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MODELING HOUSEHOLD E-COMMERCE DELIVERY RATES AND ASSESSING HOUSEHOLDS LAST-MILE DELIVERY PREFERENCES

Final Report

by

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DISCLAIMER

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EXECUTIVE SUMMARY

Over the last five years, e-commerce (online shopping and delivery services) induced package delivery has increased unprecedentedly, primarily due to the COVID-19 pandemic. For instance, in the US, the proportion of packages in total postal volume increased to 70% from 5% during the pandemic. However, the same pattern is expected to continue post-pandemic. The rapid increase in package delivery volume in the near and long-term future raises concerns about exceeding the capacity of delivery networks at different stages of the supply chains. The last-mile of delivery is an area of increasing concern for stakeholders involved in freight and logistics. Such stakeholders plan to utilize emerging technologies for last-mile delivery to meet the growing demand and delivery constraints. In this direction, autonomous technologies like robots and drones can play an important role in efficient package deliveries. An increase in e-commerce sales calls for a need to quantify the package delivery demand at a disaggregated level (households, census blocks).

The main purpose of this project is to propose a comprehensive modeling framework that simultaneously addresses e-commerce demand and package delivery demand, considering factors such as customer behavior, delivery options, and commodity types. Existing literature lacks a detailed and disaggregated demand model that captures the influence of all relevant parties. Additionally, the project aims to evaluate the impact of locational factors, level of service, and infrastructure on e-commerce and delivery preferences. Furthermore, it seeks to compare consumer preferences for different delivery modes and propose a choice-modeling approach that incorporates consumer heterogeneities and attitudes. Lastly, the study intends to compare the competitiveness of various last-mile delivery options through users' stated preferences and willingness to pay.

Goals and Objectives: the objectives of this project are to find appropriate and comprehensive answers to the following research questions: (i) How to identify purchasing and delivery preferences of customers for different commodities? (ii) How does the level of service and state of infrastructure affect the shopping and delivery preferences? (iii) What are some of the latent variables in on-line shopping behavior? (iv) What are the marginal competitive of different delivery strategies for different commodities?

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1.0 INTRODUCTION

Online shopping, also known as e-commerce, has been experiencing exponential growth worldwide over the past two decades. Since its emergence in the early 1990s, it has shown a steady upward trend, with online shopping accounting for 0.93% of total retail sales in 2000, compared to 11.01% in 2019 (US Census Bureau, 2020). According to Federal Highway Administration (2018), over 55% of people made at least one online purchase in the last month that required home delivery. This ever-increasing trend of online shopping is expected to continue. Fore instant, only for online food delivery, it is expected that the market penetration rise from 6% in 2018 to 13% by 2025 (Kim and Wang, 2021). In addition, the onset of Covid-19 has further accelerated this growth, making online shopping a regular part of our lives (Figliozzi and Unnikrishnan, 2021a; Pani et al., 2020; Unnikrishnan and Figliozzi, 2020).

With the increment of e-commerce, retail and logistics companies are facing challenges in meeting customers' high delivery expectations, leading to a search for effective strategies for fast and successful deliveries (Filiopoulou et al., 2022). Moreover, the number of delivery vehicles is expected to increase, which will cause additional emissions and space requirements that can further strain urban areas. Hence, improving efficiency delivery services and especially, last-mile delivery, as the most expensive part of the supply chain system, has gained significant attention (Allen et al., 2018; Liu et al., 2019; Lemardelé et al., 2021; Jiang and Huang, 2022; Miko and Abbas, 2023). In this regard, researchers followed two approaches. The first group investigated optimizing the traditional delivery mode by proposing new approaches to solve the Vehicle Routing Problem (VRP) (Archetti and Bertazzi, 2021; Kitjacharoenchai and Lee, 2019; Masmoudi et al., 2022; Tilk et al., 2021; Tiwari and Sharma, 2023; Yang et al., 2020). The second group focused on investigating innovative delivery methods to increase last-mile delivery efficiency. Among the most discussed innovative solutions, there are automated parcel lockers (Rossolov, 2021), crowdsourcing logistics (Punel et al., 2018a), reception boxes and pick-up points (Kedia et al., 2017), autonomous delivery robots (Pani et al., 2020) and drones (Aurambout et al., 2019; Imran et al., 2023). However, the question that researchers, urban planners, and logistic specialists are dealing with is that which of these innovative solutions will be more successful (Boysen et al., 2021).

The success of innovative strategies involves their performances, and consumers' participation (Ma et al., 2022). Literature provides valuable studies on performance analyses (Lemardelé et al., 2021; Ghelichi and Kilaru, 2021; Glick et al., 2022; Seghezzi et al., 2022; Alves et al., 2022), adoption and acceptance (Kim and Wang, 2022; Koh et al., 2023; Pani et al., 2020; Zhou et al., 2020) analysis of single innovative delivery methods, while, few studies have compared the different delivery methods with each other. To the best of our knowledge, only two studies compared multiple last-mile delivery strategies together. Cai et al. (2021) compared the usage behavior of consumers of buy-online-pickup-instore, smart locker, and drone delivery, using a theoretical model which integrates the factors of habit and attitude into the unified theory of acceptance and use of technology. Merkert et al. (2022) compared the competitive priorities and Willingness to Pay (WTP) for key attributes of parcel lockers, aerial drones, and traditional post service, using a conditional logit model with added error components to describe preference heterogeneity concerning different delivery modes. Therefore, the main goal of the current study is to predict and compare the success of different new delivery methods. Four modes of delivery methods, traditional regular delivery, sidewalk Autonomous Delivery Robots (ADR), Crowdsourced Delivery, and Automated Parcel Lockers (APL), will be investigated to provide insight into consumers' delivery preferences.

On the other hand, investigating and planning for new delivery methods and planning for managing urban facilities, e.g., parking and curbsides, require an accurate and disaggregate e-commerce demand estimation (Mirzanezhad et al., 2022). Despite the importance of evaluating the impacts of e-commerce demand on logistics solutions, there is a lack of disaggregated and comprehensive e-commerce demand models that can reflect the condition of the real world (Fabusuyi et al., 2020). A realistic framework should be able to measure the impact of individual characteristics (e.g., income, education, race, household's lifecycle, etc.), product type (e.g., grocery, fashion, etc.), and delivery service options (e.g., delivery time windows, drop up locations, and signature required) (Sakai et al., 2022). Studies in the literature treated the e-commerce demand and the delivery options as two separate processes, while delivery systems exist due to e-commerce demand (Kim and Wang, 2022). Therefore, the second goal of this study is to develop a comprehensive e-commerce demand model, to assess consumers' shopping and delivery preferences.

2.0 LITERATURE REVIEW

Since the current study follows two general goals, understanding consumer shopping and delivery preferences. This section is divided into two sections. The first section reviews the best practices in e-commerce demand modeling and shopping preferences, and the second section provides a literature review on consumer preferences for last-mile delivery methods.

2.1 E-COMMERCE DEMAND MODELING

In one of the earliest studies, Wang and Zhou (2015) predicted the delivery frequency, using individual, household, and urban characteristics by using a binary choice model and a right-censored negative binomial model. The U.S. National Household Travel Survey 2009 (NHTS) data was incorporated. The adoption of online grocery shopping in the Belgian supermarket chain Colruyt was studied by Van Droogenbroeck and Van Hove (2017). They discovered that customers' decisions depended more on the household level than the individual level. Nguyen et al. (2019) evaluated the customer preferences for online shopping considering three categories of variables: price-oriented, time and convenience-oriented, and value-for-money-oriented, and found that the most important factor is the delivery fee. A household-level e-commerce model that predicts participation in e-commerce and the ratio of delivery to on-site shopping was proposed by (Stinson et al. (2019), which later was incorporated by Stinson et al. (2020) to estimate parcel delivery truck tours in POLARIS. (Jaller and Pahwa, 2020) developed a multinomial logit model that predicts a shopping decision each day, where the alternatives included ‘no shopping’, ‘in-store’, ‘online’, and ‘both’. Unnikrishnan and Figliozzi (2020) studied the impacts of COVID-19 on home deliveries using a survey - they reported that higher-income households, younger residents, and those with high technology usage are more likely to use e-commerce. Sousa et al. 2020) focused on the effect of geographic area and stated that online shopping disparities between rural and urban consumers. (Fabusuyi et al., 2020) developed a model to estimate online package delivery for small geographic areas, referred as to micro-analysis zones, and showed how these estimates vary across different areas. (Sakai et al., 2022) a theoretical demand modeling framework that predicts e-commerce demand given the household characteristics and the delivery modes/options offered, using an agent-based urban freight simulation (SimMobility Freight). (Mirzanezhad et al., 2022) developed methods for data imputation and synthetic demand estimation for future years without the actual ground truth data to address the problem of infrequent and missing data. This study gives the explanatory variables that are significant in estimating the amount of home deliveries, in addition to the estimates' increased dependability.

Moreover, the literature is very rich in providing insights into the effect of different socio-demographic factors on e-commerce demand (Figliozzi and Unnikrishnan, 2021b). Age is a significant factor in e-commerce adoption, and typically, older individuals are less inclined to embrace online shopping compared to their younger counterparts (Ding and Lu, 2017; Schmid and Axhausen, 2019; Melović et al., 2021; Hermes et al., 2022). Reports showed that households above the poverty line are “almost twice as likely to make online purchases compared to respondents in households below the poverty level (i.e., 61% versus 33%)” (Federal Highway Administration, 2018). Also, higher-income households are more likely to make purchases online (Schmid and Axhausen, 2019; Fabusuyi et al., 2020; Kim and Wang, 2022, 2021). The likelihood of online buying rises with the use of smartphones, internet connectivity, and laptops (Wang and Zhou, 2015; Ding and Lu, 2017; Schmid and Axhausen, 2019). Variables associated with a household structure such as the number of members with driver licenses (Fabusuyi et al., 2020) vehicle ownership (Dias et al., 2020), presence of workers (Figliozzi and Unnikrishnan, 2021b), ethnicity (Shah et al., 2021) etc. affect the frequency of online shopping. In addition to socio-demographic factors, locational characteristics play an important role in e-commerce demand (Sousa et al., 2020). Loo and Wang (2018) reported that distances to the nearest subway station and the nearest shopping option are significant factors influencing the time spent on online shopping. Cheng et al. (2021) highlighted the importance of the level of urbanization, transit, and shopping accessibility on e-commerce demand. However, reviewing literature on the effect of locational factors showed that results are mixed and vary by the case studies (Farag et al., 2007; Zhou and Wang, 2014; Cheng et al., 2021)

2.2 CONSUMER’S DELIVERY PREFERENCES

Due to the importance of improving last-mile delivery, user acceptance of innovative delivery methods has received significant attention in the literature. Since the current study targets three innovative last-mile delivery methods- Autonomous Delivery Robots (ADRs), Crowdsourced Delivery (CRWD), and Automated Parcel Lockers (APL), the best practices in the literature are provided. ADRs are unmanned robots that can travel along sidewalks to the consumers' specified destination at pedestrian speeds and are designed to assist with last-mile logistics (Ostermeier et al., 2022). ADRs delivery concept is already implemented by companies such as DHL, UPS, and Amazon (Hoffmann and Prause, 2018), while mass adoption mandates understanding and conforming to customers’ needs, motivation, and expectations (Srinivas et al., 2022). Despite the accelerated deployment of ADRs, not many studies focused on consumer acceptance of ADRs (Koh and Yuen, 2023). Among the limited literature focused on this topic, two theoretical theories (i.e., the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Usage of Technology 2 (UTAUT2)) are used more often (Kapser and Abdelrahman, 2020). For instance, Hinzmann and Bogatzki (2020) identified the factors influencing consumers’ acceptance of ADRs in Germany and incorporated TAM to determine the behavior of potential consumers. Kapser et al. (2021) extended UTAUT2 and analyzed the data using structural equation modeling. The results indicated that trust in technology, price sensitivity, innovativeness, performance expectancy, hedonic motivation, social influence, and perceived risk determine behavioral intention to use ADRs. (Pani et al., 2020) addressed the need for research on public acceptance of ADRs and analyzed customers’ WTP during Covid-19, by developing a discrete choice model. In a recent study, Koh and Yuen (2023) examined consumers' intention to adopt ADRs through health and technology perspectives.

