0.89	N/A	N/A

N/A: unreliable delivery rates due to insufficient data

It appears that middle-aged individuals and those living with children between 5 and 18 years old received more deliveries than others. Middle-aged highly educated individuals had the highest number of deliveries. It is speculated that the presence of dependents discourages physical shopping at the grocery stores. It is perhaps more likely the presence of children in the household increases grocery needs, and thus increases the number of deliveries. The effect of education on delivery rates seems unclear.

9.3.3 Prepared Food (PF)

Like grocery delivery rates, Table 48 shows that those with a bachelor's degree or higher and between 31 and 45 years had the highest number of deliveries for PF. Also, no clear pattern is seen for education and delivery rates. However, those between 31 and 45 years ordered PF more than other age groups.

Table 48. Delivery Rates for Prepared Food

Age group	Educational level	Living with children aged 5-18		
		None	One	Two or more
18-30	High school graduate or less	1.49	1.74	1.62
	Some college or associate degree	1.12	1.07	2.96
	Bachelor's degree or higher	2.39	1.89	N/A
31-45	High school graduate or less	1.18	2.07	2.60
	Some college or associate degree	2.07	1.27	1.66
	Bachelor's degree or higher	1.79	1.83	3.92
46-64	High school graduate or less	1.12	1.13	1.90
	Some college or associate degree	1.12	1.44	1.59
	Bachelor's degree or higher	1.15	1.49	1.29
65 or more	High school graduate or less	0.22	N/A	N/A
	Some college or associate degree	0.81	N/A	N/A
	Bachelor's degree or higher	0.68	N/A	N/A

N/A: unreliable delivery rates due to insufficient data

9.3.4 Clothing, Shoes, Watches, Jewelry (CSWJ)

Table 49 shows the delivery rates for CSWJ by age group, income and living with children between 5 and 18 years old. Generally, young and middle-aged individuals had more deliveries for CSWJ than the older ones. However, online shopping for CSWJ seems to be used generally by the groups. And while those living with two or more children between 5 and 18 years old received more deliveries for CSWJ than those living with one child, it appears that having no children is also linked with a high number of monthly deliveries for CSWJ.

Table 49. Delivery Rates for Clothing, Shoes, Watches, and Jewelry

Age group	Income level	Living with children aged 5-18		
		None	One	Two or more
18-30	Less than $25,000	2.09	2.35	1.54
	$25,000 - $49,999	1.59	1.55	2.60
	$50,000 - $99,999	1.59	2.20	2.46
	$100,000 or more	2.03	1.43	N/A
31-45	Less than $25,000	1.44	1.71	1.83
	$25,000 - $49,999	1.47	1.73	2.72
	$50,000 - $99,999	1.50	2.26	2.37
	$100,000 or more	2.08	1.68	2.88
46-64	Less than $25,000	0.96	1.48	1.98
	$25,000 - $49,999	1.27	1.84	2.56
	$50,000 - $99,999	1.06	0.95	1.63
	$100,000 or more	1.58	0.92	1.61
65 or more	Less than $25,000	0.67	N/A	N/A
	$25,000 - $49,999	0.74	N/A	N/A
	$50,000 - $99,999	1.07	N/A	N/A
	$100,000 or more	1.05	N/A	N/A

N/A: unreliable delivery rates due to insufficient data

9.3.5 Beauty and Health (BH)

Table 50 shows clear delivery rate patterns for BH products by age group, gender and income. Females received an average of 2.1 deliveries for BH products more than males. It also appears that as individuals age, deliveries for BH products reduced. Higher income earners received more deliveries for BH products.

Table 50. Delivery Rates for Beauty and Health

Age group	Gender	Income			
		Less than $25,000	$25,000 - $49,999	$50,000 - $99,999	$100,000 or more
18-30	Male	0.63	1.04	1.37	0.84
	Female	1.69	1.61	1.74	1.24
31-45	Male	1.01	0.98	1.25	1.17
	Female	1.28	1.28	1.45	2.24
46-64	Male	0.50	0.76	0.72	0.48
	Female	1.24	1.08	1.04	1.96
65 or more	Male	0.20	0.47	0.56	0.49
	Female	0.96	0.79	1.00	0.53

9.3.6 Home, Garden and Tools (HGT)

Table 51 shows the delivery rates for HGT by age group, education and income. Generally, those with a bachelor's degree or higher received more deliveries for HGT than those with lower education for all age groups. While young and middle-aged individuals had more deliveries, no clear pattern between HGT delivery rates and income is noticeable.

Table 51. Delivery Rates for Home, Garden, And Tools

Age group	Educational level	Income			
		Less than $25,000	$25,000 - $49,999	$50,000 - $99,999	$100,000 or more
18-30	High school graduate or less	0.46	0.49	0.75	0.28
	Some college or associate degree	0.69	0.59	0.52	0.46
	Bachelor's degree or higher	1.46	1.02	1.51	1.13
31-45	High school graduate or less	0.54	0.59	0.95	N/A
	Some college or associate degree	0.56	0.50	0.54	0.35
	Bachelor's degree or higher	1.08	0.89	0.89	0.96
46-64	High school graduate or less	0.23	0.45	0.62	N/A
	Some college or associate degree	0.26	0.44	0.29	0.26
	Bachelor's degree or higher	0.37	0.44	0.50	0.45
65 or more	High school graduate or less	0.06	0.19	0.37	0.69
	Some college or associate degree	0.21	0.25	0.27	0.21
	Bachelor's degree or higher	0.37	0.40	0.39	0.31

N/A: unreliable delivery rates due to insufficient data

9.3.7 Pet Supplies (PS)

Table 52 shows the delivery rates for PS by age group, employment status and race. Those who have full-time, part-time work or were self-employed received more deliveries than those not in the labor force. Among those not working, deliveries seem to increase with age. Whites overwhelming received more deliveries than other races.

Table 52. Delivery Rates for Pet Supplies

Age group	Employment	Race			
		White	Black	Asian	Other
18-30	Non-worker	0.71	0.46	N/A	0.15
	Worker	1.23	0.60	0.46	1.04
31-45	Non-worker	0.74	0.55	0.29	0.07
	Worker	1.30	0.57	0.91	0.60
46-64	Non-worker	0.73	0.56	N/A	0.38
	Worker	0.85	0.49	0.83	0.45
65 or more	No distinction	0.54	1.16	N/A	N/A

N/A: unreliable delivery rates due to insufficient data

9.3.8 Toys, Kid, and Baby (TKB) Products

Table 53 shows the delivery rates for TKB by age group, living with children between 5 and 18 years old, and living with children less than 5 years old. Having children in general increased the number of deliveries for TKB, although deliveries seem to decrease with age.

Table 53. Delivery Rates for Toys, Kid, and Baby Products

Age group	Living with children less than 5 years old	Living with children aged 5-18		
		None	One	Two or more
18-30	No child	0.43	0.64	1.21
	At least one child	2.56	2.31	4.58
31-45	No child	0.40	1.16	1.96
	At least one child	1.71	2.03	1.47
46-64	No child	0.39	0.69	0.90
	At least one child	1.07	N/A	N/A
65 or more	No distinction	0.36	0.82	1.70

N/A: unreliable delivery rates due to insufficient data

9.4 Impact Assessment Summary

We have estimated the delivery rates for specific products among Florida residents using the cross-classification method. Variables used in the cross-classification were selected and ranked using random forest machine learning method. Although the importance of the predictive variables varies by product type, age group, having children between 5 and 18 years, education, and income tend to be among the top three variables affecting the delivery rates of products in general. One implication from this estimation is that those with a bachelor's degree or higher (especially middle-aged individuals) tend to receive more deliveries than those with lower education. Thus, there is a potential for online shopping to reduce physical store shopping for highly educated individuals. Another implication from the estimation is that the impact of socio-demographic variables on delivery rates are not always linear. For example, middle-aged individuals received more grocery deliveries than either young or older individuals. This helps to provide more insight into freight planning and management strategies.

There are some limitations to the estimation of delivery rates in this study. First, we assumed that the respondents' online shopping frequency bore a tight correspondence to the number of deliveries received. However, some online shopping websites may decide to split an order (especially an heterogenous one) into multiple packages to be delivered at different times. Second, it was assumed that all deliveries made by households were delivered to home locations. While the majority of orders may arrive at consumers' homes, some orders are made and delivered at offices, especially prepared food. However, the data used are representative of the Florida population and the estimated delivery rates are useful in predicting the approximate number of delivery rates for specific products based on the most important variables.

10 CONCLUSION

This study examined e-commerce demand and its impact on the transportation system in residential areas. Various SEMs, with the latent attitudinal factors as mediating variables, were developed to examine the shopping travel effects of e-commerce. Although model results showed that travel effects tended to differ by product type, overall, e-commerce tended to exhibit complementary effects on travel. This suggests that transportation planners should expect that as e-commerce continues to grow and delivery demand increases, there will be an increase and freight and passenger trips in residential areas.

There are various factors that drive these effects found in this study, including various socio-economic, demographic and household characteristics, and attitudes. It should be noted that these effects and drivers of these effects vary by product types. Also, discrete choice experiments, with three alternatives (home delivery, curbside pickup, and in-store) and five time-cost attributes (product price, shopping time, delivery time, delivery cost, and travel time), were constructed to understand how consumers tradeoffs attribute in their shopping decision. It was found that delivery cost had the highest disutility, and in-store shopping remains the dominant shopping alternative. A second wave of this study was conducted, and further complementary effects were found, confirming the results in the first wave. Also, many other differences and similarities were observed.

Considering that food delivery platforms like DoorDash and GrubHub now provide delivery services and increase the complexity of transportation activities in residential areas, there is a need for the design of more complex network systems and vehicle routing strategies to mitigate the traffic effects. Also, return-related travel and reverse logistics may also increase, necessitating the need to promote outbound and reverse logistics models that prioritize traffic effects and yield low return rates. Time slot allocation approaches, for example, should consider traffic demand in their delivery and return pricing. For individuals who have unattended delivery concerns, the use of parcel boxes where the delivered items can be safely put when out of the home can be considered. Moreover, equity issues for households with low income and technology savviness in suburban areas may arise as stores get converted to warehouses. To address equity issues for senior citizens, online retail companies should be encouraged to simplify shopping websites, offer different navigation options, use larger font sizes, and outreach campaigns. Overall, it is expected that the findings in this study will be informative to transportation planners in framing effective transportation demand policies.

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Appendix A – Survey Questionnaire

INTRODUCTION

Florida International University
FIU IRB Protocol #21-0024

Dear Respondent:

The Florida Department of Transportation is requesting your participation in an eCommerce (the activity of electronically buying products on online services or over the Internet) survey. In this study, approximately 2,000 people will be asked to complete a survey about their purchasing decisions for the purpose of gathering information regarding the use of eCommerce and the changing nature of commerce. This information will assist the Department in providing a safe and efficient transportation system that ensures the mobility of people and goods. This survey will take about 20 minutes to complete.
There are no foreseeable risks associated with this study. However, your participation is voluntary. Moreover, if you feel uncomfortable answering any questions, you can withdraw from the survey at any point.
Your survey responses will be strictly confidential and data from this research will be reported only in the aggregate. If you have questions at any time about the survey or the procedures, you may contact Dr. Xia Jin by email at xjin1@fiu.edu.
Thank you for your participation.

