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The Role of Attitude, Travel-Related, and Socioeconomic Characteristics in Modal Shift to Shared Autonomous Vehicles with Ride Sharing

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Abstract: The integration of automation and shared mobility services would significantly affect transportation demand, especially mode choice. However, little is known about how attitudes, travel attributes, and demographic factors affect the modal shift to shared autonomous vehicles (SAVs). A stated preference survey was designed to determine the preferences of car and transit users in relation to a modal shift to SAVs. The binary logit models' results revealed distinct behavior patterns and systematic heterogeneity among transit and private car users based on a representative sample of 607 individuals in 2021. The shifting behavior of both users is positively affected by attitudinal factors, including consumer innovativeness, perceived usefulness, sharing intention, and ecological awareness, while negatively affected by privacy concerns. In terms of travel-related attributes of SAVs, car users are eight times more sensitive to waiting times compared to transit users, who are three times more concerned with travel costs. Further, privacy concerns, the number of passengers sharing a trip, and the ratio of waiting time to travel time of SAVs were the major barriers to shifting the likelihood of car users' behavior. In light of these findings, based on the likely effects of SAVs on shifting behavior, a number of practical implications are suggested for more effective policy making.

Keywords: attitudinal factors; dynamic ridesharing; modal shift analysis; shared autonomous vehicle; stated preference

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1. Introduction

The use of private cars in developing countries is much higher than the use of public transit, which leads to a variety of adverse effects in many aspects [1–3]. According to some forecasts, autonomous vehicles (AVs) will significantly reduce the private car market share and increase the share of transit, cycling, and walking, as well as facilitating car sharing and ridesharing services, which shows how automation contributes to creating sustainable and efficient transportation systems [4–6]. Nevertheless, one of the major barriers is the high cost of AVs for personal use [7,8], particularly within large urban networks where travel demand is high and space is limited [9,10]. Due to the fact that the sustainable development goals (SDGs) are becoming global strategic development goals [11,12], the possibility of a transition from AVs to shared AVs (SAVs) will become more likely in the future [6,13]. In shared mobility, a dynamic ride-sharing (DRS) service enables riders to request on-demand or prearranged rides through smartphone applications [14]. DRS leads to a reduction in travel costs because it involves sharing a trip with strangers [15–17]. The integration of automation and DRS will likely result in considerable changes to urban transportation, particularly travel behavior [18,19]. For instance, SAVs with DRS offer a variety of unique advantages over other modes, such as lower costs, enhanced comfort, and the ability to reduce adverse environmental impacts, which makes them more popular than AVs [13,14]. However, their impact will be felt both by transit and private transport systems, resulting in changes in modal share [20,21]. For instance, there is a lower likelihood of private car users shifting to SAVs because there is no waiting time for accessing their cars and the travel time is not prolonged due to sharing the vehicle with strangers [22,23]. Other studies suggest that ridesharing services may affect private car ownership because consumers are significantly more receptive to a service-based transportation system, thus decreasing the demand for private cars [24]. Among transit users, some individuals are not interested in shifting to SAVs because of the higher travel cost, whereas others are interested due to better accessibility [6,21]. Hence, contradictory findings highlight the need for a more comprehensive examination of travel behavior, preference for transit, and private car users' shift to SAVs. In addition, a precise study of individuals' preferences and attitudes is widely recognized as being essential for the successful implementation of any policy [25].

Despite some key insights gained from research on the factors that contribute to the modal shift to automation technology, further investigation is needed [13,21,26]. More research is needed to shed light on the psychological determinants of the modal shift to SAVs with DRS, in addition to sociodemographic and travel characteristics. Considering psychological latent constructs is critical for studies examining the adoption and usage of current and emerging mobility services for developing proactive strategies for promoting equitable, safe, and community-driven AV systems, as well as enhancing the prediction fit of the proposed model [27]. Hence, the authors have attempted to fill in previous gaps by exploring how sociodemographic, travel-related, and psychological factors affect transit and private car users' shifting behavior to SAVs with DRS, particularly in light of the COVID-19 outbreak. In this study, we are trying to respond to questions such as "Which factors have a significant impact on shifting behavior of transit and private car users to SAVs?" and "Which of the significant variables have the highest impact on modal shift likelihood of transit and private car users?"

This paper is structured as follows: Section 2 reviews the factors affecting consumers' mode choice preferences in the era of AVs. A methodology approach, including the research framework, survey design, and data processing, is introduced in Section 3. Section 4 presents the data analysis and results, as well as several recommendations for policy and practice. Finally, in Section 5, the conclusion and suggestions for future research are discussed.