Crowdsource Delivery (CRWD) or crowd-shipping is an emerging package delivery method, where non-professional couriers use their own vehicles to deliver packages from warehouses, stores, or fulfillment centers to customers. CRWD is built on the concept of matching and connecting customers who need to send a package with drivers who have unused space in their vehicle and are willing to deliver the package (Punel et al., 2018b). Punel et al. (2019) explored push and pull factors affecting the adoption of CRWD and found that crowd-shipping is more likely for men, full-time employed, younger respondents, and for areas of higher population density yet the lower density of employment opportunities. (Seghezzi et al., 2021) evaluated the profitability of an urgent delivery crowdsourcing logistics initiative in an urban area and compared it with the traditional pony express system. (KARLI et al., 2022) investigated university students' perceptions of CRWD and identified factors that influence crowdsourced delivery platform acceptance as a consumer and as a driver in Turkey. Results showed that performance expectancy, price sensitivity, social influence, and perceived risk affect consumer acceptance. (Wang et al., 2023) investigated consumers' willingness to atop CRWD by integrating the TAM and norm activation model with the considerations of trust, social influence, and loss of privacy. Yuen et al. (2023) explored the factors affecting customer loyalty to CCRWD through the unified theory of acceptance and use of technology, the health belief model, the perceived value theory, and the trust theory.

Automated Parcel Locker is a technology-based delivery method, which provides 24/7 parcel delivery services to customers through unmanned, self-service terminals. APL is suggested as a system to make last-mile deliveries more sustainable and less time-consuming for e-commerce (Rossolov, 2021). APL is one of the most discussed last-mile delivery solutions and benefits both the supply system, by simplifying the process of delivery, and the customer, by providing flexibility on selecting a preferred time and location for collection (Tsai and Tiwasing, 2021). In an early study, De Oliveira et al. (2017) assessed the potential users of APL in Brazil and provided an approach to integrate the impact of final consumers' preferences on shaping last-mile operations. Mitrea et al. (2020) investigated e-commerce consumers' attitudes toward APLs as an alternative to traditional home delivery in Italy. Results showed that age, internet usage, using care-sharing, and household size are effective parameters to determine APL adoption. Ma et al. (2022) by mentioning that existing research on APL has largely overlooked the required interaction between the consumer and operations management, proposed a dual-perspective framework to fill this gap and integrate both viewpoints. Tsai and Tiwasing (2021) evaluated the consumers' intention to use APLs by combining resource matching theory, innovation diffusion theory, and the theory of planned behavior. An et al. (2022) examined consumers' decision to select parcel locker service with regard to privacy concerns and perceptions toward a technology based on protection motivation theory and TAM. Alves et al. (2022) developed a framework based on Agent-based modeling (ABM) and simulations to evaluate the use of APLs.

2.3 RESEARCH GAPS AND CONTRIBUTIONS

The main purpose of this project is to address the e-commerce demand and delivery together. Generally, compared to e-commerce demand modeling, fewer studies have addressed package delivery demand modeling, which is mostly rooted in the lack of data availability. Despite the importance of developing a comprehensive and detailed e-commerce demand model for logistic and freight planners, the literature fails to provide a comprehensive and disaggregated demand model that captures the effect of all effective parties, customers, delivery options, and commodity types. Moreover, as mentioned earlier, studies mostly address the e-commerce demand and delivery demand separately, while the existence of each depends on the other, and they need to be modeled together. Hence, the first objective of this report is to propose a modeling framework to simultaneously model e-commerce and delivery demand for different commodity types, which considers in-store shopping behavior as well. In addition, among e-commerce demand determinants, locational factors showed mixed results on the demands of e-shopping and different delivery types, and literature suggests more studies in this area. Moreover, although factors such as neighborhood type (e.g., urban, or rural, and population density) are incorporated in demand modeling, evaluating factors such as level of service and state of infrastructure is rare in the literature. Therefore, the second objective of this study is to evaluate how neighborhood type, the level of service, and the state of infrastructure affect the shopping and delivery preferences of different types of products.

In the consumer delivery preferences section, studies mostly have focused on evaluating consumer acceptance of single last-mile delivery service, while it is important to compare consumer preferences for different delivery modes for different commodities. In this regard, the main objective of modeling consumer last-mile delivery preferences is to evaluate and compare the competitiveness of three innovative last-mile delivery options, ADR, CRWD, and APL, with the current delivery option (regular delivery) and with each other. Moreover, the other gap in the literature is in the modeling frameworks. Studies in the literature typically used discrete choice models that assume certain decision-making mechanisms. For instance, the Random Utility Maximization (RUM) rule is one such mechanism in which the decision-maker is assumed to choose the alternative that provides the highest utility. Within the class of discrete choice models, the multinomial logit(MNL), and its generalizations (e.g., nested logit, cross nested logit, etc.) are commonly used to analyze consumer choices. In these models, the utilities of different alternatives are specified as a function of different observed variables collected from household survey data that can affect the choice being modeled. However, several important aspects including the attitudes and preferences, the consideration choice set, and the decision-making mechanism are typically not observed in the survey data. Hence, the other objective of this report is to propose a choice-moldering approach that takes into consideration the heterogeneities among consumers (latent classes), and consumer attitudes (latent variables) in the decision-making process. Therefore, the third objective of this report is to develop a consumer adoption model which incorporates both “hard information” (i.e. socio-demographic) and “soft information” (i.e., shopping preferences and attitudes). And finally, the fourth objective of this study is to compare the competitiveness of different last-mile delivery options for different commodity types, by comparing users’ stated preferences and willingness to pay (WTP).

To sum up, this study contributes to the literature by answering the following research questions: (i) How to identify purchasing and delivery preferences of customers for different commodities? (ii) How does level of service and state of infrastructure affect the shopping and delivery preferences? (iii) What are some of the latent variables in on-line shopping behavior? (iv) What are the marginal competitive of different delivery strategies for different commodities? The rest of the report is organized as follows. The next section presents the data collection and the study area. The modeling framework to model both e-commerce demand and consumer last-mile delivery preferences are provided in section four. The fifth and sixth sections provide the results and discussion. Finally, the conclusion section presents a summary of the report and avenues for future research.

3.0 DATA

This study uses survey data collected from residents of the State of Tennessee, USA. The population of the study area in 2022 was 6,975,219. The study area and the distribution of the participants are presented in **Figure 1**. The majority of responses were collected from four major metropolitan areas in the state of Tennessee, Memphis, Nashville, Chattanooga, and Knoxville. Institutional Review Board (IRB) of the University of Memphis approved the survey instrument in the Qualtrics platform (IRB#: PRO-FY2023-268). A web-based survey questionnaire was developed which comprises seven major sections. A market research company was employed to collect responses from its existing consumer panel. All members residing in the study area and aged over 18 years were drawn from this panel and sent the invite for responding to the survey.

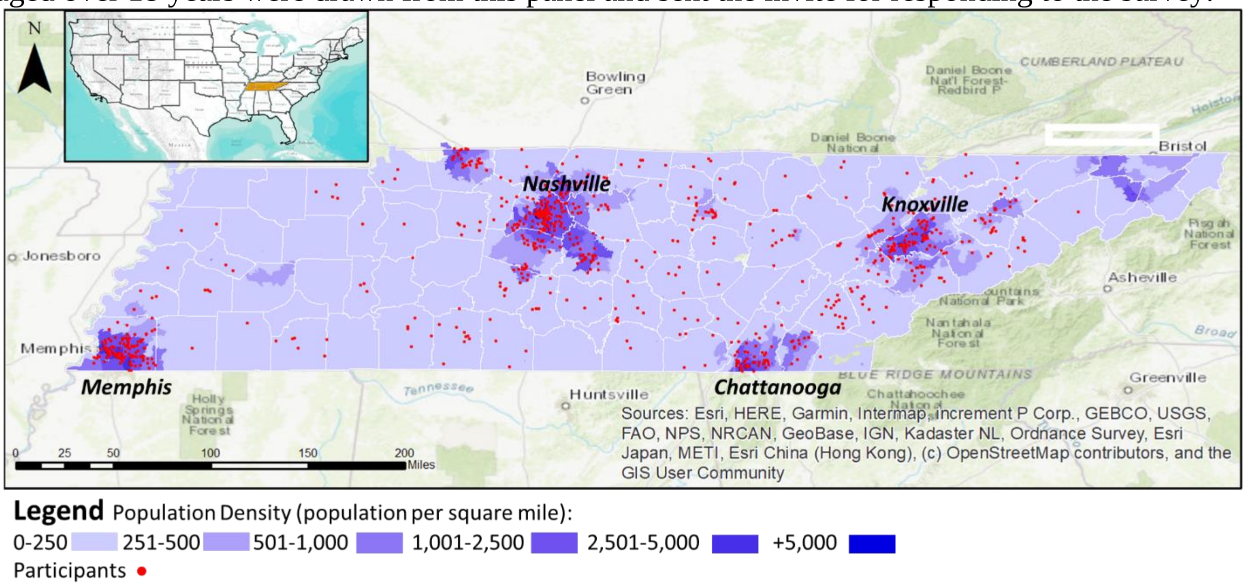


Figure 1: Study area and the distribution of the participants.

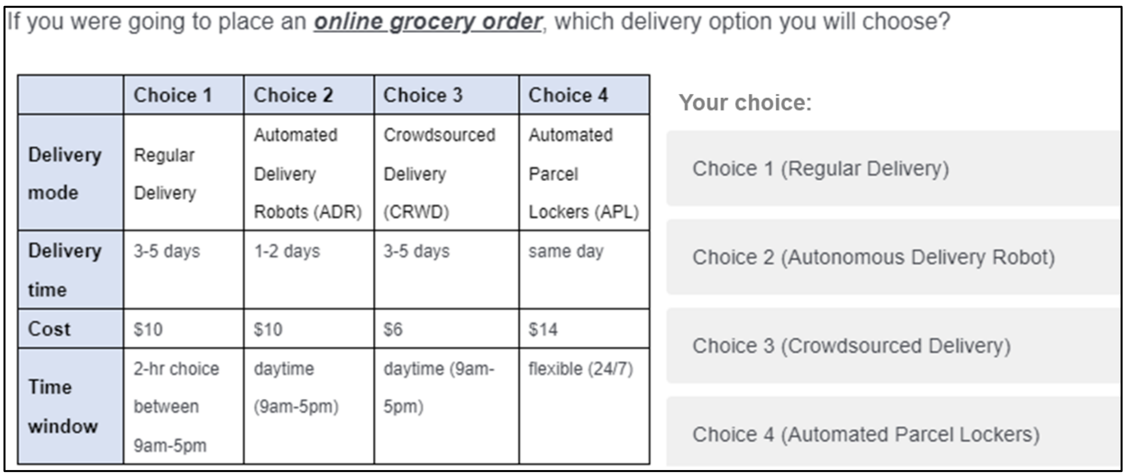
1.1. SURVEY DESIGN

The designed survey consisted of eight parts, out of which the first part included the consent form. Participants were provided with preliminary information about the survey, data confidentiality, and incentives. Also screening questions to check whether the participant agreed to the consent, is more than 18 years of age, and is a resident of the study area. Only the participants satisfying these criteria filled out the survey. The second part collected demographic and locational information at the individual level and the third part collected household-related information. The fourth sections provide brief information about new delivery methods (i.e., ADRs, CRWD, and APLs), how they look, and the delivery process of each. The fifth section was dedicated to collecting individuals' attitudes toward new technologies. Individuals' Intention to Use (IUT), Perceived Benefits (PB), Perceived Risk (PR), and Perceived Ease of Use (PEU) for new delivery methods were measured using a five-point Likert scale. In the sixth section, a choice experiment was designed to collect information on participants' last-mile delivery preferences. The choice experiment consisted of 4 attributes which are tabulated in **Table 1**. Participants had to choose between regular delivery, ADR, CRWD, and APL. 40 scenarios were designed while each participant had to answer to 5 randomly selected scenarios. **Figure 2**. presents an example of the designed scenarios. The seventh section collected information regarding shopping behavior, such as, number of home deliveries, pick-ups, and in-store shopping for different types of commodities in the last month, and the number of returned and failed deliveries. And finally, the last part of the survey was dedicated to collecting participants shopping preferences.

Table 1: Attribute levels of the designed choice experiment.

Attributes	Num. of Levels	Level
Commodity type	4	Grocery, electronics, beauty and health care, and fashion
Delivery time	3	Same day, 1-2 days, and 3-5 days
Delivery cost	4	\$6, \$10, \$14, \$18
Time window	3	Daytime (9 am – 5 pm), 2-hr choice between 9 am – 5 pm, and 24/7 flexible*

*Only for APLs


If you were going to place an ***online grocery order***, which delivery option you will choose?

