



User Preferences for Automated Shared Mobility Services: An Alternative-Specific Mixed Logit Regression Approach

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Abstract

Ridesharing transportation services as the leading transport systems in recent years have already invested in shared autonomous vehicles (SAVs) as the next generation of shared transportation systems. Recent years have seen a noticeably accelerating rate in utilizing advanced communications and mapping service technologies that opened new doors to the ridesharing operators to provide a better quality of service to the users; therefore, it is necessary to have a better insight in-to the preferences of the users for using SAVs. This study aims to identify individuals' preferences for using SAVs and investigate related demographic characteristics and travel behavior attributes. An online Adaptive Choice-Based Conjoint (ACBC) survey will be designed and implemented between March to May 2020 in the United States. Then a series of mixed logit models (MXLs) were used to estimate participants' preferences. The results show that females are more tended to use door-to-door services, younger riders are more interested in using SAVs and also accept longer travel times, and riders with high-income levels are willing to use SAVs with higher equipment and convenience door-to-door service and not share their trips with others. Furthermore, more educated riders are more likely to use door-to-door service, select a service with shorter travel time, and pay a little more money to insure their trip against possible delays.

Keywords Shared autonomous vehicle · Autonomous vehicle · Mixed logit model · Automated mobility · Travel behavior

Abbreviations

ACBC Adaptive Choice-Based Conjoint

AV Autonomous Vehicle

CNL Cross-Nested Logit

DDA Descriptive Data Analysis

ESMS Electric Shared Mobility Services

HOV High-Occupancy Vehicle

IIA Independence of Irrelevant Alternatives

LCM Latent Class Model

MXL Mixed Logit Model

MNL Multinomial Logit Model

MDCP Multiple Discrete-Continuous Probit

RA Regression Analysis

SAV Shared Autonomous Vehicle

WTP Willingness-To-Pay

WTU Willingness-To-Use

1 Introduction

The advent of autonomous vehicles (AVs) technology may allow for the emergence of novel sharing systems such as shared autonomous vehicles (SAVs), which could provide inexpensive mobility-on-demand services, use significantly less energy [1–3] and could play a vital role in sustainable transportation systems [4–6]. The topic of evaluating the possible impact of SAVs on future transportation networks, users' preferences, and travel behavior has been widely considered in recent years [7–11]. In recent years, several researchers conducted studies to estimate the growth of SAVs and investigate their benefits on urban and suburban mobility [12–17]. Some studies provided optimistic estimates for SAV market penetration, such as up to 90% of

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all passenger miles traveled in 2030 [8]. While other studies investigated the system-wide coordination of SAVs to decrease congestion, facilitate the integration of advanced propulsion systems [18], and their role in reducing private car ownership levels [19]. In addition to SAVs undeniable benefits, some unforeseen events such as COVID-19 deployment may change its performance [20]. Coronavirus outbreak has caused upheaval around the world and has caused our daily routines to change quickly. The impacts of pandemic and after pandemic periods on travel behavior and travel patterns of the transportation systems' users are obvious and, more specifically, alterations in the activities people engage in and transportation modes they use to reach their activity locations. It is necessary for the decision-makers, to have a better insight into different types and degrees of behavioral changes among various groups of society. Therefore, this study investigates user preferences for automated shared mobility services. Since the survey for this study was conducted during the COVID-19 pandemic lockdown, the results can show how the COVID-19 pandemic impacted the users' preferences for SAVs. During our research, individuals' preferences for SAVs using an appropriate statistical approach are identified, demographic characteristics and travel behavior attributes related to people's preferences for SAVs are investigated, and insight into how the COVID-19 situation have changed travel behavior is evaluated. In addition to the aforementioned objectives, this research tries to inform policymakers about the preferences of the users in the future. The design of effective transport policies during and post-pandemic aims to realize the potential benefits of SAVs. It requires an understanding of how users will adopt SAVs. Yet, at this stage, little is known about how travelers will employ SAVs during and after the pandemic. This study intends to consider the role of shared mobility in the future (during and post-pandemic), investigate what features of SAVs are preferred among different demographic groups, and what attributes will affect using SAVs according to their characteristics. The remainder of this study is structured as follows: The Literature review is presented in section 2, the methodology of the research is proposed in section 3, the results are explained in section 4, and the discussion and conclusion are stated in section 5. References are presented in the last section of this manuscript.

2 Literature Review

As mentioned in the introduction, the topic of understanding preferences for shared autonomous vehicles has been widely considered in recent years [21, 22]. Some studies conducted a comprehensive literature review on the SAVs and investigated various components of the SAVs, including safety,

modeling, travel behavior, public acceptance, prospective regulations, etc., [23, 24].

Spurlock et al. [25], by using multi-logit model (MLM) investigated the adoption patterns for shared mobility, electrified vehicle technologies, and vehicle automation was analyzed by focusing on four types of factors: demographics (e.g., age, income, gender), location-specific factors (e.g., walkability, population density, commute distances), preferences for mode attributes (e.g., social interactions, convenience), and human characteristics (e.g., risk preferences, personality). The proposed multi-logit model indicated that young people are greatly interested in SAV technologies. In another study, Hudson et al. [26] investigated people's attitudes toward SAVs across all EU countries using regression analysis (RA), and found substantial differences by country; thus, the elderly, retired, unemployed, less educated, and women tend to be less hostile to SAVs. In a similar study in the U.S., Kim et al. [27] by using Cross-nested logit (CNL) model analyzed Georgia State residents' willingness-to-use (WTU) in 2017–2018 for the SAVs. A survey was conducted to determine age, income, vehicle ownership, and neighborhood type. Then, the cross-nested logit (CNL) model was used to appropriately reflect the shared unobserved variables influencing common elements of a residential location/vehicle ownership choice bundle. The results highlighted that young, lower-income, pro-suburban, and/or pro-non-car-modes were more likely to use SAVs. In a different approach, Winter et al. [28] tried to identify the potential user classes for SAVs using a stated choice experiment and latent class model (LCM) on mode choice among a Dutch urban population sample. An online survey was distributed, and latent class choice models (A 3-class nested logit model) were used to capture the heterogeneity in preferences among the respondents. The results specified the preferences toward SAVs is highest for those currently combining car and public transport for their commute.

