Transportation Research Part E 197 (2025) 104067

Contents lists available at ScienceDirect

Transportation Research Part E

journal homepage: www.elsevier.com/locate/tre

Evaluating consumer shopping, delivery demands, and last-mile preferences: An integrated MDCEV-HCM approach

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ARTICLE INFO

Keywords:
E-commerce Demand Modeling
Last-mile Delivery
Autonomous Delivery Robots
Crowdsourced Delivery
Automated Parcel Lockers

ABSTRACT

The effective implementation of innovative last-mile delivery approaches depends on understanding two key elements: (i) consumer demand (who places an online order, where, and how) and (ii) consumers' delivery needs and preferences. This study, first, proposes a disaggregated online demand modeling framework utilizing Multiple Discrete-Continuous Extreme Values (MDCEV) to estimate consumer shopping behavior and households' home delivery and pick-up demands across different commodity types. Second, a Hybrid Choice Model (HCM) is introduced to assess the competitiveness of three innovative last-mile delivery modes, (i) Autonomous Delivery Robots, (ii) Crowdsourced Delivery, and (iii)Automated Parcel Lockers, considering consumer attitudes toward these technologies. Subsequently, we conduct elasticity analysis for cost and commodity type, revealing consumers' Willingness-to-Pay for various last-mile delivery methods. The proposed framework is applied to a dataset acquired through an online survey distributed among residents of the State of Tennessee, USA. Analyzing results show that consumers can be categorized into five latent segments according to their shopping preferences: traditional shoppers, benefit seekers, e-shopping enthusiasts, omnichannel consumers, and Indifferent customers. Results indicate that businesses should focus on delivery time for e-shopping enthusiasts and omnichannel consumers, while accessibility to APLs may encourage traditional shoppers and benefits seekers to transition to online shopping. Also, latent variable analysis shows that while perceived risk hinders adoption, perceived benefits and ease of use drive acceptance. The findings of this study highlight the importance of a tailored approach to adopting innovative delivery solutions, ensuring a balance between cost, accessibility, and consumer priorities to meet evolving demands.

1. Introduction

E-commerce has witnessed exponential growth worldwide over the past two decades. The COVID-19 pandemic has further accelerated this trend, solidifying online shopping as an integral part of our daily lives (Figliozzi and Unnikrishnan, 2021a; Pani et al., 2020; Riahi Samani et al., 2024; Unnikrishnan and Figliozzi, 2020). However, this surge has created significant challenges for retail and logistics companies in meeting consumers' increasing delivery expectations. Addressing these challenges necessitates the development and implementation of innovative delivery methods (Filiopoulou et al., 2022; Pani et al., 2023), which itself requires a

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https://doi.org/10.1016/j.tre.2025.104067
Received 10 April 2024; Received in revised form 2 March 2025; Accepted 4 March 2025
Available online 16 March 2025

comprehensive understanding of e-commerce demand and consumer delivery preferences. Moreover, a critical comparison of these methods is required to identify those that align most closely with consumer preferences and operational efficiency.

In recent years, a variety of delivery methods have emerged, including – but not limited to – automated parcel lockers, crowdsourcing, reception boxes, pick-up points, autonomous delivery robots, and drones. However, researchers, urban planners, and logistic specialists are confronted with a critical question: which of these innovative solutions will prove to be most effective? (Boysen et al., 2021). The effectiveness of these methods is contingent upon their performances and the level of consumer engagement (Ma et al., 2022). Existing literature has significantly contributed to enhancing the understanding of the performance of delivery methods (Alves et al., 2022; Bhattarai et al., 2020; Ghelichi and Kilaru, 2021; Glick et al., 2022; Lemardelé et al., 2021; Seghezzi et al., 2022) and their adoption and acceptance (Kim and Wang, 2022; Koh et al., 2023; Pani et al., 2020; Simpson et al., 2019, 2022; Simpson and Mishra, 2021; Zhou et al., 2020). While the literature provides valuable insights into the adoption of emerging delivery methods, previous studies primarily analyze individual delivery methods in isolation. There remains a gap in comprehensively comparing different delivery methods to uncover consumer preferences across diverse delivery options. To bridge this gap, this study assesses and compares the consumers' preferences and potential demand for four major delivery modes: traditional delivery, sidewalk Autonomous Delivery Robots, crowdsourced delivery, and automated parcel lockers. Each of these methods exhibits unique attributes and potential to reshape the last-mile delivery. These methods are likely to see widespread adoption, primarily thanks to significant investments from major logistics companies (Alverhed et al., 2024; Elsokkary et al., 2023; Pani et al., 2022; Ranjbari et al., 2023; Talebian and Mishra, 2018, 2022).

In addition, an accurate understanding of e-commerce demand and consumer delivery preferences is foundational to successfully implementing these innovative strategies (Liatsos et al., 2024; Mishra et al., 2022; Mirzanezhad et al., 2022). This requires a disaggregated modeling approach capable of capturing the complexity of real-world shopping behaviors (Kim and Wang, 2022). Such a model should encompass customer characteristics (e.g., income, education, race, and household lifecycle), shopping alternatives (e.g., in-store versus online), and delivery options (e.g., home delivery or pick-up) across multiple commodity categories (e.g., groceries, electronics, fashion, etc.). However, the current literature lacks such a comprehensive and detailed demand model, primarily due to limitations in data availability. A robust demand modeling framework can provide critical insights into consumer behavior and inform the development of logistics solutions.

The objective of this study is twofold. First, we develop a disaggregated e-commerce demand model that comprehensively assesses consumer shopping and delivery preferences for different commodity types. Second, we evaluate and compare the consumers' preference of various delivery methods. By offering a detailed analysis of consumer preferences and delivery performances, this study aspires to enrich the discourse on innovative delivery solutions and provide actionable insights for the future of logistics in the e-commerce era.

The remainder of the paper is organized as follows. In the subsequent section, we provide a comprehensive review of the literature concerning e-commerce demand modeling and consumer delivery preferences. This review will serve as the basis for highlighting research gaps and contributions of the paper. In Section 3, we delve into our data collection process and provide descriptive statistics of the gathered data. Section 4 elaborates on the methodologies underlying the Multiple Discrete-Continuous Extreme Values and Hybrid Choice Model. Section 5 presents our results, followed by discussions in Section 6. In Section 7, we conclude the paper by presenting a summary of major findings and outlining directions for future research.

2. Literature review

2.1. E-commerce demand modeling

Significant efforts in the literature have focused on developing e-commerce demand models and examining explanatory variables. These investigations primarily addressed user-related factors (i.e., individual, household, and locational variables) or delivery service characteristics. Wang and Zhou (2015) conduced a pioneering study using binary choice and right-censored negative binomial models to predict the delivery frequency based on the data from the 2009 U.S. National Household Travel Survey (NHTS). Their results indicated that individual and household attributes, such as race, education level, household size, and income, were more influential than locational factors such as population density. Subsequent research has continued to explore the impact of socio-demographic variables on e-commerce demand (Figliozzi and Unnikrishnan, 2021b). Age emerged as a critical factor, with older individuals generally less inclined to engage in online shopping compared to younger ones (Ding and Lu, 2017; Schmid and Axhausen, 2019a; Melović et al., 2021; Hermes et al., 2022). Some studies found ethnicity to be significant, noting a higher propensity for online shopping among white individuals. Unnikrishnan and Figliozzi (2020) studied the impacts of COVID-19 on home deliveries, where they observed higher e-commerce usage among tech-savvy individuals. Additionally, education level was found to be an effective variable in explaining online deliveries, with a greater likelihood of placing online orders by individuals with higher levels of education (Irawan and Wirza, 2015; Lopez Soler et al., 2021; Le et al., 2022).

Van Droogenbroeck and Van Hove (2017) investigated the adoption of online grocery shopping within a Belgian supermarket chain and found a stronger reliance on household-level factors in customers' decisions compared to individual-level factors. Stinson et al. (2019) proposed a household-level e-commerce model to predict both participation in e-commerce and the ratio of delivery to in-store shopping. Their results showed that households with high-incomes, more adults, and low accessibility to retail stores are more likely to place online orders. Furthermore, evidence suggests that households with income above the poverty line are nearly twice as likely to make online purchases compared to those below it (Federal Highway Administration, 2018). Similarly, higher-income households exhibit a stronger preference for online shopping (Schmid and Axhausen, 2019a; Fabusuyi et al., 2020; Kim and Wang, 2022, 2021).

The likelihood of online purchases also increases with the use of smartphones, the internet, and laptops (Wang and Zhou, 2015; Ding and Lu, 2017; Schmid and Axhausen, 2019a). Variables representing household structure, such as the number of driver license holders, vehicle ownership, and the presence of workers, affect online shopping frequency (Dias et al., 2020; Fabusuyi et al., 2020; Figliozzi and Unnikrishnan, 2021b; Shah et al., 2021).

Additionally, locational characteristics play a significant role in shaping e-commerce demand (Samani and Amador-Jimenez, 2023; Sousa et al., 2020). For example, Loo and Wang (2018) observed that proximity to subway stations and shopping centers significantly influences online shopping duration. Using a negative binomial regression model, Fabusuyi et al. (2020) estimated online package delivery rates across micro-analysis zones and discussed variations across areas. The results highlight the effect of population density on the rates. Similarly, Cheng et al. (2021) underscored the importance of urbanization level, transit availability, and shopping accessibility in determining e-commerce demand. However, our review of the literature on locational factors yields mixed results, with findings varying according to specific case studies (Farag et al., 2007; Zhou and Wang, 2014; Cheng et al., 2021).

Moreover, some studies have focused on the effect of delivery service attributes on e-commerce demand. Among all, Nguyen et al. (2019) assessed customer preferences for online shopping, considering price, time- and convenience-oriented, and value-for-money variables. They identified the delivery fee as the most influential factor. Sakai et al. (2022) employed an agent-based urban freight simulation model to predict e-commerce demand based on household characteristics and delivery options. Their framework simultaneously predicts total e-commerce expenditure, order value, delivery mode, and option choices. The authors underscored the significance of delivery service attributes in shaping online shopping demand, outweighing the influence of user-related factors.

2.2. Consumer delivery preferences

The concept of Autonomous Delivery Robots (ADRs) is rapidly gaining traction in last-mile logistics, with companies such as DHL, UPS, and Amazon already implementing the technology (Hoffmann and Prause, 2018). However, mass adoption requires to comprehend and address consumers' needs, motivations, and expectations (Srinivas et al., 2022). While the deployment of ADRs is increasing, there remains a notable gap in research focused on consumer acceptance (Koh and Yuen, 2023). Relevant to this, Kapser et al. (2021) conducted structural equation modeling to identify factors influencing the behavioral intention to use ADRs. Their analysis revealed critical determinants including trust in technology, price sensitivity, innovativeness, performance expectancy, hedonic motivation, social influence, and perceived risk. Pani et al. (2020) also underscored the importance of understanding public acceptance of ADRs, particularly by examining customers' WTP during the COVID-19 pandemic, thus shedding light on the economic aspect of consumer acceptance. Most recently, Koh and Yuen (2023) studied consumers' intention to adopt ADRs from both health and technology perspectives, which also contribute to a broader comprehension of the factors that drive consumer acceptance in this domain.

Crowd-shipping (CRWD) is an emerging package delivery method that leverages non-professional drivers to transport packages from warehouses, stores, or fulfillment centers to end customers. This model operates by matching individuals requiring package delivery with drivers with available vehicle capacity and willingness to undertake the tasks (Punel et al., 2018). Recent studies have explored various aspects of CRWD. For instance, Punel et al. (2019) identified demographic and environmental factors influencing CRWD adoption, including a higher likelihood among men, full-time employees, younger individuals, and in areas with higher population density and lower employment opportunities. Seghezzi et al. (2021) conducted a comparative analysis of the economic viability of urgent delivery crowdsourcing versus traditional logistics systems in an urban setting. Karli et al. (2022) investigated university students' perceptions toward CRWD and demonstrated that consumer acceptance is shaped by factors such as performance expectations, price sensitivity, social influence, and perceived risk. More recently, Yuen et al. (2023) studied customer loyalty toward CRWD using multiple theoretical frameworks including the unified theory of acceptance and use of technology, health belief model, perceived value theory, and trust theory.