	Choice 1	Choice 2	Choice 3	Choice 4
Delivery mode	Regular Delivery	Automated Delivery Robots (ADR)	Crowdsourced Delivery (CRWD)	Automated Parcel Lockers (APL)
Delivery time	3-5 days	1-2 days	3-5 days	same day
Cost	\$10	\$10	\$6	\$14
Time window	2-hr choice between 9am-5pm	daytime (9am-5pm)	daytime (9am-5pm)	flexible (24/7)

Your choice:

Choice 1 (Regular Delivery)

Choice 2 (Autonomous Delivery Robot)

Choice 3 (Crowdsourced Delivery)

Choice 4 (Automated Parcel Lockers)

Figure 2: A screenshot of one of designed choice experiments.

1.2. SURVEY RESPONSES

The survey was hosted in the Qualtrics platform and was administered by Dynata – a market research company. The respondents who matched the eligibility criteria were identified from Dynata's respondent panel and were sent survey invitations by email and phone texts. Upon providing the informed consent and completing the 12-minute survey, the respondents received compensation provided through Dynata. The data collection took place between April and May 2023. A total 1,451 participants agreed to participate in the study, 465 participants were not eligible for the study, did not finish the survey or were excluded from the response pool due to in-survey quality violations based on the attention-check question, therefore 986 completed surveys were collected. The final sample size is higher than the minimum sample size requirement for the targeted population at 99% confidence level and a margin of error of ±4%. **Appendix A** compares the sample with the quotas set for the survey. Overall, deviations of the sample from the population in age, ethnicity, and gender are rather small and hence demonstrate the representativeness of the sample in comparison with the study area population. **Table 2** provides descriptive statistics for both categorical and continuous variables collected through the survey. In addition to data collected from the survey, based on participants location (participants were asked to select the nearest street to their house), neighborhood conditions, such as, population and facilities (number of different types of stores) densities were collected using census data and InfoUSA data set. InfoUSA provides detailed information for companies from local shops to global enterprises.

Table 2: Descriptive statistics categorical and continuous variables in the full dataset, and the subsets.

Variable (Categorical)				Frequency	Percentage
Age	18 to 24			172	13.87%
	25 to 44			463	37.34%
	45 to 59			318	25.65%
	60 +			287	23.15%
Ethnicity	White			953	76.85%
	African American			192	15.48%
	Others			95	7.66%
Gender	Female			673	54.27%
	Male			567	45.73%
Education	High school or blow			521	42.02%
	Bachelor’s degree or equivalent			358	28.87%
	Master’s degree or higher			361	29.11%
Income	Below $50,000			620	50.00%
	$50,000 to $100,000			395	31.85%
	More than $ $100,000			221	17.82%
Employment status	Full-time employment			575	46.37%
	Part-time employment			104	8.39%
	Unemployed			184	14.84%
	Retired			231	18.63%
	Student			50	4.03%
	Self-employed			96	7.74%
Work status	Office			524	42.26%
	Home			437	35.24%
	Hybrid			233	18.79%
Households size	One			226	18.23%
	Two			427	34.44%
	Three			259	20.89%
	Four or more			337	27.18%
Car ownership	none			87	7.02%
	One			440	35.48%
	Two			459	37.02%
	Three or more			254	20.48%
Hours spend on internet per day	Less than an hour			131	10.56%
	1-5 hours			565	45.56%
	5-10 hours			316	25.48%
	More than 10 hours			228	18.39%
Having elderly (65+) in household	No			918	74.03%
	Yes			322	25.97%
Having someone with special disease or disability	No			969	78.15%
	Yes			271	21.85%
Delivery subscription	No			420	33.87%
	Yes			820	66.13%
Population Density (Population per square mile)	less than 250 per square mile			431	34.76%
	250 -750 per square mile			281	22.66%
	750 – 1,500 per square mile			220	17.74%
	More than 1,500 per square mile			309	24.92%
Continuous (Categorical)		**Min**	**Max**	**Mean**	**SD**
	Age	18	84	45.91	16.9
Number of Facilities per square mile	Grocery stores	0	14	1.675794	2.29321
	Health-related stores	0	95	4.98	10.62
	Fashion-related stores	0	32	4.824754	5.770649
	Electronic shops	0	62	6.696605	9.729734
	Post offices	0	18	1.352683	2.169474

In addition to data presented in **Table 2**, the number of home-delivery, pick-up, and in-store shopping each individual has made in the last month for five different commodities, grocery, electronic, health and beauty, fashion, and other, were collected. **Figure 3** presents an example question from the designed survey, asking about the number of home-delivery orders for different types of products an individual has made in the last 30 days.

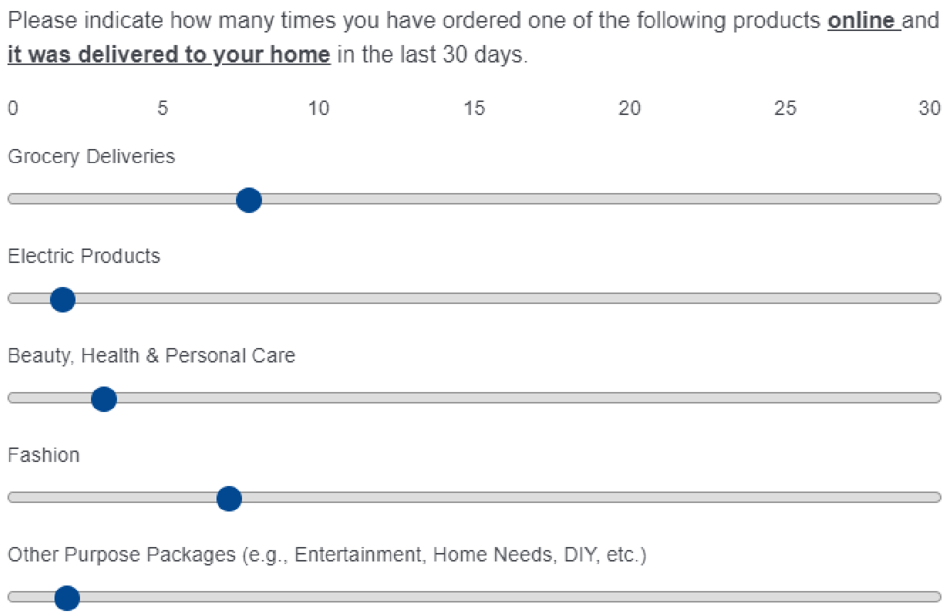


Figure 3: A screenshot of the example question regarding the number of online home delivery an individual has made in the last 30 days.

4.0 METHODOLOGY

This report aims to, first, develop a comprehensive and realistic framework to model consumers shopping and delivery preferences for different types of commodities; and second, compare the competitiveness of three innovative last-mile delivery methods for different types of commodities. In this study, individuals' choices between two shopping options (i.e., online and in-store), two delivery types (i.e., home delivery and store pick-up), five types of commodities (i.e., grocery, electronic, beauty and health care, fashion, and other), and four types of last-mile delivery (i.e., regular delivery, ADRs, CRWD, and APL).

The modeling section can be divided into two sections, the first section models shopping and delivery preferences simultaneously. An extended Multiple Discrete Continues Extreme Value (MDCEV) approach is proposed to model the number of times an individual purchase a specific type of good in-store or online and if it was delivered to home or picked-up from store, considering individuals' socio-demographic, households' information, locational characteristics (e.g., level of accessibility, neighborhood's type, and state of infrastructure). The second section is responsible for modeling consumers' choices on the type last-mile delivery modes. A Hybrid Choice model (HCM) is proposed to assess individuals' preferences on the different last-mile delivery modes, considering individuals' socio-demographics, households' information, locational characteristics, and individual attitudes. In order to measure attitudes toward new technologies and innovative delivery methods, individuals' Intention to Use (IU), Perceived Risk (PR), Perceived Benefit, and Ease of Use (EU) are considered. Figure 4 illustrates a general picture of the proposed modeling framework. Also, each of mentioned modeling approaches are discussed in length in the following subsections.

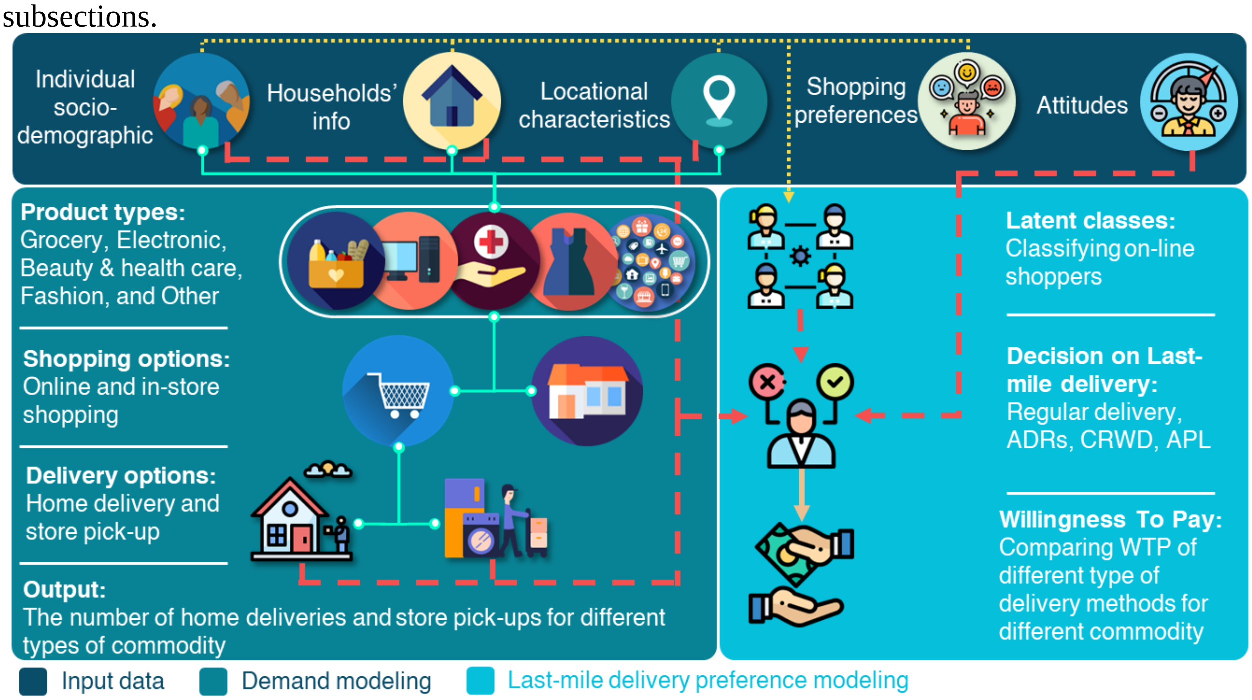


Figure 4: Proposed modeling framework flowchart.

4.1. E-COMMERCE DEMAND MODELING, USING EXTENDED MDCEV

The first section of the proposed modeling frame incorporates an extended version of MDCEV. Examples of these situations include activities performed during the day, grocery shopping, investment allocation, etc. Traditional choice models are not well suited for these situations, as they only allow the choice of a single alternative. Continuous models, on the other hand, often underestimate the probability of zero consumption for individual alternatives, also known as the ‘‘corner solution’’. Joint models, where the continuous choice is conditional on the discrete one, usually lack a strong grounding in economic theory, though there are exceptions (Hausman et al., 1995).

Substitution and complementarity define relationships between the demand for pairs of products. If the demand for one of them increases, then the demand for the other is reduced in the case of substitution and increased in the case of complementarity (Hicks and Allen, 1934). For example, in our case, when individuals buy their groceries online, the number of in-store grocery shopping reduces. On the other hand, a high number of grocery pick up makes it more likely for individuals to also pick up other orders from stores too.