Sincerely,
Xia Jin, Ph.D., AICP
Department of Civil and Environmental Engineering, Florida International University
10555 W Flagler St., EC 3603 Miami, FL 33174

Clicking on the forward button and moving to the next page implies that you are a Florida resident 18 years or older, you have read the above statement, and you agree to participate in this study.

VERIFICATION QUESTIONS

Q1.1- Before you proceed to the survey, please complete the captcha below.

- ☐ I'm not a robot.

Q1.2- We care about the quality of our survey data and hope to receive the most accurate measures of your opinions, so it is important to us that you thoughtfully provide your best answer to each question in the survey.
Do you commit to providing your thoughtful and honest answers to the questions in this survey?
(Skip to end of block if "I will provide my best answers" is not selected)

- ☐ I will provide my best answers.
- ☐ I will not provide my best answers.
- ☐ I can't promise either way.

SOCIO-DEMOGRAPHIC CHARACTERISTICS

Q2.1- Please indicate your age.
(dropdown list of states in the US)
(Skip to end of block if "Florida" is not selected)

Q2.2- Please indicate your age.
(dropdown list ranging from 18 to 100)
(Skip to end of block if "less than 18" is selected)

Q2.3- Please indicate your gender.

- ☐ Male
- ☐ Female

Q2.4- What is the highest level of education you have completed or the highest degree you have received?

- ☐ Less than high school
- ☐ High school graduate
- ☐ Some college, but no degree
- ☐ Associate degree (2-year)
- ☐ Bachelor's degree (4-year)
- ☐ Graduate/post-graduate degree (Master's/PhD or equivalent)
- ☐ Professional Degree (JD, MD)

Q2.5- Do you consider yourself Spanish, Hispanic or Latino?

- ☐ Yes
- ☐ No

Q2.6- Which category best describes your primary racial group?

- ☐ White
- ☐ Black or African American
- ☐ Asian
- ☐ American Indian or Alaska Native
- ☐ Native Hawaiian or Pacific Islander
- ☐ Multi-racial

Q2.7- Please specify your annual **household income in 2020** (before tax, including all household members).

- ☐ Less than $10,000

☐ $10,000 - $14,999
☐ $15,000 - $24,999
☐ $25,000 - $34,999
☐ $35,000 - $49,999
☐ $50,000 - $74,999
☐ $75,000 - $99,999
☐ $100,000 - $124,999
☐ $125,000 - $149,999
☐ $150,000 - $199,999
☐ $200,000 or more

Q2.8- What is your marital status?

☐ Single (Never married)
☐ Married
☐ Separated
☐ Divorced
☐ Widowed

Q2.9- What is your primary occupational/employment status?

☐ Employed full-time (35+ hours/week, paid)
☐ Employed part-time (fewer than 35 hours/week, paid)
☐ Self-employed
☐ Student
☐ Unpaid volunteer or intern
☐ Homemaker
☐ Retired
☐ Not currently employed

Q2.10- Please select the county where you live now
(dropdown list of counties in Florida)

Q2.11- Please enter your home location zip code
(US Postal Code validation)

Q2.12- What type of home do you live in?

☐Detached single house
☐Townhouse, row house
☐Apartment in building with 2-4 units
☐Apartment in building with more than 5 units
☐Other

Q2.13- Indicate the number of people (including yourself) who currently live in your household, according to each of the following categories.

(Multiple dropdown list ranging from 0 to 10)

a) Total number of household members
b) Children less than 5 years old
c) Children between 7 to 18 years old
d) Individuals aged 65 years or more
e) Individuals with a drivers' license

SHOPPING PATTERN

This section focuses on the **general shopping pattern**. When you answer the following questions, please consider shopping activities for **<u>your entire household</u>**, including purchases from all members of the household.

Q 3.1- How many times **in the past month** did **<u>your household</u>** purchase each of the following types of products online and in a physical store?
(2 columns of multiple dropdown list, showing online and in-store)
(Alternatives: Never, < 5 times, 6 - 10 times, 11 - 15 times, 16 - 20 times, 21 - 30 times, > 30 times)

- Books and electronics
- Prepared food
- Grocery
- Home, garden, and tools (appliance, furniture, bed and bath, lighting, furniture, home decor)
- Clothing, shoes, jewelry, watches
- Beauty and health
- Pet supplies
- Toy, kids, and baby

Q3.2- How much **did your_household spend** on each of the following types of products **in the past month,** online and in-store?
(Alternatives: Not applicable, < $100, $100-$500, $501-$1,000, $1,001-$2,000, > 2,000)

- Books, and electronics
- Prepared food
- Grocery
- Home, garden, and tools
- Clothing, shoes, jewelry, watches
- Beauty and health
- Pet supplies
- Toy, kids, and baby

Q3.3- For each of the types of products below, how long did **<u>you or your household members</u>** regularly travel to purchase them? (**one-way trip in miles**).
(Alternatives: 0 to 5 miles, 6 to 10 miles, 11 to 15 miles, 16 to 20 miles, > 20 miles)

(For each product type in Q3.1 (in-store column), If Answer= Never, do not show that product type here)

- Books and electronics
- Prepared food
- Grocery
- Home, garden, and tools
- Clothing, shoes, jewelry, watches
- Beauty and health
- Pet supplies
- Toy, kids, and baby

Q3.4 Approximately, what percentage of your household in-store purchases are being done online now compared to pre-pandemic?
(Alternatives: 100%, 75%, 50%, 25%, 0%)

- Grocery
- Non-grocery

Q3.5 Have you returned any purchased products **in the past month**?

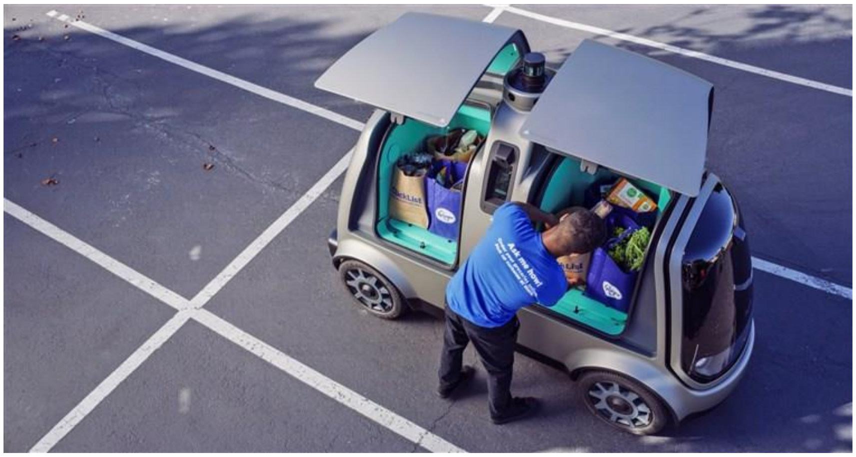
- Yes
- No

Q3.6 How many returns have you initiated **in the past month** by the following methods? (Select by clicking on or moving all the sliders)
(Display question if answered Yes to Q3.4)
(Sliders: 0 to 10)

- A trip to the post office
- Picked up by a carrier
- Return to store

ROBOT DELIVERY

Assume you can receive your next grocery or food purchases by a driverless car (robot delivery), similar to the figure below:



Q4.1- Would you be interested in receiving your purchases via robot delivery?

- Definitely yes
- Probably yes
- Might or might not
- Probably not
- Definitely not

Q 4.2- From the following statements about **technology**, please indicate how much you personally disagree or agree with each of the statements.
(Alternatives: strongly disagree, disagree, indifferent, agree, strongly agree)
(Order of choice questions randomized)

- I frequently use smartphone apps
- I am highly engaged in online activities
- Without technology, my life would be boring
- I have had too many frustrating experiences while using new technology
- Most new technologies are unnecessary or useless

Q 4.3- From the following statements about **automation**, please indicate how much you personally disagree or agree with each of the statements.
(Alternatives: strongly disagree, disagree, indifferent, agree, strongly agree)
(Order of choice questions randomized)

- I am willing to pay more money to collect delivery items from a robot than a human
- I hesitate to use automation technologies
- I do not like using robotic delivery due to the potential impact on the job market
- Robot delivery would be safer and more reliable than human delivery

MOST FREQUENT GROCERY PURCHASE

Please consider a **grocery purchase** that you or your household member make on a regular basis, and answer the following questions.

Q5.1- Was this purchase in-store or online?

- In-store
- Online

Q5.2- How much money did you spend**?**
(Alternatives: less than $50, $51-$100, $101-$150, $151-$200, more than $200)

Q5.3- For this grocery trip, which **transportation mode(s)** did you use for the trip? (If you used multiple modes in one trip, select all that apply)

(Display question if "in-store" in Q5.1 is selected)

- Private vehicle
- Transit
- Taxi
- Ridesourcing/car sharing
- Walk/bike/scooter/mopeds

Q5.4- What was your travel distance for this trip (**one-way trip**)?
(Alternatives: less than 5 miles, 5 to 10 miles, 11 to 20 miles, more than 20 miles) (if selected in-store)

Q5.5- How long did it take you to get to the store (**one-way trip**)?
(Alternatives: less than 10 mins, 11-20, 21-30, more than 30 mins) (if selected in-store)

Q5.6- How long did you spend shopping for the purchase in the store?
(Alternatives: less than 15 mins, 15-30 mins, 31-45 mins, 46-60 mins, more than 60 mins) (if selected in-store)

Q5.7- For this grocery purchase, how long did you spend searching and placing the order online?
(Alternatives: less than 15 mins, 15-30 mins, 31-45 mins, 46-60 mins, more than 60 mins) (if selected online)

Q5.8- How long was the **delivery time**? (if selected online)

☐ 6-8 hours ☐ same day ☐ next day ☐ 2-3 days

Q5.9- How much did you pay for the **delivery** (% of the total purchase)? (if selected online)

☐0% ☐5% ☐10% ☐%15 ☐%20 ☐%25

STATED PREFERENCE SCENARIOS - GROCERY

For the next set of questions, consider the most frequent or most recent **grocery purchase** you indicated in the previous section, and select your most preferred option for each of the given scenarios.

The questions consist of hypothetical scenarios that present you with three options in making grocery purchases:

Online purchase: you search for products online, place an order online and the products will be delivered to your specified location. You will have the products a few hours or days later, plus (often) an additional delivery cost.

Curbside pickup purchase: you may pick up products at your convenient time, without the need to wait for the products to be delivered. There may be a delivery cost involved, but often cheaper if purchased online.

In-store purchase: you travel to the store, experience the products, and decide on buying the products right away.