In recent years with the emerging COVID-19 pandemic, some studies tried to consider the possible impacts of the COVID-19 pandemic on the users' preferences for SAVs. Rahimi et al. [29] by using bivariate ordered probit model (BOP) explored the risk individuals perceive toward the SAVs in the Chicago region. The results showed that the sociodemographic variables, built environment, health condition, virus spread, travel behavior, and restriction factors influenced the perceived risk of using shared transportation systems. In a similar study, Turoń et al. [30] examined WTU of electric shared mobility services (ESMS) during the COVID-19 Pandemic and found that the most important factors in the operation of the electric shared mobility market could be costs, safety issues, the status of the vehicle and the legal requirements.

In the conclusion of the literature review, previous studies highlighted that travel cost was a decisive factor

in mode choice. It has been shown in many studies [6, 25, 26] that men are more likely to use shared mobility [27], high-income people are more willing to pay for saving commuting time, and higher employment densities or household incomes may increase willingness-to-pay (WTP) for SAVs, the busier commuters (i.e., more trips per day) are less likely to use SAVs [28], people with high educational attainment tend more to use SAVs. In contrast, they were more concerned that [25] and older users ages 50 and older are less likely to use SAVs than younger users ages 18 to 49 [31, 32]. Various statistical-based methods have been implemented to identify users' preferences and factors of SAVs. In addition to the aforementioned models, descriptive data analysis (DDA) [33], multiple discrete-continuous Probit (MDCP) [34], multinomial probit model (MNP) [34], and mixed logit model (MXL) [35] have been utilized.

Given that delay time is a constituent of the total travel time, it may serve as a meaningful indicator for appraising the efficacy of an on-demand transit system however, there is a little knowledge available in the literature review on how the riders interact with the possible unexpected delays. Table 1 shows an overview of the variables considered, the proposed methodology, and the limitations of the proposed approaches. Table 1 illustrates how our paper fills the gaps and overcomes the challenges of previous studies.

Table 2 summarizes selected recent relevant studies on user's preferences for SAVs. As shown in Table 2, the influence of delay has not been considered in the previous studies. This research investigates the impression of delay on SAVs' WTU and WTP. Moreover, another innovation of this study is to use more realistic SAV use features according to the current incentive plans of well-known ride-hailing services in the U.S.

3 Methodology

Although some studies used simulation-based approaches to predict travel behavior and potential impacts of SAVs on the transportation network, most previous studies stated preference approaches to anticipate travel behavior and potential impacts of SAVs. The methodology of this study has the stated preferences choice modeling basis, and it utilizes an MXL model because of its more flexible heterogeneous capability to provide more realistic choice patterns regarding the factors that influence respondents' final decisions. Also, it has been proven that MXL models can provide more accurate conditional predictions rather than standard MNL models [37].

3.1 Online Survey

The online survey was administered from March 30, 2020, through May 30, 2020. The survey was designed and developed using Sawtooth software [38]. The survey links were released nationwide in the U.S. through social media and other personal networks. The collected data have been archived electronically. All participants were informed about the aim of the study and confidentiality statements of the survey on the first screen of the survey. The online survey consisted of two sections: first, the most important socioeconomic characteristics, travel behavior information, and the current spatial-temporal pattern of daily trips. The second section concentrated on respondents' stated preferences for using a shared mobility service.

The survey was designed to show how the respondents choose between different options with different attribute values to build their preferred service. The survey let the participant make their ideal selection among suggested attributes and corresponded levels. Participants were asked to indicate which self-build shared mobility service they would choose if they considered using a shared autonomous vehicle, considering their current and expected future situations. Prices were calculated according to the reviewed studies, existing costs, and the current feature costs of main car manufacturers. It is worth mentioning that prices varied depending on the chosen level by the participants. However, conditional pricing of $\pm 30\%$ change in prices has been considered to avoid variation effects in the actual WTP of participants. Figure 1 shows the selected most likely to travel via a ride-hailing service attribute by each participant.

The screener section (Fig. 2) comes after selecting the ideal service by the participant. Similar stimuli were provided to respondents to understand whether the presented stimuli were considered.

3.2 Measures of Dispersion

A total of 216 valid responses from the participants were collected and used for the analysis. The number of required participants was determined by Eq. (1) as suggested by Smith [63].

$$NRP = \frac{\frac{z^2 * p(1-p)}{e^2}}{1 + \left(\frac{z^2 * p(1-p)}{e^2 * N} \right)}, \quad SS = NRP + N \quad (1)$$

Where,

SS is the required valid sample size

Table 1 The limitation of previous studies and the contributions of this paper

Author(s)	The considered SAV variables	The suggested methodology	disadvantages (limitations) of the proposed approaches	Advantage of our paper
Spurlock et al., (2019)	gender, level of education, travel time, travel cost, predictable arrival time, safety, environmental impact, social interactions	Multi-logit model (MLM) to analyze the impact of explanatory factors on adoption and interest in adoption of SAV in California	<ol style="list-style-type: none"> Using only highly educated and high income participants in the model A significant percentage of the participants was female 	<ol style="list-style-type: none"> 64.4% male and 33.5% female participants Using participants with different financial and educational backgrounds
Hudson et al., (2019)	Age, Gender, Education, location of the travelers ODS	Using regression by ordered probit analysis to find the attitudes to AVs	<ol style="list-style-type: none"> The participants increment to choose AVs “during the time” has not been questioned. The individuals’ educational background has not been investigated The “trust ability” of participants to AVs has not been questioned. Geographic limitation of the survey questioned 	<ol style="list-style-type: none"> In our research, the effect of “time” was considered Various groups of participants with different “education level” were considered
Kim et al., (2020)	Age, Income, location of the travelers ODS, travel distance, Gain time flexibility, vehicle attributes	Using cross-nested logit models with random utility maximization theory	<ol style="list-style-type: none"> Attitudinal or behavioral preferences of the drivers regarding long-term trust ability to AVs The attitude of people who live in rural areas or suburbs that may motivate them to relocate their residence place has not been efficiently investigated The role of “the people daily activities” should be better evaluated population heterogeneity was speculated by the authors 	<ol style="list-style-type: none"> In terms of the participant’s attitude toward using SAVs, different variables were taken into account
Winter et al., (2020)	age group, education, mode preferences (private, public), Travel costs and parking costs, and Travel time	Using Latent class choice models (3-class nested logit model) for various nesting structures related to car ownership, vehicle automation, the level of privacy in the vehicle, driving tasks and the demand responsiveness of a mode	<ol style="list-style-type: none"> The applied model does not represent a full mode choice model Due to considering bias of variables, the choice experiment has been complex in the compositions of the choice alternatives The role of “additional mode alternatives, trip purpose, and trip distance” has not been evaluated “Waiting time and travel time” were not included in the choice experiment 	<ol style="list-style-type: none"> The bias and error of each variable were determined in Table 4 The variables e.g., additional mode alternatives, trip purpose, trip distance, waiting and travel time were asked from the participants