Automated Parcel Locker (APL) is a technology-driven delivery method, enabling round-the-clock parcel retrieval through unmanned self-service terminals. Regarded as a promising solution for last-mile logistics in e-commerce, APLs enhance the delivery process by providing customers with flexibility in selecting preferred collection times and locations (Rossolov, 2021; Tsai and Tiwasing, 2021). De Oliveira et al. (2017) identified the potential APL users in Brazil and proposed an approach to incorporate consumer preferences into organizing last-mile delivery operations. In Italy, Mitrea et al. (2020) found that factors such as age, internet usage, car-sharing practices, and household size impact consumer adoption of APLs as an alternative to traditional home delivery. Drawing on theories of resource matching, innovation diffusion, and planned behavior, Tsai and Tiwasing (2021) further explored consumers' intention to use APLs. An et al. (2022) investigated consumer decisions to utilize parcel locker services while accounting for privacy concerns and perceptions through the lens of protection motivation theory and the technology acceptance modeling. Alves et al. (2022) developed an agent-based modeling framework to simulate and evaluate the implementation of APLs. In a more recent study, Jang et al. (2024) used structural equation modeling to investigate the psychological and latent factors influencing APL adoption. Their results emphasized the roles of perceived risk of Covid-19, perceived usefulness, perceived ease of use, and prior experience.

2.3. Literature gaps, study objectives, and contributions

Our review of the literature on consumers' shopping and delivery preferences reveals four major research gaps. First, there have been fewer studies addressing package delivery demand modeling, compared to shopping behavior modeling. This gap is largely due to limited data, which has prevented the development of a detailed demand model that integrates relevant parties, delivery options, and

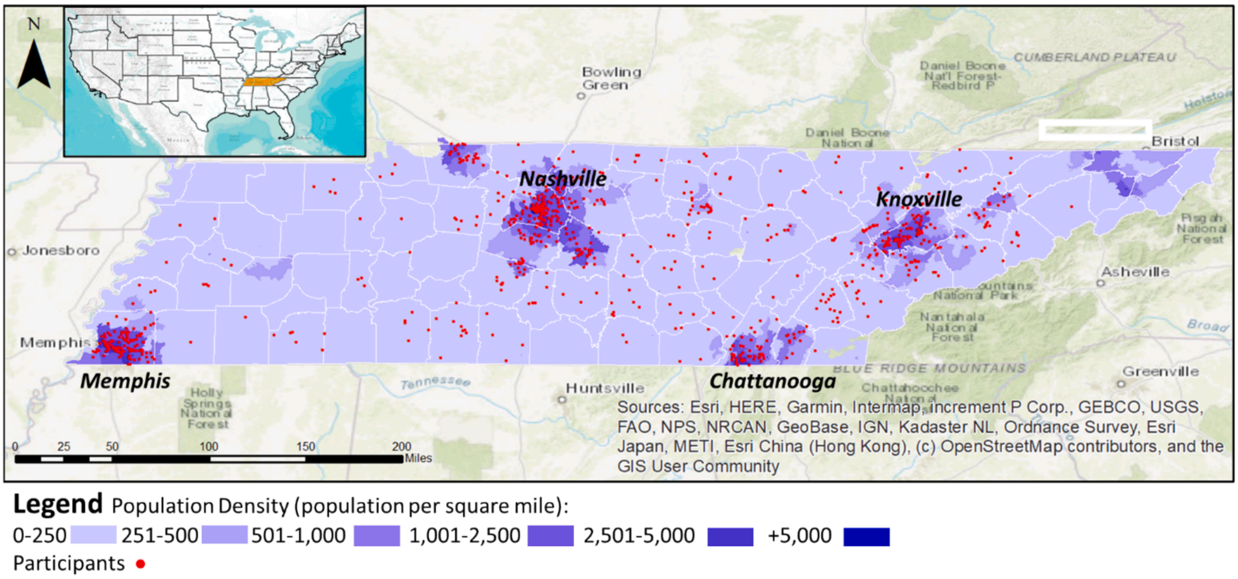

Fig. 1. Study area and the distribution of participants.

commodity types. Second, previous studies have primarily concentrated on evaluating consumer acceptance of an individual last-mile delivery service. However, it is crucial to simultaneously examine consumer preferences across various delivery modes for different commodities to effectively assess the competitiveness of each in distinct business sectors (e.g., food, retail, health, and entertainment). Third, the literature presents mixed insights regarding the impact of locational factors on e-shopping demand and delivery mode, highlighting the need for further research. Additionally, while factors such as neighborhood type (e.g., urban or rural) and population density have been incorporated into demand modeling, the evaluation of the level-of-service and state of infrastructure is insufficiently explored in the literature. The fourth gap involves methodological limitations. Previous studies mostly relied on discrete choice models. The commonly used modeling approach is based on Random Utility Maximization, where each decision-maker chooses the alternative with the highest utility, specified as a function of different household-level observed variables. Multinomial logit and its generalized variant (e.g., nested logit and cross nested logit) are frequently utilized to characterize consumer choices. However, attitudes and preferences, the actual choice set of an individual, and the decision-making mechanism may not be observed in the collected data.

In light of the identified gaps, this paper aims to achieve the following objectives:

1. Proposing a modeling framework that simultaneously addresses e-commerce and delivery demand for different commodity types while also considering in-store shopping behavior.
2. Evaluating the influence of neighborhood type, level-of-service, and state of infrastructure on shopping and delivery preferences for different commodity types.
3. Assessing competitiveness in innovative last-mile delivery options (i.e., ADR, CRWD, and APL). This assessment includes:
   - Analyzing how ADR, CRWD, and APL measure up against traditional delivery.
   - Conducting a comparative analysis of ADR, CRWD, and APL across various commodity types.
   - Investigating users' stated preferences and their willingness-to-pay for ADR, CRWD, and APL.
4. Propose a choice-modeling framework that accounts for the heterogeneities among consumers (latent segments), and consumer attitudes (latent variables) in the decision-making process. This framework integrates "hard information" (i.e., socio-demographic) and "soft information" (i.e., shopping preferences and attitudes).

Our study contributes to the literature by effectively answering the following research questions:

i. How can purchasing and delivery preferences of customers for different commodities be identified?
ii. What is the impact of the level-of-service and state of infrastructure on shopping and delivery preferences?
iii. What are latent variables in on-line shopping behavior?
iv. What are the marginal competitive advantages of different delivery modes for different commodities?

3. Data

This study utilizes survey data collected from residents of the State of Tennessee, USA, which had a population of 7,126,489 in 2023. Fig. 1 illustrates the study area and the distribution of participants. Approval for the Qualtrics survey instrument was obtained

Table 1
Attribute levels of the designed choice experiment.

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

* Only for APLs.

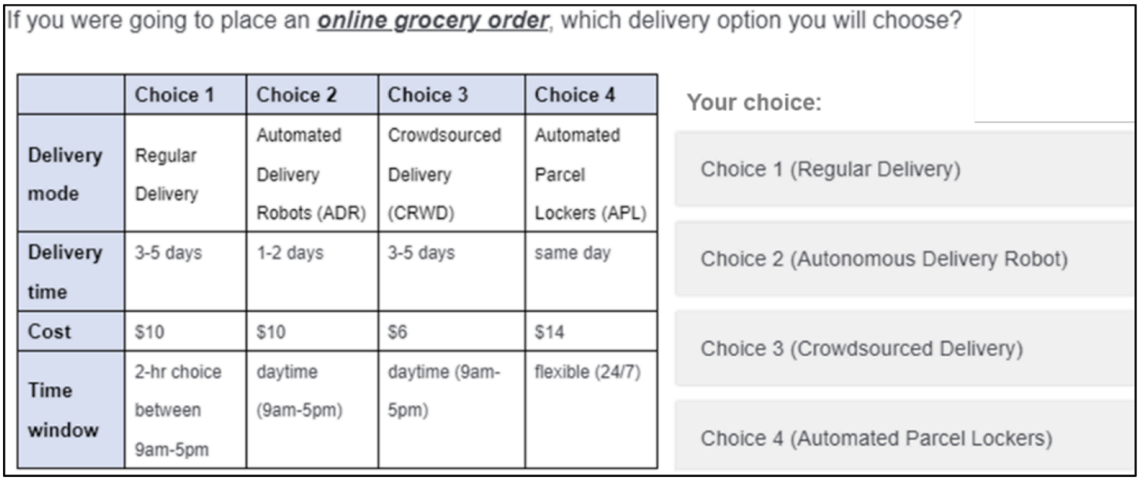

Fig. 2. A screenshot of one of the designed choice experiments.

from the University of Memphis Institutional Review Board (IRB#: PRO-FY2023-268). We developed a web-based survey questionnaire consisting of eight major sections. A market research firm was commissioned to collect responses from its consumer panel. Invitations to participate in the survey were extended to all panel members over the age of 18 residing in the study area.

3.1. Survey design

The designed survey consisted of eight sections, with the first part comprising the consent form. Participants were provided with preliminary information about the survey including data confidentiality, and incentives, along with screening questions to confirm their agreement to participate, age above 18, and residency in the study area. Only participants meeting these criteria proceeded to fill out the survey. The second section collected demographic and locational information at the individual level, while the third section gathered household-related information. In the fourth section, participants were briefed on new delivery methods (i.e., ADRs, CRWD, and APLs), including their appearance and the delivery process of each. The fifth section aimed to collect information on individuals' attitudes toward new technologies by measuring Individuals' Intention to Use (ITU), Perceived Benefits (PB), Perceived Risk (PR), and Perceived Ease of Use (PEU), each assessed using a five-point Likert scale. These factors were chosen due to their demonstrated effects in previous studies, their relevance to the adoption of innovative delivery services, and usefulness in facilitating comparisons across different delivery methods. In the sixth section, a choice experiment was conducted to collect information on participants' last-mile delivery preferences. This experiment included four attributes, as detailed in Table 1, with participants choosing among regular delivery, ADR, CRWD, and APL. Considering the four attributes and their respective levels, 40 scenarios (10 per commodity type) were selected from 144 possible scenarios employing a fractional factorial design. This method is recognized for its efficiency in exploring diverse attribute combinations while minimizing the overall number of scenarios. Following the factorial analysis, professional judgment was applied to ensure that the selected scenarios were realistic and relevant. To maintain the survey's manageable length while avoiding potential biases in the collected data, each participant was presented five randomly selected scenarios from the 40 designed. An example of these scenarios is presented in Fig. 2. The seventh section collected information regarding participants' shopping behavior, including the number of home deliveries, pick-ups, and in-store shopping for different commodity types in the last month, as well as the number of returned and failed deliveries. Finally, the eighth section was dedicated to collecting participants' shopping preferences.