Each option incurs some level of cost and time involved with the purchase. All three options involve the **product price** (total price of products to be purchased), while in-store and curbside pickup purchases involve **travel time** (travel time to the store and back) and **shopping time** (the time spent in-store), and the online purchase incurs **delivery time** (the time from your make the order till you receive the order), **delivery cost** (the cost that you pay for delivery), and **ordering time** (the time spent online searching and purchasing the products).

Assume these options presented are the only options available to you for this **grocery purchase**, and answer all **seven** choice questions.

Scenario example:

Q - A different choice situation is presented for your **grocery** purchase:

	Online	**Curbside**	**In-store**
Product price	$45	$55	$50
Ordering time / shopping time	27 mins	27 mins	35 mins
Delivery time	6-8 hr delivery	-	-
Travel time (both ways)	-	20 mins	20 mins
Delivery cost	$3	$6	-

Which option would you choose?

- Online
- Curbside
- In-store

(Order of choice questions in each block is randomized)

(If Q5.2 is "less than $50", randomly display one of Block 1 - Grocery $50, Block 2 – Grocery $50, or Block 3 - Grocery $50)

(If Q5.2 is "$51-$100" or "$101-$150", randomly display one of Block 1 - Grocery $100, Block 2 – Grocery $100, or Block 3 - Grocery $100)

(If Q5.2 is "$151-$200" or "more than $200", randomly display one of Block 1 - Grocery $200, Block 2 – Grocery $200, or Block 3 - Grocery $200)

YOUR MOST FREQUENT NON-GROCERY PURCHASE

Please consider your most frequent or most recent **non-grocery purchases** and answer the following questions.

Q6.1 Was this purchase in-store or online?

- ☐In-store
- ☐online

Q6.2- What types of products did you buy? (select all that apply)

- ☐Books and electronics
- ☐Home, garden, and tools
- ☐Clothing, shoes, jewelry, watches
- ☐Beauty and health
- ☐Pet supplies
- ☐Toy, kids, and baby

Q6.3- How much money did you spend?
(Alternatives: less than $100, $100-$300, $301-$500, $501-$750, more than $750)

Q6.4- For this non-grocery trip, which transportation modes did you use? (If you used multiple modes in one trip, select all)
(if selected in-store)

- Private vehicle
- Transit
- Taxi
- Ridesourcing/car sharing
- Walk/bike/scooter/mopeds

Q6.5- How long did you travel for this trip (**one-way trip**)?
(Alternatives: less than 5 miles, 5 to 10 miles, 11 to 20 miles, 21 to 30 miles more than 30 miles) (if selected in-store)

Q6.6- What was your travel time for this trip (**one-way trip**)?
(Alternatives: less than 10 minutes, 10-20 mins, 21-30 mins, 31-60 mins, more than 60 mins) (if selected in-store)

Q6.7- How long did you spend shopping for the purchase in the store?
(Alternatives: less than 15 mins, 15-30 mins, 31-45 mins, 46-60, more than 60 mins) (if selected in-store)

Q6.8- For this non-grocery purchase, how long did you spend searching and placing the order online?
(Alternatives: less than 15 mins, 15-30 mins, 31-45 mins, 46-60, more than 60 mins) (if selected online)

Q6.9- How long was the delivery time? (if selected online)

☐ Same day ☐ Next day ☐ 2-3 days ☐ 1 week

Q6.10- How much did you pay for the delivery? (if selected online)

☐$0 ☐$1-$10 ☐$11-$20 ☐more than $20

Q6.11- How many individual packages were delivered from this order? (if selected online)

☐1
☐2
☐3
☐4
☐5
☐6
☐7
☐8
☐9
☐10 or more

STATED PREFERENCE SCENARIOS- NON-GROCERY

For the next set of questions, consider the most frequent or most recent **grocery purchase** you indicated in the previous section, and select your most preferred option for each of the given scenarios.

The questions consist of hypothetical scenarios that present you with three options in making grocery purchases.

Online purchase: you search for products online, place an order online and the products will be delivered to your specified location. You will have the products a few hours or days later, plus (often) an additional delivery cost.

Curbside pickup purchase: you may pick up products at your convenient time, without the need to wait for the products to be delivered. There may be a delivery cost involved, but often cheaper if purchased online.

In-store purchase: you travel to the store, experience the products, and decide on buying the products right away.

Each option incurs some level of cost and time involved with the purchase. All three options involve the **product price** (total price of products to be purchased), while in-store and curbside pickup purchases involve **travel time** (travel time to the store and back) and **shopping time** (the time spent in-store), and the online purchase incurs **delivery time** (the time from your make the order till you receive the order), **delivery cost** (the cost that you pay for delivery), and **ordering time** (the time spent online searching and purchasing the products).

Assume these options presented are the only options available to you for this **non-grocery purchase**, and answer all **seven** choice questions.

Scenario example:

Q - A different choice situation is presented for your **non-grocery** purchase:

	Online	**Curbside**	**In-store**
Product price	\$90	\$110	\$100
Ordering time / shopping time	41 mins	41 mins	52 mins
Delivery time	Next-day delivery	-	-
Travel time (both ways)	-	40 mins	40 mins
Delivery cost	\$0	\$4	-

Which option would you choose?
- Online
- Curbside
- In-store

(Order of choice questions in each block is randomized)

(If Q6.3 is "less than \$100", randomly display one of Block 1 – Non-grocery \$100, Block 2 – Non-grocery \$100, or Block 3 – Non-grocery \$100)

(If Q6.3 is "\$100-\$300" or "\$301-\$500", randomly display one of Block 1 – Non-grocery \$300, Block 2 – Non-grocery \$300, or Block 3 – Non-grocery \$300)

(If Q6.3 is "\$501-\$700" or "more than \$700", randomly display one of Block 1 – Non-grocery \$750, Block 2 – Non-grocery \$750, or Block 3 – Non-grocery \$750)

SHOPPING ATTITUDES

Q7.1- From the following statements about **shopping method**, please indicate how much you personally disagree or agree with each of the statements.
(Alternatives: strongly disagree, disagree, indifferent, agree, strongly agree)
(Order of choice questions randomized)

- I prefer buying products online because I do not have to carry them
- I do not like online shopping because it does not fit my lifestyle
- Please select "Strongly Agree" here
- Strolling through shopping areas is enjoyable and refreshing
- I sometimes use shopping as an excuse to leave my house or place of work

Q7.2- From the following statements about **local stores**, please indicate how much you personally disagree or agree with each of the statements.
(Alternatives: strongly disagree, disagree, indifferent, agree, strongly agree)
(Order of choice questions randomized)
(Skip to the end of survey if "Strongly Agree" is not selected in Q7.1)

- I would rather buy at small local stores than at big, well-established stores
- Local stores sell mostly low-quality products
- I do not think purchasing from a local store necessarily helps my community
- I like to purchase from the local stores because I know the people behind the business
- Local stores provide personalized services as they know the community and their needs

Q7.3- From the following statements about **delivery experience**, please indicate how much you personally disagree or agree with each of the statements.
(Alternatives: strongly disagree, disagree, indifferent, agree, strongly agree)
(Order of choice questions randomized)

- I do not like missing an attended delivery (i.e., delivery that involves collecting purchased products from the deliveryman)
- I do not like it if a product is left in my house compound unattended to
- I do not mind curbside pickup at a store
- I prefer to pick up my orders at a collection and delivery point, at a convenient time
- I often receive damaged packages from online stores

Q7.4- From the following statements about **social interaction**, please indicate how much you personally disagree or agree with each of the statements.
(Alternatives: strongly disagree, disagree, indifferent, agree, strongly agree)
(Order of choice questions randomized)

- Shopping in physical stores is too stressful and tiring
- Because I love meeting people, I often opt to shop in real stores
- I like shopping without interacting with anyone

- It is important for me to talk to someone before making my final purchase decision

Q7.5- From the following statements about **data security**, please indicate how much you personally disagree or agree with each of the statements.
(Alternatives: strongly disagree, disagree, indifferent, agree, strongly agree)
(Order of choice questions randomized)

- Too much personal information is required for online purchase
- Most online stores have secure websites
- I trust online shopping
- I have heard much bad news about online shopping scams
- I am concerned about putting my debit or credit card information online

(NOTE: In addition to randomizing the order of choice questions/statements within each question, order of questions is randomized within the block)

LIFESTYLE PREFERENCES

Q8.1- From the following statements about **cost**, please indicate how much you personally disagree or agree with each of the statements.
(Alternatives: strongly disagree, disagree, indifferent, agree, strongly agree)
(Order of choice questions randomized)

- After being aware of a product, I will first check the price before assessing the quality
- I find it stressful waiting to find sales and special offers before buying products
- I often make purchases when I want them and not necessarily when their prices are lower
- I always look for the best deals
- If after purchasing a product I later find I could have bought the product at a lower price, I will be upset with myself

Q8.2- From the following statements about **time**, please indicate how much you personally disagree or agree with each of the statements.
(Alternatives: strongly disagree, disagree, indifferent, agree, strongly agree)
(Order of choice questions randomized)

- I will shop online or in-store inasmuch as it saves me time
- Once I start shopping, I go straight to where to find the products without wasting time
- I often shop multiple times before making my final purchase
- Since I am often busy, it is a good idea for other people to shop for me
- I love to take my time when I shop

Q8.3- From the following statements about **convenience**, please indicate how much you personally disagree or agree with each of the statements.
(Alternatives: strongly disagree, disagree, indifferent, agree, strongly agree)

(Order of choice questions randomized)

- I would not mind driving to the store for shopping even in bad weather
- When I shop, it's important that someone is available to help me out when I need help
- Shopping online is not as convenient as shopping in person
- It is important for me to be able to return faulty products easily
- Unlike online stores, it takes time for me to check the availability of products in physical stores
- I like to easily compare multiple products and their prices when shopping

Q 8.4- From the following statements about **environment**, please indicate how much you personally disagree or agree with each of the statements.
(Alternatives: strongly disagree, disagree, indifferent, agree, strongly agree)
(Order of choice questions randomized)

- I do not think about any negative environmental impacts before driving to stores
- It makes sense to raise the price of gasoline to reduce air pollution
- The government should not regulate car travel to reduce traffic congestion
- Because I am passionate about saving trees, I look for ways to use fewer paper products
- I do not like too much product packaging because it wastes environmental resources
- Global warming is a hoax
- I like electric cars because they emit less than gasoline vehicles

(NOTE: In addition to randomizing the order of choice questions/statements within each question, order of questions is randomized within the block)

PURCHASING PREFERENCES

Q9.1- **How important** were the following factors in choosing the store to shop from? Please select the most relevant option for each one of the following items:
(Alternatives: Highly important, Somewhat important, Not important)

- Travel time/distance
- Store crowdedness
- Price level
- Other's reviews
- Store brand
- Opening and closing hours
- On-site parking
- Neighborhood safety

Q9.2- **How concerning** were the following aspects of online shopping to you? Please select the most relevant option for each one of the following **negative** aspects:
(Alternatives: Highly concerning, Somewhat concerning, Not concerning)

- Not being able to try or examine
- Possibilities of inaccurate info on the websites
- Not having the item I bought momentarily (i.e., waiting for it to ship)
- Shipping costs
- Privacy of my info
- The return process

Q9.3- **How appealing** were the following aspects of online shopping to you? Please select the most relevant option for each one of the following **positive** aspects:
(Alternatives: Highly concerning, Somewhat concerning, Not concerning)

- Shopping 24/7
- Comparing prices
- Avoid going to stores
- Avoid crowds
- Having a greater variety of choices
- Finding items in high demand

MOBILITY PREFERENCES

Q10.1- How many motorized vehicles (owned/leased) are available in your household?