One of the constraints of the MDC is a budget requirement. while determining a budget can be easy in some applications, it can be challenging in others, such as our case. Therefore, in this study, we incorporate an extended version of MDC proposed by (Palma and Hess, 2022) which addresses the substitution of and complementarity relations between demand for purchases and also eases the necessity of the availability of budget by considering implicit (also called infinite) budget which has also been proposed by (Bhat, 2018). In this method, an individual n must decide what products k to consume from a set of alternatives, by maximizing his/her utility subject to a budget constraint. This can be formulated, considering utility maximization, as follows:

$$Max_{x_n}\, u_0(x_{n0}) + \sum_{k=1}^{K} u_k\,(x_{nk}) + \sum_{k=1}^{K} \sum_{l=k+1}^{K} u_{kl}\,(x_{nk}\,, x_l\,) \tag{1}$$

$$subject\ to\ x_{n0}\, p_{n0} + \sum_{k=1}^{K} x_{nk}\, p_{nk} = B_n \tag{2}$$

where $n = 1 \dots N$ indexes individuals and $k = 1 \dots K$ alternatives, $x_n = [x_{n0}, x_{n1}, \dots, x_{nK}\,]$ is a vector grouping the consumed amount of each alternative (product), p_{nk} is the price of alternative k faced by individual n, and B_n is the total budget available to individual n. In the approach incorporated in this study, the B_n is assumed to be very large (infinite) . x_{n0} is an outside or numeraire good, i.e. a good that aggregates all consumption outside of the category of interest. In this study, the total in-store purchase that individuals make is considered as the outside good. Besides, this approach assumes the following functional forms for the different parts of utility functions (Bhat, 2008):

$$u_0(x_{n0}) = \psi_{no} x_{n0} \tag{3}$$

$$u_k\,(x_{nk}) = \psi_{nk\gamma_k}\, \log(\frac{x_{nk}}{\gamma_k} + 1) \tag{4}$$

$$u_{kl}\,(x_{nk}\,, x_l\,) = \delta_{kl}(1 - e^{-x_{n\,k}})(1 - e^{-x_{nl}}) \tag{5}$$

Where, ψ_{nk} refers to alternative k’s base utility and can be inferred to the marginal utility at zero consumption with respect to product k. The γ_k parameters, on the other hand, relate mainly to consumption satiation, by altering the curvature of alternative k’s utility function. In general, a higher γ_k indicates higher consumption of alternative k, when consumed. While a common interpretation is that ψ_{nk} and γ_k determine what and how much of alternative k to consume, respectively, this is not completely true.

$$\psi_{no} = e^{\alpha z_{n0}} \tag{6}$$

$$\psi_{nk} = e^{\beta_k z_{nk} + \varepsilon_{nk}} \tag{7}$$

Where, z_{n0} is a column vector of characteristics of the decision maker that are expected to correlate with that individual's marginal utility of the outside good (e.g. socio-demographics); α is a row vector of parameters representing the weights of those characteristics on the marginal utility of the outside good; z_{nk} are attributes of alternative k; β_k are vectors of parameters representing weights of those attributes on the alternative's base utility; and ε_{nk} is a random disturbance term. For more information regarding the extended MDCEV with an implicit budget, please see (Palma and Hess, 2022).

4.2. LAST-MILE DELIVERY PREFERENCE MODELING USING HCM

Built on the collected data, the second section of the current study aims to compare consumers preferences on last-mile delivery modes. An HCM modeling approach is proposed to address this condition, HCM has evolved to explicitly incorporate an individual's attitude/perceptions with the goal of enhancing the behavioral representation of decision making in choice modelling (Ben-Akiva et al., 2002; Hess and Daly, 2010). In an HCM environment, the structural model explains the latent variable using observable qualities of the individual whereas the measurement model depicts the link between indicators and the unobserved variable (commonly referred to as the latent variable) (Adnan et al., 2019).

The latent variable in this study is evaluated considering four psychological factors, which are Intention to Use (IU), Perceived Risk (PR), Perceived Benefits (PB), and Ease of Use (EU). Exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) are applied to perform factor analysis. First, EFA was conducted to investigate factor dimensions and assess internal consistency. Principal Component Analysis (PCA) was employed to identify the best factor dimensions by varimax rotation, and the scale reliability and internal consistency were measured by Cronbach's alpha. Then, CFA was used by AMOS24 to test the suitability of data and theoretical framework. The model fit indexes contain chi-square (χ^2) and root mean square error of approximation (RMSEA). Then a Multiple Indicators Multiple Causes model (MIMIC) is incorporated to model the latent variable. The MIMIC contains two parts: the structural equation model (SEM) and the measurement equation model. Socio-demographic characteristics are linked to latent variables in structural equations, and latent variables are linked to corresponding indicators in measurement equations. The MIMIC model can better identify indicators related to psychological factors, and various reasons (e.g., age or gender) that affect them (Etzioni et al., 2021). The structural equation is as **Eq. 8** and the measurement equations can be expressed as **Eqs. 9** and **10**:

$$\eta_n = \alpha X_n + \omega_n \tag{10}$$

where, η_n is the latent variable vector for individual n; X_n is a vector combining the socio-demographic variables for individual n; The α is the coefficient vector to be estimated. And ω_n is an error term that followed normal distribution across individuals (i.e., $\omega_n \sim N(0,1)$).

$$I_{pn} = \begin{cases} 1 \quad if\ (-\infty) < I_{pn}^{*} \leq \tau_{p1} \\ 2 \quad if\ \tau_{p(1} < I_{pn}^{*} \leq \tau_{p2} \\ \vdots \\ K \quad if\ \tau_{p(k-1)} < I_{pn}^{*} \leq \infty \end{cases} \tag{11}$$

Where,

$$I_{pn}^{*} = \sum_{l} \gamma_{lp} \,.\, \eta_{ln} + \upsilon_{pn} \tag{12}$$

In Eq. 11, I_{pn} is the response k in the p^{th} indicator for individual n and I_{pn}^{*} is the continuous variable that contains the latent variable and the normally distributed error term υ_{pn}. $\gamma_{lp}$is the coefficient of the l^{th}latent variable and $\tau_{p(k-1)}$ is the k^{th} threshold in the p^{th} indicator.

In addition to the latent variable, a latent class structure is combined to capture the heterogeneity among online shoppers. In a latent class model, observations are divided into S distinct classes where each of these classes have its parameter. In this regard, the unconditional probability of an individual n being in the shopping category i can be calculated through **Eq. 13:**

$$P_{in} = \sum_{\forall S} P_{ns} P_{ni|s} \tag{13}$$

Eq. 13 consists of two parts, class allocation probability (P_{ns}) and conditional choice probability ($P_{ni|s}$). The class allocation probability, which is shown in **Eq. 14**, is estimated by where Z_n is a vector of characteristics that determine class s probabilities for observation n, and αc is a corresponding vector of estimable parameters.

$$P_{ns} = \frac{\exp{(\theta_s Z_n)}}{\sum_{\forall S} \exp{(\theta_s Z_n)}} \tag{14}$$

$$P_{ni|s} = \frac{\exp{(\beta_{is} X_{in})}}{\sum_{\forall I} \exp{(\beta_{is} X_{in})}} \tag{15}$$

The class allocation probability, which is shown in **Eq. 14,** is expressed by the class membership variable Z_n, with the coefficient vector θ_s, which captures the heterogeneity among different groups of shoppers. Also, the conditional choice probability is estimated through **Eq. 15**, and is referred to as the probability of discrete outcome i, for observation n, which is a member of unobserved class s. In **Eq. 15** β_{is} is a vector of estimable parameters for discrete outcome i and class s; X_{in} is a vector of the observable characteristics that determine discrete outcomes n. Considering **Eqs. 13** to **15**, The latent class model can be expressed by a utility function that determines I possible discrete outcomes. Considering ε_{in}, that is a disturbance term and is assumed to follow logistic distribution, the utility functions can be formulated as follows (Washington et al., 2020):

$$U_{in} = \beta_{is}\, X_{in} + \varepsilon_{in} \tag{13}$$

In this study, individuals are classified considering, individual socio-demographics, household info, locational characteristics, and their shopping preferences.

5.0 RESULTS

This section is divided into two subsections. In the first section, the results of modeling e-commerce demand using MDCEV are provided, while the second section presents the results of modeling consumers' last-mile delivery acceptance using HCM.

5.1. DEMAND MODELING

In order to model the e-commerce demand, the MDCEV model was applied to the data collected. The MDCEV models two questions at the same time, which product and individual will select to purchase and how much? As it was mentioned earlier, in this study we are interested to investigate if an individual is supposed to address their daily needs (e.g., grocery, electronic, health and beauty, fashion, and other), through the three provided methods, in-store, online with home delivery, and online with pick-up option, which method they will select and how many purchases they will make through each. Since the main purpose of this research is to model e-commerce demand, the number of in-store shopping is modeled as the outside good. The results of applying MDCEV are provided in separate tables. First, the results of estimates and t-ratio for the outside goods (in-store shopping behavior), which were denoted by α in **Eq. 6** are provided in **Table 3**. Second, the results of the discrete choice section of the MDCEV are provided in **Table 4**. Third, the results of the continuous part are tabulated in **Table 5**. The results in **Tables 4 and 5** are divided into two sections, home delivery and pick-ups. Also, each section is divided into five columns, each presenting a product type. And Finally, Table 6 provides the results of complementarity and substitution analyses.

As **Table 3** shows, the number of in-store shopping increase as the participants' age increases. Also, age shows the largest magnitude in the coefficient of modeling outside goods and is the most significant indicator. In addition to age, participants who are living in areas with higher population density and grocery and fashion stores will have higher in-store shopping. It can be inferred that people in urban areas will conduct generally purchase more products compare the rural area the share of in-store shopping is higher in areas with better levels of service and welfare. On the contrary, participants with higher density of electronic and health-related stores (such as drug stores), and post offices will have lower in-store shopping.

Table 3. Results of estimates for outside goods (in-store shopping), denoted by $\boldsymbol{\alpha}$ in Eq. 6

Variable	**Estimates (t-ratio)**
Age	3.81 (6.97)
Number of population density	2.1 (2.71)
Number of health-related stores	-2.5 (-4.13)
Number of grocery stores	0.61 (1.8)
Number of fashion-related stores	0.55 (2.91)
Number of electronic shops	-0.11 (-0.12)
Number of post offices	-0.16 (-1.65)

Table 4 presents the estimates and t-ratio for the discrete section of applying the MDCEV model. This table provides insights into individual choices on whether they want to answer their needs to purchase different types of products first, online or in-store, and then if they would rather

online shopping, whether they would rather home delivery or pick-ups. Starting from individual's characteristics, age has negative effects on online shopping, as the coefficients of age in both home delivery and pick-up are negative for all types of commodities. The coefficients of age in pick-up are larger than home-delivery, showing that older participants have less interest in pick-ups and rather home deliveries. The largest coefficient belongs to purchasing other type products online (e.g., entertainment, home Needs, DIY, etc.) and picking them up from the store or post office. The effect of gender varies through different products and delivery services. Females are less likely to purchase electronic devices online, while females are more likely to have home deliveries for health and beauty and fashion products and pick-up orders for other products. Two variables are tested to evaluate the effect of ethnicity on the likelihood of online purchases. Although African American are less likely to select home delivery for electronic products, they are more likely to have home delivery for fashion, and pick-up for electronic, health and beauty and fashion. Also, they rather home deliveries over pick-up for fashion products. Other ethnicities showed negative effect on the likelihood of fulfilling an online order, as all the coefficient for this variable is negative in both delivery services and all product types. Education of individuals was not very effective in the probability of online shopping. Participants with bachelor's degree showed negative effect on having home delivery orders for other products, and participants with master's degree or higher showed positive effect on having online home delivery for electronic products. Individual's income only showed significant effects on fashion home delivery shops, where higher income individuals will have higher chance to have fashion products delivered to their house. Finally, if the working status of an individual is work from home, the probability of home delivery increase compared to pick-up. Working from home showed significant effect for possibility of home deliveries for electronic, health and beauty, and other products. On the other hand, if participants' working environment was hybrid (office and home) they would have less probability to have home deliveries.

Five variables are tested related to household information. First, car ownership showed positive effects on the possibility of pick-up orders. As **Table 4** shows, increases in the number of cars a household owns, the likelihood of having online orders with pick-ups delivery service, increases. Also, households' size showed positive effect on the probability of having at least one grocery, electronic, and health and beauty products delivered to home. Also, the probability of having grocery and other pick-up orders increases with increase in the household's members. I there is a senior in the household, the probability of having online grocery shopping (both home delivery and pick-ups) and home delivery for fashion will reduce. Having someone with a special disease or disability in the household will increase the probability of making at least one online order (both home delivery and pick-ups), as it was expected. And finally, having a delivery subscription is the last variable related to household's characteristics which was tested in the model. This variable showed the largest positive effect on the probability of having at least one home delivery in all products types. Among different products type, the coefficients of delivery subscription were larger for health and beauty and grocery, respectively.