3.2. Survey responses

The data collection period spanned from April and May 2023. Out of a total of 1,451 participants who initially agreed to participate in the study, 465 were deemed ineligible, did not complete the survey, or were excluded from the response pool due to in-survey

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

Variable (Categorical)				Frequency	Percentage
Age	18 to 24			137	13.87 %
	25 to 44			368	37.34 %
	45 to 59			253	25.65 %
	60 +			228	23.15 %
Ethnicity	White			758	76.85 %
	African American			153	15.48 %
	Others			76	7.66 %
Gender	Female			535	54.27 %
	Male			451	45.73 %
Education	High school or blow			414	42.02 %
	Bachelor's degree or equivalent			285	28.87 %
	Master's degree or higher			287	29.11 %
Income	Below $50,000			493	50.00 %
	$50,000 to $100,000			314	31.85 %
	More than $100,000			176	17.82 %
Employment status	Full-time employment			457	46.37 %
	Part-time employment			83	8.39 %
	Unemployed			146	14.84 %
	Retired			184	18.63 %
	Student			40	4.03 %
	Self-employed			76	7.74 %
Work status	Office			417	42.26 %
	Home			347	35.24 %
	Hybrid			185	18.79 %
Households size	One			180	18.23 %
	Two			340	34.44 %
	Three			206	20.89 %
	Four or more			268	27.18 %
Car ownership	none			69	7.02 %
	One			350	35.48 %
	Two			365	37.02 %
	Three or more			202	20.48 %
Hours spend on internet per day	Less than an hour			104	10.56 %
	1–5 h			449	45.56 %
	5–10 h			251	25.48 %
	More than 10 h			181	18.39 %
Having elderly (65 +) in household	No			730	74.03 %
	Yes			256	25.97 %
Having someone with special disease or disability	No			771	78.15 %
	Yes			215	21.85 %
Delivery subscription	No			334	33.87 %
	Yes			652	66.13 %
Population Density (Population per square mile)	less than 250 per square mile			343	34.76 %
	250—750 per square mile			223	22.66 %
	750 – 1,500 per square mile			175	17.74 %
	More than 1,500 per square mile			246	24.92 %
Continuous (Categorical)		**Min**	**Max**	**Mean**	**SD**
Demographic Info	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

quality violations. Consequently, 986 complete surveys were collected. This sample size surpasses the minimum requirement for the targeted population at a 99 % confidence level and a margin of error of ±5 %. In Appendix A, a comparison between the sample and census data is presented, demonstrating its representativeness in terms of age, ethnicity, and gender. Descriptive statistics for categorical and continuous variables in the survey are provided in Table 2. Additionally, neighborhood attributes such as population and facility densities were collected based on participants' locations using census data and InfoUSA data set. (InfoUSA offers comprehensive information on companies' characteristics ranging from local shops to global enterprises.) Additionally, we collected information on the number of home-delivery, pick-up, and in-store shopping trips made by each individual within the last month for five different commodity categories (i.e., grocery, electronic, health and beauty, fashion, and other). Fig. 3 illustrates an example question from the survey, inquiring about the number of home-delivery orders for different product types. This point should be mentioned here that even though grocery shopping/orders have distinct characteristics compared to other types of commodities, since the objective of this research is to conduct a comprehensive study on delivery demand and adoption across various commodity types, grocery items

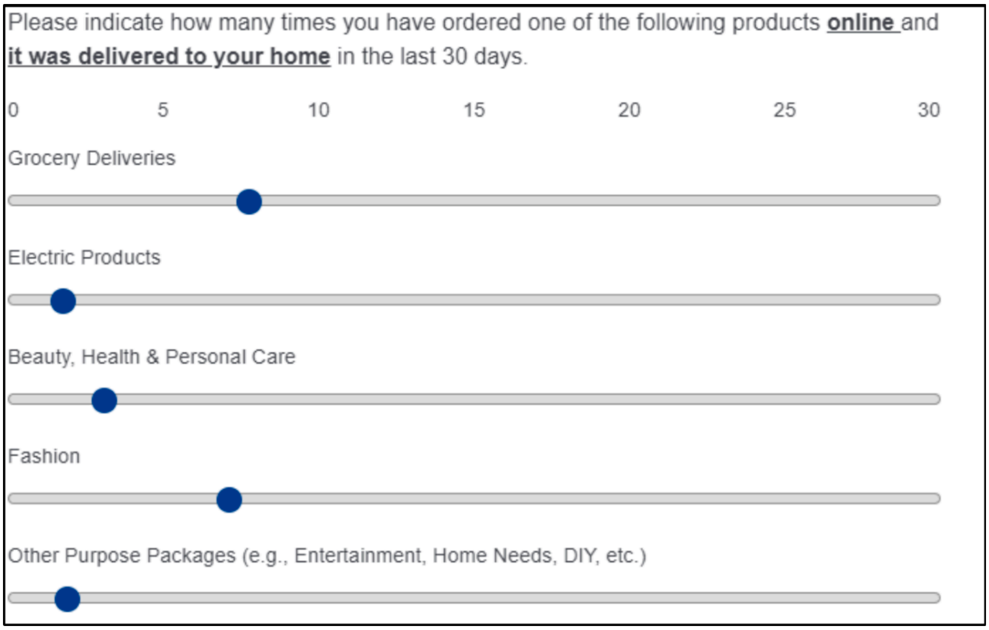

Fig. 3. Example question capturing the frequency of online home delivery made by individuals within the last 30 days.

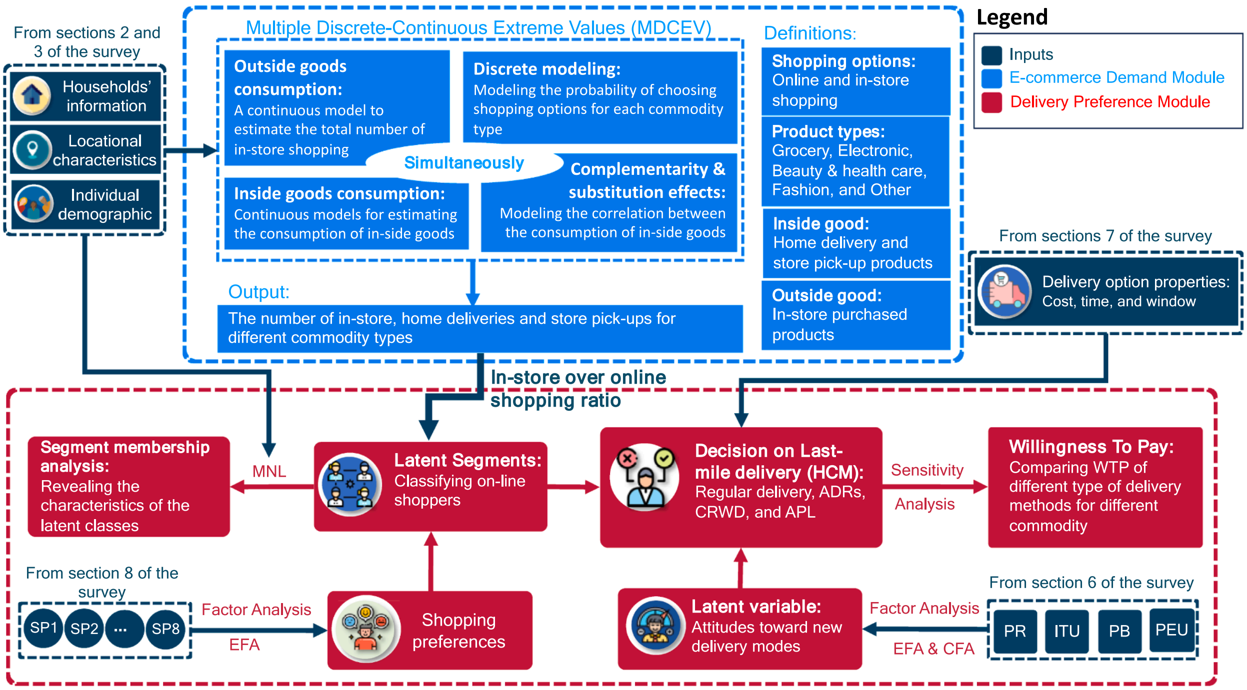

Fig. 4. Various components of the proposed modeling framework.

were included in our data collected and modeling process.

4. Methodology

Our modeling framework integrates two primary modules, as illustrated in Fig. 4. In the first module (labeled as the e-commerce demand module), we simultaneously model shopping and delivery preferences using an extended Multiple Discrete Continuous Extreme Value (MDCEV) approach to model individuals' purchase frequency of specific goods, both in-store and online, and whether these goods are delivered to their homes or picked up from stores. This model accounts for individuals' socio-demographic attributes,

Table 3
Table of notations.

	Notation	Description
E-commerce demand module	n	Individuals, $n = 1, 2, ..., N$
	k	Products, e.g., home delivered grocery shopping, $k = 1, 2, ..., K$
	x_{nk}	A vector containing the number of times individual n purchases each product k, $x_{nk} = [x_{n0}, \cdots, x_{nK}]$
	x_{n0}	The consumption of an outside good (i.e., total in-store purchase)
	b_{nk}	Price of product k for individual n
	B_n	Total budget available to individual n
	$u_0(x_{n0})$	Utility function for out-side goods
	z_{n0}	A column vector of characteristics influencing individual n's decision on consuming outside goods
	α	A row vector of parameters representing the weights of characteristics in z_{n0}
	$u_k(x_{nk})$	Utility function for in-side goods (i.e., online shopping for each commodity type)
	ψ_{nk}	Product k's base utility that can be interpreted as the scale of the utility of product k
	γ_{nk}	The quantity consumed of alternative k by individual n
	z_{nk}	Attributes of alternative k
	β_{nk}	The coefficients of attributes for alternative k and individual n
	$u_{kl}(x_{nk}, x_l)$	Utility function for the complementarity and substitution effects between in-side goods
	δ_{kl}	Complementarity/substitution parameter between products k and l, $\delta_{kl} = 0$ shows an independent consumption, $\delta_{kl} > 0$ indicates complementarity, and $\delta_{kl} < 0$ reveals substitution effect between alternatives k and l
Delivery preferences module	η_n	The latent variable vector for individual n
	X_n	A vector combining socio-demographic variables for individual n
	c	The coefficient vector for socio-demographic variables
	ω_n	The error term that follows a normal distribution across individuals
	I_{pn}	The response to the p^{th} latent variable indicator for individual n
	$\tau_{p_{(q-1)}}$	The q^{th} interval in the p^{th} indicator
	I^*_{pn}	Continuous latent variable for the p^{th} latent variable indicator
	η_{ln}	The l^{th} latent variable for individual n
	γ_{lp}	The coefficient of the latent variable l^{th}
	e_{pn}	The error term that follows a normal distribution
	i	Delivery method (i.e., regular, ADR, CRWD, and APL)
	P_{ni}	The unconditional probability of individual n belonging to delivery method i
	P_{ns}	The segment allocation probability
	$P_{ni\|s}$	The conditional choice probability of individual n belonging to segment s
	Z_n	The vector of characteristics determining probabilities of individual n belonging to segment s
	θ_s	The corresponding vector of parameters for Z_n
	X_{in}	The vector of observable characteristics determining discrete outcome n
	β_{is}	The vector of parameters for discrete outcome i and segment s
	U_{in}	The utility function to model latent segments
	ε_{in}	The error term that follows a normal distribution
	$E^{P(j)}_{v_{hj}}$	Elasticity of variable h on outcome j
	$P(j)$	the probability of outcome j
	v_{hj}	the value of variable h for outcome j
	λ_{hj}	the coefficient of variable h for outcome j

household-level information, and locational characteristics such as the level of accessibility to shopping facilities, neighborhood type, and infrastructure condition. The e-commerce demand module comprises four components: outside goods consumption, a discrete model, a continuous model, and complementarity and substitution effects. The output of this module provides the number of in-store, home delivery and store pick-ups for different types of commodities, which in turn is used to calculate the ratio of in-store to online shopping, an input for the second module.

In the second module, labeled as the delivery preference module, we leverage a Hybrid Choice Model (HCM) to assess individuals' preferences for various last-mile delivery options, accounting for socio-demographic factors, household characteristics, locational characteristics, shopping preferences, and personal attitudes. Here, shopping preferences are evaluated using a set of statements designed to capture participants' attitudes toward online and in-person shopping. We measure attitudes toward innovative delivery methods by examining individuals' Intention to Use (ITU), Perceived Risk (PR), Perceived Benefit (PB), and Ease of Use (EU). The following subsections provide detailed explanations of each module. Notations used in the paper are presented in Table 3.

4.1. E-commerce demand modeling using extended MDCEV

The multiple Discrete-Continuous method (MDC) is utilized to model the joint choice of multiple alternatives and their corresponding consumption quantities. In this study, we employ an extended version of this model, known as MDCEV, which incorporates the substitution and complementarity effects without imposing the budget constraint (Hausman et al., 1995). Substitution and complementarity delineate relationships between demand values for product pairs: an increase in the demand for one product may lead to a decrease in the demand for another in the case of substitution, while it may increase in the case of complementarity. For example, a rise in online grocery shopping may diminish in-store grocery purchases, yet a high frequency of grocery pickups may increase the likelihood of picking up other orders from stores. Determining a budget is necessary in the traditional MDC model, which can be challenging in certain scenarios, such as in our application. The model proposed by Palma and Hess (2022) alleviates the requirement for explicit budget availability by considering an implicit (or infinite) budget.