- ☐ 0
- ☐ 1
- ☐ 2
- ☐ 3
- ☐ 4
- ☐ 5
- ☐ 6
- ☐ 7
- ☐ 8 or more

Q10.2- How often do you have access to a private vehicle when you need to drive?

- ☐ Always
- ☐ Sometimes
- ☐ Rarely
- ☐ Never

Q10.3- On average, **how many trips** did you make **each month** to the following places, **before COVID-19 (i.e., before March 2020)**, and **in the past month**? (2 columns: "Before COVID-19", "in the past month")

- ☐ Work
- ☐ School
- ☐ Recreation
- ☐ Grocery store

☐ Convenience store
☐ Retail store
☐ Daycare
☐ Friends
☐ Restaurants
☐ Medical facilities
☐ Entertainment
☐ Airports

Q10.4- On average, **how many hours** did you spend **each week** on the following activities **before COVID-19**, and **in the past month**? (2 columns: "Before COVID-19", "in the past month")

☐ Telework
☐ Online entertainment
☐ Online social
☐ Online school
☐ Online shopping
☐ Tele-medicine
☐ Other online services

Q10.5- How often did you travel in each of these modes **before** COVID-19 (not including walks or bike rides around your neighborhood for exercise, fresh air, dog walking, etc.)? (Alternatives: less than once a year or never, a few times a year, 1-3 times a month, 1-3 times a week, daily or almost daily)

☐ Drive alone
☐ Carpool
☐ Transit
☐ Taxi
☐ Ridesourcing (e.g., Uber, Lyft)
☐ Carsharing (e.g., ZipCar)
☐ Bike, e-scooter, moped
☐ Walk

Q10.6- In the **past seven days**, approximately how many trips did you make by each of the following modes (not including walks or bike rides around your neighborhood for exercise, fresh air, dog walking, etc.)?
(Column: "Number of trips in the past week")

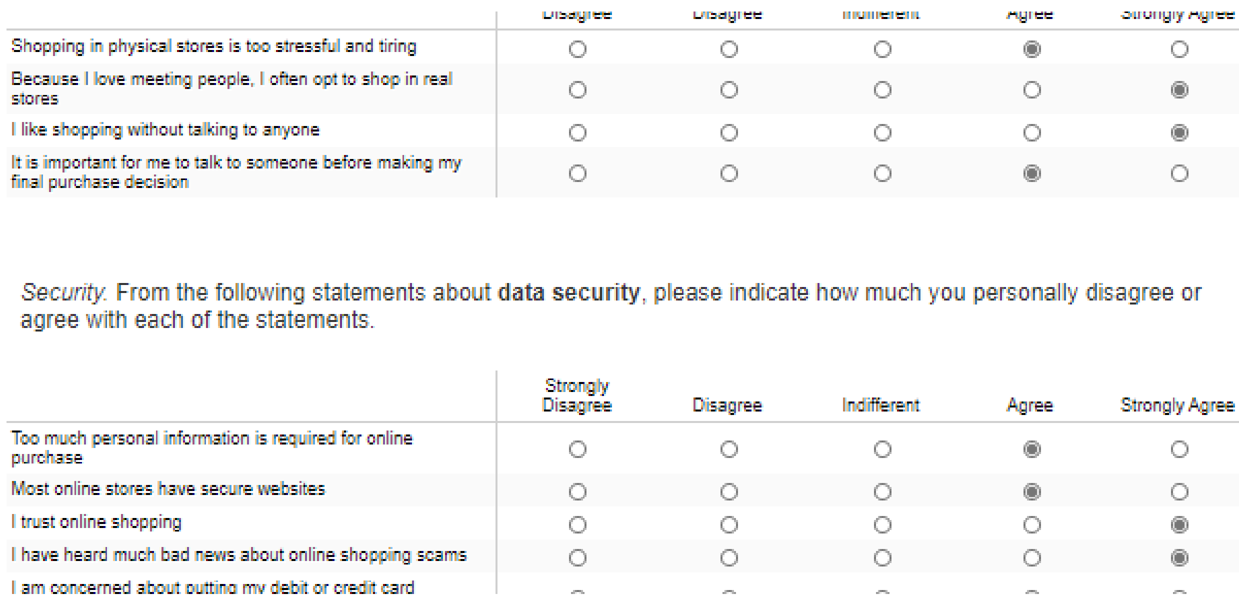
☐ Drive alone
☐ Carpool
☐ Transit
☐ Ridesourcing or carsharing
☐ Walk/bike/scooter/moped
☐ Something else, please specify

Q10.7- From the following statements about **general mobility preferences**, please indicate how much you personally disagree or agree with each of the statements.
(Alternatives: strongly disagree, disagree, indifferent, agree, strongly agree)
(Order of choice questions randomized)

- I prefer driving to stores with my own vehicle because it is more convenient.
- I like using public transportation for shopping to help in reducing traffic congestion.
- I regularly ride public transportation to stores to save money.
- I do not use public transportation for shopping trips because it is not safe.
- Please select "Agree" here
- Shared mobility options (e.g., Uber, Lyft) are convenient and efficient.
- I can multitask on my shopping trip when using shared mobility options.
- I cannot afford a private vehicle and prefer using alternative modes to stores.
- I like to share rides with strangers on shopping-related travels.

(Skip to the end of block if "Agree" is not selected)

Appendix B – Examples of Unreliable Responses

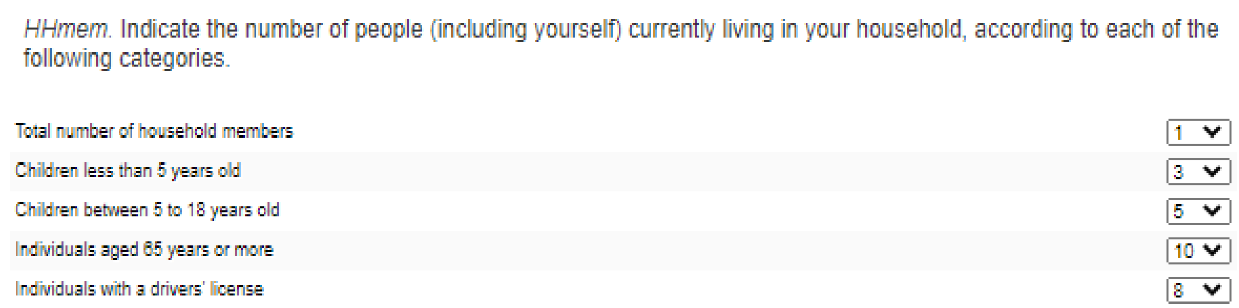


	Disagree	Disagree	Indifferent	Agree	Strongly Agree
Shopping in physical stores is too stressful and tiring	○	○	○	●	○
Because I love meeting people, I often opt to shop in real stores	○	○	○	○	●
I like shopping without talking to anyone	○	○	○	○	●
It is important for me to talk to someone before making my final purchase decision	○	○	○	●	○

Security. From the following statements about **data security**, please indicate how much you personally disagree or agree with each of the statements.

	Strongly Disagree	Disagree	Indifferent	Agree	Strongly Agree
Too much personal information is required for online purchase	○	○	○	●	○
Most online stores have secure websites	○	○	○	●	○
I trust online shopping	○	○	○	○	●
I have heard much bad news about online shopping scams	○	○	○	○	●
I am concerned about putting my debit or credit card					

Figure 42. An example of a response with double straight-lining



HHmem. Indicate the number of people (including yourself) currently living in your household, according to each of the following categories.

Total number of household members	1
Children less than 5 years old	3
Children between 5 to 18 years old	5
Individuals aged 65 years or more	10
Individuals with a drivers' license	8