The last group of variables which were tested on the discrete part of the MDCEV model, were locational variables. Generally, the effects of this group of variables were low to the probability of making online orders. Population density showed positive effect on the home delivery grocery purchases showing the higher chance of urban areas making compared to rural on placing home delivery grocery orders. The density of health and beauty related stores, reduces the probability of purchasing these products online. Participants are more likely to answer their health-related needs in-store if the service is provided in their neighborhoods.

Table 4: Results of developing MDCEV model on online shopping demand (Discrete part)

Variable	Home delivery					Pick-up from store				
	Grocery	Electronic	H & B	Fashion	Other	Grocery	Electronic	H &B	Fashion	Other
Age*	-0.86 (-2.58)			-1.08 (-3.47)	-0.92 (-2.99)	-1.62 (-4.99)	-1.67 (-4.59)	-1.4 (-4.14)	-1.54 (-4.37)	-2.12 (-6.34)
Gender										
Female		-0.84 (-4.21)	0.75 (4.05)	0.67 (3.57)			-1.04 (-4.59)			0.68 (3.36)
Ethnicity										
White	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)
African America		-1.41 (-4.78)		1.62 (5.4)			0.83 (2.69)	0.72 (2.45)	1.07 (3.55)	
Others				-0.95 (-2.88)	-0.73 (-2.31)	-1.65 (-4.54)		-0.99 (-2.64)	-1.09 (-2.78)	-1.04 (-2.86)
Education										
Less than high school	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)
Bachelor’s degree					-1.41 (-2.41)					
Master’s degree or higher		1.22 (2.41)								
Income										
Below $50,000	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)
$50,000 to $100,000				0.65 (2.86)						
More than $ $100,000				0.89 (3.1)						
Working status										
Working from home		0.76 (2.74)	0.77 (3.03)		0.7 (2.93)		-0.76 (-2.54)		-1.49 (-5.19)	
Hybrid (office and home)	-0.77 (-2.88)	-1.51 (-5.51)		-1.08 (-4.32)						
Car ownership										
None	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)
One							1.04 (2.34)	1.02 (2.38)		
Two or more							1.86 (3.37)	1.62 (3.17)	1.44 (2.63)	1.3 (2.8)
Household size										
One person	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)
Two persons			1.15 (2.38)							
Three people	1.42 (2.43)		2.05 (3.31)			1.4 (2.41)				0.95 (3.02)
Four people or more	2.12 (3.25)	1.53 (2.33)				1.57 (2.44)				
Having seniors in home										
Yes	-1.23 (-2.6)			-0.74 (-2.1)		-1.44 (-2.8)				
Having someone with a disability										
Yes			0.06 (1.57)					1.37 (4.36)		
Delivery subscription										
Yes	2.82 (4.43)	1.83 (3.91)	3.22 (5.34)	1.93 (3.79)	1.87 (3.76)	0.05 (1.67)				
Neighborhood condition*										
Population density	0.09 (1.12)									
Num. of health-related stores^{+}			-0.09 (-1.78)					-0.08 (-1.63)		
Num. of grocery stores^{+}	0.08 (1.5)					0.03 (1.42)				
Num. of fashion- stores^{+}									-0.17 (-2.00)	
Num. of electronic shops^{+}										

*Continuous variables and $^{+}$ Per square mile

The results of a continuous section of the MDCEV model are presented in **Table 5**. The results of this table provide insight into the effective variables, individual, household, and locational characteristics, on the number of online purchases a household will make in 30 days. Similar to the discrete part, age is one of the most important variables and shows a negative effect on the number of online purchases in a month. Contrary to in-store shopping, the number of online purchases reduces if the age increases. Females will have more home delivery grocery shopping, and health and beauty and fashion pick-ups. However, females showed negative effects on the number of online electronic orders and other product pick-ups. African Americans showed a positive effect on the number of home delivery fashion products, while other ethnicities showed significant negative effects on most types of online orders and delivery services, where the largest effect of other ethnicities on the number of purchases belongs to grocery pick-ups. The level of education showed significant effects only when participants had a master’s or higher degree, where the coefficients sing where positive for home delivery electronics, grocery, and health and beauty products pick-ups. Individual income level showed significant effects on online shopping, where the results showed that a person with higher income will place more home delivery electronics and fashion, and pick-up fashion orders. While high-income participants showed negative effects on the number of grocery and other product pick-ups. Interesting results were observed on the effect of work status. As **Table 5** shows, working from home increases the home delivery rates for grocery, electronic, fashion, and other product types. However, the number of pick-ups reduces when if the participant is working from home. On the contrary, hybrid work condition, increases the number of pick-ups, especially for grocery and other products, and reduces the number of home delivery grocery and electronic orders. Finally, the number of hours and individual on average spends on the internet showed that generally, the more people surf on the internet, the more they will place online orders. The largest effect of this variable was observed for electronic and pick-up orders.

As **Table 5** shows, household information showed significant effects. Stating from car ownership, increases in the number of cars a household owns reduces the online shopping rates, especially, for home delivery grocery and fashion, and electronic pick-up orders. Household size showed the most effective parameter in the online order rates. As **Table 5** shows, the number of online orders directly is affected by the number of household members. In all delivery services and commodity types, the coefficients of households with 4 or more members are greater than other household sizes. These results were expected as the more populated households have more goods needs to answer. Comparing the effects of household size between home delivery and pick-ups shows that this variable is more significant in the number of home delivery orders as the coefficients are larger. If the household has a senior member (someone older than 65 years old) in the household has negative effects on the number of electronic and health and beauty home deliveries, and electronic pick-ups. However, if a member of the house is disable or has a special disease, the home delivery rate increases for groceries, health and beauty, and other products. These results show the importance of sustainability of delivery services. In addition to home delivery, grocery pick-up increases if there is a member with a disability or special disease. Finally, as it was expected, the home delivery order rates increase if a household has a delivery service, where the largest coefficient belongs to fashion-related orders.

The last category of variables is neighborhood condition. Population density showed a positive effect of the number of home delivery orders for grocery, fashion, and other products. Also, the number of grocery and fashion pick-ups increase in the more populated areas.

Table 5: Results of developing the MDCEV model on online shopping demand (Continuous part)

	Home delivery					Pick-up from store				
Variables	**Grocery**	**Electronic**	**H & B**	**Fashion**	**Other**	**Grocery**	**Electronic**	**H &B**	**Fashion**	**Other**
Age*		-2.2 (-2.84)	-1.75 (-2.)	-2.79 (-3.2)	-1.91 (-2.2)	-3.7 (-4.46)	-4.24 (-5.51)	-3.78 (-4.83)	-3.85 (-4.77)	-3.37 (-3.98)
Gender										
Female	1.05 (2.32)	-2.6 (-5.72)					-2.57 (-5.7)	1.34 (2.93)	1.22 (2.59)	-1.9 (-3.83)
Ethnicity										
White	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)
African America				2.58 (3.22)						
Others			-2.01 (-2.36)	-2.76 (-3.01)		-2.83 (-3.24)	-1.93 (-2.38)		-2.53 (-2.98)	-2.12 (-2.38)
Education										
Less than high school degree	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)
Master’s degree or higher		0.33 (0.47)				2.23 (1.98)		3.11 (2.23)		
Income										
Below $50,000	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)
$50,000 to $100,000				3.14 (2.7)					1.9 (2.63)	
More than $ $100,000		2.65 (1.73)		4.36 (2.85)		-2.02 (-2.25)				-1.61 (-2.89)
Working status										
Working from home	0.46 (1.01)	2 (3.25)		2.28 (3.29)	2.37 (3.38)		-2.65 (-4.34)	-1.94 (-3.12)	-2.73 (-4.25)	
Hybrid (office and home)	-3.85 (-6.43)	-3.7 (-6.14)				1.72 (2.49)				1.32 (1.49)
Hours spent on the internet										
Less than an hour	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)
1-5 hours		0.93 (1.46)			0.63 (1.16)					
5-10 hours	1.06 (3.15)	1.68 (2.28)			1.61 (2.18)		2.59 (3.2)		1.8 (3.53)	
Car ownership										
One							-3.23 (-2.69)			
Two or more	-4.07 (-3.14)				-3.34 (-2.65)		-4.02 (-3.11)			
Household size										
One person	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)
Two persons	4.28 (3.6)	6.7 (4.42)	4.27 (3.42)	3.18 (2.37)	4.45 (3.28)	2.66 (2.08)			3.52 (2.83)	
Three people	4.21 (3.07)	7.27 (4.35)	4.92 (3.4)	3.53 (2.27)	4.44 (2.83)	3.11 (2.11)			3.4 (2.37)	
Four people or more	6.83 (4.53)	7.46 (4.63)	6.7 (4.23)	5.77 (3.38)	7.69 (7.46)	4.38 (2.7)	4.66 (3.11)	3.7 (2.65)		
Having seniors in home										
Yes		-0.07 (-1.08)	-3.45 (-2.05)				-2.19 (-3.11)			
Having someone with a disability										
Yes	0.19 (2.77)		3.92 (5.97)		1.31 (2.18)	1.93 (3.41)				
Delivery subscription										
Yes		1.72 (2.67)	1.8 (2.66)	1.98 (2.76)	1.31 (2.18)					
Neighborhood condition*										
Population density	0.16 (2.36)			0.31 (1.66)	1.06 (2.65)	0.05 (0.98)			0.54 (1.21)	
Num. of health-related stores⁺			-0.37 (-2.87)					-0.38 (-3.05)		
Num. of grocery stores⁺	0.06 (1.06)					2.11 (4.2)				
Num. of fashion- stores⁺				0.99 (1.95)					0.09 (2.34)	
Num. of electronic shops⁺		0.17 (4.56)					0.71 (2.43)			

*Continuous variables and ⁺ Per square mile

These results show that more online orders are placed in an urban area compared to rural areas, although the value of the coefficients is not very large. As **Table 5** shows, the last category of variables is neighborhood condition. Population density showed a positive effect of the number of home delivery orders for grocery, fashion, and other products. Also, the number of grocery and fashion pick-ups increase in the more populated areas.

These results show that more online orders are placed in urban areas compared to rural areas, although the values of the coefficients are not very large. The density of different facilities in the neighborhood has mostly had a positive effect on the online parches of the same product but for health-related products. As results show, increases in the density of health and beauty shops will reduce home delivery and pick-up orders. The largest positive coefficient belongs to grocery pick-up. These results make sense as grocery pick-up orders are highly dependent on the availability of grocery stores. The number of electronic and fashion online orders increases if the density of similar stores increases in the neighborhood. Finally, the density of post offices has a direct correlation with online orders for other products and health and beauty pick-ups.

Finally, the estimated coefficients and t-ratios for the complementarity and substitution (δ in Eq. 4) are tabulated in **Table 6**. The estimated values in this table show the relationship between the consumption of each online shopping option. If the sign of the coefficient is negative it shows that the consumption of one will reduce the consumption of other options. For instance, as **Table 6** shows, the estimated coefficients for the relation between home-delivery grocery vs pick-up grocery is negative, which means the higher home-delivery grocery orders, the lower pick-up grocery orders, and vice versa. The same relationship was estimated for home delivery electronic vs pick-up electronic and home delivery fashion vs pick-up fashion. However, when the sign of the estimated coefficients is positive, the consumption of one option increases the consumption of the other. As Table 6 shows, as the number of home deliveries for other products increases the number of pick-up orders for the same goods category increases as well. Moreover, increases in the number of home delivery orders for other surges the number of home deliveries of electronic products. The same relationship was observed between Pick-up beauty versus Pick-up fashion and Pick-up electronic versus Pick-up other.

