Evaluating Public Acceptance of Autonomous Delivery Robots During COVID-19 Pandemic

Agnivesh Pani[1], Sabya Mishra[1*], Mihalis Golias[1], and Miguel Figliozzi[2]

[1]*Department of Civil Engineering, University of Memphis, Memphis, TN 38152*

[2]*Department of Civil and Environmental Engineering, Portland State University, OR 97201*

[1*] Corresponding Author

Email Addresses: agniveshpani@gmail.com (Pani), smishra3@memphis.edu (Mishra), mgkolias@memphis.edu (Golias), mafiglio@pdx.edu (Figliozzi)

ABSTRACT

Autonomous delivery robot (ADR) technology for last-mile freight deliveries is a valuable step towards low-carbon logistics. The ongoing COVID-19 pandemic has put a global spotlight on ADRs for contactless package deliveries, and tremendous market interest has been pushing ADR developers to provide large-scale operation in several US cities. The deployment and penetration of ADR technology in this emerging marketplace calls for collection and analysis of consumer preference data on ADRs. This study addresses the need for research on public acceptance of ADRs and offers a detailed analysis of consumer preferences, trust, attitudes, and willingness to pay (WTP) using a representative sample of 483 consumers in Portland. The results reveal six underlying consumer segments: Direct Shoppers, E-Shopping Lovers, COVID Converts, Omnichannel Consumers, E-Shopping Skeptics, and Indifferent Consumers. By identifying the WTP determinants of these latent classes, this study provides actionable guidance for fostering mass adoption of low-carbon deliveries in the last-mile.

Keywords: Low-carbon Delivery; Consumer Acceptance; Attitude-based Segmentation; Willingness to Pay; Latent Class Analysis; COVID-19.

1. INTRODUCTION

In the backdrop of coordinated global efforts to implement sustainable transport solutions (UNFCCC, 2015), the introduction of autonomous delivery robots (ADRs) is a crucial initiative towards achieving emission reduction targets and mitigating the global warming crisis (Figliozzi, 2020). The existing approach of using light commercial vehicles, cars, or motorbikes for last-mile household deliveries creates approximately 158.4g CO_2 per km per order, considerably higher than the widely accepted emission target of 0.147g of CO_2 per km per order (European Commission, 2019). One of the practical challenges for fostering a shift to carbon-free alternatives is the increased demand for just-in-time deliveries of perishable goods (e.g., groceries, prepared meals), with more than a quarter of consumers willing to pay more for faster deliveries (Edwards et al., 2010). This demand is forcing E-commerce companies, retailers, and food vendors to deploy larger delivery fleets, as it is difficult to integrate multiple deliveries into a single delivery tour. Even in cases where distribution tours can be effectively integrated (e.g., postal service), increased delivery failure rates are a growing concern with economic and environmental consequences (Edwards et al., 2010; Song et al., 2012). Hence the promotion of ADRs is expected to be a valuable step to zero-emission logistics in the US (Figliozzi, 2020). Even marginal improvements in the delivery efficiency of ADRs can foster substantial gains in the efforts to decarbonize last-mile deliveries, given the size and growth of the E-commerce sector. Depending upon the range of operation, ADRs are classified into two: road-based ADRs and sidewalk-based ADRs (Jennings and Figliozzi, 2020). While the deployment of road-based ADRs with more extended range is currently at the pilot-level, sidewalk-based ADRs with relatively shorter range are expanding to large-scale operations with "mothership" vans carrying them close to the delivery zone of the service area (Jennings and Figliozzi, 2019). For example, SADRs developed by Amazon, FedEx, Starship, and

Nuro are deployed in multiple US cities with capacities expanded from hundreds of deliveries a day to thousands (Mims, 2020).

The ongoing COVID-19 pandemic has created a surge in the public interest and demand for ADRs since it can provide contactless delivery, a highly sought-after service under the directives of social distancing. As a result, consumers, businesses, and governments have switched from being cautious beta testers into eager early adopters. Despite this unprecedented requirement necessitated by the pandemic, SADRs and RADRs need to be deployed by logistics service providers and government agencies conforming to the expectations, needs, and motivations of consumers. Therefore, it is imperative to conduct micro-level behavioral research on user acceptance early in the deployment roadmap of delivery robots to be able to promote them as an acceptable delivery alternative that meets consumer expectations. To date, however, scientific investigations on ADRs have focused on the technical and regulatory challenges, and little attention has been given to evaluating user acceptance. The behavioral component and psychological determinants of ADRs require urgent research attention because last-mile delivery is a service that depends on responding promptly to consumer needs, and consumer expectations drive companies' business and logistics decisions.

This paper addresses the research gap in linking consumer's attitudes towards shopping and willingness to pay (WTP) for ADRs. The contingent valuation method adopted in this study asks the respondents to state their WTP for the imaginary scenario of ADRs being provided as a last-mile delivery option to their next internet order. Further, the latent class analysis (LCA) approach adopted in this study accounts for the fact that consumers are is heterogeneous in their preferences. Thus, the fundamental hypothesis investigated in this study is that there are multiple types of consumers differing in their attitudes and motivations towards purchasing goods, and, in turn, in their preferences and WTP towards ADRs. Since understanding preference heterogeneity is a crucial insight in successfully deploying any new technology, this paper contributes to the literature on ADR technology by identifying consumer segments using LCA before proceeding to analyze their WTP determinants. The membership probabilities of LCA will be used to label and profile the latent classes. The WTP determinants for each latent class will provide insights into how promotional campaigns of ADRs need to target a diverse consumer base to foster a sustainable shift to low-carbon autonomous deliveries in the last-mile.

The rest of the paper is structured in the following manner: Next section presents the research background of the segmentation and WTP valuation approach adopted in our research methodology; Section 3 presents the methodological framework and Section 4 describes the survey design and sample description; Section 5 presents the model estimation results and interprets them; Final section concludes the paper with discussions and practical implications.

2. BACKGROUND

Compared to the wealth of literature available on public acceptance of autonomous technology for shared-travel or vehicle ownership, significantly less work focuses on the consumer acceptance of autonomous technology for delivering goods to them (Kapser and Abdelrahman, 2020). The COVID-19 pandemic has put a global spotlight on ADRs for contactless package deliveries, and the tremendous market interest has been pushing ADR developers to provide large-scale deployments required by several real-world businesses (Mims, 2020). A timely study on the factors that affect consumer acceptance of ADRs will not only enhance the academic literature on consumer acceptance to alternate delivery mechanisms but also provide actionable guidance for successful deployment and market penetration. To the best of our knowledge, this study is first-of-its-kind aiming to address the issue of consumer heterogeneity before examining the determinants of acceptance and WTP for ADRs. A background on the segmentation and WTP valuation approach is given below.

2.1 Consumer Acceptance: Importance of Attitude-based Segmentation

In a market-based economy, consumers are increasingly substituting physical travel to retail stores with online shopping and having goods delivered to their households. As the technological landscape and delivery services continue to evolve, goods that previously required, or mostly purchased through physical shopping are increasingly being accomplished online through virtual interactions. Due to wide variation in consumers' needs, expectations, and motivations regarding the purchase of goods, effective market penetration of ADRs depends on introducing them in a way that attracts all types of consumers (Kapser and Abdelrahman, 2020). By developing models that capture the average public acceptance or WTP of consumers to emerging technologies like ADRs, the issue of consumer heterogeneity is overlooked. It is thus imperative to define theory-driven consumer segments that are reasonably homogeneous within themselves, to create successful deployment strategies and promotion measures for introducing ADRs as a sustainable delivery alternative (Fürst, 2014). Segmenting the market also helps to offer insights into individual behaviors and consumer preferences (Gong et al., 2020). The identified segments enable policymakers to foster widespread adoption of ADRs among consumers by addressing the specific requirements of different target groups early in their development process (Axsen et al., 2016).

Existing segmentation approaches in consumer research primarily rely on sociodemographic variables (Waygood and Avineri, 2016), actual travel behavior (e.g., the trip frequency) across different modes of transportation (Diana and Mokhtarian, 2009), generational cohorts or life stages (Grimal, 2020), and expenditure patterns (Pani et al., 2019). Because of the direct connections to actual travel behavior, attitudinal variables have shown significant influence on the willingness to shift to environmentally sustainable transport modes (Hunecke et al., 2010). An attitude-based segmentation approach could, therefore, be ideal for segmenting the consumer base in situations where logistical innovations like ADRs are deployed (Haustein and Hunecke, 2013). However, the use of attitude-based segmentation is still rather rare in consumer research (Fürst, 2014; Potoglou et al., 2020), and this study aims to address this discernible gap in the context of ADRs. The attitude scale used for this purpose is adapted from the scale proposed by Swinyard and Smith, (2003) and validated in multiple studies. The individual statements included in this scale are strongly founded in the literature of psychographic market segmentation. More information about the attitude statements and their validation can be found in Huseynov and Özkan Yıldırım, (2019).

2.2 Measuring Consumers' WTP: Valuation Methods

WTP is a critical method for the economic valuation of public goods, such as new energy vehicles (Agrawal et al., 2010; Potoglou et al., 2020). Two types of direct surveys are generally conducted for WTP measurement: consumer surveys and expert judgments. In diverse market environments, the availability of prior knowledge about heterogeneous consumer base becomes a critical issue, and consumer surveys are thus preferred over expert judgments. Consumer surveys can either belong to revealed preference (RP) and stated preference (SP) elicitation method (Ortúzar and Rodríguez, 2002): In the case of RP method, WTP is *revealed* by indirectly examining the purchases of related goods, which include market simulation method (Greene et al., 2020), and hedonic price method (Matos et al., 2013). Alternatively, SP methods measure WTP by asking the consumers directly how much they value the (public) goods and investigating the expressed or stated preference (Potoglou et al., 2020). Two types of SP methods can be distinguished in the literature: choice experiment (CE) and contingent valuation method (CVM). Consumers are asked to select their most preferred choice in CE design, where each alternative is decomposed into their attributes and into the levels exhibited by them (Dave et al., 2018). In the CVM approach, consumers are asked to directly report their WTP by assuming that the product already exists in the market. The "valuation" estimates provided by this approach said to be "contingent" on the value perceived by the consumers for the "constructed market" (Carson and Hanemann, 2005). In the absence of pre-existing knowledge about a rapidly emerging market, CVM is generally preferred over CE to determine consumers' WTP (Liu et al., 2019; Xie and Zhao, 2018).