Figure 43. An example of a response with numerical errors

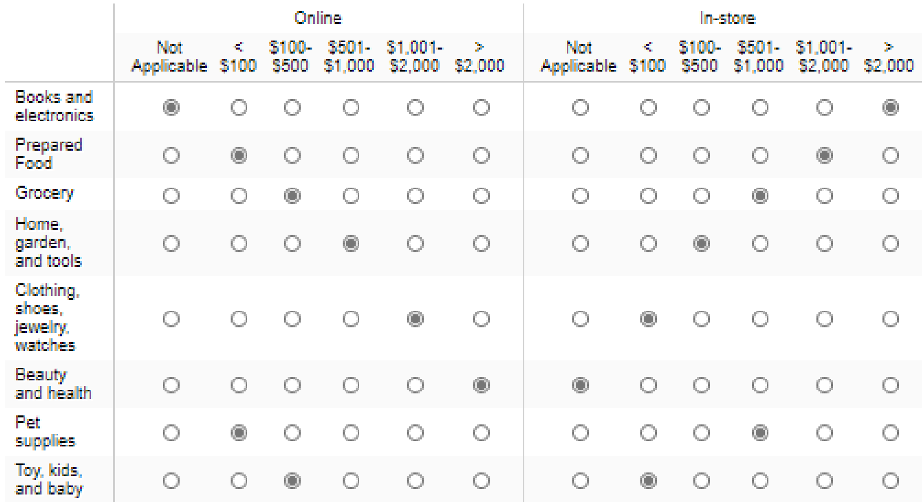


Figure 44. An example of a response with implausible patterns

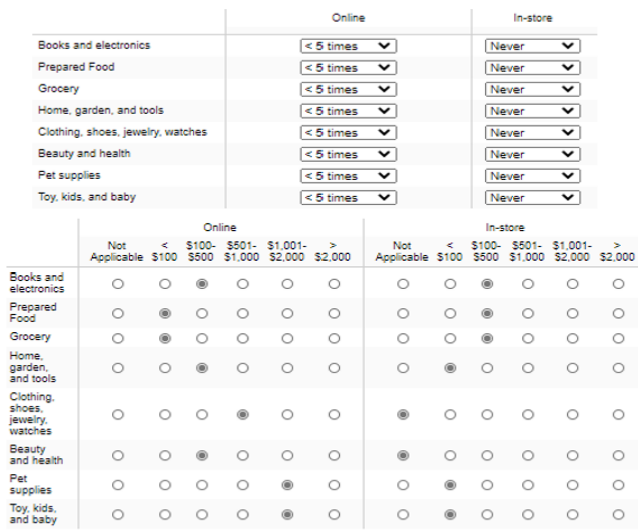


Figure 45. An example of incompatibility between purchasing frequency and cost

Appendix C – Summary of Past Findings

Table 54. Summary of Studies on Factors Affecting Online-Shopping Behavior

Author	Year	Sample size	Location	Methodology	Product type	Main Findings	Implications	Limitations
Swaminathan et. al	1999	428	Georgia, USA	Survey; factor analysis to measure constructs; multiple regression	–	**i)** reliability of vendor (or seller), convenience of placing orders and contacting vendors, price competitiveness and access to information positively affected the frequency of shopping; **ii)** perceived security of electronic exchanges did not influence frequency of online shopping; **iii)** consumers, who are motivated primarily by convenience, namely those with higher levels of education and income, and males as compared to females were more likely to make purchases online; **iv)** those who value social interactions shop less frequently online	social interaction may be a deterrent of Internet shopping	Possible selection bias through an email survey
Limayem et. al	2000	705	Unspecified	Questionnaire; partial least squares	–	**i)** intentions and behavioral control equally influenced online shopping behavior; **ii)** personal innovativeness and perceived consequences were found to significantly affect attitude and intentions to shop online, as attitude towards online shopping had the strongest effect on the intentions to shop online.	–	The variety of products bought, and the change in online shopping behavior over time was not considered
Mokhtarian	2003	Literature review paper				The impacts of e-shopping on travel are complex: some factors would reduce travel, while other factors would increase travel. Thus, it does not seem that e-shopping will have any reducing effect on travel overall, but rather negative impacts from increase in travel. Also, adoption of online and store shopping would generally continue, as consumers would blend both forms in their shopping activities.		–
George	2004	193	USA	Survey; partial least squares	–	**i)** Internet trustworthiness was a bigger concern for consumers than unauthorized use of personal data; **ii)** Internet trustworthiness beliefs significantly affected consumers' attitudes, and attitudes toward Internet purchasing, in turn, affected actual purchasing behavior.	Internet trustworthiness and self-efficacy positively affected actual purchasing behavior	Students were respondents; only two antecedents to attitudes were considered.

Author	Year	Sample size	Location	Methodology	Product type	Main Findings	Implications	Limitations
Farag et. al	2006	634 respondents in Minneapolis, USA and 360 in Utrecht, the Netherlands	Minneapolis and Utrecht	Chi-square tests, logistic and ordinary least-squares regressions	Daily vs. non-daily products	**i)** online buying was affected by socio-demographics and spatial characteristics of people, their Internet experience, and their attitudes towards in-store shopping; **ii)** males in both samples, and younger respondents in the U.S. sample bought online more often; **iii)** car ownership was linked to higher likelihood of e-shopping in Netherlands, but not in the U.S.; **iv)** interestingly, travel time to shops showed no significance in the likelihood to shop online in the U.S., but online buyers with short travel times actually shopped significantly more online than individuals with larger travel times in the Netherlands; **v)** gender, education and income affected online buying.	The tendency to engage in recreational shopping or to use the Internet to prepare for in-store shopping suggest that the relationship between online buying and in-store shopping is of complementarity. However, online buying [frequency] decreases the duration of average shopping activity	–
Hsiao	2009	300	Taiwan	stated preference experiment; binary logit	Bookstore shopping	The coefficients of travel cost, travel time, and delivery time were all negative and significant for those with e-shopping experience, but only the coefficient of travel time was not significant for those without e-shopping experience. It was estimated that the value of travel time is US$5.29/hr (the ratio of coefficient of TTIME to coefficient of TCOST) and value of delivery time is US$0.53/day hr (the ratio of coefficient of DTIME to coefficient of TCOST).	Online purchase may be more inviting to consumers in saving travel time and travel cost than taking shopping trips, even at the cost of waiting for a delivery of purchased products	SP may not be as accurate as RP. Also, the value of product delivery time is dependent on product type. Lack of consideration for trip chaining
Cao et. al	2012	539	Minneapolis, USA	SEM	Non-daily purchases such as books, clothes or electronics, as opposed to groceries	**i)** education and level of income positively affected the likelihood of making online purchases; **ii)** older people tended to make in-store shopping trips, and frequent internet browsers were more likely to make more online searches and actual purchases; **iii)** cost-conscious people, time-conscious people, and impulsive shoppers tended to make more product information searches online; **iv)** online searching frequency positively affected both online and in-store shopping frequencies; **v)** the total effect of online searching on in-store shopping exceeds that of online buying	A complementary effect is seen between e-shopping and in-store shopping. Moreover, the total effect of online searching [frequency] on in-store shopping [frequency] exceeds that of online buying [frequency]	–

Author	Year	Sample size	Location	Methodology	Product type	Main Findings	Implications	Limitations
Xinyu Cao	2012	540	urban Minneapolis	Binary logit models	Search goods: books, CDs, VCDs, videotapes, and album	**i)** the medium by which shoppers became aware of the product, searched product information, or tried the product were very likely to be the medium by which purchase was made; **ii)** internet availability at a store may reduce personal shopping trips	Hybrid shopping process online generates shopping trips to traditional stores, while in-store transactions may reduce travel demand if internet access is available at stores	–
Mokhtarian & Tang	2011	452	Northern California	Trivariate probit (TVP) model	Clothing or shoes	**i)** pre-purchase choice of store was positively associated with the perceived convenience of store channel, quantity of product types previously purchased in a store; and negatively affected by income; **ii)** pre-purchase choice of Internet was positively associated with favorable perception of Internet shopping, and pro-exercise attitude; **iii)** in determining purchase choice between store and internet, three experience indicators, three general attitudes, and three context variables were significant; **iv)** gifts were more likely to be purchased online; **v)** the greater the number of items to be purchased, the higher the likelihood the items would be purchased in a store; **vi)** age and income were the only two significant socio-demographic variables in predicting the likelihood of online purchase, however, when experience variables were excluded from the model, only age was significant.	There was dependence across the three choices (store pre-purchase, online pre-purchase, and purchase variables)	–
Chuang& Hsu	2013	242	Asia	survey; SEM with partial least squares model	–	**i)** all four dimensions of trust affected perceived risk, while three of the dimensions of trust affected attitude; **ii)** perceived risk was found to negatively affect attitude, which in turn affects intention to purchase; **iii)** privacy and security, and IT quality influenced members' trust in a website, while reputation influenced members' trust in a vendor; **iv)** however, vendor size does not positively affect members' trust.	The four dimensions of trust are significant in online shopping	Group-buying site was used. Also, lack of longitudinal data
Amaro & Duarte	2013	Literature review: 54 papers				**i)** middle-aged individuals (aged 25-55) possessing higher levels of education and income were more likely to purchase travel online; **ii)** intentions to purchase travel online or actual usage were unrelated to Internet experience, frequency of Internet use, computer usage, or travelers' prior experience with online shopping; **iii)** however, having a positive attitude towards the Internet seem to positively affect online travel shopping, and attitude toward online shopping is a determinant of intention to purchase travel online.	–	Literature review is predominantly based on articles from tourism and travel journals.

Author	Year	Sample size	Location	Methodology	Product type	Main Findings	Implications	Limitations
Chocarro et. al	2013	1600	Navarra, Spain	Questionnaire; binary logit model	Products were sorted by level of involvement (high or low), and into search or experience goods	**i)** likelihood of online purchase increases as distance-to-store or clarity of website layout increases, and as physical store tidiness decreases; **ii)** purchases being considered 15 mins before store-closing time are also more likely to be made online; **iii)** the restrictions imposed by traditional store opening hours are a potential driver of online purchase intentions, regardless of product category and urgency of purchase; **iv)** number of children, level of education, perceived suitability of each product category for online purchase and their frequency of online purchase all had a positive impact on the likelihood of online purchase; **v)** likelihood of online purchase increased with distance-to-store when considering purchasing a search good than when considering purchasing an experienced good; **vi)** purchasing high-involvement goods online is positively influenced by social interaction; **vii)** time-of-day-of-purchase has equal impact on both search goods and experience goods; **viii)** the higher the frequency of Internet usage the higher the probability of online purchase, especially if the desired item is a search good; **ix)** although level of education has a significant effect in the choice of purchase of search and experienced goods, gender effect is observed only in the purchase of search goods.	Results show that physical, social, and time-related dimensions are relevant to consumer preferences on online versus physical purchase channels.	Only two product classifications were considered
Rotem-Mindali & Weltevreden	2013	Literature review paper				**i)** many empirical studies support the substitution effect (at least prior to 2013), and differences in the extent of the substitution effect can be attributed to variations in methodology, and to time and geographical context of the data collection; **ii)** quantitative outcomes are affected by nature of the sample, definitions of e-shopping (i.e., searching activities, purchasing, and delivery) and e-shopper (level of frequency of activity-specific e-shopping), definition of transportation impact, hypotheses tested, and the class of product considered.	Reaching a single conclusion regarding the impact of e-commerce on travel is complicated and depends on a range of factors	–
Crocco et. al	2013	562 online and 654 in-store consumers	urban Cosenza and Rende, Italy	descriptive statistical analysis and binary logistic regression models	Different kinds of products	**i)** propensity to purchase online was positively affected by being male and young, being a student and having a high family income, and experience with new technologies; **ii)** online consumers were likely to purchase computer hardware and notebooks, while in-store consumers were more likely to purchase articles of clothing; **iii)** in-store consumers tended to have recreational shopping; **iv)** convenience positively affected usage of online shopping, while perceived risk concerning credit card negatively affected the usage of online shopping	–	–

Author	Year	Sample size	Location	Methodology	Product type	Main Findings	Implications	Limitations
Scarpi et. al	2014	120	–	Questionnaire; SEM	Single product category - clothing	**i)** in the offline context, there was no significant differences in price consciousness for customers who shop for fun and those who shop for needs; **ii)** however, in the online context, price consciousness was significantly affected by the way consumers experienced their shopping expedition; **iii)** customers shopping for fun are more likely to be loyal to a brick-and-mortar store than to an online store; **iv)** shopping environment determines WOM communication, as customers shopping for fun are more likely to spread WOM communication, both in the online and the offline context.	point (iii) indicates that recreational shopping for clothing is higher with physical store than online store	Study is based on data from a single product category (clothing), and restricted to individuals who actually made a purchase
Zhou & Wang	2014	85,663	All U.S.	SEM	No distinction or specificity	**i)** people tend to make more shopping trips during weekends rather than weekdays; **ii)** the higher the frequency of in-store shopping, the lower the likelihood of online shopping; **iii)** there was a positive relationship between online searching frequency and in-store shopping frequency; **iv)** urban residents made more online shopping than non-urban residents; **v)** those who spent more time on daily travel had statistically insignificant less (frequent) shopping trips	Point **(ii)** seem to indicate in-store shopping experience suppress the desire to shop online, and point **(iii)** indicates that online shopping seems to generate more shopping trips.	–
Lee et. al	2015	2043	Davis, Californi a	survey; binary logistic regression. Mann–Whitney U-tests were used to examine attitudinal differences between online and in-store shoppers.	General	**i)** books and electronic media were the most frequently shopped-for items online; **ii)** in-store trips outperformed online shopping 85.9% to 75.2% in resulting to actual purchases; **iii)** age negatively affected online shopping, while income and level of education positively affected online shopping; **iv)** full-time workers were more likely to shop online than other employment groups; **v)** though females were more likely to shop for clothing and home supplies and males more frequently purchased electronics and sporting goods, the rates of online shopping between males and females were nearly identical; **vi)** younger respondents, males, and those with online shopping experience in the previous year had relatively favorable perceptions regarding online shopping; **vii)** surprisingly, online shoppers reported a greater preference for active travel modes than in-store shoppers, and distance to the nearest shopping center did not affect likelihood of online shopping.	–	Other variables, such as residential density or retail density, may have better uncovered built environment effects