Table 1 (continued)

Author(s)	The considered SAV variables	The suggested methodology	disadvantages (limitations) of the proposed approaches	Advantage of our paper
Turoń et al., (2021)	Travel cost, safety, automation status	Descriptive analysis (expert interviews, and social network analysis (SNA))	<ol style="list-style-type: none"> 1. Data were gathered from different electric car-sharing service providers (no survey) in Poland to analyze the results. 2. It was not clear how the effects of “mobile apps”, “security of vehicles”, “user security”, “weather”, and “urban traffic congestion” during the pandemic would change people’s usage of SAVs. 	<ol style="list-style-type: none"> 1. Using real-world data from a comprehensive survey 2. Our research has taken into account the less-explored factors in this study
Miller et al., (2022)	Gender, Age, Education, Mode of Transport, Ease of boarding/alighting, convenience, and Safety and in-vehicle security	Using the survey, interview, and the open-ended questions for collecting AV attitude data from 6 groups of participants including 1) blind and visually impaired; 2) deaf and hard of hearing; 3) individuals using mobility aids, such as wheelchair, scooter, or cane; 4) individuals with autism and their caregivers; 5) families with young children and pregnant women; 6) seniors (age 60+).	<ol style="list-style-type: none"> 1. Migrant workers, or non-resident users were not included in this study. Furthermore, less digitally inclined participants were not effectively considered in the sample. 2. Resident public transport users in Singapore with different mobility needs and requirements only was investigated in this study. 3. The case study was conducted on Singapore, a city with a well-established public transport. 	<ol style="list-style-type: none"> 1. Several groups of people can be represented by the case study in our research, including geographically located individuals and digitally inclined individuals. 2. The survey was conducted not only on well-established public transport
Gkartzonikas et al., (2022)	Age, Education, travel time, travel cost, Income, reliability of travel, travel safety, sharing the trips with others	Using a stated preference survey and a mixed logit model	<ol style="list-style-type: none"> 1. Some of the questions were hypothetical in nature. Hence, low awareness, lack of understanding of participants, or lack of interest/motivation of the participants were not clearly explained during the research. 2. The participant’s convenience and delay time were not investigated. 	<ol style="list-style-type: none"> 1. Apart from studying “the participant’s awareness,” our research also studied motivation, convenience during the trip, and delay time.
Shin et al., (2015)	Gender, Age, Income, Annual vehicle mileage, cost, Automation status	Multiple discrete–continuous probit (MDCP) model for first part & multinomial probit model (MNP) for second part	<ol style="list-style-type: none"> 1. Changes in travel demand during the time with progress of technologies 2. The behavioral learning mechanisms, the heterogeneity associated with participant’s preferences, and time to adoption to new technologies in terms of AVs or SAVs were not clearly studied 	<ol style="list-style-type: none"> 1. As part of our research, we evaluated how travel time, delay time, user convenience, and sharing trips affected user decisions.

Table 1 (continued)

Author(s)	The considered SAV variables	The suggested methodology	disadvantages (limitations) of the proposed approaches	Advantage of our paper
Bansal & Kockelman, (2016)	Travel distance, travel time, travel cost, Gender, Education level, Convenience level, Employment status, Age, Annual VMT, Income	Using an internet-based survey, and ordered probit model to find travel characteristics on Austinites' WTP	1. The survey did not ask whether each respondent travels mostly as a driver or as a passenger 2. Similar to other variables in our research, the effect of "delay time" and "sharing the trips" were not studied in this research.	1. As a result of our study, the gaps in this research were filled.

Table 2 Summary of selected recent relevant studies on users' preferences for SAVs

Study	Shin et al., 2015 [34]	Gkartzonikas et al., 2022 [36]	Miller et al., 2022 [33]	Turoń et al., 2021 [30]	Rahimi et al., 2021 [29]	Winter et al., 2020 [28]	Kim et al., 2020 [27]	Hudson et al., 2019 [26]	Spurlock et al., 2019 [25]	Bansal & Kockelman, 2016 [35]	This study
Country	South Korea	USA	Singapore	Poland	USA	Netherland	USA	European countries	USA	USA	USA
Method	MDCP & MNP	MXL	DAA	DAA	BOP	LCM	CNL	RA	MLM	MXL	MXL
Cost	x	x	x	x	x	x	x	x	x	x	x
Time	x	x	x	x	x	x	x	x	x	x	x
Automation Status	x	x	x	x	x	x	x	x	x	x	x
Convenience	x	x	x	x	x	x	x	x	x	x	x
Walking ¹			x								
Sharing the trip				x	x						
Delay		x									x

¹Walking time to reach the pickup location or drop-off location to the final destination

Fig. 1 Select the attributes by the participant which he/she most likely to travel via a ride-hailing service

Attribute	Select Feature	Cost for Feature
Type of the Vehicle	Autonomous (Driverless) Vehicle	\$ 0
Travel Time	15 minutes (+ \$5)	\$ 5
Equipments and Convenience Features	Seats'arrangements are more comfortable than normal vans (+ \$2)	\$ 2
Walking Time to Reach the Pickup Location	I should be picked up at my home/work (+ \$5)	\$ 5
Status of the Ridesharing	I do not want to share my ride with another person (+ \$4)	\$ 4
Trip Delay Insurance	Full refund for delay of more than 1 minute (+ \$4)	\$ 4
Total		\$ 20

Fig. 2 The Screening Section

Here are a few bundles you might like. For each one, indicate whether it is a **possibility or not**.