Table 6*: Results of modeling complementarity and substitution, denoted by δ in Eq. 4*

Variable	Estimate (t-ratio)
Home delivery grocery vs Pick-up grocery	-0.71 (-11.22)
Home delivery electronic vs Pick-up electronic	-0.11 (-5.7)
Home delivery fashion vs Pick-up fashion	-0.08 (-0.98)
Home delivery other vs Pick-up other	0.15 (6.8)
Home delivery other vs home delivery electronic	0.11 (6.1)
Pick-up beauty vs Pick-up fashion	0.24 (7.6)
Pick-up electronic vs Pick-up other	
	5.32 8.2)

5.2. LAST-MILE DELIVERY STRATEGY ADOPTION

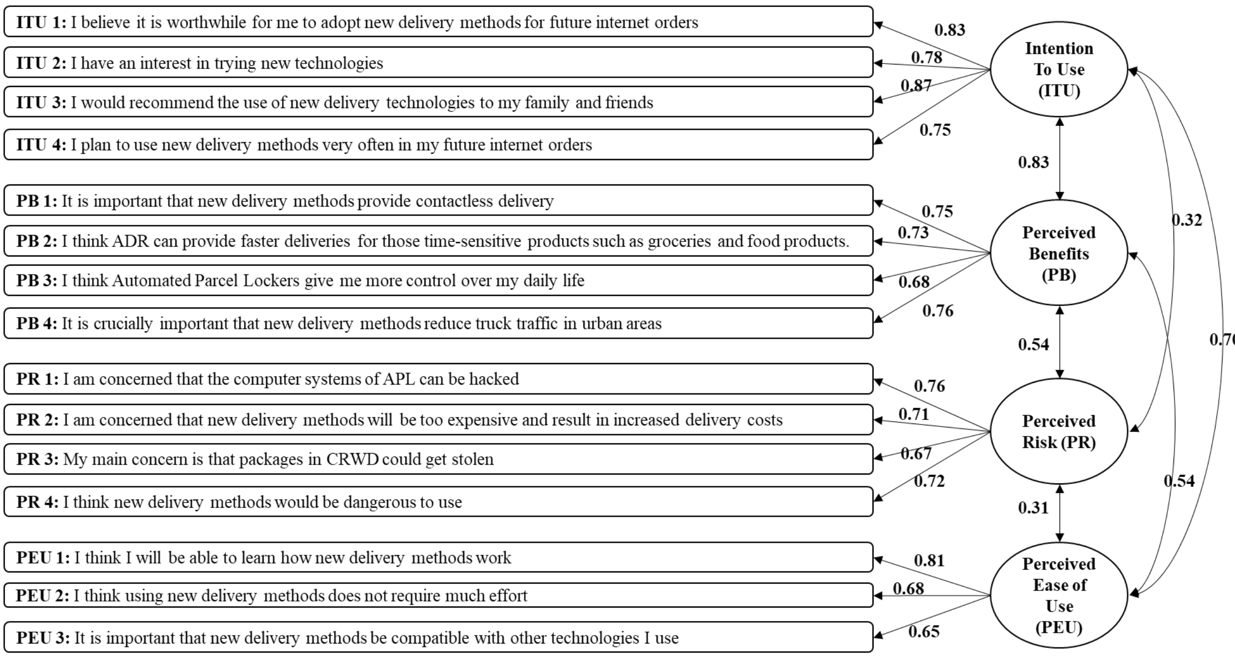
In this subsection, the results of modeling consumers' last-mile delivery adoption, using HCM, are provided. In the following, first, the results of factor analysis are provided, discussing the selection of latent variable measurement. Then the latent class allocation and class membership analyses are discussed to identify the latent classes of consumers. The result of the discrete choice model is provided next followed by a discussion on the competitiveness of different delivery modes and the WTP for each mode for different commodity types.

5.2.1. Factor analysis

In this section results of factor analyses, EFA and CFA, are provided. First, **Table 7** presents the result of EFA. In this table, Cronbach's alpha and factor loading are provided where, Cronbach's alpha higher than 0.7 represents good internal consistency across latent constructs, and factor loading higher than 0.5 indicates a good fit. Items with factor loadings below 0.50 are removed, each item identified by EFA has only one dimension and has the highest factor loadings corresponding to the respective latent variable, indicating that items correspond to only a unique latent variable. In addition to EFA, CFA is implemented to evaluate measurement model fit and refine measurement items for the construct of latent variables. Four groups' constructs are incorporated in this study, ITU, PB, PR, and PEU. **Figure 5** shows the items of each construct and the results of the confirmatory factor analysis. The threshold is that RMSEA is <0.6, and CFI and TLI are higher than 0.9. The model test results are as follows χ^2= 236.181, df = 84, $p < 0.001$, RMSEA = 0.064, CFI = 0.932, and TLI = 0.915, which suggests a good fit.

Table 7: Results of conducting Exploratory Factor Analysis (EFA) for attitude measurements.

Item	Factor loading	Cronbach's alpha	Mean	SD
IUT1	0.772	0.816	4.166	0.613
IUT2	0.698		4.354	0.565
IUT3	0.889		4.161	0.596
IUT4	0.827		4.044	0.589
PB1	0.698	0.713	3.868	0.633
PB2	0.633		3.886	0.688
PB3	0.584		4.095	0.523
PB4	0.691		4.237	0.522
PR1	0.717	0.786	3.934	0.66
PR2	0.722		4.09	0.663
PR3	0.681		4.017	0.647
PR4	0.779		3.217	0.782
PEU1	0.846	0.769	4.577	0.393
PEU2	0.636		4.079	0.56
PEU3	0.742		4.467	0.41



χ^2 =236.181, df=84, p < 0.001, RMSEA = 0.064, CFI = 0.932, and TLI = 0.915

Figure 5: Confirmatory factor analysis results.

5.2.2. Identifying latent classes of consumer

In order to identify the latent classes of consumers, first, a class allocation model was incorporated to classify consumers. The main criteria for classifying consumers were their shopping preferences and in-store over online shopping behaviors ratio. In this regard, a set of statements were provided to measure consumers' shopping preferences. **Table 8** provides the shopping preference statements, and also, the results of conducting EFA analyses (factor loading) are provided to show the strength and direction of the relationship between items and the underlying latent factor (shopping preference). Consumers' shopping preferences were measured using a five-point Likert scale.

Table 8: Shopping preferences measurements and EFA results

Item	Description of the statement	Factor loading	Mean	SD
SP1	*"I like not having to leave home when shopping"*	0.742	2.608	1.404
SP2	*"I like the helpfulness available at local stores"*	0.711	3.159	1.416
SP3	*"I don't want to give my credit card number to a computer"*	0.690	3.505	1.240
SP4	*"I feel internet shopping is easier than in-person shopping at local stores"*	0.698	2.816	1.203
SP5	*"I think Internet shopping has delivery problems"*	0.861	3.546	1.258
SP6	*"I prefer Internet shopping since I can save time"*	0.673	2.821	1.396
SP7	*"I do not trust online shops for expensive purchases"*	0.749	2.608	1.404

A set of latent class models is estimated by varying the number of classes from one to seven for identifying the appropriate number of consumer segments, as shown in **Table 9**. The optimal solution was assessed using BIC values, which weigh both model-fit and parsimony. The variation in BIC values suggested that a five-class is optimal. The estimated probabilities of attitudinal statements and shopping behavior are then incorporated to characterize and label each latent class. The probability values of each response, which are tabulated in **Table 10,** lead to labeling the latent classes as: (i) Class 1: Traditional shoppers; (ii) Class 2: Benefit seekers; (iii) Class 3: E-shopping lovers; (iv) Class 4: Indifferent consumers; (v) Class 5: Omnichannel consumers. The average membership probabilities of these latent classes are 24.06%, 21.30%, 19.15%, 6.86%, and 28.63% respectively.

Table 9: Model fit statistics where the number of classes is varied from one to seven.

Model	Number of parameters	LL	AIC	BIC(LL)
1-Class	58	-5590.05	21295.99	21575.11
2-Class	117	-4880.09	19994.18	20557.23
3-Class	176	-4201.68	18755.36	19602.33
4-Class	235	-3901.06	18272.12	19403.02
5-Class	**294**	**-3528.16**	**17644.31**	**19059.14**
6-Class	353	-3376.06	17758.12	19156.88
7-Class	412	-3230.55	17885.11	19267.79

- *Class-1: Traditional shoppers:* as the label suggests the consumers in this latent class prefer traditional shopping behavior (shopping in the physical stores). This behavior was obvious based on the in-store/online ratio and their responses to the shopping preferences statements, almost all of the consumers in this group shop in-store more than online and more than 57% of consumers had in-store shopping twice on-line shopping. Also, more than 40% of consumers strongly like the helpfulness in the physical stores, they do not trust online shopping for expensive purchases (~43%), do not like to give their credit card number to a computer (~49.42), and think that online shopping has delivery problems (~45%).
- *Class-2: Benefit seekers:* consumers in this group are labeled as “Benefit seekers” as their response probability showed that they would like to use the advantages of both online and in-store shopping, while the ratio of in-store/online ratio was not dominated in any of categories and showed similar rates. Also, consumers in this category mentioned that they strongly like the helpfulness of the local stores (~31%), like the time that they can save through online shopping (~39%), and that they do not need to leave the home when shopping (~43%). However, about 43% of consumers in this class believe that online shopping has delivery problems.
- *Class-3: E-shopping lovers:* the consumers in this category were labeled as “E-shopping lovers” mainly because of their shopping behavior as they were the only class in which the majority of them had more online shopping than in-store shopping. Also, they have mentioned that they like that they do not need to leave home when shopping (~53%), they do not like the helpfulness in the local stores (~30%), they do not mind giving their credit card number to a computer (~52%), think that internet shopping is easier than in-store shopping (~45%), and like that, they can save time with on-line shopping (~50%). Also, consumers of this class trust online shopping for expensive products (~38%).
- *Class-4: Indifference consumers:* the consumers in this class mostly showed indifferent attitudes toward the shopping preferences questions and responded neutrally mostly in the survey. They formed about 7% of the total consumers and mostly like to purchase their needs through physical stores, based on the in-store/online shopping ratio.
- *Class-5: Omnichannel consumers:* the last latent class belongs to omnichannel consumers. They are the largest group in the data set and about 29% of participants are assigned to this class. The shopping behavior of this group showed mixed behavior. Although the majority of consumers showed a larger response probability to have more in-store shopping, they showed the second highest probability of having more online shopping than in-store shopping (~20%). While they

like not to leave the house when shopping (~30%), they like the helpfulness available at local stores too (~29%). However, they do not trust online shopping for expensive products (~42%).

Table 10: Response probabilities of latent classes to various attitude statements

Statement and responses	**Class 1** Traditional Shoppers	**Class 2** Benefit Seekers	**Class 3** E-shopping lovers	**Class 4** Indifferent consumer	**Class 5** Omnichannel Consumers
Class percentage	24.06%	21.30%	19.15%	6.86%	28.63%
Indicator Variables: Shopping behavior					
In-store over online shopping ratio					
0 – 1	0.0189	0.1562	**0.3154**	0.1179	0.1962
1 – 1.5	0.1192	0.2751	0.2981	0.2748	0.2852
1.5 – 2	0.2875	**0.2897**	0.2329	0.2924	**0.3225**
2 +	**0.5744**	0.2790	0.1536	**0.3149**	0.2002
Indicator Variables: Shopping preferences and attitudes					
"I like not having to leave home when shopping"					
Not at all like me	0.1915	0.2706	0.0677	0.0855	0.0194
Somewhat not like me	0.1229	0.0700	0.0316	0.1657	0.1078
Neutral	0.1775	0.0910	0.1027	**0.508**	0.2994
Somewhat like me	**0.2658**	0.1309	0.2673	0.1835	0.2726
Exactly like me	0.2423	**0.4375**	**0.5307**	0.0574	**0.3007**
"I like the helpfulness available at local stores"					
Not at all like me	0.0511	0.0839	0.1942	0.0915	0.0737
Somewhat not like me	0.0566	0.1406	**0.2960**	0.2486	0.2675
Neutral	0.1252	0.2215	0.2719	**0.3478**	0.2463
Somewhat like me	0.3632	0.2367	0.12	0.2064	**0.2889**
Exactly like me	**0.4039**	**0.3173**	0.1179	0.1057	0.1236
"I don't want to give my credit card number to a computer"					
Not at all like me	0.1664	**0.4289**	**0.5152**	0.166	0.301
Somewhat not like me	0.1642	0.0869	0.1657	0.256	**0.4249**
Neutral	0.1751	0.1261	0.1632	**0.3679**	0.2188
Somewhat like me	**0.2955**	0.094	0.0536	0.1447	0.0553
Exactly like me	0.1987	0.2641	0.1023	0.0654	0
"I feel internet shopping is easier than in-person shopping at local stores"					
Not at all like me	0.1453	0.2574	0.0049	0.0241	0.001
Somewhat not like me	0.1453	0.0887	0.0533	0.2009	0.057
Neutral	**0.2415**	0.1263	0.1452	**0.4336**	0.181
Somewhat like me	0.2302	**0. 3773**	0.3526	0.2813	0.353
Exactly like me	0.2377	0. 1503	**0.4441**	0.0601	**0.408**
"I think Internet shopping has delivery problems"					
Not at all like me	0.1271	0.0001	0.2085	0.0624	0.2499
Somewhat not like me	0.1369	**0.4304**	**0.2914**	0.2549	**0.2875**
Neutral	0. 2703	0.2376	0.2281	**0.4367**	0.2821
Somewhat like me	**0.3120**	0.0378	0.0997	0.2368	0.1062
Exactly like me	0.1537	0.2942	0.1723	0.0092	0.0744
"I prefer Internet shopping since I can save time"					
Not at all like me	0.1919	0.3000	0.0122	0.0125	0.0188
Somewhat not like me	0.2644	0.0990	0.067	0.2095	0.0198
Neutral	**0.2823**	0.0666	0.1428	**0.4143**	0.1987
Somewhat like me	0.1592	0.1415	0.2857	0.3388	**0.3873**
Exactly like me	0.1020	**0.3930**	**0.4923**	0.0249	0.3754
"I do not trust online shops for expensive purchases"					
Not at all like me	0.1869	**0.3840**	**0.3751**	0.0737	0.0757
Somewhat not like me	0.1698	0.1980	0.1904	0.2675	0.1626
Neutral	0.1889	0.0849	0.2375	**0.3489**	0.1652
Somewhat like me	0.2171	0.0766	0.0939	0.2264	0.172
Exactly like me	**0.2379**	0.2565	0.1031	0.0835	**0.4244**