The elicitation format adopted in CVM is another determining factor of CVM results (Oerlemans et al., 2016). The standard formats include open-ended (OE) direct question, payment card, single or multiple-bound dichotomous choice, and bidding game (Carson and Hanemann, 2005). Compared to other approaches, OE format reduces the respondent burden and avoids starting point bias in WTP estimation (Xie and Zhao, 2018). The main drawback of OE format, however, is that it gives rise to a large number of "zero" WTP responses (Lee et al., 2020). A practical approach to investigating the zero WTP responses is to sort them into two types: genuine zero responses and "protest" zero responses. The present study employs CVM in OE format to quantify WTP for ADRs with a conditional follow-up question to further distinguish the zero WTP responses.

3. METHODOLOGICAL FRAMEWORK

This study uses latent class analysis (LCA) to address the issue of heterogeneity in consumers' shopping attitudes. The primary purpose of LCA is to reveal unobserved consumer segments in the sample, whose members show homogeneous attitudes towards shopping within each segment, but present heterogeneous attitudes across segments (Molin et al., 2016). The responses given to the eight statements shown in Table 1 are used in this study to estimate the basic LCA models with active covariates denoting the socio-demographic and locational characteristics of the consumers. These statements are adapted from the cross-culturally validated consumer attitude scale (Huseynov and Özkan Yıldırım, 2019; Swinyard and Smith, 2003). Each attitudinal statement in LCA results will be given a probability value of belonging to each of the resultant segments in the optimal clustering solution, where values sum to 1 within a class.

Table 1 Statements measuring the shopping attitudes of consumers

Variable	Description of Statement (*5-point Likert scale*)
Att_1	*"I like having merchandise delivered to me at home"*
Att_2	*"I find it hard to judge merchandise quality on Internet"*
Att_3	*"I like not having to leave home for shopping"*
Att_4	*"I use internet shopping mainly because of the COVID-19 outbreak"*
Att_5	*"I like that car is not necessary in the case of Internet shopping"*
Att_6	*"I like the helpfulness available at local stores"*
Att_7	*"I think Internet buying has delivery problems"*
Att_8	*"I do not want to give my credit card number to a computer"*

Considering the need to incorporate unobservable heterogeneity in WTP estimation, LCA allows us to assign consumers probabilistically to each class as a function of the active socioeconomic covariates like age, gender, income, and education levels. To overcome the challenge of not knowing 'a priori' the optimal number of latent classes, LCA models need to be estimated with varying number of segments (e.g., 1 to 10), and the optimal solution is the one giving the lowest Bayesian information criterion (BIC). After identifying and labelling the optimal LCA solution, membership functions need to be developed for allocating consumers to each latent class by treating them as a dependent latent multinomial measure. The latent classes will further be used for developing WTP prediction models using the CVM approach. An overview of the latent class modeling framework adopted in this study is presented in Figure 1.

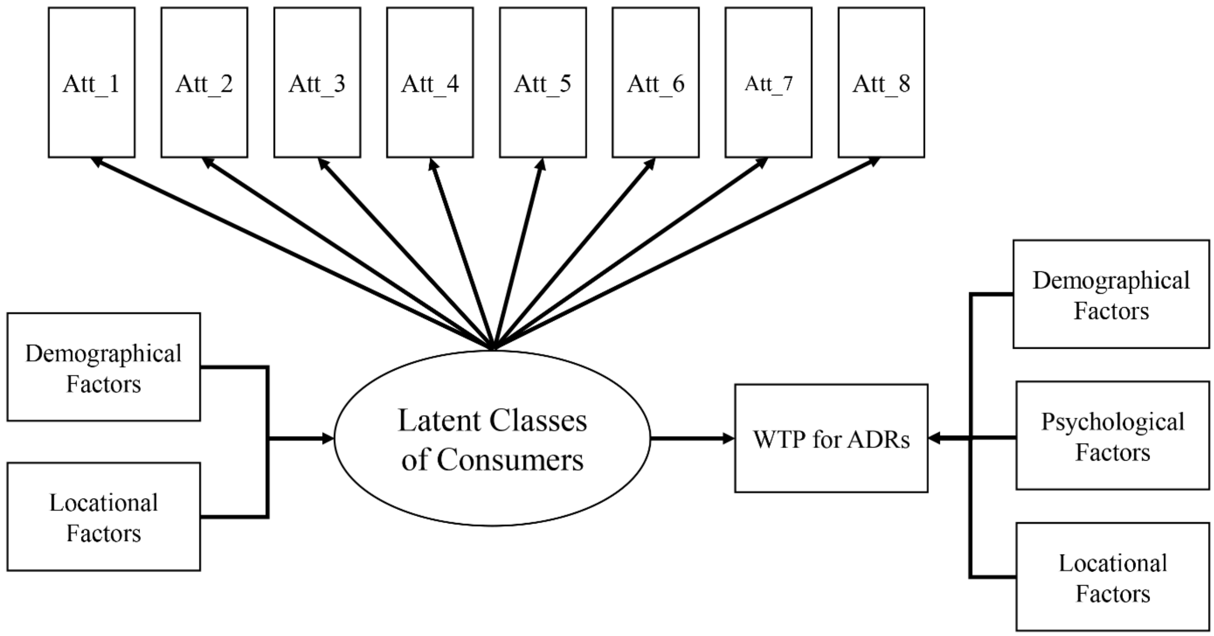


Figure 1 Latent class framework to identify consumer segments and predict WTP for ADRs

Since a significant share of respondents are expected to state a zero WTP, the resulting skewness in dependent variable will need meet the normality assumption required by conventional ordinary least squares (OLS) regression analysis (Saz-Salazar et al., 2020). After censoring the protest responses, a latent class Tobit model is used in this study for estimating WTP. Without addressing the issue of the censored distribution, WTP studies are reported to lead to biased and inconsistent parameters. The specification of Tobit models is given using an index function in Eq. (1) and (2).

$$WTP_i = \begin{cases} WTP_i^* & if\ WTP_i^* > 0 \\ 0 & Otherwise \end{cases} \tag{1}$$

$$WTP_i^* = \beta X_i + \varepsilon_i \tag{2}$$

where WTP_i is the observed willingness-to-pay for ADRs by each consumer i, WTP_i^* denotes the indirectly observable value of consumer i's actual willingness-to-pay response; X_i is a vector denoting the consumer's demographic characteristics (age, gender, income, education), familiarity, and attitudes with the technology, β is the model coefficient vector of willingness-to-pay, and ε_i denotes the error term. For each of the subpopulations delineated based on latent classes, separate Tobit models are estimated to capture the variation in WTP due to consumer heterogeneity. The resultant model termed as latent class Tobit model is given in Eq. (3).

$$WTP_i^* \mid (Class = c) = \beta_C X_i + \varepsilon_{i|C} \tag{3}$$

where β_C is the WTP determinants for each latent class $c \in \{1, 2, \dots, C\}$ and $WTP_i^* \mid (Class = c)$ is the willingness-to-pay for ADRs by consumer i in class c. The density function of observed WTP values $f(\, WTP_i^*)$, corresponding log-likelihood ($logL$) and logit probabilities $\left(P_{i,c}\right)$ can be computed as per Eq. (4) to (6).

$$f(\, WTP_i^* \mid Class = c, X_i, \beta_c, \sigma_c) = \left[\varphi\left(\frac{\beta_c X_i}{\sigma_c}\right)\right]^{1-d_i} \left[\frac{1}{\sigma_c}\phi\left(\frac{WTP_i - \beta_c X_i}{\sigma_c}\right)\right]^{d_i} \tag{4}$$

$$logL = \sum_{i=1}^{N} log\left[\sum_{c=1}^{C} P_{i,c}\,(\gamma_c, z_i) f(\, WTP_i^* \mid Class = c, X_i, \beta_c, \sigma_c)\right] \tag{5}$$

$$P_{i,c}(\gamma_c, z_i) = \frac{\exp\,(\gamma_c, z_i)}{\sum_{c=1}^{C}(\gamma_c, z_i)} \tag{6}$$

where d_i is the dummy variable distinguishing the positive WTP values, φ is the standard normal probability distribution function, ϕ denotes the cumulative density function, $P_{i,c}(\gamma_c, z_i)$ denote the logit probabilities of consumers belonging to a particular latent class, z_i denotes consumer's observed characteristics and attitudes while belonging to one latent class and γ_c is the associated vector of LC-Tobit model coefficients.

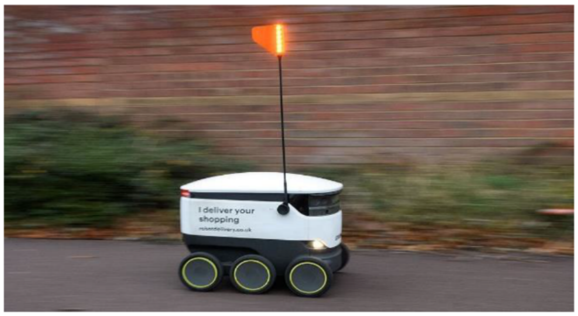
4. DATA

4.1 Survey Instrument

The data used for this study is collected for Portland Metropolitan Statistical Area (MSA) centered Oregon, USA. The study area consists of two major urban centers, out of which one is Portland city in Oregon and the other is Vancouver city in Washington. The final survey instrument consisted of four parts, out of which the first part is the informed consent letter stating the details of the survey to the respondents. The second part collected demographic characteristics and mobility tools of the respondents, such as age, gender, annual net-income, employment status, education levels, ethnicity, car ownership, and availability of a driver's license. The next part of the questionnaire contained the statements requiring answers on respondents' shopping perceptions and attitudes, along with an additional question aimed at understanding the changes in shopping preference due to the COVID-19 pandemic. An information sheet was provided before the fourth part of the questionnaire to inform the respondents about the quality of ADR deliveries (e.g., delivery speed, convenience, package weights, time window), as shown in Figure 2. The details given in the information sheet are collected from the delivery standards reported by ADR developers in the market and values reported in the literature (Figliozzi, 2020; Jennings and Figliozzi, 2019). The last part of the questionnaire consisted questions on the respondents' preferences, familiarity, and willingness to pay (WTP) for ADRs. The items on trust attitude and preferences for ADRs are included in this section are adapted from the literature (see Kapser and Abdelrahman, 2020) and are measured using a five-point Likert scale.

Information Sheet about Autonomous Delivery Robots (ADRs)

Autonomous delivery robots (ADRs) are defined as **self-driving ground vehicles**, which can deliver parcels or other goods like groceries and prepared meals to the doorstep. ADRs look like **little robots** (picture 1) or like a **mobile parcel locker** (picture 2) and they drive at a speed of approximately **5–10 km/h** sidewalks. Once the ADR arrives at the delivery destination, consumer can authorize and receive their order by scanning QR codes. The short-range local deliveries by ADRs (up to 4 miles) typically handle packages weighing up to 30 pounds and follow a time window between **10.30 AM and 8.30 PM**. Depending up on the store location and vehicle availability, ADRs generally offer **deliveries within two hours** after placing the order.