(1 of 5)

Type of the Vehicle	Conventional Vehicle	Autonomous (Driverless) Vehicle	Autonomous (Driverless) Vehicle
Travel Time	15 minutes	15 minutes	25 minutes
Equipments and Convenience Features	Highly packed seats' arrangements like normal vans	Seats'arrangements are more comfortable than normal vans	Seats'arrangements are more comfortable than normal vans
Walking Time to Reach the Pickup Location	I should be picked up at my home/work	5 minutes walking	I should be picked up at my home/work
Status of the Ridesharing	Share my ride with only one person	I do not want to share my ride with another person	I do not mind sharing my ride with multiple people
Trip Delay Insurance	Full refund for delay of more than 1 minute	I do not need trip delay insurance	Full refund for delay of more than 1 minute
Total Price	\$13	\$18	\$8
	<input type="radio"/> A possibility <input checked="" type="radio"/> Won't work for me	<input checked="" type="radio"/> A possibility <input type="radio"/> Won't work for me	<input type="radio"/> A possibility <input checked="" type="radio"/> Won't work for me

N is population Size. In the first step of survey, 151 participant’s responses were received (N = 151).

e is margin of Error (as a decimal). The margin of error (e) is considered due to the fact that no sample will be perfect, so it is crucial to decide how much error to allow. Based on the confidence interval, it is determined how much higher or lower the sample mean can fall than the population mean. e value is usually

determined between 4% and 8% at the 95% confidence level. e = 4% was considered in this paper.

Z is confidence Level (as a z-score). It is generally set at 90%, 95%, or 99%. In our research, the z-score is 1.96 for 95%.

and **p** is percentage Value (as a decimal). p = 5% was considered in this paper.

NPR describes the required number of participants to ensure that incorrect answers from the participants will not negatively impact the accuracy of statistical analysis. The required sample size is the sum of initial number of participants (=151) and NPR.

Unobserved heterogeneity describes the presence of immeasurable differences between study participants or samples despite (observed) variables of interest. In our research, unobserved heterogeneity was determined by using maximum simulated likelihood based on Stata. In mixed logit model, we assumed throughout our analysis that the unobserved heterogeneity α is identically and independently distributed over the participants among the sample and it follows a multivariate normal distribution with mean a and variance–covariance matrix S , $\alpha \sim f(a, S)$ [64]. Furthermore, it was assumed that as standard in mixed logit models, the unobserved heterogeneity α is required to be independent of the explanatory variables (=the model's variables) [65].

Table 3 describes the demographic characteristics of the participants.

Gender was rather biased toward males, with 64.4% male and 33.5% female respondents, which is somewhat incompatible with the national average [39]. The age distribution of allowed respondents was comparable to the national statistics. For education, 54.8% had higher academic education (master's degree and doctoral degree) degrees at graduate levels—noticeably beyond the national average of 12% [39]. The recruitment process was highly based on advertising on professional networking platforms and research and academic centers. This led to an overrepresentation of more participants with higher education attainment. The median household income level of respondents was in line with the national statistics [39]. The researchers compared other socioeconomic variables to the national statistics and found the measures of dispersion were nearly the same, making the sample relatively representative. It is worth mentioning that the variables were recognized after reviewing the state-of-the-art. Considering frequently used variables in previous studies, the paper proposes travel delay as an innovative variable not previously examined. Previous studies highlighted that sociodemographic variables e.g., gender or education can be identified insignificant as specified by the following studies:

In some studies of ride-hailing, gender has not been recognized as a significant factor [66, 67] and as Winter et al., explored [68], neither gender nor the number of children significantly improved the clustering of observed choices.

In the findings of study by Islam et al. [69], the driving and demographic backgrounds would not affect the intention to possess AVs or using SAVs. On the same line with the previous study, Wang and Safdar [70] investigated the effect of sociodemographic variables on people's attitude in terms of using SAVs in two case studies including Lahore and

Dalian. The “education” was not recognized significant with any of the transportation alternatives in Dalian. In another research conducted by Lécureux, Bonnet et al. [71], “gender” has not been recognized significant in 11 papers and 5 other papers find a negative effect. Furthermore, “Education” showed no significant effect in 2 papers.

3.3 Explanation of Attributes

After a complete research and evaluations of the considered attributes in past studies, the authors selected six main attributes – the type of vehicle, travel time, types of equipment and convenience features, walking time to reach the pickup location, status of the ridesharing, and trip delay insurance – as the main attributes that may influence riders' decision to use a shared mobility service. The statistical value of each attribute was calculated based on the gender, age, income, and education of participants in the survey. Furthermore, the z-test, p-test, upper bound, and lower bound were analyzed. It is worth mentioning that the survey attributes were designed according to a pilot study.

3.3.1 Preferred Type of Vehicle

The attribute was included in asking respondents what type of vehicle they wanted to use in the shared mobility service. It is still a controversial issue to predict what portion of the people will choose an SAV. However, past studies concluded that the average operating cost of a fully autonomous shared vehicle would be around 0.50 US\$ per mile only, and a fare of 1.00 US\$ per trip-mile for an AV taxi, 0.60 US\$ - 1.00 US\$ per mile, but less than driver-operated taxis 2.00 US\$ - 3.00 US\$ per mile, and 0.44 US\$ per trip-mile (operating cost plus 30% profit margin) [40–42]. For purpose-built SAVs used as pooled taxis, the price per trip-mile as only 0.16 US\$ has been estimated [40–42]. The lower-bound cost of fully shared autonomous vehicles was proposed to be less than 0.20 US\$ per passenger-mile and the upper bound to be 0.30 US\$ per passenger-mile [40–42]. This attribute has two levels, and the participants were asked to choose between the autonomous and conventional vehicles.