Author	Year	Sample size	Location	Methodology	Product type	Main Findings	Implications	Limitations
Irawan & Wirza	2015	281	urban Indonesia	SEM	No distinction or specificity	**i)** e-shopping had a negative effect on the frequency of shopping trips; **ii)** e-searching increased the likelihood of both online shopping and in-store shopping; **iii)** number of productive family members, number of family members who have obtained a drivers' license, and number of vehicle owned by household positively influenced online shopping, but negatively influenced in-store shopping; **iv)** Age, educational attainment, and income had a positive effect on frequency of shopping trip, but a negative effect on e-shopping; **v)** internet experience and fast internet connection had the most significant effect (positive) on online searching and online buying, and even shopping trip; **vi)** shopping attitude also influenced e-shopping and in-store shopping	Online shopping is suggested to potentially exhibit a substitution effect on shopping trip. However, online searching may have a complementary effect on in-store shopping.	–
Suel et. al	2015	452	Greater London	Two-week travel diary; bivariate correlations and two-stage multivariate analysis	Grocery shopping	**i)** choice of online shopping was negatively affected by age and household sizes, positively affected by income, but not significantly affected by gender, employment status and car ownership; **ii)** shopping basket characteristics had significant effect on channel choice (online or in-store).	There was net substitution effect between [the frequency of] purchasing groceries online and in-store.	–
Zhen et. al	2016	963	Nanjing, China	Joint ordered probit model	clothing vs. books vs. daily goods vs. electronics	**i)** online purchasing frequency positively affected in-store purchasing frequency for all four types of products; **ii)** time consciousness was negatively associated with online purchasing frequency for clothing, but not for electronics; **iii)** cost consciousness was negatively associated with store purchasing frequencies for both clothing and electronics; **iv)** shopping enjoyment was positively associated with store purchasing frequency for daily goods but negatively associated with store purchasing frequency for electronics; **v)** gender, possession of a driver's license, income, education, number of children under 12 years old, and number of children under 6 years old all had significant effect on in-store purchases, but varied across product type.	There exists a complementary effect between online shopping and in-store shopping. However, the extent of the complementarity varies by product type, as less frequently purchased products showed a larger effect	–
Schmid et. al	2016	339	urban Zurich, Switzerland	Integrated choice and latent variable (ICLV) modeling approach	experience goods (groceries) vs. search goods (electronic appliances)	**i)** there are purpose-specific shopping channel preferences: grocery shopping was mainly conducted in stores; **ii)** Low cost sensitivity is associated with negative attitudes towards online shopping; **iii)** in-store shopping trips are mostly conducted on Saturdays, while online transactions are mostly conducted on weekdays and they show a decreasing pattern from Monday to Sunday	There seemed to be a potential substitution effect on the number of trips mediated via the attitudes. However, the statistically significance of the effect was not validated	–

Author	Year	Sample size	Location	Methodology	Product type	Main Findings	Implications	Limitations
Hagberg & Holmberg	2017	1,694	Sweden	Descriptive statistics, bivariate correlations, and stepwise multiple linear regression	Grocery shopping	**i)** cars were the most dominant modal choice in terms of distance and frequency for grocery shopping in Sweden; **ii)** age, income, and place of residence (urban area) were the most significant socio-demographic characteristics positively associated with home delivery; **iii)** car usage increased the frequency of in-store grocery shopping, and car loading capacity was not linked with reduction in in-store grocery shopping frequency; **iv)** frequent car users travel a longer distance to the grocery store	Home delivery complements in-store grocery shopping	–
Shi et. al	2019	710	Chengdu, China	Regression models	clothes and shoes, electronics, food and drink, and cosmetics	**i)** frequent online purchases were positively affected by gender (women as compared to men), age (surprisingly), and education, but negatively affected by income and internet experience; **ii)** car ownership tended to reduce shopping trips; **iii)** 44% of the respondents claimed that they make fewer shopping trips due to e-shopping, as opposed to 14.9% of respondents who said they increased their shopping trip frequency; **iv)** the substitution effect of e-shopping on shopping trips was found to be influenced by private car ownership. However, people who purchased online frequently were less likely to reduce shopping trip frequency.	Point (iii) indicate e-shopping may have a substitution effect on the frequency of shopping trips. The extent of this effect seems moderated by car ownership and high frequency of online purchases	–
Ramirez	2019	16,145	All U.S.	ANOVA tests and negative binomial regression models	No distinction or specificity	**i)** millennials, females, higher income households, higher educated people, public transportation commuters, individuals living in urban areas, and households with multiple drivers were more likely than others to make frequent online purchases; **ii)** there was correlation between online shopping and the number of home-based shopping trips.	A complementary relationship is suggested between online shopping and home-based shopping trips	–
Kedia	2019	355	New Zealand	Non-parametric tests and ordinal logistic (OL) regression	No distinction or specificity	**i)** frequency of online shopping was negatively affected by age, and positively affected by online shopping experience, living alone, number of cars available in household, frequency of missing attended deliveries; **ii)** there was no statistical significance in the effect of consumers' travel for in-store shopping or item collection at delivery points on online shopping frequency.	A neutral effect of online shopping [frequency] on consumers' in-store shopping travel [frequency] was suggested.	–
Hoogendoorn-Lanser et. al	2019	833	the Netherlands	Cluster analysis and multivariate analysis	Grocery vs non-grocery	There were minor differences in the effect of each group's pre-purchase activities on their shopping-related travel behavior. Also, shopping trip distances for non-grocery shopping were longer than those for grocery shopping	Online shopping frequency positively affected shopping trip distances for non-grocery shopping, but not for grocery shopping.	This study did not consider in-store shopping frequency

Author	Year	Sample size	Location	Methodology	Product type	Main Findings	Implications	Limitations
Dias et. al	2020	705	Seattle, U.S.	Multivariate ordered probit model	Grocery vs. non-grocery vs. meals	**i)** household income and density area positively affected in-person eat-out activities, and online shopping for goods, groceries, and meals; **ii)** frequency of both online and in-person shopping episodes for goods, groceries, and meals increase with household size; **iii)** higher car ownership was associated with a greater propensity of all in-person activity categories; **iv)** in-store shopping itself leads to online shopping	Evidence of complementary effect for non-grocery shopping, and substitution effect for grocery items	–
Unnikrishnan & Figliozzi	2020	1018	metro area of Oregon-Washington	Online survey; backward selection procedure within ordinal logit regression framework.	Different kinds of products	**i)** the likelihood of spending more money on home deliveries and making online deliveries increased with household income during the COVID-19 lockdown; **ii)** older customers were less likely to use online delivery services; **iii)** the amount of time spent per week spent on desktop, laptop, or smartphone positively affected the likelihood to spend more money on household deliveries; **iv)** respondents who wanted groceries, electronics, and recreational items were more likely to spend more during the lockdown, and those who wanted groceries and meals expected same-day or next-day services; **v)** concerns about product costs at brick and mortar stores negatively affected levels of house deliveries, while concerns about health issues positively affected levels of house deliveries.	–	–
Berg & Henriksson	2020	22	urban areas in Sweden	Qualitative interviews and travel diaries	–	The reasons informants gave for buying groceries online were: **i)** difficulty shopping with young children; **ii)** boredom, meaninglessness, and the time-consuming nature of shopping; **iii)** difficulty in carrying heavy shopping bags; **iv)** how shopping online enables healthier and more organized eating habits; **v)** lack of impulsive buying leading to cheaper choices as opposed to physical shopping and; **vi)** reduction of physical activity during the day. Also, shopping for groceries in physical stores was perceived as meaningful or useful, and will continue until significant life changes occur, such as the children grow older and move. And when the choice of physical shopping was substituted by e-shopping, it might be so that time can be spent on activities that are higher valued, such as exercise, spending time with family or reading.	Since the informants had the necessary financial resources to shop at online grocery stores, it could be implied that e-commerce does not necessarily reduce the total number of trips made, regardless of the means of travel, but rather enables a car-free lifestyle in the city, and cars can be used for many other errands than food purchases	–

Table 55. Summary of Studies on the Travel Impacts of Online Shopping

Author	Year	Sample size	Location	Methodology	Product Type	Main Findings	Implications	Effect on Travel
Mokhtarian	2003	Literature review paper				The impacts of e-shopping on travel are complex: some factors would reduce travel, while other factors would increase travel. Thus, it does not seem that e-shopping will have any reducing effect on travel overall, but rather negative impacts from increase in travel. Also, adoption of online and store shopping would generally continue, as consumers would blend both forms in their shopping activities.	_	Complex (LR)
Farag et. al	2006	634 respondents in Minneapolis, USA and 360 in Utrecht, the Netherlands	Minneapolis and Utrecht	Chi-square tests, logistic and ordinary least-squares regressions	Daily vs. non-daily products	**i)** online buying was affected by socio-demographics and spatial characteristics of people, their Internet experience, and their attitudes towards in-store shopping; **ii)** males in both samples, and younger respondents in the U.S. sample bought online more often; **iii)** car ownership was linked to higher likelihood of e-shopping in Netherlands, but not in the U.S.; **iv)** interestingly, travel time to shops showed no significance in the likelihood to shop online in the U.S., but online buyers with short travel times actually shopped significantly more online than individuals with larger travel times in the Netherlands; **v)** gender, education and income affected online buying.	The tendency to engage in recreational shopping or to use the Internet to prepare for in-store shopping suggests that the relationship between online buying and in-store shopping is of complementarity. However, online buying [frequency] decreases the duration of average shopping activity	In-store shopping freq: online buying freq - **C.** Average shopping activity duration: online buying freq - **S**
Hsiao	2009	300	Taiwan	binary logit, and SP survey	Bookstore shopping	The coefficients of travel cost, travel time, and delivery time were all negative and significant for those with e-shopping experience, but only the coefficient of travel time was not significant for those without e-shopping experience. It was estimated that the value of travel time is US$5.29/hr (the ratio of coefficient of TTIME to coefficient of TCOST) and value of delivery time is US$0.53/day hr (the ratio of coefficient of DTIME to coefficient of TCOST).	Online purchase may be more inviting to consumers in saving travel time and travel cost than taking shopping trips, even at the cost of waiting for a delivery of purchased products	_
Cao	2009	Literature review paper				The impact of e-shopping on travel behavior was documented in four ways: substitution, complementarity, modification, and neutrality. Also, the methodologies that have been used to assess the effects of e-shopping on individuals' travel were highlighted, alongside their advantages, disadvantages, and the outcomes those methodologies yielded	_	Complex (LR)