In the basic structure of the extended MDCEV model, an individual n selects product k (e.g., home delivered grocery shopping) to consume from a given set of alternatives such that his/her utility is maximized, subject to the budget constraint. Mathematically, this can be expressed as the following utility maximization problem:

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

$$subjectto x_{n0} b_{n0} + \sum_{k=1}^{K} x_{nk} b_{nk} = B_n \quad (2)$$

where $n = 1, 2, \ldots, N$ represents individuals, $k = 1, 2, \ldots, K$ denotes alternatives (i.e., various products), $x_{nk} = [x_{n0}, x_{n1}, \cdots, x_{nK}]$ is a vector containing the number of times that individual n purchases each alternative (product), t_{nk} represents the price of alternative k for individual n, and B_n is the total budget available to individual n, which is assumed to be very large (infinite). x_{n0} represents the consumption of an outside good, encompassing all consumption outside of the category of interest. In this study, total in-store purchase serves as the outside good. Additionally, this approach assumes the following functional forms for various parts of the utility functions, as specified by Bhat (2008):

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

$$u_k(x_{nk}) = \psi_{nk} \gamma_{nk} \log\left(\frac{x_{nk}}{\gamma_{nk}} + 1\right) \quad (4)$$

$$u_{kl}(x_{nk}, x_{nl}) = \delta_{kl}(1 - e^{-x_{nk}})(1 - e^{-x_{nl}}) \quad (5)$$

where, ψ_{nk} refers to alternative k's base utility, representing the marginal utility at zero consumption. The parameter γ_{nk} relates to consumption satiation by altering the curvature of alternative k's utility function. A higher value of γ_{nk} indicates a higher level of consumption of alternative k, if it is consumed at all. Parameters ψ_{nk} and γ_{nk} commonly determine the choice of alternative k and the quantity consumed, respectively. Parameters ψ_{no} and ψ_{nk} are determined according **Eqs. (6) and (7)** below:

$$\psi_{no} = e^{\alpha z_{n0}} \quad (6)$$

$$\psi_{nk} = e^{\beta_{nk} z_{nk} + \varepsilon_{nk}} \quad (7)$$

where z_{n0} is the column vector of characteristics of decision maker individual n, which is correlated with the individual's marginal utility of the outside good (i.e., total in-store shopping); α is the row vector of parameters representing the weights of these characteristics in the marginal utility of the outside good; z_{nk} denotes attributes of alternative k; β_{nk} represents the vector of parameters indicating their respective weights; and ε_{nk} is the random disturbance term.

Finally, $u_{kl}(x_{nk}, x_{nl})$ in **Eq. (5)**, captures the complementarity and substitution effects between in-side goods, here the number of home delivery and store pick-up. In Eq.5, δ_{kl} is called complementarity/substitution parameter. If $\delta_{kl} > 0$, there exists a complementarity effect between alternatives k and l, as this component will increase the overall utility. On the other hand, $\delta_{kl} < 0$ signifies a substitution effect between alternatives k and l, as u_{kl} decreases as x_{nk} and x_{nl} increase. If $\delta_{kl} = 0$, the consumption of both alternatives is independent of each other. For further details on the extended MDCEV with the implicit budget, readers are referred to Palma and Hess (2022).

4.2. Last-mile delivery preference modeling using HCM

HCM has evolved to explicitly incorporate individuals' attitudes and perceptions to enhance the behavioral representation of decision-making in choice modeling (Ben-Akiva et al., 2002). The structural model of the HCM elucidates the latent variable using observable qualities of the individual. In this study, the latent variable is evaluated considering four psychological factors: Intention to Use (ITU), Perceived Risk (PR), Perceived Benefits (PB), and Ease of Use (EU). We employ exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to conduct factor analysis. First, we perform EFA to explore factor dimensions and assess internal consistency. We then utilize Principal Component Analysis (PCA) to identify the most appropriate factor dimensions and evaluate the congruence between the data and theoretical framework.

Subsequently, a Multiple Indicators Multiple Causes model (MIMIC) is integrated to capture the latent variable. The MIMIC model is capable to identify indicators associated with psychological factors and diverse determinants of them (e.g., age or gender) (Ma et al., 2023). The MIMIC comprises two components: the structural equation model (**Eq. (8)** and the measurement equation model (**Eqs. (9) and (10)**:

$$\eta_n = cX_n + \omega_n \quad (8)$$

$$I_{pn} = \begin{cases} 1 & if(-\infty) < I_{pn}^{*} \leq \tau_{p1} \\ 2 & if\tau_{p_1} < I_{pn}^{*} \leq \tau_{p2} \\ & \vdots \\ q & if\tau_{p_{(q-1)}} < I_{pn}^{*} \leq \infty \end{cases} \tag{9}$$

where,

$$I_{pn}^{*} = \sum_{l} \gamma_{lp} \cdot \eta_{ln} + e_{pn} \tag{10}$$

In **Eq. (8)**, η_n*is* the latent variable vector for individual n; X_n is a vector combining socio-demographic variables for individual n; c is the coefficient vector to be estimated; and ω_n represents the error term that follows a normal distribution across individuals (i.e., ω_n $N(0, 1)$). In **Eq. (9)**, I_{pn} is the response to the p^{th} latent variable indicator for individual n and $\tau_{p_{(q-1)}}$ is the q^{th} interval in the p^{th} indicator. In **Eq. (10)**, I_{pn}^{*} is the continuous variable that contains the l^{th} latent variable for individual n (η_{ln}) and its corresponding coefficients (γ_{lp}) and the normally distributed error term e_{pn}.

In addition to the latent variable, a latent class structure is incorporated to account for the heterogeneity among online shoppers. In a latent class model, observations are segmented into S distinct classes (or segment), each characterized by a specific set of parameters. We note that the terms 'class' and 'segment' are used interchangeably throughout this paper. The unconditional probability of individual n belonging to delivery service i can be calculated as follows:

$$P_{ni} = \sum_{\forall S} P_{ns} P_{ni|s} \tag{11}$$

This probability is computed using two components**:** the segment allocation probability (P_{ns}), which is estimated in **Eq. (12)**, and the conditional choice probability ($P_{ni|s}$), expressed by **Eq. (13)**. The segment allocation probability is estimated by Z_n, which is the vector of characteristics determining probabilities of observation n belonging to segment s, and θ_s is the corresponding vector of parameters which should be estimated. θ_s Essentially captures the heterogeneity among different shopper groups. The conditional choice probability estimated in **Eq. (13)**, is referred to as the probability of discrete outcome i, for observation n, which is a member of unobserved segment s. In **Eq. (13)**, β_{is} is the vector of parameters for discrete outcome i and segment s, and X_{in} is the vector of observable characteristics determining discrete outcome n.

$$P_{ns} = \frac{\exp(\theta_s Z_n)}{\sum_{\forall S} \exp(\theta_s Z_n)} \tag{12}$$

$$P_{ni|s} = \frac{\exp(\beta_{is} X_{in})}{\sum_{\forall I} \exp(\beta_{is} X_{in})} \tag{13}$$

Taking into account **Eqs. (11) to (13)**, the latent class model can be expressed through a utility function that outlines i possible discrete outcomes. Considering the error term ε_{in}, the utility functions is formulated in **Eq. (14)**, following Washington et al. (2020):

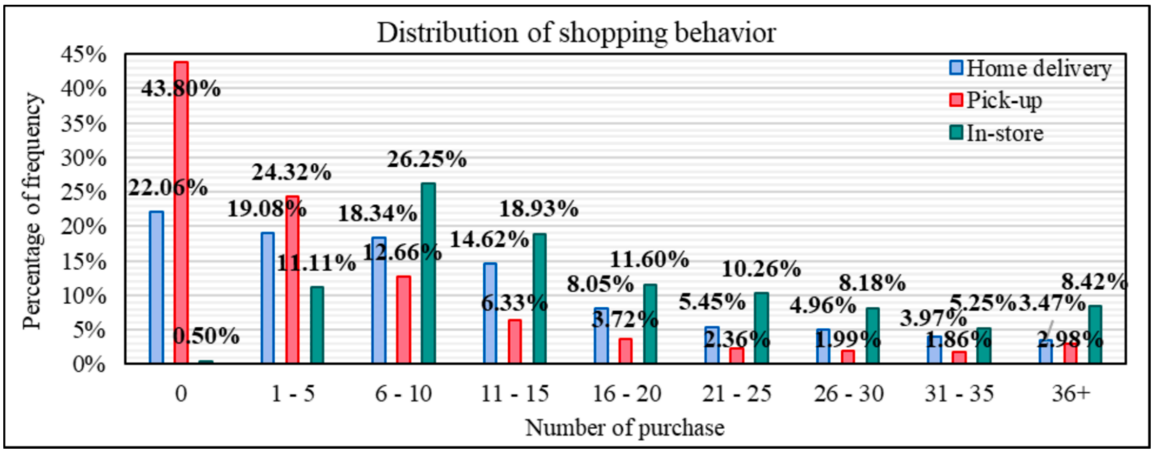

Fig. 5. The distribution of monthly purchases of participants (While reporting more than 36 pick-ups or home deliveries per month may seem uncommon, we retained these records as they passed our rigorous quality control checks. Moreover, the questionnaire specifically asked respondents to report on the last 30 days (rather than an average over time). This could make it plausible for some individuals to have high counts of pick-ups or home deliveries, especially given the survey's statewide distribution).

Table 4
The mean and standard deviation (in parenthesis) of monthly purchases of participants.

Commodity type	Home delivery	Pick-up	In-store
Grocery	2.14 (4.05)	2.46 (4.45)	8.51 (6.93)
Electronic	1.46 (3.11)	0.86 (2.08)	1.31 (2.63)
Health and beauty	2.42 (3.27)	1.32 (2.76)	4.02 (4.52)
Fashion	3.02 (4.26)	1.25 (3.13)	2.72 (3.96)
Other (e.g., entertainment, home needs, DIY, etc.)	3.93 (4.89)	1.65 (3.28)	4.25 (5)
All types	10.6 (12.25)	5.76 (8.15)	16.1 (17.35)

$$U_{in} = \beta_{is} X_{in} + \varepsilon_{in} \tag{14}$$

5. Results

In this section, we provide the results of modeling e-commerce demand using MDCEV, followed by the findings from consumer last-mile delivery acceptance modeling using HCM.

5.1. Demand modeling

Fig. 5 illustrates the distribution of household purchases per month across various shopping channels, including online (home delivery and pick-up) and in-store shopping. The data reveals that only 22.06 % of participants reported zero online home delivery, while this figure increases to 43.80 % for pick-up services. Remarkably, less than 1 % of participants indicated no in-store shopping activity. Moreover, 80 % of participants had fewer than 15 pick-up orders in the last month, fewer than 25 home-delivered orders, and about 30 in-store shopping orders. Furthermore, to offer deeper insights into participants' shopping behavior, Table 4 presents the mean and standard deviation of monthly purchases across different commodity types. Notably, the average frequency of in-store grocery shopping is nearly four times higher than home delivery and pick-ups. Conversely, for electronic products, participants made more purchases via home delivery than through other channels, with participants averaging 1.46, 0.86, and 1.31 electronic purchases via home delivery, pick-up, and in-store shopping, respectively. Similarly, in the case of health and beauty products and other miscellaneous items (e.g., entertainment, home essentials, and do-it-yourself (DIY) supplies), in-store shopping tends to be more prevalent. However, participants, on average, completed more home deliveries, than in-store shopping for fashion products.

5.1.1. Simultaneous modeling of product purchase and quantity

The MDCEV model addresses two key questions simultaneously: which product and individual will select to purchase, and how much? Given our primary focus on modeling e-commerce demand, the number of in-store shopping occurrences is modeled as the outside good. The results, including parameter estimates and t-stats, obtained from applying the MDCEV are presented separately. Table 5 presents the discrete choice part of the MDCEV, followed by the result of the continuous part in Table 6. Lastly, Table 7 provides the estimates related to outside goods (in-store shopping behavior), complementarity, and substitution parameters. The numbers in these three tables represent the variable coefficients, with the t-values shown in parentheses. Additionally, the missing values in Tables 5 and 6 indicate that the corresponding variables were either insignificant or led to a model with poor goodness-of-fit.