Picture 1

Picture 2

Figure 2 Description of ADRs to the respondents

The WTP part of this study follows the contingent valuation method (CVM) and asks the following question to the respondents: "*Assuming that autonomous delivery robot option is available for your next order, how much extra money would you be willing to pay per order?*". A total of 8 options were provided, such as "*No, I will not pay extra*" to "*$6*". The starting point bias associated with OE format is avoided by randomly allocating them for different respondents. If respondents answered "No" they were given six possible options for attributing their reason for the negative response to the WTP question. These choices, adapted from the recent CVM studies, such as Liu et al., (2019) and Kyriakidis et al., (2015), are as follows .: (A) "*I am willing to pay, but the household income is not enough to bear the additional cost*"; (B) "*The existing delivery methods are good enough and does not need to be improved using ADRs*"; (C) "*The additional cost should be paid by the government and E-commerce companies*"; (D) "*The cost has been included in the taxes and fees*", and (E) "*I have other reasons not listed*". The first two alternatives (i.e., A and B) are considered to be genuine zero responses, which indicates that ADR technology is of no benefit to the consumers selecting them. Subsequently, the selection of options other than income constraints and satisfaction with status-quo (i.e., alternatives C, D, and E) are considered as protest responses, which indicate that the ADR technology is perceived to have no value by the respondent. These viewpoints obtained through the survey help to uncover the factors restricting respondents to have positive WTP values and may give guidance for targeting the consumers with the appropriate inclination to respond to marketing measures and, in turn, fostering large-scale adoption of low-carbon deliveries using ADRs.

4.2 Participants, Survey Procedures and Sample Description

Institutional Review Board (IRB) of the University of Memphis approved the survey instrument in the Qualtrics platform. The information recorded for the study was anonymous. A market research company was employed to collect responses from its existing consumer panel. All members residing in Portland MSA and aged over eighteen years were drawn from this panel and sent the invite for responding to the survey. The instructions in the first part of the study specifically informed the respondents about the aim of the study and notified in advance that survey duration is approximately 9 minutes. Age and gender were used as the strata for Quota sampling adopted in the study. The incomplete responses were automatically discarded by the system, leading to only complete responses. The data collection took place between June and July 2020. To account for the differences in urbanization levels and the access to shopping stores, ArcGIS Pro was used to visualize the data and compute spatial information at the level of blocks and zip codes. The GIS layers were obtained from Portland-Maps open data portal (City of Portland, 2020) and were utilized to compute the built environment attributes such as residential density and develop the streets, links, and nodes of the study area. In total, 483 usable responses were recorded and the respondent distribution across the study area is presented in Figure 2.

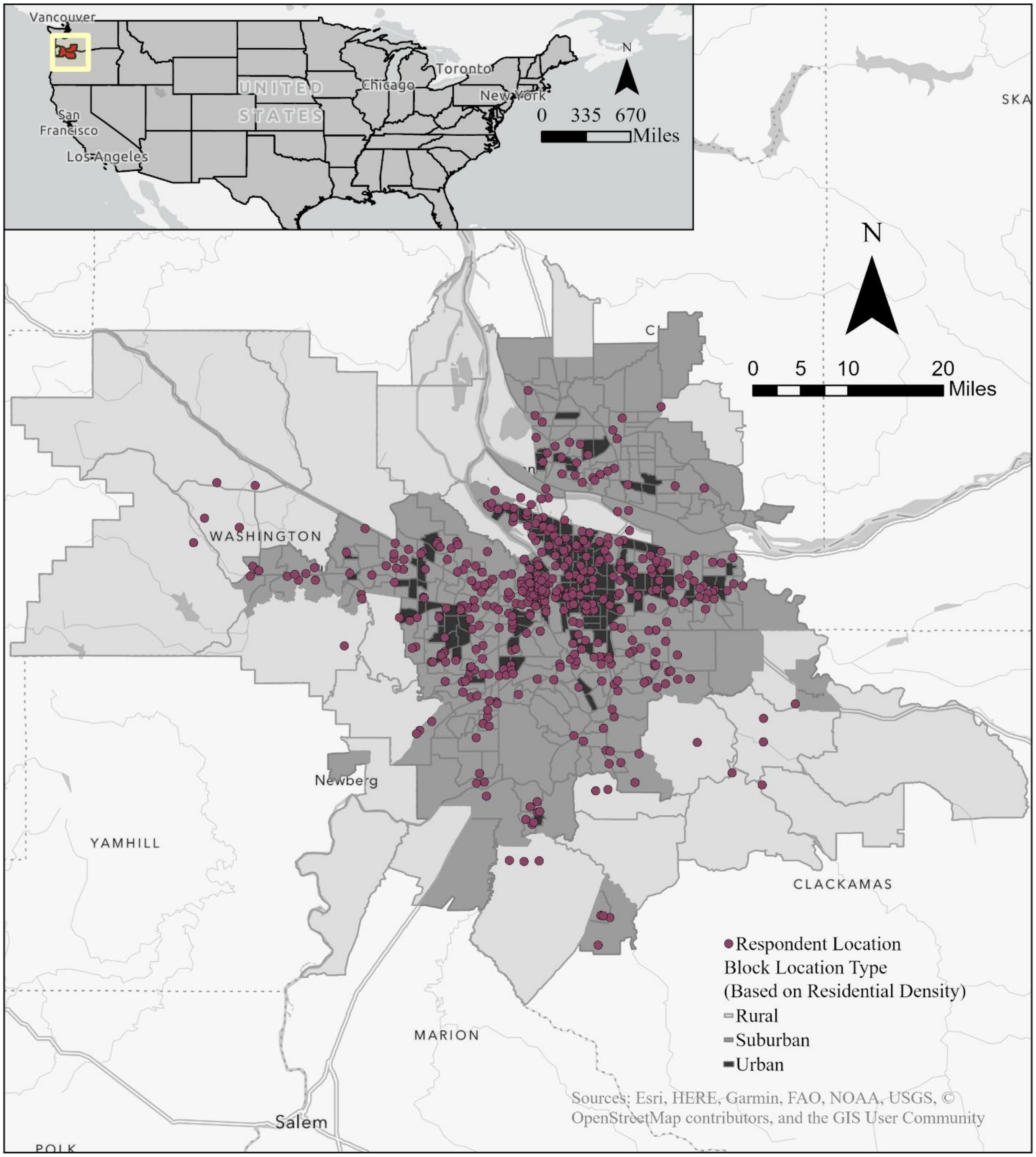


Figure 3 Study Area Map

The final sample size is higher than the minimum sample size requirement for the targeted population of 2.7 million consumers in Portland MSA at 95% confidence level and a margin of error of 5%. The survey respondents were then classified into urban, suburban, and rural areas based on the residential density of the blocks (Kolko, 2015) as follows: (i) urban areas: more than 2213 households per square mile; (ii) suburban areas: between 102 and 2213 households per square mile; and (iii) rural areas: fewer than 102 households per square mile. The distance from each respondents' location to the nearest shopping store was computed by geocoding all the shopping stores in the study area and employing the network analysis toolkit. The representativeness of final sample was compared with respect to 2010 census data and is presented in Figure 3.

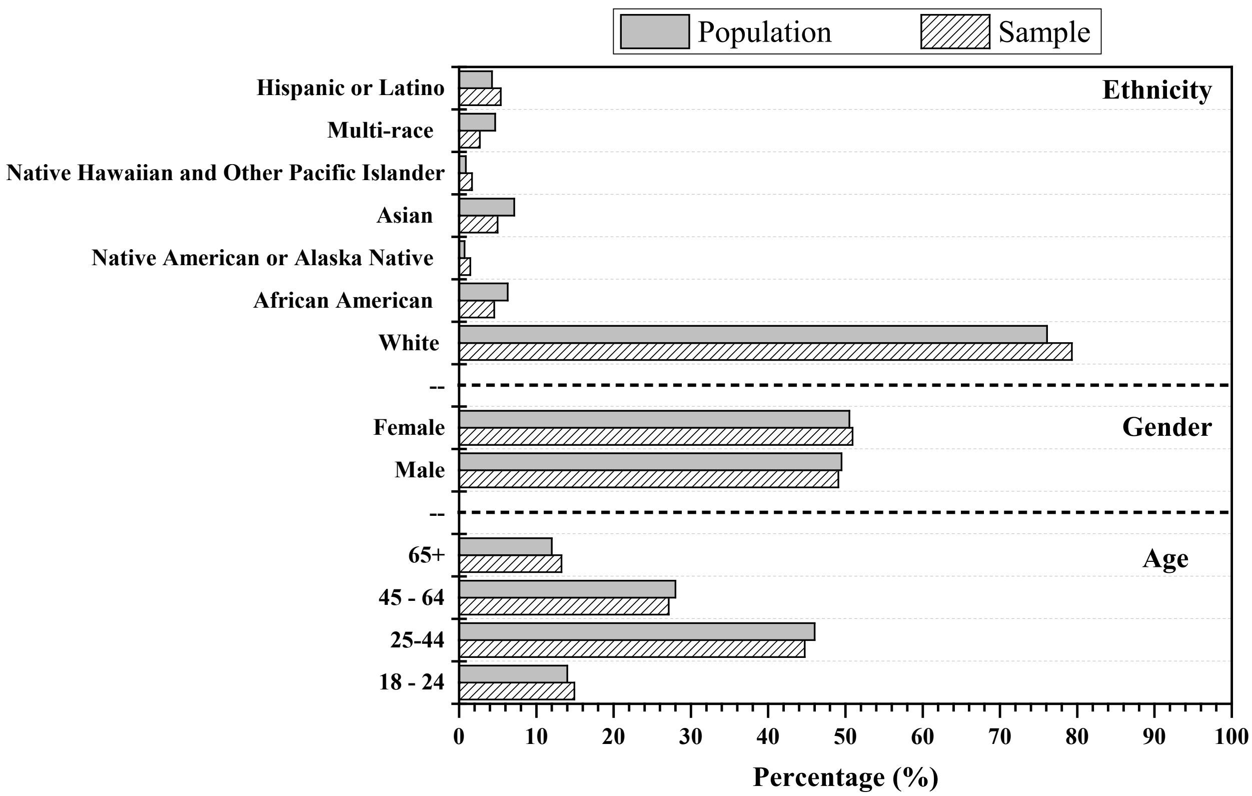


Figure 4 Comparing sample characteristics versus population characteristics

As can be seen, sample versus population comparison reveals only marginal differences in the age strata (18-24 years +0.91%; 25-44 years -1.28%; 45 to 64 years -0.88%; 65 or more years +1.25%) and gender strata (male -0.43%) in comparison to the quotas set for the survey. Additionally, the comparison across ethnicity categories also reveals that the average deviation is about 1.88%.