2. Literature Review

In this section, we critically review the existing literature regarding factors influencing travel mode choice in the presence of AVs and SAVs. A brief review of previous studies about the choice of different types of AVs is summarized in Table 1. Previous studies have primarily examined the impact of travel-related attributes as well as socioeconomic characteristics on the choice of SAVs [28,29]. Nevertheless, very few studies have examined the use of ridesharing services with SAVs from the perspectives of different users as well as considering various factors, including attitudinal, travel-related, and socioeconomic characteristics. For instance, a study conducted by Greenblatt and Shaheen [30] on AVs and their synergy with DRS concluded that many energy and environmental advantages result from the combination of both services, but this paper does not provide any quantitative measures for the likelihood of sharing a ride with strangers. Lavieri and Bhat [22] concluded that the acceptance of the increased travel time caused by picking up/dropping off other passengers as well as their consent to share a trip with strangers are essential elements for AVs with ridesharing services. Specifically, their paper examined the adoption of shared rides using the concept of willingness to share (WTS), which represents the monetary value a person attributes to traveling alone as opposed to riding with strangers. They, however, examined limited psychological factors, such as sensitivity to time and privacy. Gurumurthy and Kockelman [13] examined Americans' willingness to pay (WTP) for sharing their trip with a stranger across a number of trip types and the effects of long-distance travel. Their findings revealed valuable insights regarding privacy concerns, safety, and dynamic ride sharing. By examining the preferences of private car users in relation to SAVs through a before–after analysis, Paddeu et al. [31] concluded that AVs and SAVs would be more likely to be used by private car users after experiencing this technology.

Table 1. A brief review of previous studies in choosing different types of AVs.

Author	Variable			Model [3]
	Demographic	Travel-Related [1]	Attitudinal [2]	
Etzioni et al. [6]	✓	TC; WT; WD; TT; PS	OTM; TD	ICLV
Gurumurthy and Kockelman [13]	✓	TC; TT	PC	Two hurdle model and MNL
Lavieri and Bhat [22]	✓	TT; TC; NP	PC; TS	ICLV
Alhajyaseen et al. [26]	✓	TC; TT; CS	-	MNL
Krueger et al. [28]	✓	TC; TT; WT	-	MXL
Farzin et al. [32]	✓	TC; TT; WD; WT	PEOU; PU; SI; PR; EC; DE	MXL
Azimi et al. [33]	✓	TC; TT	Perceptions; Preferences; Vehicle ownership; AV features	MXL
Haboucha et al. [34]	✓	TC	TI; DE; PTA; PAT; EC	MXL

Abbreviations: [1]: Travel cost (TC); travel time (TT); walking distance (WD); waiting time (WT); number of passenger (NP); comfort scale (CS). [2]: Perceived ease of use (PEOU); perceived usefulness (PU); social influence (SI); perceived risk (PR); environmental concerns (EC); driving enjoyment (DE); privacy concern (PC); time sensitivity (TS); technology interest (TI); public transport attitude (PTA); pro-autonomous attitude (PAT). [3]: Mixed logit model (MXL); multinomial logit (MNL); integrated choice latent variable (ICLV).

The aforementioned studies mostly considered travel-related and sociodemographic characteristics in the likelihood of choosing SAVs. However, many studies acknowledged that psychological factors play a key role in acceptance/intention to use technologies. One of the important attitudinal factors in collaborative consumption is ecological awareness. People have become increasingly aware of the threats posed by global warming, which leads to their participation in various forms of pro-environmental behavior such as collaborative consumption [23]. In environmental concern, a person shows awareness about the risks to the environment and natural resources based on their concerns, interests, and disinterests [35]. Huang and Gao [36] found that alternatives with low carbon emissions are most likely to influence travelers' intentions. Further, Gkartzonikas and Gkritza [37] observed a higher intention to use AVs among individuals with environmental concerns. Thus, attitudes toward sharing as an indicator of individuals' environmental friendliness are positively associated with the likelihood of using SAVs [23,38]. Another psychological factor contributing to shifting behavior toward SAVs is consumer innovativeness [39,40]. This refers to consumers' willingness to engage in purchasing/using new products more often and more rapidly than their peers [34,41,42]. According to Golbabaei et al. [43], enthusiasts who are willing to try emerging technologies before others may find AVs more convenient and safer and are likely to be early adopters of this technology. An analysis of survey data collected from Hungarians showed that users' behavioral intentions to use AVs varied significantly based on their level of familiarity with technology [44].

Along with individual differences, the characteristics of the system should also be considered when studying travel mode choice. In this study, sharing attitude, ecological awareness, and consumer innovativeness are among the individual characteristics, and perceived risk and perceived usefulness are related to system characteristics. Perceived usefulness is defined as the degree to which a person believes that using a product may increase their job performance [45]. De Vos et al. [46] concluded that perceived usefulness affects individual travel mode preferences. In other words, choosing SAVs is dependent on how people perceive SAVs' usefulness in meeting their mobility needs [47]. Wadud and Huda [48] demonstrated that the intention to use AVs is positively correlated with the perceived usefulness of travel time in these vehicles. Perceived risk refers to the negative effects that consumers perceive when purchasing or using a particular product or service [49]. Ye et al. [50] and many studies acknowledge that perceived risk is the main barrier to the use of AVs and SAVs and it negatively impacts users' ridesharing intentions with SAVs [51,52].