3.3.2 Travel Time

Travel time is one of the main important factors travelers use when choosing a trip. The attribute of travel time was considered to determine to what degree respondents are willing to increase their travel time if they pay less for more extended travel. People prefer the shortest possible trip; however, this attribute aims to trade between travel time and travel costs. As Hamadneh and Esztergár-Kiss [12] found, one SAV can replace eight conventional vehicles with an acceptable average waiting time ranging

Table 3 Summary of measures of dispersion

Socioeconomics ¹	Characteristics	Research (%) ³	U.S. (%) ³
Gender	Men	64.4	49.2
	Women	33.5	50.8
	Other/Prefer not to answer	2.1	
Age	Less than 20	2.1	27.0
	20 - 24	9.4	7.0
	25 - 29	10.5	6.8
	30 - 39	30.9	13
	40 - 49	14.7	14.1
	50 - 59	25.7	13.6
	60 - 69	6.3	9.5
	70 and older	0.5	9.0
Education	Associate degree and lower	18.3	61
	Bachelor's degree	27.0	21
	Master's degree	34.8	9
	Doctoral/professional degree	20.0	3
Household annual income	Less than \$50,000	14.5	46.5
	\$50,000 – \$99,999	30.2	29.9
	\$100,000 – \$149,999	17.0	18.3
	\$150,000 – \$199,999	6.3	
	\$200,000 and more	8.5	5.3
Household size	1	19.6	27.6
	2	25.9	33.7
	3 and more	54.5	38.7
Marital status	Single	20.8	51.8
	Married	29.6	48.2
	Other/Prefer not to answer	50.5	–
Main commuting mode ²	Personal vehicle	79.4	76
	Public transportation	9.7	10
	Carpool/ridesharing/taxi	2.9	5
	Personal vehicle and public transit	5.1	–
	Bike	1.7	1
	Other	1.1	8
Status of the living area	Urban	46.4	27
	Suburban	47.3	52
	Rural	6.3	21
Status of the working area	Urban	67.0	53
	Suburban	31.3	32
	Rural	1.8	15

¹ 2011-2015 American Community Survey 5 Year Estimates for the U.S. values

² National Transportation Statistics 2018, The U.S. Department of Transportation's Bureau of Transportation Statistics

³ Percentages may not add up to 100 due to rounding

from 7 to 10 minutes. Moreover, travel time was decreased by 17% in their case study. This variable has four levels from 10, 15, 20 and 25 minutes. The travel time was the sum of the in-vehicle travel and the waiting time. After reviewing the state-of-the-art e.g., [9, 41], the 5-minute intervals were designed for the travel time. The authors speculated that the least user's travel time from the origin

to destination is 10 minutes. Hereupon, four levels of 10, 15, 20, and 25 minutes were considered.

3.3.3 Types of Equipment and Convenience Features

This attribute focused on assessing how important equipment and convenience are for using an SAV. Alessandrini

et al. [43] explored that comfort can also be expected to influence the ongoing acceptance and adoption of AVs, and this is particularly important in the case of SAVs, due to the presence of other travelers who will constrain choices about standing/sitting position in the vehicle. SAV services built around a ridesharing model will rely on social, as well as technical, innovation; there will be a future willingness amongst travelers to share a small vehicle with strangers. Therefore, interactions between trust and comfort for travelers toward SAVs were mentioned as key variables in the literature [44]. This attribute has four levels as shown in Table 4 for different levels of comfort-ability and in-built features of the vehicle.

3.3.4 Walking Time to Reach the Pickup Location

This attribute assessed how much a flexible pickup/drop-off spot might affect users' preferences in choosing an SAV. People in urban and highly built-up areas are more likely to use SAVs where people have adopted walking short first/last distances of their trip [45]. Additionally, SAVs could provide an economical mobility-on-demand service using smartphone applications that could pick the rider up at their pickup point and deliver them to their drop-off point [46]. This attribute has three levels including pick up/drop off at the place, 5 minutes and 8 minutes walking.

3.3.5 Status of the Ridesharing

This attribute determined to what degree the shared aspect of SAVs can be important for users. Shared mobility services can save costs, provide convenience, and reduce vehicle usage. As Wang et al. [47] discovered, preserving a better value and taking a lower risk are the main reasons for people to share their trips with others. This attribute has three levels as shown in Table 4, which describes different status of sharing the trip with others.

3.3.6 Trip Delay Insurance

This attribute is an innovative feature to understand how much riders are willing to pay to arrive at their destinations on time. A key reason for choosing the “delay” attribute is that the state-of-the-art does not take this attribute into account. As part of the survey, a new question was asked regarding riders' willingness to use and pay for reducing delays. When sharing their automated trips, survey participants were asked how many minutes of delay time they were willing to tolerate. As a result, three options were proposed to specify their willingness to pay and willingness to use, including “I do not need trip delay insurance”, “Full refund for delay of more than 5 minutes (\$2)”, and “Full refund for delay of more than 1 minute (4\$). The participants were informed about the total travel delay, which is the sum of normal and unpredicted delays caused by traffic congestion. Depending on the trip preferences, participants could choose between three levels. Travel time between the traveler's

Table 4 The features, attributes, and levels

Feature	Attribute	Level
Type of the Vehicle	Autonomous vehicle	1
	Conventional vehicle	2
Travel Time	10 minutes	1
	15 minutes	2
	20 minutes	3
	25 minutes	4
Equipment and Convenience Features	Highly packed seat arrangements like normal vans	1
	Seats' arrangements are more comfortable than normal vans	2
	More convenient and equipped with a built-in computer and WIFI	3
Walking Time to Reach the Pickup Location	I should be picked up at my home/work	1
	5 minutes walking	2
	8 minutes walking	3
Status of the Ridesharing	I do not mind sharing my ride with multiple people	1
	Share my ride with only one person	2
	I do not want to share my ride with another person	3
Trip Delay Insurance	I do not need trip delay insurance	1
	Full refund for delay of more than 5 minutes	2
	Full refund for delay of more than 1 minute	3

origin and destination can be estimated by the SAV and the traveler. However, there is no clear policy regarding refunds when a delay exceeds the estimated travel time. In order to compensate for the delay of more than 1 minute or more than 5 minutes, a refund was considered. In order to encourage respondents to use SAV even if SAV experiences a delay on the path, three sensible options were provided as a novel approach to address the importance of delay. The results also highlighted that the respondents are more likely to pay for the option of a full refund if their trip gets delayed.

Currently, some ride-hailing companies estimate travel time to riders before their trip request, which helps them know their total travel time. The majority of ride-hailing companies consider shorter travel times as the fundamental issue for satisfying travelers. Therefore, such companies try to minimize the total delay time from the pickup point to the drop-off point. Zhang et al. [48] believed that an on-time SAV system with dynamic ridesharing could provide a more satisfactory service level and decrease trip delays considerably. This attribute has three levels that describes.