Table 5 provides insights into the factors influencing individuals' preferences for purchasing different commodity types, considering three alternatives: "online-home delivery", "online-pickups" and "in-store". Age exhibits a negative impact on online shopping, with negative coefficients observed for both home delivery and pick-up across all commodity types. Notably, older consumers show less interest in pick-ups, compared to home deliveries, as indicated by larger negative coefficients of age for pick-up services. The largest negative effect of age is observed for other products and pick-ups. Gender effects vary across products and delivery methods, with females exhibiting lower likelihood of purchasing electronics online (both home-delivered and pick-up), but higher likelihood of opting for home deliveries for health and beauty, fashion products, and pick-ups for other items. Ethnicity also plays a role, with African Americans displaying preferences for home delivery of fashion products and pick-ups for electronics, health and beauty, and fashion, while preferring home deliveries over pick-ups for fashion items. Other ethnicities tend to prefer in-store shopping over online orders, evidenced by negative coefficients. Education levels show mixed effects, with bachelor's degree negatively impacting home delivery of other products, while Master's or higher degrees increases the likelihood of home-delivered electronic products. Income demonstrates a positive significant effect on the probability of fashion home delivery. Additionally, working from home increases the likelihood of home delivery compared to pick-up, particularly for electronics, health and beauty, and other products. However, hybrid work arrangements reduce the probability of home deliveries.

Focusing on household characteristics, car ownership shows a positive correlation with the possibility of opting for pick-up services. An increase in the number of cars corresponds to a higher likelihood of choosing pick-up. Similarly, household size exhibits positive impact on the likelihood of having at least one home-delivered grocery, electronic, and health and beauty items. Additionally, the probability of selecting grocery and other pick-up orders rises with household size. The presence of seniors in the household reduces the probability of engaging in online grocery shopping, both for home-delivered and pick-ups options, as well as for home-delivered fashion items. Conversely, having a delivery subscription demonstrates the most substantial positive effect on the probability of availing at least one home delivery across all product types. Notably, the coefficients of delivery subscription are particularly

Table 5
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										
Male	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)
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+										
Num. of post offices+			0.29 (2.03)							

[*] Continuous variables.
[+] Per square mile; Numbers in parentheses are t-values.

Table 6
Results of developing the MDCEV model for online shopping demand (Continuous part).

Variables	Home delivery					Pick-up from store				
	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										
Male	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)
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 h		0.93 (1.46)			0.63 (1.16)					
5–10 h	1.06 (3.15)	1.68 (2.28)			1.61 (2.18)		2.59 (3.2)		1.8 (3.53)	
Car ownership										
None	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)	0 (NA)
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)		
Presence of seniors in household										
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)		

(continued on next page)

Table 6 (*continued*)

Variables	Home delivery					Pick-up from store				
	Grocery	Electronic	H & B	Fashion	Other	Grocery	Electronic	H &B	Fashion	Other
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)			
Num. of post offices+					0.83 (2.83)			0.68 (2.28)		0.87 (2.69)

* Continuous variables.
+ Per square mile; Numbers in parentheses are t-values.

Table 7
Estimates for outside goods (in-store shopping), complementarity, and substitution.

Variable		Estimates (t-stats)
Outside goods parameter (α)	Age	3.81 (6.97)
	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)
Complementarity and substitution (δ)	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 others vs Pick-up other	0.15 (6.8)
	Home delivery others 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	(8.2)

Note: Numbers in parentheses are t-values.

prominent for health and beauty products, followed by groceries.

In Table 5, locational variables are examined as the final group of variables. Overall, their effects on the probability of making online orders are relatively modest. Population density exhibited a positive impact on home delivery of grocery purchases, indicating a higher likelihood of urban areas compared to rural areas for placing such orders. Conversely, the density of health and beauty stores reduces the probability of purchasing these products online. Participants tended to fulfill their health-related needs in-store when such services are available locally. Furthermore, an increase in the number of grocery stores translates into the greater probability of online grocery purchases. Contrarywise, as the number of fashion-related stores increases, participants are less inclined to place online orders and pick up from stores. Notably, the density of fashion stores displays the largest negative coefficient among variables related to the level-of-service.

Table 6 presents the result of the continuous section of the MDCEV model, focusing on the determinants of the number of online purchases a household makes in 30-day period (i.e., monthly consumption rate). Similar to the discrete part, age emerges as the most important variable, exerting a negative effect on the number of monthly online purchases. Unlike in-store shopping, online purchase frequency reduces with age. Females exhibit higher rates of home-delivered grocery and health and beauty products as well as fashion pick-ups, but fewer online orders of electronic items and other product pick-ups. African Americans demonstrate a positive effect on the number of home-delivered fashion items, while other ethnicities show significant negative effects on most types of online orders and delivery services, with the largest impact observed in grocery pick-ups. Education level exhibits significant effects only for individuals with a Master's degree or higher, where positive coefficients are observed for home-delivered electronics, groceries, and health and beauty pick-ups. Income level also influences online shopping, where income is positively associated with home-delivered electronics and fashion, as well as fashion pick-ups. However, high-income participants exhibit negative effects on the number of grocery and other product pick-ups. Work status yields interesting findings, as working from home increases home delivery rates for groceries, electronics, fashion, and other product types, while reducing pick-up frequency. Conversely, hybrid work arrangements increase pick-up rates, particularly for groceries and other products, while decreasing the number of home-delivered grocery and electronic orders. Lastly, individuals who spend more time surfing the internet tend to place more online orders, with electronic pick-ups showing the largest effect among all variables.

The subsequent set of determinants in Table 6 pertains to household characteristics. An increase in the number of cars owned by a household correlates with reduced online shopping rates, particularly evident in home-delivered groceries and fashion as well as electronic pick-ups. Household size emerges as the most influential parameter affecting online order rates, with direct impact on the number of online orders of household size. Notably, households with four or more members exhibit larger coefficients compared to smaller households. This aligns with our expectations, as larger households typically have greater consumption needs. Our observation holds true across all delivery services and commodity types. In comparison to pick-ups, household size has a more significant impact on home delivery, evident from the magnitude of coefficients. The presence of senior members in a household negatively impacts the number of home-delivered electronics and health and beauty, as well as electronic pick-ups. However, if a household member is disabled or has a specific medical condition, the likelihood of home delivery increases for groceries, health and beauty items, and other products, underscoring the importance of accessible delivery services. As anticipated, households with delivery subscriptions show higher home delivery rates, with fashion displaying the largest coefficient.

Regarding neighbourhood conditions, population density shows positive effects on the number of home-delivered groceries, fashion items, and other products. Additionally, the number of grocery and fashion pick-ups increases in more populated areas. These results suggest that urban areas witness higher online order volumes, compared to rural areas, values of the coefficients are relatively modest. In general, the density of various facilities in the neighbourhood positively correlates with the online purchases of the corresponding product type, except for health-related items. Interestingly, increases in the density of health and beauty shops lead to reduced home delivery and pick-up orders for health-related items. The largest positive coefficient is observed for grocery pick-ups concerning the density of grocery stores, which aligns with the expectations that grocery pick-up orders are closely tied to the availability of grocery stores. Similarly, the number of online orders for electronics and fashion items increases with the density of similar stores in the neighborhood. Lastly, the density of post offices shows a direct correlation with online orders for other products and pick-ups of health and beauty items.

Table 7 first presents the estimates for coefficients affecting in-store shopping behavior, denoted by α in Eq. (6). Participants' age and their location are considered to model outside goods consumption component. The rate of in-store shopping increases with age, with age showing the largest and most significant coefficient. Additionally, participants living in areas with higher population density and a greater number of grocery and fashion stores tend to shop more in-store, suggesting that urban residents generally make more purchases compared to those in rural areas. The share of in-store shopping is also higher in regions offering better service levels and welfare. Conversely, participants in areas with a higher density of post offices, electronics stores, and health-related stores exhibit lower rates of in-store shopping.

Moreover, Table 7 provides estimates for δ in Eq. (5), the parameter offering insights into the interaction effects between the consumption of different online shopping options. A negative coefficient signifies that an increase in the use of one option leads to a decrease in the other, while a positive coefficient indicates a complementary relationship where the use of one option enhances the consumption of the other. Table 7 highlights a negative relationship between home-delivery and pick-up options for groceries, electronics, and fashion items, suggesting that with an increase of home-delivery orders, pick-up orders for these categories decrease. While, for products in the other category, an increase in home-delivered orders is associated with a rise in pick-up orders. Furthermore, there are notable positive correlations between pick-up options for beauty and fashion items, as well as between electronics and other products in the pick-up segment.

5.2. Last-mile delivery method adoption

In the following subsections, we first present the results of factor analysis, elucidating the selection process for latent variable measurement. Following this, we delve into the analysis of latent segment allocation and segment membership to identify distinct consumer segments. Subsequently, we present the findings of the discrete choice model, followed by a discussion on the competitive analysis of various delivery modes and consumers' WTP.

Table 8
Results of conducting Exploratory Factor Analysis (EFA) for attitude measurements.

Item	Reference	Factor loading	Cronbach's alpha	Mean	SD
ITU1	Chawla and Joshi (2019)	0.772	0.816	4.166	0.613
ITU 2	Agarwal and Prasad (1998)	0.698		4.354	0.565
ITU 3	Yuen et al. (2018)	0.889		4.161	0.596
ITU 4	Yuen et al. (2018)	0.827		4.044	0.589
PB1	Wang et al. (2021)	0.698	0.713	3.868	0.633
PB2	Venkatesh et al. (2003)	0.633		3.886	0.688
PB3	Zhou et al. (2020)	0.584		4.095	0.523
PB4	Müller (2019)	0.691		4.237	0.522
PR1	Zhou et al. (2020)	0.717	0.786	3.934	0.66
PR2	Zhou et al. (2020)	0.722		4.09	0.663
PR3	Zhou et al. (2020)	0.681		4.017	0.647
PR4	Featherman and Pavlou (2003)	0.779		3.217	0.782
PEU1	Escobar-Rodríguez and Carvajal-Trujillo (2014)	0.846	0.769	4.577	0.393
PEU2	An et al. (2022)	0.636		4.079	0.56
PEU3	Müller (2019)	0.742		4.467	0.41

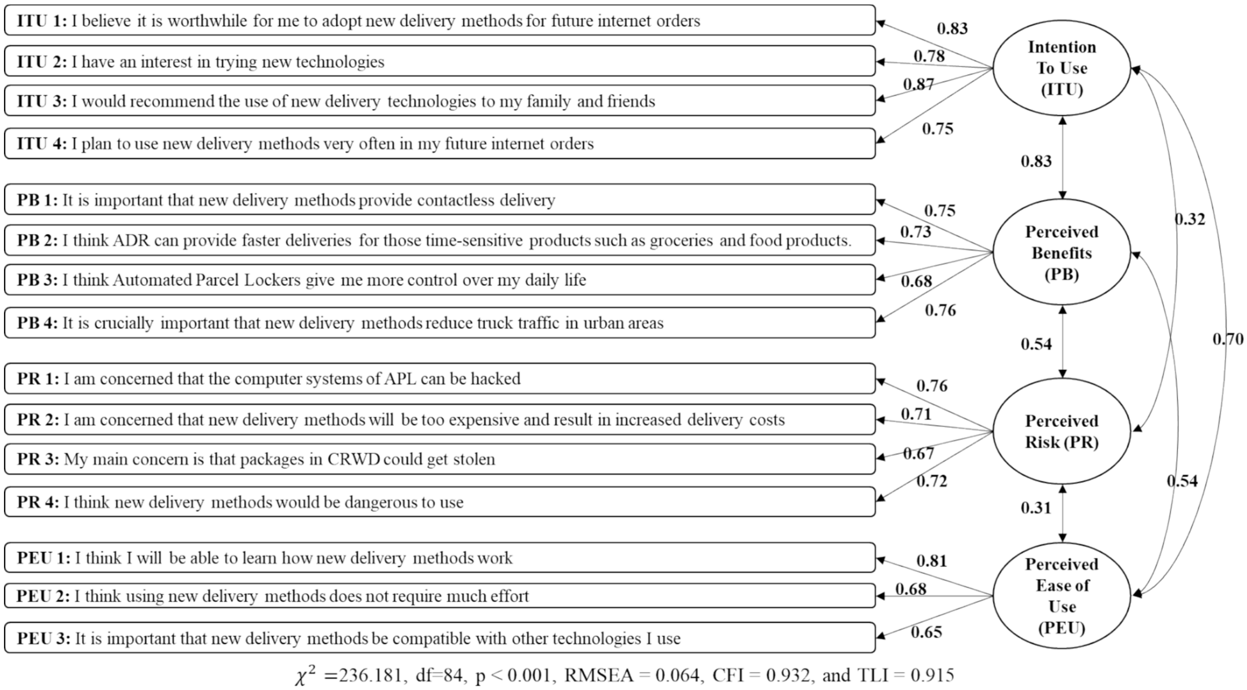

Fig. 6. Confirmatory factor analysis results.