5.2.3. Class membership analyses

In order to shed more light on the characteristics of the indicated classes, a Multinominal logit model (MNL) was developed to analyze the class memberships. The results of applying MNL are tabulated in **Table 11**, where consumers' membership to four classes is compared to class-1, traditional shoppers, considering their age, ethnicity, income education level, employment status, hours spent on internet-connected devices, household size, presence of a senior member in the household, and the population density of their area. Based on the results, compared to traditional shoppers, the probability of being categorized as benefit seekers (class 2) increases if the consumers are aged between 45 to 59, their income is between \$50,000 to \$100,000, own a Master's or higher degree, live in a populated household, have a senior in their household, and live in medium to low-density neighborhoods. However, being African American or of other ethnicities and retired, having a high salary and a bachelor's degree, and living in a dense neighborhood will reduce the probability of categorizing in the benefit seekers class. Also, benefit seekers members spend more time on the internet compared to traditional shoppers. As **Table 11** shows, E-shopping

Table 11: Class membership functions of the latent class model with *Traditional shoppers* as the reference category, coefficients (t-value).

Variable	Class 2 Benefit seekers	Class 3 E-shopping lovers	Class 4 Indifferent consumer	Class 5 Omnichannel consumers
Age (Base = 18-24)				
25-44		2.91 (3.08)*		0.79 (2.58)*
45-59	1.12 (1.98) *	-0.62 (-1.33)		1.02 (3.08)**
60+		-3.26 (-4.26)***		
Ethnicity (Base: White)				
African American	-9.43 (-3.29)**	-0.54 (-1.35)	-1.35 (-1.43)	
Other	-3.29 (-1.7).			0.58 (1.53)
Income (Base: Below \$50,000)				
\$50,000 to \$100,000	12.01 (4.14)***			
More than \$ \$100,000	-2.29 (-1.51)	0.89 (1.99)*	0.9 (1.18)	
Education (Base: Less than high school degree)				
Bachelor's degree or equivalent	-1.99 (-1.62)	0.52 (1.63)	1.51 (1.72).	-0.73 (-3.37)***
Master's degree or higher	7.48 (4.69)***	2.06 (3.32)***		
Employment status (Base: Full-time employment)				
Part-time employment		-0.68 (-1.51)		-1.54 (-4.39)***
Unemployed		-1.16 (-3.1)**	-2.21 (-1.92).	-1.57 (-5.72)***
Retired	-4.94 (-2.09)*			-0.7 (-1.51)
Student		0.93 (1.4)		-1.69 (-3.14)**
Self-employed			-1.71 (-1.58)	-0.99 (-2.66)**
Hours spent on internet-connected devices (Base: Less than an hour)				
1-5 hours	2.64 (1.72).	1.89 (2.76)**	1.9 (1.35)	0.49 (1.28)
5-10 hours	2.22 (1.49)	1.19 (2.78)**		
More than 10 hours		0.84 (2.6)**		-0.26 (-1.04)
Household size (Base: 1 person)				
2 people		0.77 (1.99)*	1.67 (2.62)**	0.51 (1.76).
3 people	5.1 (3.01)**			
4 or more people	5.9 (2.76)**			0.84 (2.16)*
Having seniors in the household (Base: No senior)				
Yes	3.0 (1.6)		-2.78 (-4)***	
Population density (less than 250 per square mile)				
250 -750 per square mile	2.25 (2.1)*			0.57 (2.01)*
750 – 1,500 per square mile		1.56 (2.33)*		1.22 (1.45)
More than 1,500 per square mile	-2.36 (-2.11)*	1.2 (2)*	0.85 (1.09)	

lovers belong to a higher salary class, are more educated on average, spend more time on the internet, have less low size households, and are mostly in more dense neighborhoods, as the coefficients of these variables showed positive signs. However, in age groups of 45-59 and 60+, having a part-time job or being unemployed, reduces the probability of being an E-shopping lover. The age more than 60, showed the largest values among all coefficients of this class. Comparing Indifferent consumers to traditional shoppers showed that, having a Bachelors' degree, a high income, spending between 1 to 5 hours on the internet, having a household of 2 persons, and living in a dense neighborhood increase the probability of labeling as an Indifferent consumer. While variables such as other ethnicities, being unemployed and self-employed, and having a senior in the household, reduce the probability of categorizing as indifferent consumers. Finally, the probability of being an Omnichannel consumer increase if the consumers are aged between 25 to 59, have an ethnicity except African American or white, come from a large size household, and live in a medium to small dense neighborhood. While, having a Masters' degree or a job status but full-time employed, and spending more than 10 hours on the internet. Being a student showed the largest value for the coefficient of the developed model for this class.

5.2.4. Discrete choice modeling

In this section, the results of developing HCM on the choice experiment designed in the survey are provided and discussed. As mentioned earlier, participants were asked to choose between four provided delivery services, regular delivery, ADR, CRWD, and APL, considering different delivery times, costs, time windows, and commodity types. Preliminary results showed that the majority of participants prefer regular delivery over other innovative delivery methods investigated in this study. **Table 12** presents the percentage of selecting different delivery modes, irrespective of the delivery time, cost, time window, and commodity types for the entire data set and for each latent class. As this table shows, regular delivery is selected 29.85% of the time. ADR is in the second place with 26.30% and APL and CRWD are in the third and fourth place with 24.81% and 19.04% selection, respectively. Comparing the selection percentages of different classes shows that, Traditional shoppers, E-shopping lovers, and Indifferent consumers, rather regular delivery over other delivery modes. While Benefit seekers and Omnichannel consumers, have selected ADR as their choice more than other delivery modes. After regular delivery, APL was the second most selected delivery mode for Traditional shoppers, Benefit seekers, and Omnichannel consumers.

Table 12: Percentage of selecting different delivery modes by each class.

Delivery mode	**Entire data set**	**Class 1** Traditional shoppers	**Class 2** Benefit seekers	**Class 3** E-shopping lovers	**Class 4** Indifferent consumer	**Class 5** Omnichannel consumers
Regular delivery	**29.85%**	**37.67%**	25.89%	**29.92%**	**39.46%**	23.01%
ADR	26.30%	19.05%	**29.29%**	28.74%	20.78%	**30.36%**
CRWD	19.04%	18.05%	18.77%	19.33%	19.10%	19.84%
APL	24.81%	25.23%	26.05%	22.02%	20.66%	26.79%

Table 13 presents the results of developing HCM to evaluate the effectiveness parameters on the delivery mode selection. This table provides the coefficients and the t-value for the delivery time, time window, cost, commodity type, and the interaction between cost and commodity types

for ADR, CRWD, and APL, considering regular delivery as the base. Also, the coefficients of each attitude measure, ITU, PB, PR, and PEU are provided in this table. In addition to **Table 13**, the estimation results of the measurement equation for latent variables are provided in **Appendix B**.

Based on the results of HCM, as it was expected, an increase in delivery time has negative effects on the selection of delivery modes. In this regard, 1-2 business days and 5 business days were the delivery time options while the same day Among all classes, E-shopping lovers, and Omnichannel consumers showed the largest coefficients for the delivery time, showing that these two classes of consumers consider the delivery time more on their decision than other types of

Table 13: Results of discrete choice modeling.

Variable	**Class 1** Traditional shoppers	**Class 2** Benefit seekers	**Class 3** E-shopping lovers	**Class 4** Indifferent consumer	**Class 5** Omnichannel consumers
Delivery time					
1-2 Business Day	-0.45 (-3.8)***	-0.44 (-2.74)**	-0.42 (-1.35)	1.1 (3.05)**	-1.08 (-3.29)**
5 Business Day	-0.82 (-6.8)***	-0.74 (-3.16)**	-1.48 (-4.46)***	-0.84 (-1.99)*	-1.34 (-3.9)***
Time window (Base: daytime, 9 am to 5 pm)					
2-hr choice	0.03 (0.34)	0.09 (0.48)	0.6 (2.2)*	-0.03 (-1.06)	0.36 (1.3)
Delivery Cost (Base: regular delivery)					
Cost × ADR	-0.37 (-3.3)***	-0.18 (-2.07)*	-0.28 (-1.67).	-0.33 (-2.36)*	-0.14 (-0.74)
Cost × CRWD	-0.36 (-4.6)***	-0.27(-3.5)***	-0.45 (-3.9)***	-0.22 (-2.52)*	-0.22 (-1.98)*
Cost × APL	-0.13 (-0.69)	-0.09 (-0.88)	-0.03 (-0.25)	-0.1 (-0.74)	-0.15 (-1)
Commodity type (Base: grocery)					
Electronic × ADR	-1.08 (-1.49)	-3.44 (-2.61)**	-0.67 (-0.31)	0.07 (0.03)	-2.93 (-1.24)
Electronic × CRWD	-0.04 (-0.06)	-2.48 (-1.83).	-0.63 (-0.36)	3.47 (1.51)	-1.01 (-0.47)
Electronic × APL	2.37 (3.58)***	1.84 (1.46)	2.71 (1.58)	3.78 (2.11)*	4.41 (2.13)*
Fashion × ADR	1.56 (2.06)*	0.48 (0.37)	2.15 (0.98)	5.5 (1.82).	0.09 (0.04)
Fashion × CRWD	-0.31 (-0.45)	-2.28 (-1.69).	1.45 (0.82)	1.51 (0.7)	1.64 (0.84)
Fashion × APL	3.31 (4.87)***	1.45 (1.13)	6.79 (3.66)***	2.37 (1.24)	5.04 (2.43)*
Health & Beauty × ADR	1.86 (2.4)*	-0.45 (-0.34)	3.29 (1.37)	0.51 (0.21)	5.04 (1.86).
Health & Beauty × CRWD	-0.56 (-0.81)	-3.11 (-2.14)*	-0.85 (-0.46)	-1.74 (-0.9)	-0.64 (-0.31)
Health & Beauty × APL	2.99 (4.43)***	2.47 (1.86).	4.4 (2.35)*	6.38 (3.15)**	4.42 (2.1)*
Interaction effect, cost × commodity (Base: regular delivery and grocery)					
Cost × Electronic × ADR	-0.01 (0.64)	-0.23 (-1.97)*	-0.05 (-0.24)	-0.09 (-0.39)	-0.25 (1.12)
Cost × Electronic × CRWD	-0.07 (-1.24)	-0.12 (-1.11)	-0.09 (-0.63)	-0.53 (-2.1)*	-0.04 (0.23)
Cost × Electronic × APL	-0.18 (-2.85)**	-0.17 (-1.38)	-0.17 (-1.04)	-0.31 (-1.72).	-0.37 (-2.01)*
Cost × Fashion × ADR	-0.2 (-2.58)**	-0.11 (-0.9)	-0.23 (-1.01)	-0.76 (-2.3)*	0.01 (0.03)
Cost × Fashion × CRWD	-0.12 (-2.1)*	-0.13 (-1.26)	-0.02 (-0.12)	-0.28 (-1.41)	-0.18 (-1.05)
Cost × Fashion × APL	-0.3 (-4.42)***	-0.17 (-1.37)	-0.68 (-3.41)***	-0.24 (-1.16)	-0.46 (-2.44)*
Cost × Health & Beauty × ADR	-0.21 (-2.74)**	-0.08 (-0.61)	-0.36 (-1.46)	-0.22 (-0.83)	-0.52 (-1.8).
Cost × Health & Beauty × CRWD	-0.12 (-2.13)*	0.18 (1.61)	-0.24 (-1.44)	-0.34 (-1.81).	0 (0.01)
Cost × Health & Beauty × APL	-0.32 (-4.8)***	-0.25 (-1.89).	-0.48 (-2.36)*	-0.72 (-3)**	-0.33 (-1.7).
Latent Variable					
Intention To Use (ITU)	0.82 (2.31)**	0.31 (1.02)	0.21 (0.96)	0.89 (3.21)**	1.09 (4.06)***
Perceived Benefits (PB)	0.7 (2.10)**	0.41 (1.5)	0.17 (0.35)	0.12 (0.26)	0.46 (1.52)
Perceived Risk (PR)	-0.67 (-1.91)*	-1.87 (-3.8)***	-0.08 (-0.12)	0.81 (2.23)**	1.19 (4.85)***
Perceived Ease of Use (PEU)	0.39 (0.93)	0.53 (1.7).	0.17(0.32)	1.21 (3.5)***	0.62 (1.83).

consumers. Indifferent consumers showed the only positive coefficient for the delivery time, where when the delivery time is 1-2 business days, the probability of selecting a delivery mode is more compared to the same-day delivery. The delivery time window showed a positive effect on the delivery selection of the participants, except for Indifferent consumers. However, the 2-hr time window only showed a significant effect on the decision made by E-shopping lovers.