3.4 Alternative-Specific Mixed Logit Model

This section will discuss the structure of the utilized MXL model. The index m ($m = 1, 2, \dots, M$) has been considered for participants, l for the features ($l = 1, 2, \dots, L$), and c for the choice occasion. Hence, the utility of the individual m associates with the features l on choice occasion c can be written as equation (2) [49]:

$$U_{mlc} = (\Gamma + \lambda_m)Z_{mlc} + \phi_{mlc} \tag{2}$$

Where,

U_{mlc} = The utility of individual m and feature l at the choice occasion c .

m = the index of participants ($m = 1, 2, \dots, M$).

l = the index of features ($l = 1, 2, \dots, L$) which explains the choice’s attributes.

c = the index of choice occasion. In fact, c explains the choice situations which individual m finally selects among all available choices in the choice set. For instance, “occasion c ” specifies the situation c of choices like out-of-home or pure recreational episodes.

Z_{mlc} = a vector of feature attributes and the interactions of attributes among themselves and with respondent’s characteristics. Z_{mlc} defines a

vector of observed attributes relating to individual m and feature l at the choice occasion c .

Γ = a corresponding vector of the mean effects of the coefficients of Z_{mlc} on feature choice.

λ_m = a vector with its n th element representing unobserved factors specific to individual m .

$\Gamma + \lambda_m$ = a vector of individual-specific coefficients.

ϕ_{mlc} = a choice-occasion specific idiosyncratic random error term assumed to be identically and independently standard Gumbel distributed (IID).

The Mixed logit model allows the coefficients in the model to vary across decision-makers. It stands to reason that different decision-makers may have different preferences. Additionally, it can also be seen that the independence from irrelevant alternatives (IIA) property no longer holds in MXL models. In eq. (1), Z_{mlc} is a vector of feature attributes and the interactions of attributes among themselves and with respondent’s characteristics, affecting the utility of individual m for feature l at the c^{th} choice occasion. Γ is a corresponding vector of the mean effects of the coefficients of Z_{mlc} on feature choice, and λ_m is a vector with its n^{th} element representing unobserved factors specific to individual m . ϕ_{mlc} represents a choice-occasion specific idiosyncratic random error term assumed to be identically and independently standard Gumbel distributed [50].

In MXL models, the probability of the selection of feature l by participant m is determined based on equation (3):

$$P_{ml} = \int \left(\frac{\exp^{\beta'x_{ml}}}{\sum_j \exp^{\beta'x_{mj}}} \right) f(\beta) d\beta \tag{3}$$

Equation (3) is developed when the utility follows the linear structure. In this equation, $f(\beta)$ is a density function, $\beta'x_{ml}$ is the observed portion of the utility which depends on the parameters β . There are two different models for the choice probability when the utility follows the linear structure or non-linear structure. Equation 3 is used when the utility follows a linear structure. In this situation, the “observed portion of the utility” is incorporated into the model as shown in Eq. 3 with $\beta'x_{ml}$ [49]. It is worth mentioning that Eq. 3 was chosen for the choice probability in this paper due to its higher accuracy.

Equation 2 is a general form of the utility model. Considering the difficulties of finding the exact value of ϕ_{mlc} in Eq. 2 (= a choice-occasion specific idiosyncratic random error term) since it is a random term with zero mean that is IID over alternatives and does not depend on underlying parameters or data, it was suggested to use Eq. 3 to specify

with greater accuracy the probability of participant m selecting feature l .

In fact, Equation 2 is the logit structure of the utility of individual m and feature l while Eq. 3 is the “Mixed” logit class of Equation 2. In equation 2, ϕ_{mlc} is defined as a random term with zero mean whose distribution over individuals and alternatives depends in general on underlying parameters and observed data relating to individual m and alternatives. Eq. 3 has the advantage of allowing the error term (ϕ_{mlc}) to take on a number of distributional forms, such as normal, lognormal, or triangular. In eq. 3, the conditional probability for choice c is logit, since the remaining error term is IID extreme value.

The variable P_{ml} in Eq. 3 is defined as the utility of individual m and feature l when the unconditional choice probability occurred. Hereupon, the variable P_{ml} is a different variable from U_{mlc} . Eq. 3 defines as the mixed logit because the choice probability P_{ml} is a mixture of logits including the mixing distribution. Additionally, the variable β in Eq. 3 associated with an attribute of an alternative as having both a mean and a standard deviation (i.e. it is treated as a random parameter instead of a fixed parameter). The variable β treats unobserved information as a separate error component in randomness.

Nevertheless, in this study, the features that participants have selected were considered as the dependent variable. Each attribute’s feature value was considered as an independent variable, and the features were considered the alternative variable. It is worth mentioning that utility scores for the attribute levels represent the participants’ valuation for having or not having that specific element [51]. The Multinomial logit model (MNL) serves as the basis function for the estimating the price preferences of participants in the model. The function estimates two issues; first, the importance of each attribute has been scrutinized relative to the others. The utility value of a given item would be calculated based on the maximum amount of the utilities of all the possible options [52]. Accordingly, the MNL modeling process models relationships between a polytomous response variable and a set of regressor variables. These polytomous response models can be classified into two distinct types, depending on whether the response variable has an ordered or unordered structure [53].

The MXL uses random coefficients to model the correlation of choices across alternatives [54]. The MXL model considers observations of heterogeneity effects and is not restricted only to normal distributions [55]. In this study, six different attributes are provided then, there should be a separate MXL model for every one of them. In these models, the goal is to find possible relationships between participants’ sociodemographic characteristics and their choices (which level of an attribute). After examining all demographic features, four variables of gender, income, education, and age

were found fit in all models. The MXL models describe the choice behavior of each range of variables for selecting a specific level of the attributes. For example, the MXL model for the status of the ridesharing explores possible relationships between people’s income levels and their choice behavior for sharing the trip with others. In this case we have observations for each participant and the selected level of each attribute. Variable choice which is a binary variable (0 or 1) will be the dependent variable in the model. When the variable ‘choice’ takes the value of 1, we can observe that the participant with a specific level of income will select that level of attribute.