5.2.1. Factor analysis

In this section, we present the results of factor analyses, encompassing those of EFA and CFA. Table 8 displays the outcomes of EFA, featuring Cronbach's alpha, factor loadings, and the source from which each statement was derived from. A Cronbach's alpha greater than 0.7 indicates robust internal consistency among latent constructs, while factor loadings higher than 0.5 denote a strong fit. Items with factor loadings below 0.50 are excluded. Each item identified by EFA corresponds to a unique latent variable, with the highest factor loadings aligned with the respective latent variable. Additionally, CFA is employed to evaluate measurement model fit and refine measurement items for the constructs of latent variables, including ITU, PB, PR, and PEU. Fig. 6 illustrates the items associated with each construct and the CFA results. The criteria for adequate fit are an RMSEA of <0.6, and CFI and TLI values greater than 0.9. The model test yields the following results: $\chi^2 = 236.181$, $df = 84$, $p < 0.001$, $RMSEA = 0.064$, $CFI = 0.932$, and $TLI = 0.915$,

Table 9
Shopping preferences measurements and EFA results.

Item	Description of the statement	Reference	Factor loading	Mean	SD
SP1	*"I like not having to leave home when shopping"*	Pani et al. (2020); Swinyard and Smith (2003)	0.742	2.608	1.404
SP2	*"I like the helpfulness available at local stores"*	Pani et al. (2020); Swinyard and Smith (2003)	0.711	3.159	1.416
SP3	*"I don't want to give my credit card number to a computer"*	Huseynov and Özkan Yıldırım (2019); Mutum and Ghazali (2006)	0.690	3.505	1.240
SP4	*"I feel internet shopping is easier than in-person shopping at local stores"*	Pani et al. (2020); Mutum and Ghazali (2006)	0.698	2.816	1.203
SP5	*"I think Internet shopping has delivery problems"*	Ishak et al. (2023)	0.861	3.546	1.258
SP6	*"I prefer Internet shopping since I can save time"*	Pani et al. (2020); Mutum and Ghazali (2006)	0.673	2.821	1.396
SP7	*"I do not trust online shops for expensive purchases"*	Swinyard and Smith (2003)	0.749	2.608	1.404

Table 10
Model fit statistics where the number of segments is varied from one to seven.

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

Table 11
Response probabilities of latent segments to attitudinal statements.

Statement and responses	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5
	Traditional shoppers	Benefit seekers	E-shopping enthusiasts	Indifferent consumers	Omnichannel consumers
Segment 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**

indicating a satisfactory fit.

5.2.2. Identifying latent consumer segments

To classify consumers into latent segments, we first employ a class allocation model that accounts for their shopping preferences and the ratio of in-store over online shopping behaviors as primary criteria. A series of statements was used to evaluate consumers' shopping preferences, with the details and sources of each statement listed in Table 9. Additionally, the results of EFA analysis (factor loadings) are presented to elucidate the strength and direction of the relationship between items and the underlying latent factor, i.e., shopping preference. Consumer shopping preferences were assessed using a five-point Likert scale.

A set of latent class models is estimated by varying the number of segments from one to seven to identify the appropriate number of consumer segments, as detailed in Table 10. The optimal number of latent segments is determined using the Bayesian Information Criterion (BIC), a model selection measure that evaluates the goodness-of-fit while penalizing models for complexity to avoid over-fitting. A lower BIC indicates a better goodness-of-fit. Based on the observed variation in BIC values, a five- segment solution was

Table 12
Segment membership functions of the latent class model with *Traditional shoppers* as the reference category, showing coefficients (t-value).

Variable	Segment 2	Segment 3	Segment 4	Segment 5
	Benefit seekers	E-shopping enthusiasts	Indifferent consumers	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 h	2.64 (1.72).	1.89 (2.76)**	1.9 (1.35)	0.49 (1.28)
5–10 h	2.22 (1.49)	1.19 (2.78)**		
More than 10 h		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)	

$p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and .$^{***}p < 0.001$

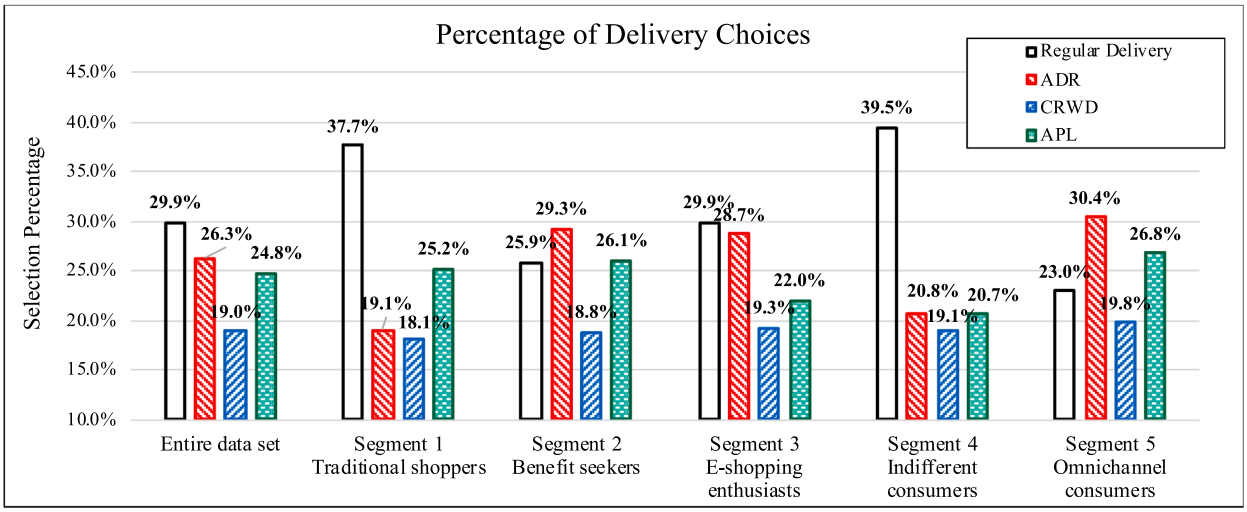

Fig. 7. Percentage of selecting different delivery modes by each segment.

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en-

Table 13
Results of discrete choice modeling.

Variable	Segment 1	Segment 2	Segment 3	Segment 4	Segment 5
	Traditional shoppers	Benefit seekers	E-shopping enthusiasts	Indifferent consumers	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)**	−1.5 (−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: regular delivery and 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)	−1.47 (−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 (5.66)***	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 (−3.4)***	−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).	−0.001 (−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)	0.91 (2.96)**	0.89 (3.21)**	1.09 (4.06)***
Perceived Benefits (PB)	0.7 (2.10)**	0.41 (1.5)	0.77 (2.31)**	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 (−2.2)**	−1.19 (−4.8)***
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).

$p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, and $.^{***}p < 0.001$

tified as optimal. The estimated probabilities of stated shopping preferences and shopping behaviors (instore/online shopping ratio) are used to define and assign labels to each latent segment. These probability values, which are presented in Table 11, are the bases for classification and labeling process by showing the most distinctive characteristics (e.g., firm opinions and attitudes) of each latent segment. The extracted latent segments are labeled as Segment 1: Traditional shoppers; Segment 2: Benefit seekers; Segment 3: E-shopping enthusiasts; Segment 4: Indifferent consumers; and Segment 5: Omnichannel consumers. The average membership probabilities for these latent segments are 24.06 %, 21.30 %, 19.15 %, 6.86 %, and 28.63 % respectively.

The five latent segments are characterized as follows:

- *Segment −1: Traditional shoppers:* As the label suggests, consumers in this latent segment exhibit a preference for traditional shopping behavior, primarily shopping in physical stores. This inclination is evident from their in-store/online shopping ratio and their responses to shopping preference statements. Nearly all consumers in this group engage in more in-store shopping than online shopping, with over 57 % of consumers opting for in-store purchases twice as often as on-line purchases. Additionally, over 40 % of consumers strongly favor the helpfulness of physical stores, express reluctance to trust online shopping for expensive purchases (∼43 %), are hesitant to provide their credit card number online (∼49.42 %), and perceive online shopping as prone to delivery issues (∼45 %).
- *Segment −2: Benefit seekers:* Consumers in this group show a propensity to leverage the advantages of both online and in-store shopping. Their response probabilities indicate a balanced preference, with no dominance in either category, reflected in similar in-store/online ratios. Also, these consumers express a strong appreciation for the helpfulness of local stores (∼31 %), value the time saved through online shopping (∼39 %), and appreciate the convenience of shopping from home (∼43 %). However, approximately 43 % of these consumers harbor concerns regarding delivery issues associated with online shopping.
- *Segment −3: E-shopping enthusiasts:* This group earns the label "E-shopping enthusiasts" primarily due to their shopping behavior as they are the only segment in which the majority engage in more online shopping than in-store. They express preferences such as appreciating the convenience of shopping from home (∼53 %), dissatisfaction with the helpfulness of local stores (∼30 %), willingness to provide credit card information online (∼52 %), belief that online shopping is easier than in-store (∼45 %),

recognition of time-saving benefits with on-line shopping (~50 %). Also, 38 % of consumers in this segment trust online platforms for expensive products.

- *Segment –4: Indifferent consumers:* The consumers in this segment predominantly show indifferent attitudes toward shopping preference questions, often responding neutrally in the survey. accounting for approximately 7 % of the total consumers, they primarily prefer purchasing their needs through physical stores, as indicated by their in-store/online shopping ratio.
- *Segment –5: Omnichannel consumers:* The final latent segment comprises omnichannel consumers, constituting the largest group in the data set with approximately 29 % of participants assigned to this segment. The shopping behavior of this group demonstrates a mixture of preferences. While the majority of consumers exhibit a higher probability of engaging in in-store shopping, a significant portion (~20 %) also show a propensity for online shopping. They appreciate the convenience of shopping from home (~30 %) while also valuing the helpfulness provided by local stores (~29 %). However, they express a lack of trust in on-line shopping for expensive products (~42 %).