The delivery cost is the next variable evaluated in this study. In order to evaluate the separate coefficients was defined the model, each presenting one delivery mode. Generally, the cost of delivery has a negative effect on the selection of a delivery option. For the ADR, the effect of cost showed a significant effect on the decision made by all latent classes, except, Omnichannel consumers. The largest coefficient belongs to the Traditional shoppers, showing that with increases in the cost, this class of consumer will lose their interest on ADR first. On the other, the decision on the selection of ADR by Omnichannel is not affected by the cost of the service. However, the cost plays significant role in the selection of CRWD as the delivery mode, as all the coefficients were significant. The E-shopping lovers showed the largest coefficient among the latent classes. By looking at the **Table 13**, the effect of cost on the selection of APL does not have any significant effect. Compared to other delivery methods the coefficients of the cost for APL have smaller values, showing that the cost is not a very effective parameter in the selection of APL.

Considering the effects of commodity types, the probability of selecting ADR by Traditional shoppers over regular delivery increases if the commodity types is fashion or health and beauty. However, the coefficients of CRWD were negative for all commodity type compared to the grocery. However, the effects of commodity types were positive for all categories. While the largest positive coefficient in this latent class belonged to APL and for the fashion-related products. For the Benefit seekers class, prefer ADR for grocery shopping, as all the coefficients for other product types were negative. Generally, all latent classes prefer to have APL for any products except grocery, as the coefficients of electronics, fashion, and health and beauty were positive in all latent classes.

6.0 CONCLUSION

This project followed two goals. First, this project aimed to propose a comprehensive modeling framework that simultaneously addresses e-commerce demand and package delivery demand, considering various factors and parties involved. It also seeks to fill gaps in the literature related to the impact of locational factors, level of service, and infrastructure on e-commerce and delivery preferences. Furthermore, this project aimed to compare consumer preferences for different delivery modes and proposed a choice-modeling approach that accounts for consumer heterogeneities and attitudes. In order to fulfill the first goal, an MDCEV model was incorporated to indicate the determinant of online shopping and delivery type choices and rates. The results from the analysis of the MDCEV model provided valuable insights into individual choices regarding online shopping preferences, including the decision to purchase products online or in-store, as well as the preference for home delivery or pick-ups. Age was found to have a negative effect on online shopping, with older participants showing less interest in pick-ups and preferring home deliveries. Gender had varying effects across different products and delivery services. Ethnicity also played a role, with African Americans showing different preferences for home delivery and pick-ups based on the product category. Education and income had limited effects on online shopping probabilities, except for higher-income individuals having a higher chance of home delivery for fashion products. Working from home increased the probability of home deliveries, while hybrid work environments decreased it. Household factors such as car ownership, household size, the presence of seniors or individuals with special needs, and having a delivery subscription all influenced the likelihood of online orders. Locational variables had a relatively low impact, with population density positively affecting home delivery grocery purchases in urban areas but the presence of health and beauty stores reducing the probability of online purchases for those products. Overall, these findings contribute to a better understanding of consumer preferences and decision-making processes in the context of e-commerce and last-mile delivery.

Also, analyzing the online shopping rate revealed several key findings regarding online shopping behavior. Age was a significant factor, with older individuals less likely to make online purchases. Gender influenced preferences, with females preferring home delivery for groceries, health and beauty, and fashion while showing less interest in electronics and pick-up services. Ethnicity had varying effects, with African Americans favoring home delivery for fashion and other ethnicities showing negative influences on online orders. Education had limited effects, except for those with higher degrees showing a higher likelihood of home delivery for electronics, groceries, and health and beauty products. Higher-income levels correlated with increased online shopping, particularly for electronics and fashion, but a negative association with grocery and other pick-ups. Working from home increased home delivery for various products, while hybrid work arrangements increased pick-up orders. Internet usage positively impacted online orders. Household factors showed that car ownership reduced online shopping rates, larger households had more online orders, and having a senior member decreased home delivery for electronics and health and beauty products. Members with special needs increased the likelihood of online orders. Subscribing to a delivery service had a strong positive effect on home delivery, especially for fashion-related orders. Locational variables indicated that population density influenced home delivery orders for groceries, fashion, and other products, while grocery and fashion pick-up orders increased in densely populated areas. The density of health and beauty shops reduced online orders, while similar store density increased orders for electronics and fashion. Post office density positively correlated with online orders. These findings provide valuable insights for businesses and policymakers to optimize e-commerce and last-mile delivery services by catering to consumer preferences.

To address the second goal of this project, an HCM approach was selected to evaluate and compare consumers' delivery mode preferences and their willingness to pay for new delivery methods. The proposed model classified consumers into 5 latent classes based on their shopping preferences statements and behavior. These classes are labeled as Traditional shoppers, Benefit seekers, E-shopping lovers, Indifferent consumers, and Omnichannel consumers. Class membership analysis showed distinct consumer classes based on age, ethnicity, income, education, employment status, internet usage, household size, and neighborhood density. Benefit seekers were more likely to be middle-aged with higher education, living in populated households, while E-shopping lovers had higher income, education, and spent more time online. Indifferent consumers had higher education and income, while Omnichannel consumers were middle-aged, from larger households, and lived in medium to small dense neighborhoods.

The analysis of the choice experiment revealed that the majority of participants preferred regular delivery over innovative methods such as ADR, CRWD, and APL. Traditional shoppers, E-shopping lovers, and Indifferent consumers showed a preference for regular delivery, while Benefit seekers and Omnichannel consumers were more inclined towards ADR. The delivery time had a negative impact on the selection of delivery modes, with E-shopping lovers and Omnichannel consumers being the most affected. Delivery cost also played a role, with higher costs leading to a lower likelihood of selecting ADR and CRWD. Commodity types influenced the choice of delivery mode, with Traditional shoppers preferring ADR for fashion and health/beauty products, and all classes showing a preference for APL except for groceries. Overall, these findings provide valuable insights into consumer preferences and can inform the development of effective last-mile delivery strategies.

This study incorporated the MDCEV modeling approach for the demand modeling section, future studies can consider incorporating MDCENV models which incorporated nested framework in their modeling procedure. By doing so, more insight might be obtained regarding the determinant of online shopping and delivery demands. This project compared consumers' preferences on three different delivery modes, ADR, CRWD, and APL to regular delivery, future studies can consider other delivery methods, such as drones, overnight delivery, and bike couriers. In addition, this study incorporated Intention to Use (ITU), Perceived Benefits (PB), Perceived Risk (PR), and Perceived Ease of Ues (PEU) to evaluate consumers' attitudes toward new delivery modes, future studies can use other attitude assessment models and constructs.

7.0 APPENDIX A

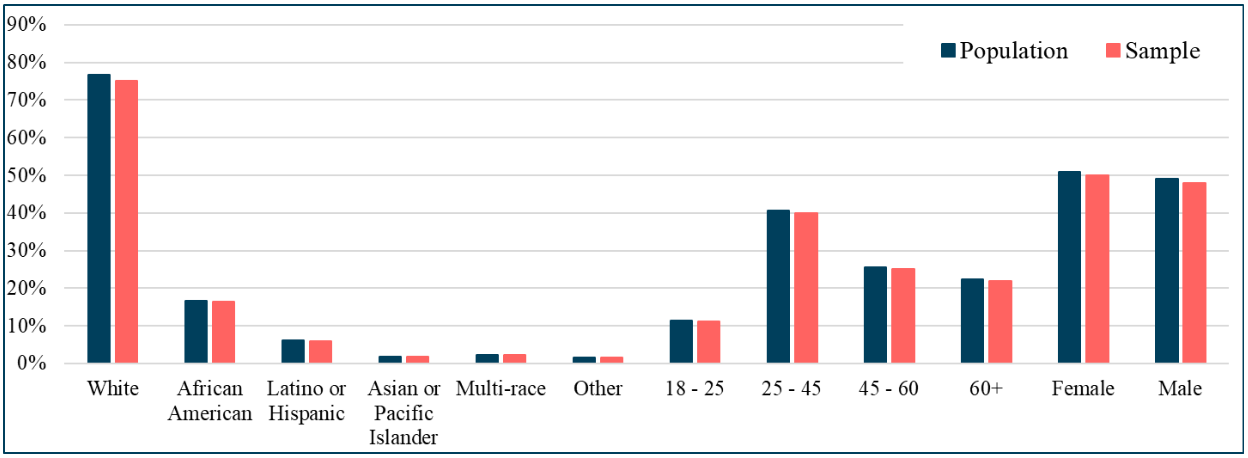


Figure 6. Comparison of survey sample with the target population.

8.0 APPENDIX B

Table 14: Estimation results of the measurement equation for latent variable.

Measurement	Estimate	Threshold parameters (τ)			
		$K = 1$	$K = 2$	$K = 3$	$K = 4$
ITU1	1.61 (3.1)	-3.13 (-3.19)	-5.8 (-3.36)	-3.1 (-2.12)	0.72 (2.4)
ITU2	1.54 (2.8)	-2.42 (-3.31)	-4.69 (-3.9)	-2.63 (-2.81)	0.01 (0.28)
ITU3	1.56 (3.64)	-3.96 (-3.51)	-4.94 (-3.78)	-1.91 (-2.65)	0.92 (3.39)
ITU4	1.77 (3.23)	-4.05 (-3.01)	-5.29 (-3.41)	-3.1 (-2.57)	-0.12 (-0.66)
PB1	1.15 (2.17)	-3.27 (-3.6)	-3.44 (-3.17)	-0.58 (-1.39)	1.74 (3.68)
PB2	1.21 (3.18)	-3.02 (-3.22)	-3.78 (-3.24)	-1.08 (-1.7)	1.37 (3.15)
PB3	1.71 (2.48)	-3.73 (-2.86)	-4.38 (-3.91)	-0.84 (-1.37)	1.65 (3.97)
PB4	1.82 (2.81)	-2.72 (-3.05)	-3.99 (-3.42)	-0.75 (-2.9)	1.21 (2.21)
PR1	1.07 (2.82)	-3.21 (-3.8)	-5.25 (-3.34)	-1.6 (-3.36)	1.23 (2.93)
PR2	1.11 (2.49)	-3.59 (-2.46)	-5.78 (-7.7)	-1.23 (-1.14)	1.46 (2.99)
PR3	-1.51 (-3.91)	-1.12 (-2.93)	0.59 (2.77)	3.2 (4.01)	5.16 (4.1)
PR4	1.06 (3.41)	-0.79 (-2.76)	0.91 (3.33)	1.96 (2.52)	4.22 (4.52)
PEU1	0.89 (3.48)	-1.79 (-3.79)	-1.03 (-4.04)	0.13 (0.44)	2.53 (5.05)
PEU2	1.51 (2.6)	-0.89 (-1.5)	-0.53 (-0.89)	1 (1.97)	4.6 (3.47)
PEU3	1.31 (2.1)	-1.13 (-2.19)	-1.8 (-3.36)	-1.1 (-1.12)	0.72 (1.4)

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