Overall, these deviations are rather small and hence demonstrates the representativeness of the sample in comparison with the Portland population.

5. RESULTS AND DISCUSSIONS

5.1 Identifying Latent Classes of Consumers

A set of latent class analysis models is estimated by varying the number of classes from one to eight, for identifying the appropriate number of consumer segments, as shown in Table 2. The optimal solution was assessed using BIC values, which weigh both model-fit and parsimony. All of the model parameters obtained in this study are estimated using LCA software package Latent Gold (Vermunt and Magidson, 2005).

Table 2 Model fit statistics where the number of classes are varied from one to eight

Model	*Npar*	*LL*	BIC(LL)	Bivariate Residuals for 6-Class Solution								
					Att_1	**Att_2**	**Att_3**	**Att_4**	**Att_5**	**Att_6**	**Att_7**	**Att_8**
1-Class	32	-5673.83	11433.55	**Att_1**	--							
2-Class	86	-5448.49	11127.80	**Att_2**	0.52	--						
3-Class	140	-5319.68	11015.11	**Att_3**	0.79	1.88	--					
4-Class	194	-5214.08	10948.85	**Att_4**	0.50	0.38	0.78	--				
5-Class	248	-5127.91	10921.44	**Att_5**	0.93	0.48	0.82	1.73	--			
6-Class	302	-5052.55	10915.65	**Att_6**	0.53	0.61	1.32	0.66	0.51	--		
7-Class	356	-5000.05	10955.59	**Att_7**	0.55	0.61	1.26	1.61	0.96	0.36	--	
8-Class	410	-4939.27	10978.96	**Att_8**	0.59	0.54	0.98	1.64	0.69	0.46	2.26	--

Npar indicate the number of model parameters; *LL* indicates the log-likelihood of the model

The variation in BIC values suggests that a six-class LCA solution is optimal. Multiple pair-wise measures, namely bivariate residuals, assess the covariance between the eight attitude indicators and the insignificant covariation ($\chi^2_{critical}$ = 3.84) observed across the six-class solution further underline the validity of the optimal solution. The estimated probabilities of attitudinal statements are then used to characterize each latent class. The probability values (Table 3) of each response lead to labelling the latent classes as: (i) Class 1 - Direct purchasers; (ii) Class 2 - E-shopping lovers; (iii) Class 3 – COVID converts; (iv) Class 4 - Omnichannel consumers; (v) Class 5 - E-shopping skeptics; (vi) Class 6 - Indifferent consumers. The average membership probabilities of these latent classes are 28.36%, 29.40%, 14.70%, 14.70%, 7.25%, and 5.59%, respectively. The within-cluster distributions of the covariates used for estimating the LCA model are given in Figure 4 and the spatial distribution of consumers in each of these segments is given in Figure 5. In the following sections, a brief discussion is provided for describing the main characteristics of latent classes.

Table 3 Response probabilities of latent classes to various attitude statements

Cluster Label	**Class 1** ***Direct Purchasers***	**Class 2** ***E-Shopping Lovers***	**Class 3** ***COVID Converts***	**Class 4** ***Omnichannel Consumers***	**Class 5** ***E-Shopping Skeptics***	**Class 6** ***Indifferent Consumers***	**Overall Sample**
Cluster Size	**28.36%**	**29.40%**	**14.70%**	**14.70%**	**7.25%**	**5.59%**	**100%**
Indicator Variables: Shopping Attitudes of the Consumers							
Att_1: *"I like having merchandise delivered to me at home"*							
Exactly like me	0.0007	**0.3238**	**0.6358**	**0.9492**	0.0579	0.0017	0.2982
Somewhat like me	0.1206	**0.5903**	**0.1545**	**0.0498**	0.2038	0.2511	0.3975
Neutral	0.2583	0.0623	0.085	0.0007	**0.3882**	**0.7467**	0.2008
Somewhat not like me	**0.6141**	0.0235	0.0895	0.0002	0.0739	0.0003	0.0621
Not at all like me	**0.0063**	0.0001	0.0352	0.0001	0.2762	0.0002	0.0414
Att_2: *"I find it hard to judge merchandise quality on Internet"*							
Exactly like me	**0.1947**	0.0535	**0.5301**	0.0373	**0.3904**	0.0379	0.1967
Somewhat like me	**0.5655**	0.309	**0.3732**	0.1853	**0.3752**	0.2157	0.4017
Neutral	0.2023	0.2348	0.0771	**0.3676**	0.0361	**0.7454**	0.207
Somewhat not like me	0.0247	**0.3614**	0.0196	0.2466	0.1195	0.0008	0.1491
Not at all like me	0.0128	**0.0414**	0.0001	0.1632	0.0788	0.0002	0.0455
Att_3: *"I like not having to leave home for shopping"*							
Exactly like me	0.0526	**0.0773**	**0.5762**	**0.8157**	0.0951	0.0012	0.2298
Somewhat like me	0.3179	**0.6977**	**0.2494**	**0.0275**	0.0752	0.2212	0.3334
Neutral	**0.3390**	0.1239	0.1026	0.0213	0.1375	**0.6037**	0.2008
Somewhat not like me	0.2903	0.063	0.0716	0.1353	**0.1304**	0.1730	0.1553
Not at all like me	0.0002	0.0381	0.0002	0.0003	**0.5618**	0.0009	0.0807
Att_4: *"I use internet shopping mainly because of the COVID-19 outbreak"*							
Exactly like me	**0.1111**	0.0489	**0.3911**	**0.3472**	0.0575	0.0012	0.1491
Somewhat like me	**0.3566**	0.1958	**0.4009**	**0.2770**	0.1471	0.0927	0.2671
Neutral	0.2534	0.1768	0.1251	0.1642	0.1985	**0.8176**	0.236
Somewhat not like me	0.2028	**0.3482**	0.0823	0.0888	**0.1007**	0.0876	0.1884
Not at all like me	0.076	**0.2304**	0.0005	0.1228	**0.4962**	0.0008	0.1594
Att_5: *"I like that car is not necessary in the case of Internet shopping"*							
Exactly like me	**0.056**	**0.1126**	**0.5287**	**0.6290**	0.0626	0.0011	0.205
Somewhat like me	**0.4466**	**0.4988**	**0.284**	**0.1594**	0.0951	0.0687	0.3313
Neutral	0.3564	0.2915	0.1487	0.1327	**0.4161**	**0.840**	0.323
Somewhat not like me	0.1409	0.0263	0.0383	0.0152	0.16	0.0899	0.0807
Not at all like me	0.0001	0.0708	0.0002	0.0637	0.2663	0.0003	0.06
Att_6: *"I like the helpfulness available at local stores"*							
Exactly like me	**0.0971**	0.0549	**0.4382**	**0.3351**	**0.2210**	0.0528	0.1428
Somewhat like me	**0.6265**	0.2463	**0.4778**	**0.1733**	**0.3879**	0.1785	0.412
Neutral	0.1959	**0.4689**	0.0831	0.1922	0.1751	**0.7399**	0.2837
Somewhat not like me	0.0804	0.2087	0.0007	0.2120	0.1253	0.0007	0.1201
Not at all like me	0.0001	0.0212	0.0001	0.0874	0.0907	0.0281	0.0414
Att_7: *"I think Internet buying has delivery problems"*							
Exactly like me	0.0134	0.0001	**0.1582**	0.0001	0.0986	0.0002	0.0373
Somewhat like me	0.1597	0.0223	**0.4402**	0.0867	0.3049	0.0855	0.1946
Neutral	**0.4751**	0.2479	0.1484	0.0913	**0.3198**	**0.8166**	0.2981
Somewhat not like me	0.3158	**0.4390**	0.2352	**0.2561**	0.1567	0.0967	0.294
Not at all like me	0.0359	**0.2908**	0.0181	**0.5658**	0.12	0.0009	0.176
Att_8: *"I do not want to give my credit card number to a computer"*							
Exactly like me	0.0694	0.0232	0.1723	0.0334	**0.4336**	0.0589	0.1118
Somewhat like me	0.3013	0.045	0.1993	0.0173	**0.1922**	0.1668	0.1656
Neutral	**0.3219**	0.227	**0.2940**	0.1654	0.0691	**0.7713**	0.2609
Somewhat not like me	0.2063	**0.3864**	0.1002	**0.2296**	0.2573	0.0018	0.234
Not at all like me	0.1011	**0.3184**	0.2342	**0.5542**	0.0477	0.0012	0.2278

Note: Highlighted cells indicate the predominant response to the attitudinal statement

5.1.1 Latent Class 1: Direct purchasers

The label 'Direct purchasers' indicates that consumers in this latent class prefer to shop in physical stores, with the following characteristics: they do not like to have merchandise delivered to their home (~62% respondents), they are unable to assess the product quality during internet shopping (~76% respondents), and they like the helpfulness available at stores (~72% respondents). The motivation for online shopping among these consumers stems from the ongoing COVID-19 pandemic (~47% respondents), and that car is not necessary in the case of Internet shopping ((~50% respondents). Interestingly, consumers in this class are primarily neutral about the perceptions that internet shopping has delivery (ATT_7) or privacy problems (ATT_8). In terms of the covariates, consumers in this class appear to be predominantly female (~54%) and aged 45 to 64 years (~36%). The spatial distribution (Figure 5) suggests that the relative share of consumers located in urban, suburban, and rural areas belonging to this latent class are 38.69%, 56.93%, and 4.38%, respectively. Most of these consumers in urban areas are found to have shopping stores located within less than 0.5 mile (71.70%) or within 0.5 to 1 mile (20.75%). The directed purchasers in rural areas are located in blocks that are greater than 2 miles away from the nearest store.