Author	Year	Sample size	Location	Methodology	Product Type	Main Findings	Implications	Effect on Travel
Mokhtarian & Tang	2011	452	Northern Californi a	Trivariate probit (TVP) model	Clothing or shoes	**i)** pre-purchase choice of store was positively associated with the perceived convenience of store channel, quantity of product types previously purchased in a store; and negatively affected by income; **ii)** pre-purchase choice of Internet was positively associated with favorable perception of Internet shopping, and pro-exercise attitude; **iii)** in determining purchase choice between store and internet, three experience indicators, three general attitudes, and three context variables were significant; **iv)** gifts were more likely to be purchased online; **v)** the greater the number of items to be purchased, the higher the likelihood the items would be purchased in a store; **vi)** age and income were the only two significant socio-demographic variables in predicting the likelihood of online purchase, however, when experience variables were excluded from the model, only age was significant.	There was dependence across the three choices (store pre-purchase, online pre-purchase, and purchase variables)	–
Cao et. al	2012	539	Minneap olis, USA	Analysis was done using the structural equation model	Non-daily purchases such as books, clothes or electronics, as opposed to groceries	**i)** education and level of income positively affected the likelihood of making online purchases; **ii)** older people tended to make in-store shopping trips, and frequent internet browsers were more likely to make more online searches and actual purchases; **iii)** cost-conscious people, time-conscious people, and impulsive shoppers tended to make more product information searches online; **iv)** online searching frequency positively affected both online and in-store shopping frequencies; **v)** the total effect of online searching on in-store shopping exceeds that of online buying	A complementary effect is seen between e-shopping and in-store shopping. Moreover, the total effect of online searching [frequency] on in-store shopping [frequency] exceeds that of online buying [frequency]	In-store shopping freq: online searching freq- **C.** In-store shopping freq: online buying freq **- C.**
Cao	2012	540	urban Minneap olis	Binary logit models	Search goods: books, CDs, VCDs, videotapes, and album	**i)** the medium by which shoppers became aware of the product, searched product information, or tried the product were very likely to be the medium by which purchase was made; **ii)** internet availability at a store may reduce personal shopping trips	Hybrid shopping process online generates shopping trips to traditional stores, while in-store transactions may reduce travel demand if internet access is available at stores	Shopping trip freq: hybrid shopping process (freq or duration? Unclear) - **C**.

Author	Year	Sample size	Location	Methodology	Product Type	Main Findings	Implications	Effect on Travel
Rotem-Mindali & Weltevreden	2013	Literature review paper				**i)** many empirical studies support the substitution effect (at least prior to 2013), and differences in the extent of the substitution effect can be attributed to variations in methodology, and to time and geographical context of the data collection; **ii)** quantitative outcomes are affected by nature of the sample, definitions of e-shopping (i.e., searching activities, purchasing, and delivery) and e-shopper (level of frequency of activity-specific e-shopping), definition of transportation impact, hypotheses tested, and the class of product considered.	Reaching a single conclusion regarding the impact of e-commerce on travel is complicated and depends on a range of factors	Complex (LR)
Crocco et. al	2013	562 online and 654 in-store consumers	urban Cosenza and Rende, Italy	descriptive statistical analysis and binary logistic regression models	Different kinds of products	**i)** propensity to purchase online was positively affected by being male and young, being a student and having a high family income, and experience with new technologies; **ii)** online consumers were likely to purchase computer hardware and notebooks, while in-store consumers were more likely to purchase articles of clothing; **iii)** in-store consumers tended to have recreational shopping; **iv)** convenience positively affected usage of online shopping, while perceived risk concerning credit card negatively affected the usage of online shopping	_	_
Scarpi et. al	2014	120	_	Survey & SEM	Single product category - clothing	**i)** in the offline context, there was no significant differences in price consciousness for customers who shop for fun and those who shop for needs; **ii)** however, in the online context, price consciousness was significantly affected by the way consumers experienced their shopping expedition; **iii)** customers shopping for fun are more likely to be loyal to a brick-and-mortar store than to an online store; **iv)** shopping environment determines WOM communication, as customers shopping for fun are more likely to spread WOM communication, both in the online and the offline context.	point (iii) indicates that recreational shopping for clothing is higher with physical store than online store	_
Zhou & Wang	2014	85,663	All U.S.	SEM	No distinction or specificity	**i)** people tend to make more shopping trips during weekends rather than weekdays; **ii)** the higher the frequency of in-store shopping, the lower the likelihood of online shopping; **iii)** there was a positive relationship between online shopping frequency and in-store shopping frequency; **iv)** urban residents made more online shopping than non-urban residents; **v)** those who spent more time on daily travel had statistically insignificant less (frequent) shopping trips	Point **(ii)** seem to indicate in-store shopping experience suppress the desire to shop online, and point **(iii)** indicates that online shopping seems to generate more shopping trips.	neither pure **S** nor pure **C** effect between shopping trip freq and online shopping freq - **Complex**

Author	Year	Sample size	Location	Methodology	Product Type	Main Findings	Implications	Effect on Travel
Lee et. al	2015	2043	Davis, California	online survey; binary logistic regression for analysis. Mann–Whitney U-tests were used to examine differences in attitudes between online shoppers and in-store shoppers.	Food, automotive parts, and Internet-specific goods, such as digital music or airplane e-tickets were omitted products	**i)** books and electronic media were the most frequently shopped-for items online; **ii)** in-store trips outperformed online shopping 85.9% to 75.2% in resulting to actual purchases; **iii)** age negatively affected online shopping, while income and level of education positively affected online shopping; **iv)** full-time workers were more likely to shop online than other employment groups; **v)** though females were more likely to shop for clothing and home supplies and males more frequently purchased electronics and sporting goods, the rates of online shopping between males and females were nearly identical; **vi)** younger respondents, males, and those with online shopping experience in the previous year had relatively favorable perceptions regarding online shopping; **vii)** surprisingly, online shoppers reported a greater preference for active travel modes than in-store shoppers, and distance to the nearest shopping center did not affect likelihood of online shopping.	–	–
Irawan & Wirza	2015	281	urban Indonesia	SEM	No distinction or specificity	**i)** e-shopping had a negative effect on the frequency of shopping trips; **ii)** e-searching increased the likelihood of both online shopping and in-store shopping; **iii)** number of productive family members, number of family members who have obtained a drivers' license, and number of vehicle owned by household positively influenced online shopping, but negatively influenced in-store shopping; **iv)** Age, educational attainment, and income had a positive effect on frequency of shopping trip, but a negative effect on e-shopping; **v)** internet experience and fast internet connection had the most significant effect (positive) on online searching and online buying, and even shopping trip; **vi)** shopping attitude also influenced e-shopping and in-store shopping	Online shopping is suggested to potentially exhibit a substitution effect on shopping trips. However, online searching may have a complementary effect on in-store shopping.	Shopping trip freq: online buying freq- **S**; online searching freq- **C**

Author	Year	Sample size	Location	Methodology	Product Type	Main Findings	Implications	Effect on Travel
Hiselius et. al	2015	4476	Sweden	Unspecified	groceries, other purchases, and pick-up of goods purchased online	**i)** there was no significant difference in the number of trips made to physical stores and the number of car trips made in general between frequent online shoppers and infrequent online shoppers; **ii)** infrequent shoppers, as compared with regular and frequent shoppers, had significantly less car trips for purposes other than shopping; **iii)** frequent online shoppers were more likely than other shoppers to travel shorter distances per day by car, but distances were similar to other shoppers when other travel modes aside cars were used; **iv)** frequent online shoppers make more trips than the other groups to pick up goods purchased online.	Time saved from online shopping is spent on more shopping trips and other trips in general. Thus, online shopping exhibits a complementarity effect on physical shopping, and facilitates a less car-dependent lifestyle	Physical shopping freq: online shopping freq- **C**
Suel et. al	2015	452	Greater London	Two-week travel diary; bivariate correlations and two-stage multivariate analysis	Grocery shopping	**i)** choice of online shopping was negatively affected by age and household sizes, positively affected by income, but not significantly affected by gender, employment status and car ownership; **ii)** shopping basket characteristics had significant effect on channel choice (online or in-store).	There was net substitution effect between [the frequency of] purchasing groceries online and in-store.	In-store grocery purchasing freq: online grocery purchasing freq- **S**
Comi & Nuzzolo	2016	800	Rome, Italy	Proposed model	clothing, electronics, foodstuffs, hygiene and household products, and other goods.	It was found that changes in demographic and socio-economic characteristics could cause significant effects, specifically increasing the use of e-shopping. Also, increase in city inhabitants over 45 years old could lead to a reduction of shopping trips, and internet shopping increase could cause more deliveries and freight vehicles in residential areas.	–	–
Zhen et. al	2016	963	Nanjing, China	Joint ordered probit model	clothing vs. books vs. daily goods vs. electronics	**i)** online purchasing frequency positively affected in-store purchasing frequency for all four types of products; **ii)** time consciousness was negatively associated with online purchasing frequency for clothing, but not for electronics; **iii)** cost consciousness was negatively associated with store purchasing frequencies for both clothing and electronics; **iv)** shopping enjoyment was positively associated with store purchasing frequency for daily goods but negatively associated with store purchasing frequency for electronics; **v)** gender, possession of a driver's license, income, education, number of children under 12 years old, and number of children under 6 years old all had significant effect on in-store purchases, but varied across product type.	There exists a complementary effect between online shopping and in-store shopping. However, the extent of the complementarity varies by product type, as less frequently purchased products showed a larger effect	In-store purchasing freq: online purchasing freq- **C**