4 Results

The MXL model was developed in STATA, a general-purpose statistical software package developed by StataCorp for data manipulation, visualization, statistics, and automated reporting [56]. Table 5 presents the results of the MXL model. STATA uses random coefficients for each attribute to model the correlation of choices across alternatives. Additionally, different levels are developed for each attribute, and the impression of each level is determined based on a base alternative. Age, gender, income, and education were considered as choice levels; additionally, the variance of each attribute was analyzed in each choice level. Previous studies showed that age, gender, income, and education have striking effects on the individuals’ preferences for SAVs. Nevertheless, the authors try to investigate the effects of these four choice levels on the individual’s preferences.

5 Discussion

The study’s outcomes, depicted in Table 5, offer several significant accomplishments concerning individual preferences for Shared Autonomous Vehicles (SAVs). This section presents the survey analysis results and the findings for each attribute obtained through the Mixed Logit regression model. Additionally, the paper compares the obtained results with the existing knowledge prior to the COVID-19 pandemic.

- 1- The trip delay insurance as an innovative attribute of this study specified that riders with higher education levels exhibit a greater willingness to pay a premium for this service. Additionally, the study found that riders are willing to pay more for this insurance when their actual travel time falls short of the estimated total travel time provided at the time-of-service booking. It is important to note that there is no prior research that has explored the impact of the delay insurance attribute on willing-

Table 5 The results of the Mixed logit model (MXL)

Attribute	Level	Characteristics	Coef.	Std. Err.	Z	P>Z	[95% conf.]
Type of the Vehicle (Ref: level 2)	1	gender ¹	0.14	0.48	0.3	0.76	-0.79 _ 1.07
		age ²	-0.37	0.17	-2.2	*0.027	-0.7 _ -0.04
		income ²	0.14	0.14	1.02	0.31	-0.12 _ 0.4
		education ²	0.08	0.19	0.4	0.69	-0.29 _ 0.44
		_cons	1.54	1.45	1.06	0.29	-1.29 _ 4.37
Travel Time (Ref: level 2)	1	gender	-0.20	0.65	-0.3	0.76	-1.48 _ 1.08
		age	0.28	0.23	1.2	0.23	-0.17 _ 0.74
		income	0.11	0.20	0.56	0.57	-0.28 _ 0.5
		education	-0.53	0.27	-2	*0.046	-1.05 _ -0.01
		_cons	-0.38	1.85	-0.21	0.84	-3.99 _ 3.23
	3	gender	-0.20	0.57	-0.36	0.72	-1.31 _ 0.9
		age	0.30	0.20	1.47	0.14	-0.1 _ 0.7
		income	-0.08	0.17	-0.47	0.64	-0.4 _ 0.24
		education	-0.39	0.23	-1.74	0.08	-0.83 _ 0.04
		_cons	0.24	1.56	0.16	0.88	-2.81 _ 3.3
	4	gender	-0.49	0.60	-0.82	0.41	-1.66 _ 0.68
		age	0.65	0.22	2.95	*0.003	0.21 _ 1.08
		income	0.01	0.17	0.06	0.95	-0.32 _ 0.34
		education	-0.33	0.25	-1.31	0.19	-0.81 _ 0.16
		_cons	-1.68	1.94	-0.87	0.39	-5.48 _ 2.11
Equipment's and Convenience Features (Ref: level 2)	1	gender	0.68	0.62	1.09	0.28	-0.54 _ 1.89
		age	0.16	0.21	0.76	0.45	-0.25 _ 0.57
		income	-0.50	0.19	-2.59	*0.01	-0.88 _ -0.12
		education	-0.15	0.22	-0.68	0.50	-0.59 _ 0.28
		_cons	-0.53	1.59	-0.33	0.74	-3.65 _ 2.59
	3	gender	-0.05	0.52	-0.1	0.92	-1.07 _ 0.97
		age	-0.24	0.20	-1.21	0.23	-0.62 _ 0.14
		income	0.39	0.18	2.16	*0.031	0.03 _ 0.73
		education	-0.08	0.22	-0.37	0.71	-0.5 _ 0.34
		_cons	-1.27	1.63	-0.78	0.44	-4.46 _ 1.93
Walking Time to Reach the Pickup Location (Ref: level 1)	2	gender	-1.00	0.46	-2.18	*0.029	-1.89 _ -0.1
		age	-0.20	0.16	-1.19	0.24	-0.51 _ 0.12
		income	-0.10	0.13	-0.78	0.43	-0.36 _ 0.15
		education	-0.04	0.19	-0.2	0.84	-0.4 _ 0.32
		_cons	2.89	1.47	1.97	*0.049	0.01 _ 5.77
	3	gender	-0.52	1.17	-0.44	0.66	-2.82 _ 1.78
		age	0.12	0.35	0.36	0.72	-0.55 _ 0.8
		income	-0.90	0.45	-2.02	*0.044	-1.77 _ -0.02
		education	-0.85	0.47	-1.8	0.07	-1.77 _ 0.07
		_cons	3.76	2.68	1.4	0.16	-1.49 _ 9.02
Status of the Ridesharing (Ref: level 1)	2	gender	-0.44	0.56	-0.79	0.427	-1.54 _ 0.65
		age	-0.03	0.20	-0.15	0.878	-0.41 _ 0.35
		income	0.05	0.16	0.29	0.769	-0.27 _ 0.36
		education	-0.06	0.22	-0.27	0.788	-0.49 _ 0.37
		_cons	0.16	1.57	0.1	0.92	-2.91 _ 3.23
	3	gender	-0.13	0.48	-0.27	0.788	-1.06 _ 0.81
		age	0.03	0.17	0.2	0.839	-0.29 _ 0.36
		income	0.30	0.15	2.02	*0.043	0.01 _ 0.6
		education	-0.27	0.20	-1.37	0.17	-0.66 _ 0.12
		_cons	-0.31	1.43	-0.22	0.828	-3.11 _ 2.49

Table 5 (continued)

Attribute	Level	Characteristics	Coef.	Std. Err.	Z	P>Z	[95% conf.]
Trip Delay Insurance (Ref: level 1)	2	gender	0.71	0.65	1.21	0.31	-0.564 _ 1.984
		age	-0.14	0.19	-0.76	0.447	-0.51 _ 0.22
		income	0.04	0.14	0.31	0.758	-0.24 _ 0.32
		education	0.85	0.24	3.63	*0.00	0.39 _ 1.31
		_cons	-4.02	1.36	-2.96	0.003	-6.69 _ -1.36
	3	gender	0.43	0.28	1.25	0.21	-0.12 _ 0.98
		age	0.27	0.61	0.45	0.653	-0.92 _ 1.46
		income	-0.27	0.34	-0.8	0.426	-0.94 _ 0.4
		education	2.18	1.11	1.97	*0.048	0.01 _ 4.35
		_cons	-14.26	7.08	-2.01	0.044	-28.13 _ -0.39

1 Binary variable

2 Categorical variable

ness to pay for ride-hailing services, making it challenging to compare the results with the current state-of-the-art literature.