5.2.3. Segment membership analysis

To further elucidate the characteristics of the five latent segments, we develop a Multinomial logit model (MNL) to assess segment memberships. The results are presented in Table 12, comparing consumers' memberships to traditional shoppers across various demographic and socioeconomic factors such as age, ethnicity, income, internet usage, household size, and neighborhood population density. Our findings reveal that compared to traditional shoppers, the probability of being classified as benefit seekers increases among consumers aged 45 to 59, with an income ranging from $50,000 to $100,000 and high internet usage, possessing a Master's degree or higher, residing in low- to medium-density neighborhoods, living in populated households, and having a senior in the

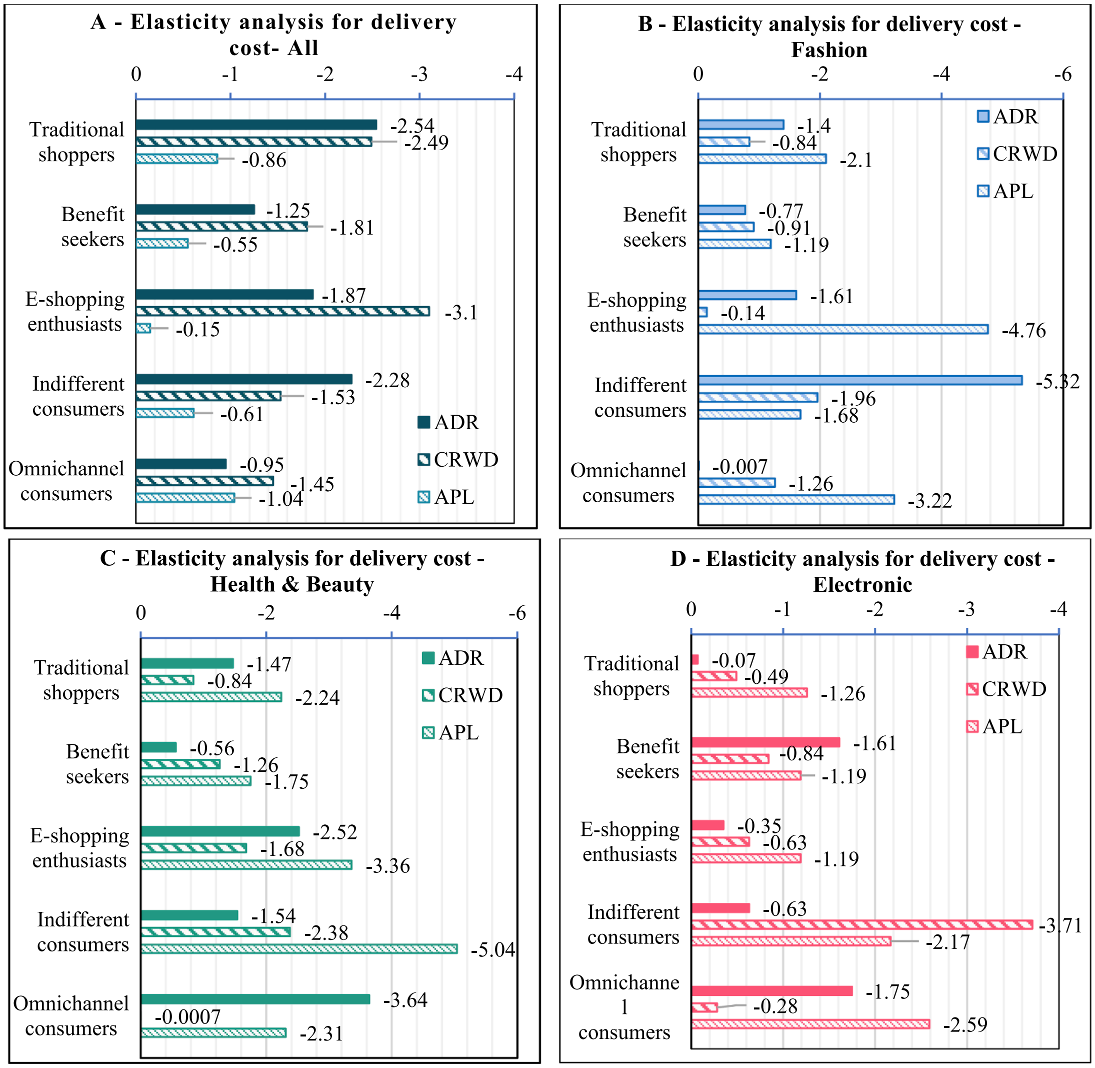


Fig. 8. Elasticity analysis for cost and various commodity types.

household. Conversely, factors such as African-American ethnicity or belonging to other ethnicities, retired status, higher salary, possession of a Bachelor's degree, and residing in a dense neighborhood decreases the probability of belonging to the benefit seekers segment.

E-shopping enthusiasts tend to belong to higher salary brackets, possess higher educational qualifications, have higher internet usage, live in smaller households, and predominantly inhabit dense neighborhoods. However, age groups of 45–59 and 60+, and part-time employment status or unemployment negatively impact the likelihood of being categorized as e-shopping enthusiasts. Notably, the age group 60+ exhibits the largest coefficient value within the segment. The probability of being an Omnichannel consumer is higher among consumers aged 25 to 59, belonging to large households, and living in low- to medium-density neighborhoods. Conversely, possessing a Master's degree or being employed full-time, along with spending over 10 h on the internet, reduces the likelihood of being classified as an Omnichannel consumer.

5.2.4. Consumers delivery method choice modeling

In this section, we present the results of Hybrid Choice Modeling analysis on participants' preferences among four available delivery services (regular delivery, ADR, CRWD, and APL). This analysis considers factors such as delivery times, costs, time windows, and commodity types. Preliminary findings indicate a clear preference among participants for regular delivery over the alternative delivery modes studied. Fig. 7 illustrates the distribution of delivery mode selections across the five consumer segments. Specifically, regular delivery is chosen 29.85 % of the time, followed by ADR at 26.30 %, APL at 24.81 %, and CRWD at 19.04 %. Traditional shoppers, E-shopping enthusiasts, and Indifferent consumers tend to prefer regular delivery over the other modes. Conversely, Benefit seekers and Omnichannel consumers show a preference for ADR. Additionally, after regular delivery, APL is the second most selected option for Traditional shoppers, Benefit seekers, and Omnichannel consumers.

Table 13 presents the outcomes of HCM aimed at evaluating the effective parameters influencing delivery mode selection. The table delineates the coefficients and the t-stats corresponding to delivery time, time window, cost, commodity type, and the interaction between cost and commodity for ADR, CRWD, and APL, with regular delivery serving as the reference. Additionally, it includes coefficients of each attitude measure – ITU, PB, PR, and PEU. Furthermore, the estimation results of the measurement equation for latent variables are provided in Appendix B**.** The analysis reveals a preference for shorter delivery options among consumers, with 1–2 business day and 5 business days exhibiting negative effects on delivery mode decisions compared to same-day delivery, except for Indifferent consumers who favor the former over the latter. Notably, most coefficients for delivery time demonstrate a significant effect, except for the 1–2 business days option, which is insignificant for E-shopping enthusiasts, suggesting this group is less perturbed by an additional 1–2 days in delivery. E-shopping enthusiasts and Omnichannel consumers exhibit the largest coefficients for delivery time across all consumer segments, indicating their heightened sensitivity to delivery timing. The effect of the time window varies among consumer segments, with the 2-hr time window compared to daytime significantly influencing the decisions of E-shopping enthusiasts, and subsequently, Omnichannel consumers. Moreover, all consumer segments display a positive inclination toward a 2-hr time window, with the exception of Indifferent consumers.

The model incorporates delivery cost as alternative specifics, resulting in separate coefficients estimated for each delivery mode. In general, the delivery cost exerts a negative influence on the selection of a delivery option. For ADR, cost exhibits significant effects on the decision-making process across all latent segments, except for Omnichannel consumers, indicating that this segment's choice of ADR remains unaffected by service cost. This finding particularly intriguing given that Omnichannel consumers demonstrate a preference for ADR over other delivery modes, as illustrated in Fig. 7. Notably, the largest coefficient relates to Traditional shoppers, suggesting that cost increases may deter this consumer segment's interest in ADR more than others. Conversely, cost significantly influences the selection of CRWD across all latent segments, with E-shopping enthusiasts demonstrating the largest coefficient among all segments. However, the effect of cost on APL selection is statistically insignificant. Compared to other delivery modes, APL's cost coefficients are relatively smaller, indicating that cost plays a less significant role in APL selection.

In addition to cost, the commodity type was included as an alternative specific to evaluate consumers' delivery preferences for different product categories. Overall, all latent segments exhibit a preference for APL for all product types except but groceries, where the coefficients of electronics, fashion, and health and beauty are consistently positive and significant across all latent segments. For Traditional shoppers, the probability of selecting ADR over regular delivery increases when the commodity type is fashion or health and beauty, whereas coefficients for CRWD are negative for all commodity types compared to the groceries. Also, we observe statistically significant interactions between ADR and two product types (fashion and health and beauty) as well as between APL and all commodity types. Among Benefit seekers, ADR and CRWD are preferred for grocery shopping, as indicated by negative coefficients for other product types. Significant interaction effects are observed between ADR and electronics, CRWD and all product types, and APL and health and beauty. For E-shopping enthusiasts, only interactions between APL and fashion and health and beauty are statistically significant. They generally prefer all delivery modes over regular delivery, except for CRWD and ADR for electronics and CRWD for health and beauty. These preferences align closely with those of Omnichannel consumers. In addition, the interaction between delivery mode, cost, and product type is evaluated to provide deeper insights into consumer preferences, which will be discussed in more detail in the following subsection.

In addition, Table 13 shows the substantial influence of latent variables on consumer preferences for last-mile delivery methods, with each consumer segment demonstrating unique sensitivities. ITU significantly affects Omnichannel consumers and E-shopping enthusiasts, with coefficients of 1.06 ($p < 0.001$) and 0.91 ($p < 0.01$), respectively. This suggests that a higher intention to use strongly motivates these segments to adopt innovative delivery options, potentially due to their comfort with flexible and technology-driven solutions. In contrast, PR is a critical deterrent for Traditional shoppers, with a significant negative effect, indicating that risk-averse consumers are more likely to favor conventional delivery options over alternatives like ADR or crowdsourcing. However, the impact of ITU and PB is stronger than Perceived PR for Traditional shoppers, suggesting that positive motivators can still play a role in their decision-making. Moreover, PEU plays an essential role for E-shopping enthusiasts, highlighting that ease of use and convenience are key drivers for this tech-savvy consumer group.

5.2.5. Sensitivity analysis of delivery cost

To enhance our understanding of consumers' delivery preferences and their Willingness-to-Pay for various delivery mods, we conduct a sensitivity analysis on cost-related variables. While discrete choice models identify significant determinants, they often fail to quantify the magnitude of their effects. Therefore, we calculate elasticities for each statistically significant variable. Elasticities measure the extent of a specific variable's impact on outcome probabilities and are derived from the partial derivative for each observation, expressed as follows:

$$E_{v_{hj}}^{P(j)} = \frac{\partial P(j)}{\partial v_{hj}} \times \frac{v_{hj}}{P(j)} \tag{15}$$

where $P(j)$ is the probability of outcome j, and v_{hj} represents the value of variable h for outcome j. By taking the partial derivative, **Eq. (15)** can be expressed as follows:

$$E_{v_{hj}}^{P(j)} = [1 - P(j)]\lambda_{hj} v_{hj} \tag{16}$$

where λ_{hj} is the coefficient of variable h for outcome j.

Calculated elasticities are provided in Fig. 8, illustrating the impact of a 1 % increase in delivery cost on the probability of selecting each delivery mode. Fig. 8 is divided into four charts: Fig. 8A presents elasticity analysis for all commodity types, while Fig. 8B to 8D focus on fashion, health and beauty, and electronics, respectively. In Fig. 8A, E-shopping enthusiasts exhibit the highest elasticity, with a 1 % increase in delivery cos resulting in a 3.1 % decrease in the probability of selecting CRWD. Conversely, APL demonstrates the lowest elasticity among E-shopping enthusiasts, with a 1 % increase in cost reducing the probability of selecting APL by only 0.15 %. Generally, CRWD displays the largest elasticity, while APL exhibits the lowest across all latent segments. Moreover, Traditional shoppers consistently demonstrate substantial sensitivity to delivery cost across all delivery modes.

Elasticity analysis for fashion products (Fig. 8B) reveals that the highest elasticity relates to ADR and among Indifferent consumers, with a 1 % increase in ADR delivery cost resulting in a 5.32 % reduction in its selection probability as the last-mile delivery mode. Following closely, the second highest elasticity is identified for E-shopping enthusiasts choosing APL at −4.76. Indeed, APL demonstrates the highest elasticity for fashion-related products across all latent segments, except for Indifferent consumers, in comparison to other delivery modes. In Fig. 8C, Indifferent consumers exhibit the highest elasticity, particularly for APL, at −5.04. Omnichannel consumers display the highest elasticity for ADR. However, CRWD shows lower elasticity for fashion and health and beauty products compared to the other two delivery modes, indicating less sensitivity in their selection for these product types. Lastly, Fig. 8D presents elasticity analysis for electronic products. Similar to the other two product types, Indifferent consumers exhibit the highest elasticity for selecting CRWD at −3.71. Generally, the impact of cost on consumers' decisions is less pronounced for electronic products compared to others.

6. Discussions

Businesses typically focus on two key approaches when planning their last-mile delivery strategies: first, pleasing existing customers, and second, attracting potential customers. In this context, the latent segments identified in this study could provide valuable insights for carriers and retailers in devising effective strategies tailored to these two approaches. E-shopping enthusiasts and Omnichannel consumers represent segments already engaged in online shopping. Addressing the needs of these groups is essential for system improvement. Notably, these segments demonstrate the largest coefficients for delivery time, suggesting a strong emphasis on timely delivery in the decision-making process of these consumers. Carriers may prioritize addressing concerns related to delivery time, as it is a primary consideration for most customers. Offering faster delivery options could enhance customer satisfaction, particularly for loyal customers, such as E-shopping enthusiasts, who prefer a 2-hour delivery window. Additionally, Omnichannel consumers exhibit a preference for ADR, irrespective of cost considerations. Given the segment's significant size, investing in ADR infrastructure for this group may yield substantial returns for major carriers such as FedEx and Amazon.