Author	Year	Sample size	Location	Methodology	Product Type	Main Findings	Implications	Effect on Travel
Schmid et. al	2016	339	urban Zurich, Switzerland	one-week travel diary, (SP); Integrated choice and latent variable (ICLV)	experience goods (groceries) vs. search goods (electronic appliances)	**i)** there are purpose-specific shopping channel preferences: grocery shopping was mainly conducted in stores; **ii)** Low cost sensitivity is associated with negative attitudes towards online shopping; **iii)** in-store shopping trips are mostly conducted on Saturdays, while online transactions are mostly conducted on weekdays and they show a decreasing pattern from Monday to Sunday	There seemed to be a potential substitution effect on the number of trips mediated via the attitudes. However, the statistically significance of the effect was not validated	Number of trips: online shopping freq - **S** (probable, but not validated)
Ding & Lu	2017	537	suburban Shangdi, China	Travel diary; structural equation model	No distinction or specificity	**i)** Frequency of online buying positively affected the frequency of both in-store shopping and online searching; **ii)** Online buyers tended to shop in stores on weekends rather than weekdays; **iii)** In-store shopping frequency positively affected the frequency of online searching and shopping trip chaining; **iv)** Online buying negatively affected the frequency of out-of-home leisure activities; and **v)** In-store shopping frequency was negatively affected by household size, positively affected by shopping accessibility and car users; **vi)** surprisingly, income, employment and educational background had no significant impact on online shopping frequency; **vii)** Online buying was negatively affected by age; **viii)** online searching and buying were positively affected by Internet use.	Results generally show a complementary effect, but (iv) may indicate substitution	In-store shopping freq: online shopping freq- **C.**
Hagberg & Holmberg	2017	1,694	Sweden	Descriptive statistics, bivariate correlations, and stepwise multiple linear regression	Grocery shopping	**i)** cars were the most dominant modal choice in terms of distance and frequency for grocery shopping in Sweden; **ii)** age, income, and place of residence (urban area) were the most significant socio-demographic characteristics positively associated with home delivery; **iii)** car usage increased the frequency of in-store grocery shopping, and car loading capacity was not linked with reduction in in-store grocery shopping frequency; **iv)** frequent car users travel a longer distance to the grocery store	Home delivery complements in-store grocery shopping	Grocery in-store shopping freq: home delivery freq- **C**
Zhai et. al	2017	952	Santa Clara and Davis, California	Questionnaire; binary logit model	Search goods (books) vs. experienced goods (clothing)	**i)** there were differences between the pre-purchasing processes of search goods and experienced goods; **ii)** consumers were more likely to make in-store visits for both information search and product trial if the product was clothing (experienced good) rather than books (search good); **iii)** store buyers were more likely to shop for books than clothing through multiple channels; **iv)** "pre-purchase behaviors through the internet were more likely to facilitate cross-channel shopping than those at a store"	The effect of e-shopping on travel behavior was inconclusive	–

Author	Year	Sample size	Location	Methodology	Product Type	Main Findings	Implications	Effect on Travel
Suel et. al	2017	168	Barnet, Enfield, and random parts of London	longitudinal study; hazard based model	Grocery shopping	**i)** online grocery shopping reduced shopping trip rates, but had no significant effect on the overall shopping activity frequency; **ii)** online grocery shopping episodes increased inter-shopping-trip durations, but had no significant effect on inter-shopping-event durations	A substitution effect between online shopping frequency and shopping trip rates was suggested	Grocery shopping trip rates: online grocery shopping freq- **S**
Zhen et. al	2018	963	Nanjing, China	Questionnaire; trivariate probit model	Search goods (books) vs. experienced goods (clothing)	**i)** those residing and working in suburban areas were more likely than others to conduct pre-purchase and purchase activities for books and clothing at traditional stores; **ii)** travel time to store positively affected online shopping for books, but not for clothing; **iii)** online pre-purchasing activities are negatively associated with walking or driving to stores than other modes, such as transit; **iv)** for highly educated people, online shopping substituted store shopping for books, but not for clothing; **v)** other demographic variables such as age, income, gender, household size, "number of children under 6", and credit cards or other online payment systems all significantly affected pre-purchasing activities	Substitution of store shopping by e-shopping occurs at the pre-purchase and purchase stages of the shopping process when shop accessibility is low	In-store shopping freq: e-shopping freq when shopping accesibility (in terms of travel time) is low - **S**
Schmid & Axhausen	2019	301	urban Zurich, Switzerland	One-week travel diary; hybrid choice modeling approach	search goods (standard electronic appliances) vs. experience goods (groceries)	**i)** positive attitudes towards online shopping increase the choice probability of online shopping, especially for groceries (G); **ii)** the strongest socio-economic factor influencing a high choice probability of online shopping is education; **iii)** grocery shopping was mainly done in stores, while electronic appliances were mainly purchased online; **iv)** recreational shopping did not influence the choice between in-store and online shopping; **v)** avoiding a shopping trip when distances are long produces more benefits than waiting for the delivery of the products, especially when purchasing electronic appliances; **vi)** for grocery shopping, shopping costs were perceived as less unpleasant relative to delivery costs.	price advantages are a key factor for doing online shopping in Switzerland	–

Author	Year	Sample size	Location	Methodology	Product Type	Main Findings	Implications	Effect on Travel
Shi et. al	2019	710	Chengdu, China	Regression models	clothes and shoes, electronics, food and drink, and cosmetics	**i)** frequent online purchases were positively affected by gender (women as compared to men), age (surprisingly), and education, but negatively affected by income and internet experience; **ii)** car ownership tended to reduce shopping trips; **iii)** 44% of the respondents claimed that they make fewer shopping trips due to e-shopping, as opposed to 14.9% of respondents who said they increased their shopping trip frequency; **iv)** the substitution effect of e-shopping on shopping trips was found to be influenced by private car ownership. However, people who purchased online frequently were less likely to reduce shopping trip frequency.	Point (iii) indicate e-shopping may have a substitution effect on the frequency of shopping trips. The extent of this effect seems moderated by car ownership and high frequency of online purchases	Shopping trip freq: online shopping freq- **S**
Ramirez	2019	16,145	All U.S.	ANOVA tests and negative binomial regression models	No distinction or specificity	**i)** millennials, females, higher income households, higher educated people, public transportation commuters, individuals living in urban areas, and households with multiple drivers were more likely than others to make frequent online purchases; **ii)** there was correlation between online shopping and the number of home-based shopping trips.	A complementary relationship is suggested between online shopping and home-based shopping trips	Home-based shopping trip freq: online shopping freq - **C**.
Kedia	2019	355	New Zealand	Non-parametric tests and ordinal logistic (OL) regression	No distinction or specificity	**i)** frequency of online shopping was negatively affected by age, and positively affected by online shopping experience, living alone, number of cars available in household, frequency of missing attended deliveries; **ii)** there was no statistical significance in the effect of consumers' travel for in-store shopping or item collection at delivery points on online shopping frequency.	A neutral effect of online shopping [frequency] on consumers' in-store shopping travel [frequency] was suggested.	Shopping trip freq: online shopping freq- **N**
Hoogendoorn-Lanser et. al	2019	833	the Netherlands	Cluster analysis and multivariate analysis	Grocery vs non-grocery	There were minor differences in the effect of each group's pre-purchase activities on their shopping-related travel behavior. Also, shopping trip distances for non-grocery shopping were longer than those for grocery shopping	Online shopping frequency positively affected shopping trip distances for non-grocery shopping, but not for grocery shopping.	Shopping trip distance for non-grocery: online shopping freq- **C**
Zhai	2019	963	urban China	binary logit model	search goods (books) vs. experience goods (clothing)	**i)** the channel used in the pre-purchase stage was mostly the same channel used for the actual purchase, especially when shopping for experience goods (clothing); **ii)** the propensity for cross-channel shopping increases with online pre-purchase channel than in-store pre-purchase channels	Shopping activity fragmentation can induce both substitution and complementarity effects during the shopping process	Complex

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Lachapelle & Jean-Germain	2019	8,239	Canada	A day travel diary; descriptive statistics and multinomial logistic model	No distinction or specificity	**i)** heavy Internet use (60+ mins) negatively affected overall travel time; **iii)** heavy Internet users tend to be young, male, urban dwellers, and university graduates; **iv)** time traveling for shopping was positively associated with age group (65+ years spent more time), gender (women), education attainment, Internet use; **v)** trip frequency was positively associated with age group, education, income, gender (women), and area of residence (urban dwellers); **vi)** online shopping positively affected shopping-related travel	There is complementarity between online shopping duration and shopping trip in terms of frequency and travel time	Shopping trip freq & travel time: online shopping duration- **C**
Berg & Henriksson	2020	22	urban areas in Sweden	Qualitative interviews and travel diaries	–	The reasons informants gave for buying groceries online were: **i)** difficulty shopping with young children; **ii)** boredom, meaninglessness, and the time-consuming nature of shopping; **iii)** difficulty in carrying heavy shopping bags; **iv)** how shopping online enables healthier and more organized eating habits; **v)** lack of impulsive buying leading to cheaper choices as opposed to physical shopping and; **vi)** reduction of physical activity during the day. Also, shopping for groceries in physical stores was perceived as meaningful or useful, and will continue until significant life changes occur, such as the children growing older and moving. And when the choice of physical shopping was substituted by e-shopping, it might be so that time can be spent on activities that are higher valued, such as exercise, spending time with family or reading.	Since the informants had the necessary financial resources to shop at online grocery stores, it could be implied that e-commerce does not necessarily reduce the total number of trips made, regardless of the means of travel, but rather enables a car-free lifestyle in the city, and cars can be used for many other errands than food purchases	–
Etminani-Ghasrodashti & Hamidi	2020	526	urban Shiraz, Iran	Structural equation models	No distinction or specificity	**i)** Internet usage time positively affected in-store shopping frequency; **ii)** pre-purchase online searching leads to both more online and more in-store shopping; **iii)** travel distance between respondents' homes and their preferred shopping outlets was positively associated with in-store and online shopping frequency; **iv)** the convenience of a travel mode choice influenced the respondents' decision-making about online and in-store shopping; **v)** lifestyle was associated with shopping behavior; **vi)** in-store shopping frequency was affected by living in neighborhoods with high levels of land use diversity, higher intersection density, and a well-connected street network; **vii)** socio-economic variables like age, education, and income were associated with shopping behavior, but there were no associations between gender, number of children in a family and online shopping behavior	Online shopping frequency has a complementary effect on in-store shopping. Moreover, in-store shopping likewise has a positive and stronger association with online shopping frequency	In-store shopping freq: online shopping freq- **C.** Online shopping freq: in-store shopping freq - **C.**

Author	Year	Sample size	Location	Methodology	Product Type	Main Findings	Implications	Effect on Travel
Dias et. al	2020	705	Seattle, U.S.	Multivariate ordered probit model	Grocery vs. non-grocery vs. meals	**i)** household income and density area positively affected in-person eat-out activities, and online shopping for goods, groceries, and meals; **ii)** frequency of both online and in-person shopping episodes for goods, groceries, and meals increase with household size; **iii)** higher car ownership was associated with a greater propensity of all in-person activity categories; **iv)** in-store shopping itself leads to online shopping	Evidence of complementary effect for non-grocery shopping, and substitution effect for grocery items	Non-grocery shopping trip freq: online non-grocery shopping freq **- C**. Grocery shopping trip freq: online grocery shopping freq- **S.**
Xi et. al	2020	1207	Nanjing, China	longitudinal study; ordered logit models	Five types of stores: daily goods vs. packaged foods vs. fruits and vegetables vs. catering services	Quasi-longitudinal analyses demonstrated that SDD online shopping frequency substitutes for local store shopping, while cross-sectional analyses showed either a neutral or complementarity effect exists.	Results from the quasi-longitudinal analyses was chosen, as authors contended the quasi-longitudinal approach accounts for influences of time-invariant confounding factors	Local store shopping freq: online shopping freq- **S**