- 2- A meaningful relationship exists between the type of vehicle and the participant's age. Hereupon, SAVs are preferred more by younger people. This finding is on the same page as Wang et al. [10], who specified that younger adults and males are more likely to share an AV ride. Furthermore, Susilawati and Lim [57] concluded that SAVs are more likely to be adopted by travelers between 20 to 39 years old.
- 3- Travel time is greatly influenced by education and age. Travel time determines to what degree respondents are willing to increase their travel time if they pay less for more extended travel. The results demonstrated that higher-educated riders experienced shorter travel times with SAVs. In addition, young riders spend more time in shared vehicles. Previous studies e.g., König and Gripkenoven [58] highlighted that shared trips are highly influenced by travel time. Their analysis focused on the importance of travelling time for respondents' willingness to share rides, as well as the importance of a price system that reflects ride-specific travel time.
- 4- Based on the predictions, income is correlated with equipment characteristics and convenience features. In general, riders with higher income levels choose more convenient and equipped SAVs, and they tend to travel alone rather than sharing their trip with others. A shared transit service can provide more convenience to riders, as riders can save money by choosing a shared mode and use more convenient features as a result.
- 5- In terms of walking time to reach the pickup location, gender and income are effective variables to influence the utility of the participants. As a result,

males are more likely to walk to designated pick up/drop-off locations. This finding is compatible with the results of a study by Schwieterman and Smith [59] that highlighted riders of the UberPool service in Chicago tended to have a minimum walking distance to meeting points. Furthermore, the pandemic has encouraged more people to use door-to-door services and walking time to the meeting point strongly influences travel time, so those wishing to use a door-to-door service have shorter travel times.

- 6- Ridesharing status can be affected by income. According to the results, users with higher income levels prefer to ride alone and not share their rides with others. Based on the results of the current study, income may influence SAV preferences in a way that is consistent with recent studies that found travelers tend to keep their privacy and personal space when sharing their transportation service [60–62].

Subsequently, the study presents the supplementary findings obtained from the application of the Mixed Logit Regression model.

- Compared with human-driven shared vehicles, SAVs are more preferred by younger people, and they travel longer in their shared vehicles. This finding shows the importance of “age” variable on SAV's WTU.
- The effect of “gender” can be observed in the fact that males are more likely than females to walk to the pickup/drop-off location.
- As far as the effect of “income” is concerned, riders with higher incomes are more likely to choose more convenient and equipped SAVs, they prefer to be the only rider on the vehicle and not share their trip with

others, and they prefer door-to-door services (don't walk to pick up/drop-off locations).

- With regard to the effect of “education”, riders with a higher level of education are more likely to travel faster with SAVs, they would rather pay more to use trip delay insurance, and they would prefer to use door-to-door services (not walk to a pickup or drop-off location).

The study's outcomes offer several policy recommendations. The findings suggest that the adoption of SAVs may differ among participants, and therefore, the mode choice behavior should be evaluated. Multi-modal users may leverage SAVs to enhance their multimodal transportation experience, whereas private car users may not be as receptive to using SAVs. Moreover, the study suggests that the market penetration rate of SAVs may be higher among young travelers, indicating that SAV usage may gain greater acceptance in society as the market penetration rate increases. Alternative policies to promote SAV adoption could involve tax reductions, insurance facilities, parking provisions, and the creation of dedicated HOV lanes or signalized intersections to facilitate SAV mobility during peak hours.

6 Conclusion

This study analyzes the demographic characteristics and travel behavior attributes related to people's preferences for shared automated transit services. Understanding this knowledge might help economists, policymakers, and decision-makers in industries related to the design of the next generations of transportation systems. The background studies highlighted a lack of robustness in individuals' preferences for SAV services using an appropriate statistical approach. Therefore, this research focused on conducting a comprehensive survey by considering more realistic attributes and conditions of the future shared mobility market. The survey was developed during the COVID-19 lockdown. The results indicated that females tend to use door-to-door services, younger riders are more interested in using SAVs and also accept longer travel times, riders with high-income levels are willing to use SAVs with higher equipment and convenience, and more educated riders are more likely to use door-to-door service, select a service with shorter travel time, and pay a little more money to insure their trip against possible delays. This research implemented perceptible attributes of the SAVs according to the perspective features that might be used for the future shared mobility market in the U.S.

Consequently, the following contributions were seen during this research:

1. The importance of several variables on SAVs' WTU is investigated simultaneously, such as travel time, travel cost, automation status, user convenience when using SAVs, user preference for walking to destination when sharing their trips with others, and travel delay.
2. The study conducted a comprehensive online survey to gather data on users' preferences regarding the WTU of SAVs and to analyze the associated attributes of travel behavior and demographic characteristics.
3. This research investigated the impact of each of the mentioned variables on user choice, with a particular focus on travel delay, which has not been studied in the current state-of-the-art literature.

The principal limitation of this research was the relatively low number of survey participants. Efforts were made to efficiently cover this gap during the survey; however, future studies are recommended to use a sufficient number of participants and more incentives and amenities. Furthermore, the authors suggest scrutinizing other attributes such as “more levels of privacy, more advanced features in the vehicle, and ability to do telework at the vehicle”. Also, other analysis methods can be implemented to analyze the results.

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Declarations

Conflict of Interest The authors declare that they have no conflict of interest.

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