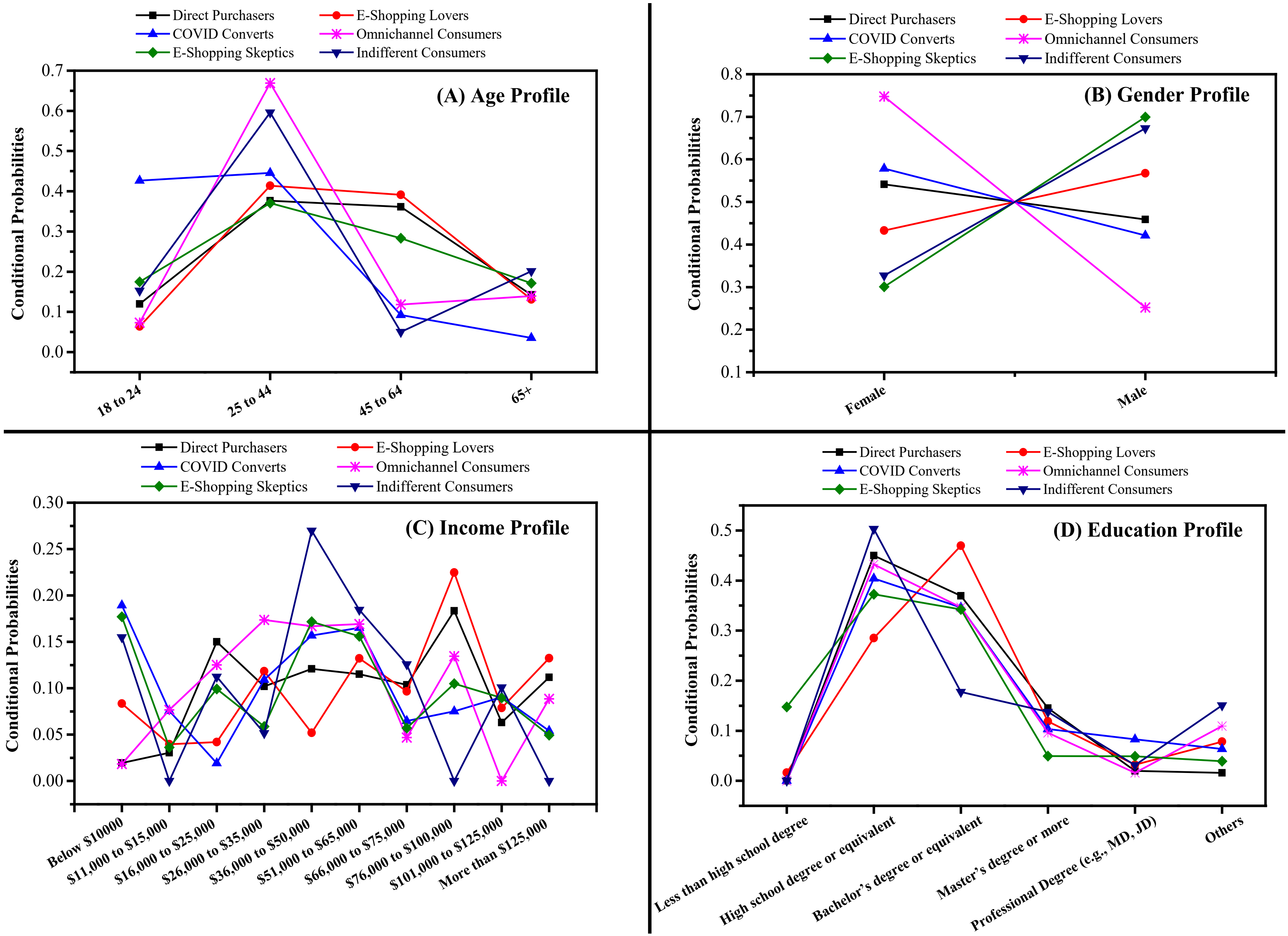


Figure 5 Profiles of Latent Classes based on the differences in (A) Age, (B) Gender, (C) Income. and (D) Education

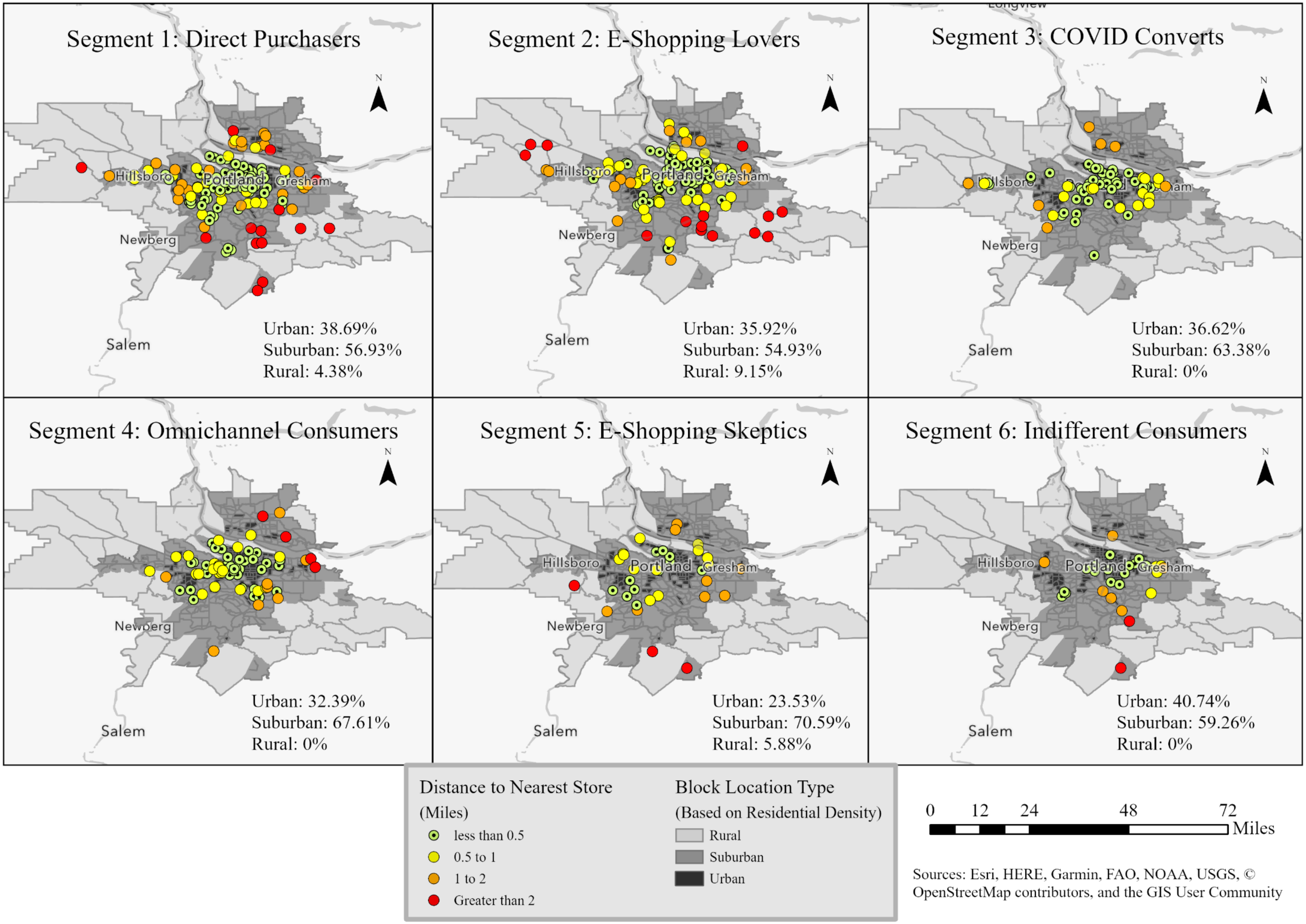


Figure 6 Spatial distribution of consumers in each latent segment

5.1.2 Latent Class 2: E-shopping lovers

Consumers belonging to this latent class are labeled "E-shopping lovers" due to the following response probabilities to attitude statements: they like online shopping to deliver packages to their households (~91% respondents), they prefer not to make physical travel for shopping (~82% respondents), they disagree that internet shopping has delivery problems (~73% respondents) and they have no privacy concerns about giving credit card information for online shopping (~70% respondents). Contrary to the previous class of direct purchasers, a significant share of these consumers (~58%) disagreed to the statements that they use E-shopping mainly because of COVID-19 pandemic. These consumers are also mostly neutral (~47%) or in disagreement (~23%) with the statement about helpfulness available at physical stores. A closer look at the demographic profile in Figure 3 reveals that E-shopping lovers are mostly male (~57%), aged 25 to 44 (~41%), and with a high-school (~29%) or Bachelor's degree (~47%). The spatial distribution of consumers in this segment follow a similar pattern as the previous segment of direct purchasers with about 36% in urban areas, 55% in suburban areas, and 9% in rural areas. Most of the urban consumers in this segment are found to have shopping stores located within 1 mile (~94%) and the suburban and rural consumers are predominantly located more than 1 mile away from the shopping store.

5.1.3 Latent Class 3: COVID converts

The unique aspect of this latent class is that a predominant share of consumers (~62%) respond that they use internet shopping, mainly because of the COVID-19 pandemic. Most of these consumers (~91%) also acknowledge that they like the helpfulness available at stores; they also perceive internet shopping to have delivery problems (~60%) and merchandise quality problems. The latent class is therefore labeled as "COVID Converts". It comprises consumers who have largely started shopping online since the onset of the pandemic but are concerned about delivery problems. The effects of income and gender are prominent since the lowest income strata (below \$10000), and females are associated with much higher conditional probabilities than others. The spatial distribution suggests that consumers in this segment are mostly located in urban and suburban areas. The absence of rural consumers indicates that the impact of COVID-19 pandemic on changing the shopping preferences in rural areas may be negligible; that is, direct purchasers may continue to purchase goods from physical stores without increasing their E-shopping orders.

5.1.4 Latent Class 4: Omnichannel consumers

This class is labeled as "Omnichannel consumers" because their attitudes towards brick-and-mortar physical stores and virtual marketplaces are similar. The response probabilities towards the two contrasting attitude statements underline the duality of consumer preferences in this class: they like having packages delivered to their homes (~98%), yet like the helpfulness available at physical stores (~51%). Despite wanting not to leave home for shopping (~84%) and liking the fact that car is not necessary for online shopping (~79%), consumers in this class believe that internet shopping has delivery problems (~81%). The demographic profile of this segment indicates that most of these consumers are female (~75%), as opposed to class-1: Direct purchasers and class-2: E-shopping lovers. Age also plays an important factor in distinguishing this class as the majority of consumers belong to the strata of 25 to 44 years (~67%). Most of the consumers in this segment are located in urban areas or suburban areas with superior access to shopping stores.

5.1.5 Latent Class 5: E-shopping skeptics

This class is in sharp contrast with all other latent classes because of the response probabilities observed for the statement on privacy: more than 63% of consumers in this class are apprehensive about giving their credit card information to a computer. The other notable distinctions about these consumers are as follows: they do not mind leaving home for shopping (~69%), they face difficulties in assessing the product quality during online shopping (~77%), and they disagree that COVID-19 has changed their shopping preferences (~60%). The notable aspects of the demographic profile are that a significant share of respondents aged over 65 (~20%) and educated less than high school (~15%) exhibit higher conditional probability to belong to this class. The consumers in this class are predominantly located in suburban areas (70.59%), followed by urban areas (23.53%). Spatial profile also reveals that a significant share of consumers is in blocks that are within 1 mile of shopping stores in the suburban (~61%) and urban (~100%) areas.