Traditional shoppers and benefits seekers, however, may require an incentive to transition to online shopping. Our findings suggest that enhancing accessibility to APLs could serve as an effective strategy for encouraging this shift. These segments exhibit considerable interest in APL, with this delivery method being their preferred choice among all innovative options. Furthermore, APL selection shows no significant association with delivery cost, indicating that expanding APL station accessibility and extending services to diverse neighborhoods could prove fruitful.

Contrary to initial assumptions that perceived risks associated with innovative delivery methods would deter consumers from transitioning away from traditional delivery, our findings suggest that while PR remains a barrier, confidence in technology usage among consumers is high. This implies that PB and PEU, rather than PR, are the more decisive factor in adoption. Although risk-averse consumers tend to prefer traditional delivery options over methods like ADR and CRWD, the positive impact of ITU and PB can significantly mitigate these concerns.

The Traditional Shopper segment—the second-largest consumer segment, characterized by older age, lower education levels, and limited internet usage—does not avoid new delivery options solely due to risk aversion. Instead, their reluctance appears rooted in uncertainty regarding the value these methods might provide. This finding suggests that targeted educational efforts emphasizing the benefits of innovative delivery methods could effectively encourage adoption within this group. By highlighting advantages such as positive environmental impacts, reduced supply chain costs, and enhanced system sustainability—particularly when paired with competitive pricing—Traditional Shoppers may be more inclined to consider these alternatives. Given that this segment demonstrates a significant impact of ITU on their delivery method choices, fostering a positive intention could play a critical role in shifting their preferences. Interestingly, PEU does not significantly affect the decision-making of Traditional Shoppers, suggesting that technological advancements may have reduced perceived complexity as a barrier to adoption. Consumers across all segments appear confident in their ability to navigate new technologies if they perceive sufficient benefits.

Building upon the above findings, we analyze how ADR, CRWD, and APL align with consumer preferences and expectations. Each delivery mode offers distinct opportunities and challenges for targeting key consumer segments, with implications for last-mile delivery strategies.

ADR emerge as a particularly promising delivery mode based on consumer interest. While ADR adoption is still limited, our study highlights a notable level of interest among participants. However, this enthusiasm varies significantly across consumer segments. For Traditional shoppers, adoption of ADR highly depends on delivery cost, with this segment losing interest in ADR faster than others when faced with price increases. This suggests that while ADR presents an opportunity to enhance delivery services, its success in capturing the interest of cost-sensitive groups hinges on providing affordable solutions. Carriers may need to devise cost-effective ADR implementation to maximize adoption across all consumer segments.

CRWD, although currently exhibiting the lowest levels of consumer interest among the methods studied, presents potential for competitive viability if positioned as a more cost-effective alternative. Participants, particularly those classified as E-shopping enthusiasts and Omnichannel consumers, displayed significant sensitivity to CRWD pricing. This suggests that affordability could play a pivotal role in broadening CRWD's appeal. Moreover, this delivery mode shows promise in enhancing grocery shopping experiences, indicating opportunities for partnerships with services such as UberEATS and DoorDash to improve last-mile delivery experiences for food and grocery retailers. Strategically leveraging cost competitiveness and market-specific use cases could enhance the feasibility of CRWD.

In contrast to other delivery modes, APL demonstrate a weaker association with cost concerns, underscoring a relatively high consumer acceptance irrespective of pricing. APL has garnered significant interest as an innovative delivery option, particularly for non-grocery items. Despite considerations from major retailers like Walmart to utilize APL for grocery orders, our findings indicate hesitance among consumers to adopt this delivery method for perishable goods. Nevertheless, APL represents a valuable opportunity for fashion retailers and similar sectors. Its utility, coupled with consumer willingness to adopt APL services at various price points, makes it a promising avenue for businesses targeting these markets.

The above findings collectively emphasize the need for a tailored approach in adopting innovative delivery solutions, balancing cost, accessibility, and consumer priorities to meet evolving market demands. By addressing the specific needs and preferences of different consumer segments, businesses and carriers can establish sustainable, customer-centric last-mile delivery systems capable of adapting to future challenges.

In addition, it should be noted that the adoption of innovative delivery services may correlate with participants' prior exposure to similar technologies. In this study, a part of this effect was captured through the use of latent variables. Additionally, our survey included questions to assess participants' previous knowledge of the delivery methods being studied, specifically asking whether they had heard of or seen any of the proposed services. The data collected indicates that 96 % and 92 % of participants, respectively, had at least heard of or seen one of the discussed methods. At the time of this study, ADRs had not been widely implemented, which was reflected in the data; participants reported encountering ADRs less frequently than other technologies. Specifically, 31 % reported having seen ADRs, compared to 53 % for CRWD and 43 % for APLs. Despite this lower exposure, ADR emerged as the most selected option among the offered choices. These results suggest that future studies should directly investigate the effect of previous experience on the likelihood of adopting innovative last-mile delivery services.

The 2017 National Household Travel Survey found 55 % of households received at least one online delivery per month, increasing to 80 % in our data, likely due to COVID-19. Remote work (Unnikrishnan and Figliozzi, 2020) and internet usage (Fabusuyi et al., 2020) rive this surge, though the latter impacts shopping frequency, not the choice between online and in-store shopping (Schmid and Axhausen, 2019b). Age is the strongest predictor of online shopping, followed by income, education, and ethnicity (Federal Highway Administration, 2018; Hermes et al., 2022; Kim and Wang, 2022). Household size plays a key role in consumption modeling (Van Droogenbroeck and Van Hove, 2017). This study also considered the needs of seniors, disabled individuals, and those with specific medical conditions. Seniors shop online less, while households with disabled members rely more on home delivery, reinforcing e-commerce's role in sustainable transportation (Garus et al., 2022; Ignat and Chankov, 2020). Despite e-commerce growth, low-income, rural, and less-educated communities remain disengaged, limiting logistics investment. However, elderly and disabled households benefit more, highlighting challenges in addressing food deserts (Kim and Pena, 2023; Mishra et al., 2023; Washington et al., 2023).

7. Conclusion

Since the early 1990 s, e-commerce has expanded significantly, with online sales rising from 0.93 % of total retail in 2000 to 11.01 % by 2019, a trend accelerated by COVID-19. This study developed a demand model incorporating household shopping and delivery preferences across various shopping options, delivery types, and commodities. Using an extended Multiple Discrete Continuous Extreme Value (MDCEV) model, we analyzed households' home delivery, pick-up, and in-store shopping demand. Results showed that age, remote work, population density, and local facilities influence preferences. While internet usage does not impact shopping mode, it affects consumption. Then, a Hybrid Choice Model categorized consumers into five segments: Traditional shoppers, Benefit seekers, E-shopping enthusiasts, Indifferent consumers, and Omnichannel consumers. Benefit seekers are middle-aged and well-educated in larger households. E-shopping enthusiasts exhibit higher income and education levels. Omnichannel consumers are middle-aged individuals from low- to medium-density neighborhoods. These insights can help optimize logistics, enhance delivery systems, and guide urban planning.

Our findings highlight the importance of tailoring last-mile delivery strategies to specific segments, with ADRs showing significant appeal among existing online shoppers, especially E-shopping enthusiasts. This suggests a clear opportunity for carriers to focus on enhancing ADR infrastructure to meet the needs of this segment. On the other hand, APL has considerable potential to attract new consumers, particularly from the Traditional shopper and Benefit seeker segments, offering a key strategy for converting cost-sensitive, less-engaged shoppers into online consumers. Additionally, pricing remains a critical factor in the adoption of CRWD. This emphasizes the importance of cost-effective solutions for consumers, particularly those in price-sensitive groups. Factors such as ITU, PB, and PR play a critical role in shaping consumers' decisions to adopt innovative delivery methods, with risk-averse groups tending to favor traditional delivery options. While educational efforts may help mitigate concerns, particularly for Traditional shoppers, prior exposure to similar technologies also influences adoption. Ultimately, our findings stress the need for a consumer-centric approach in optimizing last-mile delivery services—addressing distinct needs and preferences to improve customer satisfaction and meet evolving market demands.

Future research may expand upon demand modeling by examining geographic variations and conducting comparative analysis of demand determinants and neighborhood conditions. Furthermore, a pertinent avenue for investigation could involve evaluating the impact of package delivery on traffic condition and assessing the effect of urban design on both demand and supply dynamics within the last-mile delivery sector. Moreover, there is scope for future studies to explore alternative delivery methods, including drones, overnight delivery services, and bike couriers, to enhance the breadth of understanding in this domain. Additionally, while this study incorporated Intention to Use, Perceived Benefits, Perceived Risk, and Perceived Ease of Use to gauge consumer attitudes toward new delivery modes, future research may benefit from exploring alternative attitude assessment models and constructs. Doing so could offer deeper insights into consumer preferences and behaviors concerning to emerging delivery methods, enriching our understanding of their adoption and acceptance within the market. In the last-mile delivery adoption section, four major commodity types (grocery, electronics, health and beauty, and fashion) were included in the modeling process. Given that our data showed notable shares for other commodities (e.g., DIY, home improvement goods, entertainment, etc.) in household shopping baskets, we strongly encourage future researchers to explore last-mile delivery adoption for these other commodity types in their studies. In this study, we specifically focused on consumers' last-mile delivery preferences. However, we encourage future research to explore the preferences of other stakeholders, including residents, suppliers, e-platforms, local authorities, and logistics companies. Also, assessing the sustainability aspects of innovative delivery methods is another crucial topic that warrants further exploration. Finally, the findings of this study are derived from a dataset collected in the State of Tennessee, USA. Although various control methods were employed to enhance broader applicability, future research is encouraged to incorporate additional variables or region-specific factors to validate our findings.

CRediT authorship contribution statement

Ali Riahi Samani: Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis. **Ahmadreza Talebian:** Writing – review & editing, Methodology, Investigation. **Sabyasachee Mishra:** Writing – review & editing, Supervision, Software, Methodology, Funding acquisition, Conceptualization. **Mihalis Golias:** Writing – review & editing, Funding acquisition, Conceptualization.

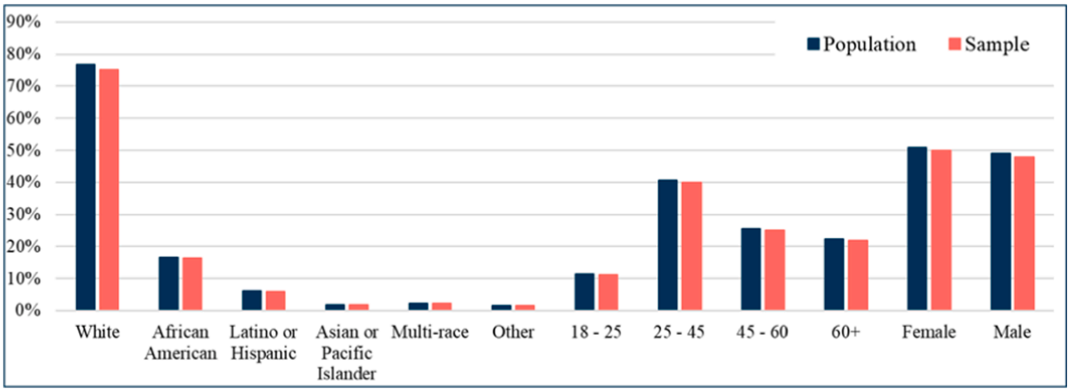
Declaration of competing interest

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

Acknowledgments

The authors would like to thank the U.S. National Science Fundation (NSF) for supporting this research through the grant number #2333354. Besides, computational facilities at the University of Memphis are greatly acknowledged. Any opinios, findings, conclusions, or recommendations expressed in this work are those of the authors and do not necessarily reflect the views of the above mentioned agencies.

Appendix A. . Comparison of survey sample with the target population



Appendix B. . 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)

Data availability

The authors do not have permission to share data.

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