5.1.6 Latent Class 6: Indifferent consumers

This latent class is labeled as "Indifferent consumers" because the response probabilities to all the eight attitude statements revealed a neutral response without any clear preference. It may be noted that these consumers are indifferent in their attitudes towards shopping online or through physical stores, and not in their attitude or WTP towards ADRs. In fact, past literature suggests that consumers indifferent in their attitudes may exhibit a significant rate of change in their response to targeted marketing activities (Dost et al., 2014). Therefore, it is equally important to investigate the WTP responses of this segment by decomposing them into genuine zero responses and protest responses. The demographic profile reveals that male consumers aged over 65 exhibit higher probability of belonging to this segment. The education levels of these consumers are mostly limited to high-school degree or its equivalent and the income levels tend to be in the range of $36,000 to $50,000. The spatial distribution of these consumers shows that about 59.26% is in suburban areas and the remaining is in urban areas.

5.2 Predicting Consumers' Membership in Latent Classes

The probability of membership in latent classes of consumers is treated as a dependent latent multinomial measure to determine how the shopping preferences are associated with the socio-demographic factors and locational factors. The membership functions of latent classes are therefore estimated using a multinomial logit (MNL) model which controls for the shared variances between predictors and the results are presented in Table 4. The latent class 1 (direct shippers) is used as the reference category of the model since it is one of the largest subs-sample and unique in terms of shopping preference towards physical stores. The strength of the association in comparison with the reference category is quantified using relative risk ratio (RRR) which is obtained by exponentiating the MNL model coefficients. The probability of choosing one outcome category over the reference category is reflected in RRR and values less than 1 suggest that the consumer is more likely to belong to the reference category (Vermunt and Magidson, 2005). The RRR values > 1 indicate that the consumer is more likely to belong to the latent class that is being compared to the reference category.

As can be seen, RRR values of age categories suggest that older consumers are more likely to be direct purchasers, as compared with other latent classes. While the COVID Converts segment exhibit RRR values > 1 for age categories indicating a positive relationship with older consumers, the effect is not statistically significant. The gender effects suggest that male consumers are show an increased likelihood of being in latent classes other than the reference category (i.e., direct purchasers), barring the exception of omnichannel consumers. Higher income is found to be associated with an increased likelihood of belonging in the latent classes such as E-Shopping lovers, COVID Converts and Omnichannel consumers.

Table 4 Class membership functions of latent class model with class-1 (Direct Purchasers) as the reference category

Variables	**E-Shopping Lovers vs. Direct Purchasers**			**COVID Converts vs. Direct Purchasers**			**Omnichannel Consumers vs. Direct Purchasers**			**E-Shopping Skeptics vs. Direct Purchasers**			**Indifferent Consumers vs. Direct Purchasers**		
	Coef.	***RRR***	***z-stat***	***Coef.***	***RRR***	***z-stat***	***Coef.***	***RRR***	***z-stat***	***Coef.***	***RRR***	***z-stat***	***Coef.***	***RRR***	***z-stat***
Age *(Base = 18 – 24)*															
25 – 44	**-1.87*****	**0.15**	**-3.24**	0.92	2.51	0.80	**-2.93*****	**0.05**	**-4.93**	-0.78	0.46	-0.96	**-1.40***	**0.24**	**-1.69**
45 – 64	**-1.02***	**0.35**	**-1.74**	0.89	2.44	0.77	**-4.22*****	**0.01**	**-5.76**	**-3.15*****	**0.04**	**-2.18**	**-2.08****	**0.12**	**-2.13**
65+	**-1.09***	**0.33**	**-1.66**	1.17	3.22	0.97	**-4.35*****	**0.01**	**-4.56**	-0.69	0.50	-0.74	-0.20	0.82	-0.22
Gender *(Base=Female)*															
Male	**0.50***	**1.65**	**1.73**	0.09	1.09	0.26	**-0.61***	**0.54**	**-1.72**	**1.48*****	**4.39**	**3.08**	**1.69*****	**5.41**	**3.24**
Income *(Base: Below $10000)*															
$11,000 to $15,000	0.29	1.33	0.32	**2.01***	**7.46**	**1.68**	0.30	1.34	0.32	**-2.08*****	**0.12**	**3.59**	0.11	1.12	0.08
$16,000 to $25,000	**3.39*****	**29.66**	**3.59**	**3.99*****	**54.05**	**2.95**	0.64	1.89	0.46	**2.32*****	**10.18**	**2.01**	**3.22*****	**25.02**	**2.67**
$26,000 to $35,000	0.32	1.37	0.44	1.30	3.66	1.09	0.68	1.96	0.88	-1.52	0.22	-1.41	-0.39	0.67	-0.33
$36,000 to $50,000	**2.23*****	**9.25**	**2.96**	**2.98*****	**19.68**	**2.45**	**2.14*****	**8.47**	**2.55**	**2.03*****	**7.61**	**2.16**	**2.14****	**8.49**	**1.97**
$51,000 to $65,000	**1.06***	**2.88**	**1.67**	1.61	5.00	1.34	**1.33***	**3.78**	**1.81**	0.64	1.90	0.71	0.50	1.65	0.48
$66,000 to $75,000	0.30	1.35	0.42	0.80	2.22	0.62	0.27	1.30	0.31	0.25	1.28	0.26	0.17	1.19	0.15
$76,000 to $100,000	0.83	2.29	1.27	**1.91***	**6.75**	**1.72**	0.03	1.03	0.04	**-2.31*****	**0.10**	**-2.92**	-0.93	0.39	-0.79
$101,000 to $125,000	0.87	2.60	1.17	0.87	2.38	0.63	0.21	1.23	0.23	-0.15	0.86	-0.34	-1.05	0.35	-0.73
More than $125,000	0.96	2.62	1.27	**1.99***	**7.31**	**1.84**	0.02	1.02	0.04	**-2.25*****	**0.11**	**-2.61**	**-2.24*****	0.11	**-2.98**
Education *(Base: Less than high school degree)*															
High school degree or equivalent	-0.92	0.40	-0.76	-1.07	0.34	-0.79	3.48	32.45	0.07	3.12	22.65	0.28	**-2.03***	**0.13**	**-1.67**
Bachelor's degree or equivalent	**-2.16***	**0.11**	**-1.79**	**-2.29***	**0.10**	**-1.67**	3.19	24.28	0.06	2.46	11.70	0.46	**-2.18***	**0.11**	**-1.82**
Master's degree or more	-1.49	0.22	-1.19	-1.71	0.18	-1.21	3.71	40.85	0.07	3.30	27.11	0.08	**-2.62****	**0.07**	**-1.99**
Professional Degree (e.g., MD, JD)	-1.65	0.19	-1.17	-1.70	0.18	-1.07	3.56	35.16	0.08	2.71	15.03	0.09	-0.19	0.83	-0.12
Others	**-4.01****	**0.02**	**-2.46**	-0.85	0.43	-0.59	3.83	46.06	0.07	1.78	5.93	0.32	-2.10	0.12	-0.27
Residential Location *(Base: Suburban or Rural)*															
Urban	-0.05	0.95	-0.16	-0.35	0.70	-0.99	**-0.78***	**2.18**	**-1.93**	-0.28	0.76	-0.51	-0.15	0.86	-0.27
Distance to nearest store *(Base: Less than 0.5 Mile)*															
0.5 to 1 Mile	0.27	1.31	0.75	-0.13	0.88	-0.31	0.34	1.40	0.77	**1.50*****	**4.48**	**2.53**	-0.54	0.58	-0.77
1 to 2 Miles	**0.94****	**2.55**	**2.16**	**-0.99***	**0.37**	**-1.90**	-0.47	0.62	-0.84	0.78	2.18	1.18	0.40	1.49	0.60
Greater than 2 Miles	0.12	1.13	0.24	**-1.16***	**0.31**	**-1.68**	**-1.11***	**0.33**	**-1.66**	0.40	1.49	0.46	-0.48	0.62	-0.52
Intercept	**1.89***	**6.62**	**1.73**	-1.44	0.24	-0.78	-3.97	0.02	-0.06	-2.21	0.11	-0.09	0.53	1.70	0.35

Notes: $^{*}p < .1$; $^{**}p < .05$; $^{***}p < .01$ for statistical significance; No. of observations = 483; Log likelihood = - 619.42; AIC = 1468.85; McFadden's pseudo R^2 = 0.214;

The income variable shows both positive and negative relationships in latent classes such as E-shopping skeptics and Indifferent consumers; nonetheless, consumers with high income levels show increased likelihood to be direct purchasers. The higher education levels are also found to be associated with the direct purchasers, in comparison with the latent classes such as E-Shopping lovers, COVID converts and indifferent consumers. The effect of residential location is found to be statistically significant only for the segment of omnichannel consumers which suggest the increased likelihood of suburban consumers in the segment. As the distance to the nearest store increases, consumers are found to be more inclined to be E-Shopping lovers, as compared to direct purchasers. However, latent classes such as COVID converts or Omnichannel consumers show a reverse relationship with distance to nearest store. To check the prediction accuracy of the model, a confusion matrix is estimated and presented in Table 5 in which each row and column highlight the observed and predicted consumers in each latent class, respectively. The overall accuracy of the model is 88.02% and the class-specific accuracies range between 83% to 95% with latent class 1 and 5 showing the highest share of true positives.

Table 5 Confusion matrix for latent class membership prediction model

Observed Class (N = 483)	**Predicted Class**							
	Class 1 (140)	*Class 2 (136)*	*Class 3 (81)*	*Class 4 (66)*	*Class 5 (32)*	*Class 6 (29)*	***Class Accuracy***	***Overall Accuracy***
Class 1 (137)	125	6	3	2	1	0	91.07%	**88.02%**
Class 2 (142)	7	122	6	4	1	2	86.16%	
Class 3 (71)	4	3	63	1	0	0	88.37%	
Class 4 (71)	2	2	8	59	0	0	83.21%	
Class 5 (45)	1	2	1	0	30	1	86.50%	
Class 6 (27)	0	1	0	0	0	26	95.98%	

5.3 Contingent Valuation of Willingness to Pay

Out of the 483 valid responses collected in this study, 187 respondents (38.72%) showed non-positive WTP responses, and 296 respondents (61.28%) showed positive responses. Among the non-positive answers, 96 respondents (19.88%) give genuine zero responses indicating either they are satisfied with the status-quo delivery method or their budget constrains them. 91 respondents (18.84%) gave protest answers as the reason for non-positive responses, out of which 15 respondents (5.06%) emphasized that the cost of ADR deployment needs to be paid by E-commerce companies or the Government. While the protest responses point towards consumers with truly zero WTP, genuine zero responses indicate that they may be willing to pay for ADRs if their perception about status-quo changes or their budget constraints reduces over time. A summary of these WTP responses segmented using six latent classes is presented in Table 6. As can be seen, Omnichannel consumers exhibit the highest average WTP for ADRs ($2.92), followed by E-shopping lovers ($2.33), COVID converts ($2.21) and Direct purchasers ($1.92).

The proportion of consumers' WTP for getting deliveries using ADRs vary significantly between the latent classes, ranging from the lowest WTP found among Indifferent consumers to the highest WTP found among Omnichannel consumers. The proportion of positive responses understandably decreases when WTP value increases. Most consumers belonging to the class of Direct shoppers would like to pay $1 or less for receiving deliveries using ADRs. The latent classes exhibiting positive attitudes to internet shopping (i.e., E-shopping lovers and Omnichannel consumers) and latent class opting for internet shopping due to COVID-19 pandemic (i.e., COVID Converts) comprises of about 42% consumers willing to pay $2 to $3 for ADRs. Regarding the genuine zero responses, it is interesting to note that the consumers belonging to Direct purchasers and E-shopping lovers exhibit a higher share of protest responses than those in the remaining classes.

Table 6 Summary of WTP Responses for autonomous delivery robots across the latent classes

Positive Responses for WTP *(61.28% of 483 Respondents)*	**Overall Sample** (N = 296)	***Direct Purchasers*** (N = 88)	***E-Shopping Lovers*** (N = 87)	***COVID Converts*** (N = 40)	***Omnichannel Consumers*** (N = 57)	***E-Shopping Skeptics*** (N = 15)	***Indifferent Consumers*** (N = 9)
$1 or less	39.19%	53.41%	34.48%	40%	24.56%	60%	66.67%
$2 to $3	38.85%	29.55%	42.53%	42.5%	42.11%	33.33%	33.33%
$4 to $5	18.24%	14.77%	19.54%	15%	26.32%	0%	0%
$6	3.72%	2.27%	3.45%	2.5%	7.02%	6.67%	0%
Mean WTP per order (Excluding Protest Responses and Genuine Zero Responses)	**$2.25** *(1.61)* *	**$1.92** *(1.56)* *	**$2.33** *(1.53)* *	**$2.21** *(1.56)* *	**$2.92** *(1.77)* *	**$1.70** *(1.45)* *	**$1.33** *(0.50)* *
Genuine Zero Responses for WTP *(19.88% of 483 Respondents)*	**Overall Sample** (N = 96)	***Direct Purchasers*** (N = 31)	***E-Shopping Lovers*** (N = 29)	***COVID Converts*** (N = 14)	***Omnichannel Consumers*** (N = 6)	***E-Shopping Skeptics*** (N = 7)	***Indifferent Consumers*** (N = 9)
"The existing delivery methods are good enough and it does not need to be improved using ADRs"	83.87%	83.87%	72.41%	92.86%	66.67%	71.43%	88.89%
"I am willing to pay, but the household income is not enough to bear the additional cost"	16.13%	16.13%	27.59%	7.14%	33.33%	28.57%	11.11%
Protest Responses for WTP *(18.84% of 483 Respondents)*	**Overall Sample** (N = 91)	***Direct Purchasers*** (N = 18)	***E-Shopping Lovers*** (N = 26)	***COVID Converts*** (N = 17)	***Omnichannel Consumers*** (N = 8)	***E-Shopping Skeptics*** (N = 13)	***Indifferent Consumers*** (N = 9)
"The additional cost should be paid by the government and E-commerce companies"	16.67%	16.67%	19.23%	23.53%	50.00%	23.08%	11.11%
"The cost has been included in the taxes and fees"	38.89%	38.89%	19.23%	23.53%	12.50%	7.69%	44.44%
"I have other reasons not listed"	44.44%	44.44%	61.54%	52.94%	37.50%	69.23%	44.44%

* Numbers in parenthesis are the standard deviation of WTP responses

The satisfaction with existing delivery methods is cited as the predominant reason for genuine zero responses regardless of the latent class. Income constraints appear to limit the WTP for ADRs mostly in the case of latent classes such as Omnichannel consumers, E-shopping lovers, and COVID converts. To further investigate how WTP determinants vary as per the latent classes, a set of latent class Tobit models are estimated in this section. The consumers who gave protest responses (18.84% of the sample) are censored from the WTP estimation sample because they are considered to violate the economic theory. The final sample used for estimating LC Tobit models consisted of 392 responses with either genuine zero responses or positive responses for WTP. The model estimation results in Table 7 show that WTP determinants are considerably different across the identified latent classes, thus highlighting the heterogeneity among consumers and the need to adopt a segmentation approach. A detailed discussion of WTP determinants with due focus given to correlate with the findings from previous technology studies follows.

5.3.1 Socio-demographic Determinants of WTP

The respondents' WTP can be observed to have a direct negative relationship with age in the overall sample, as well as the three largest latent classes. As the consumer's age increases from "*18 to 24*" to "*65+*", WTP consistently decreases with more significant effects observed for the oldest age category. These findings are in line with prior results in the case of autonomous vehicles (Bansal et al., 2016), and the pattern may be linked to the reasoning that technological efficacy and trust are generally lower in the case of older people. The marginal reduction in WTP reaches the highest value when consumers are aged over 65. Another demographical factor examined in this study is gender; however, it does not have statistical significance in the general Tobit model. The statistically significant effect of gender is present only in the case of two latent classes: Omnichannel consumers and E-shopping lovers. The model coefficients in these two classes suggest that males exhibit slightly higher WTP for ADRs, as compared to females. This gender difference is in line with the general findings in psychology, behavioral research, and acceptance of autonomous vehicles (Hulse et al., 2018), which suggests that women tend to perceive higher risk about the emergence of a disruptive technology. This study also examines the effects of income on WTP. A strong positive relationship exists between income and WTP, although it loses its explanatory power in some latent classes. The most substantial effects of income can be found in the segment of Omnichannel consumers. The model coefficients also confirm education levels to have a positive impact on WTP in the overall sample. However, disaggregated results show that the effects of education are limited to two latent classes: Omnichannel consumers and E-shopping skeptics.

5.3.2 Psychological Determinants of WTP

Familiarity hypothesis often explored in technology acceptance studies suggest the following: a respondent who had heard of a particular technology will express higher WTP for the technology, than those who had not (Liu et al., 2019). Our findings underline the familiarity hypothesis by demonstrating that the consumers who are very familiar with ADR technology exhibit higher WTP in the latent class of Direct purchasers. Similarly, consumers who have never heard of ADR technology exhibit lower WTP in two latent classes: Direct purchasers and COVID converts. However, the effect of familiarity is not statistically significant in the Tobit model estimated for the overall sample. Two other psychological factors examined in this study are: enthusiasm towards emerging technology and perceived trust on ADR technology. Past studies have demonstrated the positive relationships of trust and general interest towards technology (i.e., tech-savvy nature) towards intention to use autonomous vehicles (Liu et al., 2019); sufficient trust and enthusiasm are regarded as the precondition for mass adoption of technology. To the best of our knowledge, the reported model coefficients are the first to reveal the influence of trust and tech-savvy attitude to positive WTP for ADRs.

Table 7 WTP determinants for six latent classes and the overall sample

Variables	General Tobit Model *(N =392)*		Latent Class Tobit Model												
			Direct Purchasers *(N =119)*		***E-Shopping Lovers*** *(N=116)*		***COVID Converts*** *(N=54)*		***Omnichannel Consumers*** *(N=63)*		***E-Shopping Skeptics*** *(N=22)*		***Indifferent Consumers*** *(N=18)*	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Constant	-0.86	-1.48	-6.13	-0.16	1.20	1.18	-2.38	-1.00	**-2.79*****	-2.71	-2.18	-0.88	-1.90	-0.53
Age *(Base = 18 – 24)*														
25 – 44	**-1.12*****	-3.17	**-2.58****	-2.23	**-1.36****	-2.21	**-5.72*****	-2.79	--	--	--	--	**-1.66*****	-3.61
45 – 64	**-1.72*****	-4.47	**-2.91*****	-2.54	**-2.01*****	-3.12	**-6.84*****	-3.13	**-1.91****	-2.16	--	--	--	--
65+	**-1.96*****	-4.07	**-2.87****	-2.31	**-2.63*****	-3.13	**-5.76*****	-2.74	**-2.00***	-1.86	--	--	--	--
Gender *(Base=Female)*														
Male	--	--	--	--	**0.81***	1.72	--	--	**0.66***	1.71	--	--	--	--
Income *(Base: Below $10000)*														
$11,000 to $15,000	**1.25****	2.39	--	--	--	--	--	--	--	--	--	--	--	--
$16,000 to $25,000	--	--	--	--	--	--	--	--	**1.83****	2.60	--	--	--	--
$26,000 to $35,000	--	--	**1.21***	1.68	--	--	**2.62*****	2.75	--	--	--	--	--	--
$36,000 to $50,000	**0.79***	1.72	**1.71***	1.79	--	--	**3.11*****	2.55	**1.54****	2.05	--	--	--	--
$51,000 to $65,000	--	--	**2.81****	2.36	--	--	**4.12*****	2.05	**1.49****	2.44	--	--	--	--
$66,000 to $75,000	--	--	--	--	--	--	--	--	**2.44*****	2.42	--	--	--	--
$76,000 to $100,000	**1.01***	1.96	--	--	--	--	--	--	**2.55*****	3.29	--	--	--	--
$101,000 to $125,000	--	--	--	--	--	--	--	--	**1.89***	1.93	--	--	--	--
More than $125,000	**0.92***	1.67	**1.82***	1.66	--	--	**3.45*****	-2.37	**3.57*****	3.38	--	--	--	--
Education *(Base: Less than high school degree)*														
High school degree or equivalent	**1.91****	2.28	--	--	--	--	--	--	**2.09*****	3.64	**1.99***	1.80	--	--
Bachelor's degree or equivalent	**1.40***	1.66	--	--	--	--	--	--	--	--	--	--	--	--
Master's degree or more	--	--	--	--	--	--	--	--	--	--	--	--	--	--
Professional Degree (e.g., MD, JD)	--	--	--	--	--	--	--	--	--	--	--	--	--	--
Others	--	--	--	--	--	--	--	--	--	--	--	--	--	--
Familiarity with Delivery Robots *(Base: I had never heard of ADRs before taking this survey)*														
I have heard, but do not know much	--	--	**-0.79***	-1.82	--	--	**-0.87***	-1.77	--	--	--	--	--	--
I am somewhat familiar with ADRs	--	--	--	--	--	--	--	--	**0.66***	1..69	--	--	--	--
I am very familiar with ADRs	--	--	**3.55***	1.73	--	--	--	--	--	--	--	--	--	--
I have received ADR orders	--	--	--	--	--	--	--	--	--	--	--	--	--	--

Variables	General Tobit Model (N =392)		Latent Class Tobit Model (Table Continued)											
			Direct Purchasers (N =119)		*E-Shopping Lovers* (N=116)		*COVID Converts* (N=54)		*Omnichannel Consumers* (N=63)		*E-Shopping Skeptics* (N=22)		*Indifferent Consumers* (N=18)	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Enthusiasm towards Technology - Do you get excited about buying newly-launched Gadgets or accessories? *(Base: About Half the Time)*														
Never	-0.83*	-1.71	--	--	-1.05*	-1.73	--	--	--	--	-1.49*	-1.83	--	--
Sometimes	--	--	--	--	--	--	--	--	1.79*	2.18	--	--	--	--
Most of the time	0.67*	1.89	--	--	--	--	--	--	2.09***	2.61	--	--	--	--
Always	1.35***	3.51	0.84*	1.65	--	--	1.38*	1.80	3.06***	4.16	--	--	--	--
Perceived Trust on ADR Technology – I think autonomous delivery robots are reliable *(Base: Neutral)*														
Strongly disagree	-1.24*	-1.94	--	--	--	--	-1.79*	-1.67	-2.10**	-1.99	--	--	--	--
Somewhat disagree	-0.59*	-1.65	--	--	--	--	-1.96*	-2.03	--	--	-3.49**	-2.07	--	--
Somewhat agree	0.36*	1.73	--	--	1.54***	3.18	--	--	--	--	--	--	--	--
Strongly agree	1.52***	3.21	--	--	2.96***	2.72	2.80**	1.94	0.79*	1.17	--	--	--	--
Residential Location *(Base: Suburban or Rural)*														
Urban	0.54**	2.17	--	--	--	--	0.14*	1.81	2.08***	3.58	--	--	--	--
Distance to nearest store *(Base: Less than 0.5 Mile)*														
0.5 to 1 Mile	0.53	1.89	--	--	--	--	0.98*	1.88	--	--	--	--	--	--
1 to 2 Miles	0.52	1.71	--	--	--	--	1.23*	1.76	1.25*	1.92	--	--	--	--
Greater than 2 Miles	--	--	--	--	--	--	--	--	2.48**	2.56	2.14*	1.97	--	--
Loglikelihood	-768.3		-213.01		-219.11		-208.68		-102.45		-21.05		15.29	
McFadden's Pseudo R^2	0.09		0.12		0.15		0.18		0.29		0.14		0.13	

Notes: *p < .1; **p < .05; ***p < .01 for statistical significance; Coefficients that are not significant at 90% confidence level or more are omitted.

5.3.3 Locational Determinants of WTP

The general Tobit model shows that the willingness to pay for ADRs is higher among consumers in urban areas than suburban/rural consumers. The same is true for consumers located beyond 0.5 miles (~10-minute walking time) from the shopping stores, although the effect is not statistically significant for distances greater than 2 miles. These results are consistent with previous studies on the adoption of autonomous vehicles (AVs); for example, Bansal et al., (2016) showed that individuals living in urban areas are more likely to use shared AVs. However, the effects of locational determinants are not consistent across the latent classes of consumers. The positive relationship with urban location or distance to the nearest store is statistically significant in the case of three segments: COVID Converts, Omnichannel consumers, and E-Shopping Skeptics. Perhaps the consumers in a segment like COVID Converts are exhibiting higher WTP for urban areas due to their risk perceptions of COVID-19 and the perceived need for contactless deliveries by ADRs. The omnichannel consumers may be perceiving ADRs as a solution for faster deliveries in urban areas since about 81% of consumers in this segment perceive internet shopping to have delivery problems (see Table 3). Interestingly, the WTP for ADRs is higher among consumers in the E-Shopping skeptics segment if they are located beyond 2 miles from the nearest shopping store. The non-significance of locational determinants of WTP for Direct purchasers may be linked to the general propensity of consumers in this segment to purchase goods from physical stores. Similarly, the satisfaction and familiarity with existing delivery methods of online shopping may be linked to the non-significance of locational determinants for the segment of E-shopping lovers. Overall, the existence of spatial differences in WTP further highlights the need to adopt a segmentation approach that accounts for consumer heterogeneity and enables ADR deployment in a way that maximizes the public acceptance.

6. CONCLUSIONS AND FUTURE RESEARCH DIRECTIONS

This research offers timely insights into the acceptance of ADRs for receiving online shopping deliveries and the US consumers' willingness to pay for this emerging technology. This study is the first-of-its-kind in addressing the issue of preference heterogeneity for logistical innovations and thus contributing to the emerging body of literature on ADR technology. Six underlying consumer segments are revealed in the latent class analysis of attitudinal responses: Direct shoppers, E-shopping lovers, COVID converts, Omnichannel consumers, E-shopping skeptics, and Indifferent consumers. The membership probabilities of latent classes are modeled using sociodemographic and locational factors and the strength of association is demonstrated using relative risk ratios. Subsequently, the analysis of consumer preference data showed that there is an overall positive WTP since 61.28% of consumers are willing to pay extra to receive deliveries using ADRs. Among the latent classes, Omnichannel consumers exhibited the highest average WTP for ADRs ($2.92), followed by E-shopping lovers ($2.33), COVID converts ($2.21) and Direct purchasers ($1.92). The zero WTP responses given by 38.74% of respondents are decomposed into genuine zero responses (19.88%) and protest responses (18.84%). The satisfaction with existing delivery methods is found to be the predominant reason for genuine zero responses. Censoring the protest responses that violate the economic demand theory, this study estimated WTP determinants for each of the six latent classes.

In analyzing WTP determinants, latent class Tobit regression results further reaffirmed the large extent of preference heterogeneity in consumer sample and accordingly suggest that consumers can no longer be treated as a single homogeneous group. Estimating the overall WTP determinants without distinguishing the underlying consumer segments may lead to inaccurate determinants of WTP and incorrect decision-making. The model coefficients revealed that age has a strong inverse relationship with WTP for ADRs, which is consistent with the findings from prior technology acceptance studies. The study also revealed that gender is weakly correlated with WTP in latent classes with strong E-shopping motivations; however, the statistical significance is not consistent in the general Tobit model. Income and education levels of the consumers are found to be positive predictors of WTP, although the effect is not consistent across all latent classes. Regarding psychological determinants, this study finds that familiarity, perceived trust, and tech-savvy attitude are strong predictors of WTP; these factors are thus definite preconditions for the mass adoption of ADRs, especially in certain latent classes. For instance, WTP determinants among consumers in COVID converts and Omnichannel consumers show that WTP reduces if consumers are wary about the reliability of ADRs. The locational determinants of WTP suggest that consumers in located in urban areas or areas that are located beyond 0.5 miles from shopping stores exhibit higher WTP for ADRs. The positive relationships urban location or distance to the nearest store are only present in certain latent classes such as COVID converts and could be linked to the higher risk perceptions or lifestyle preferences. The spatially induced preference heterogeneity and WTP displayed by the consumers further highlight the need for developing a area-specific targeted pricing mechanism that ensures that delivery fees will not hinder the ADR adoption of consumer segments with a significant share of genuine zero WTP responses.

There are several practical implications of this study. First, the study findings offer insights on the perceived value of the emerging ADR technology among US consumers. Second, this study sketches the profile of potential adopters using consumer attitudes and provides valuable insights on their differential acceptance of ADR technology. Third, model estimation results explain the psychological, demographical, and locational determinants of WTP. Insufficient trust, familiarity, and lack of enthusiasm towards new technology are identified to be major psychological barriers of WTP for ADRs. However, the effects of psychological determinants vary significantly across the latent consumer segments, underlining the importance of consumer segmentation in WTP studies. As the general awareness about ADR technology increases and the delivery experiences start proliferating in public peer-networks, the proportion of consumers with non-positive WTP responses (38.72%) are also expected to change their perspectives. Considering that 19.88% of them are genuine zero responses arising from income constraints or satisfaction with existing delivery methods, it is recommendable that delivery fees to the consumers should initially be priced lower or at least the same as existing van-based deliveries. The real-time pricing mechanisms should particularly consider the possibility of spatially induced preference heterogeneity and the need to facilitate effective adoption in suburban/rural areas exhibiting lower WTP values. As the lack of familiarity and trust are found to be significant psychological barriers to ADR adoption, E-commerce companies and on-demand delivery platforms should also focus on publicizing the operational procedures (e.g., interactive unlocking, theft prevention measures) and potential advantages (e.g., delivery speed, flexibility, contactless handling, and convenience) of ADRs to the end-users.

In closing, as with any research effort, this study has its limitations and the findings open the window for many research extensions that warrants attention. The current data sample used for this study is restricted to a specific metropolitan statistical area and large-scale data collection efforts covering multiple US states are required to validate the geographical stability of consumers segments and better trace the preference heterogeneity in ADR adoption. An immediate future research direction will be to examine how consumer preferences and WTP change across the latent classes after the society recovers from the COVID-19 pandemic. Considering the spatial differences in WTP values revealed in this study, another recommended research direction will be to examine the effects of neighborhood-level factors and the consumers' perceived accessibility on the preferences for ADRs. A comparative analysis of consumer preferences to other delivery mechanisms, such as smart-delivery lockers or delivery drones, are also needed to account for the possibility that consumers may be interested in the relative advantages of each delivery option over ADRs. Overall, this study is expected to offer actionable insights on how ADR delivery options need to be priced with due consideration of the underlying variation of consumer preferences to maximize public acceptance and large-scale adoption of the technology.

Authorship Contribution Statement

Agnivesh Pani: Conceptualization, Methodology, Writing – original draft, review & editing. **Sabya Mishra**: Conceptualization, Writing - review & editing, Methodology, Supervision, Funding acquisition, Project administration, Resources. **Mihalis Golias**: Writing - review & editing, Funding acquisition. **Miguel Figliozzi**: Writing - review & editing, Funding acquisition.

Acknowledgements

This research is funded by the Freight Mobility Research Institute (FMRI), a US Department of Transportation University Transportation Research Center.

Declaration of Competing Interest

The author declares no conflicts of interest in this article.

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