Based on the literature, previous research has studied the factors affecting the modal shift to AVs and SAVs, but, in this paper, we have attempted to address a number of gaps. For instance, most previous studies have focused on travel-related and socioeconomic characteristics, while fewer have explored the attitudinal factors associated with the modal shift to SAVs with DRS from the perspective of transit and private car users. Moreover, few studies have provided a comprehensive framework that takes into account socioeconomic, travel-related, and psychological factors simultaneously. Finally, in the current study, apart from socioeconomic characteristics, individual differences in latent factors, such as ecological awareness, consumer innovativeness, and sharing intentions, especially in the era of the COVID-19 outbreak where sharing is severely limited, have been addressed. In addition, in relation to system characteristics, travel attributes such as travel cost, number of passengers sharing the ride, travel time, and waiting time are taken into account. Further, attitudes toward system characteristics such as perceived risk and perceived usefulness have also been studied.

Finally, Figure 1 illustrates the conceptual model framework of the current study. It demonstrates that a wide range of attitudinal, travel-related, and socioeconomic factors have been considered for determining private car and transit users' preferences toward shifting to SAVs.

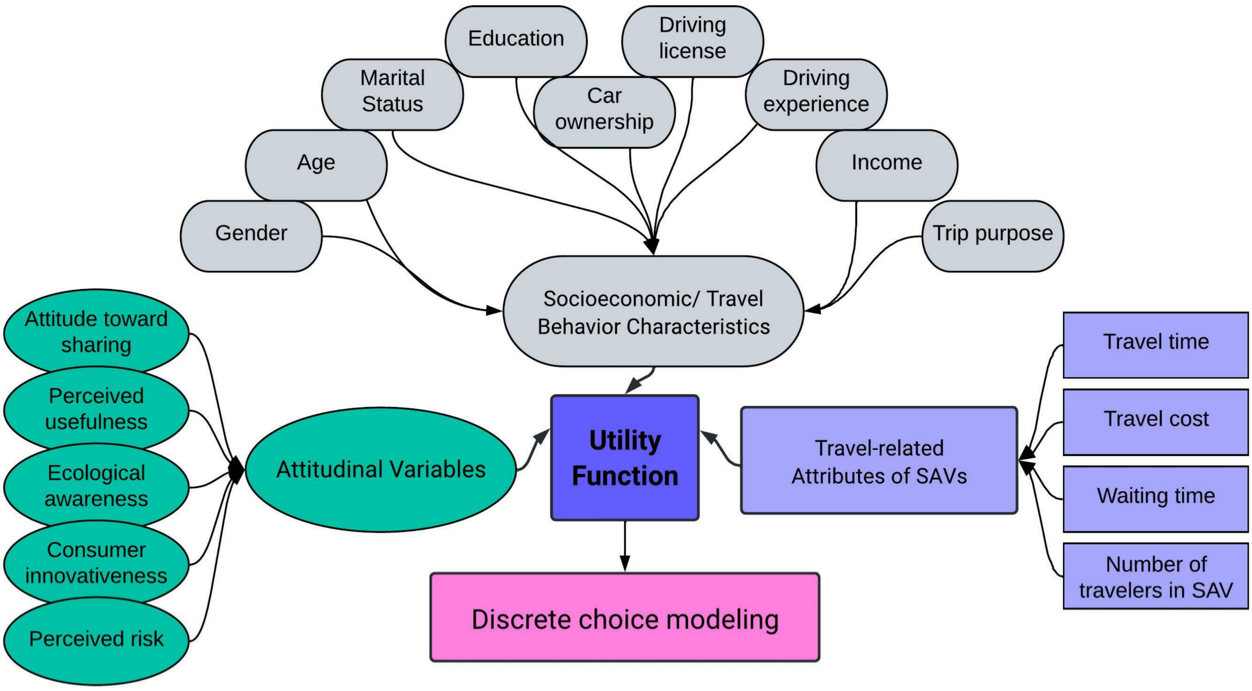

Figure 1. Conceptual model framework for assessing the modal shift preference to SAVs with DRS.

3. Methodology

The flowchart of the research methodology (Figure 2) shows that after a thorough review of previous studies, the research gaps and the key factors affecting mode choice in the presence of AVs were identified. Using a choice experiment design (Section 3.1), a stated preference survey was designed. The designed survey (Section 3.1) consisted of attitudinal, travel-related, and socioeconomic questions. Then, an internet-based survey (Section 3.2) was conducted to gather the required data. A confirmatory factor analysis (Section 4.1) was conducted using attitudinal questions and Amos v.24 to derive the latent constructs associated with respondents' modal shift behavior. Using Nlogit v.5, two binary logit models (Section 4.2) were estimated to examine transit and car users' shifting preferences to SAVs. The evaluation of proposed models was performed based on goodness of fit indices. Finally, if the evaluation criteria were met, the best-fit models were reported, and the sensitivity analysis was conducted via the calculation of marginal effect values. Otherwise, the model was respecified to achieve a valid model.

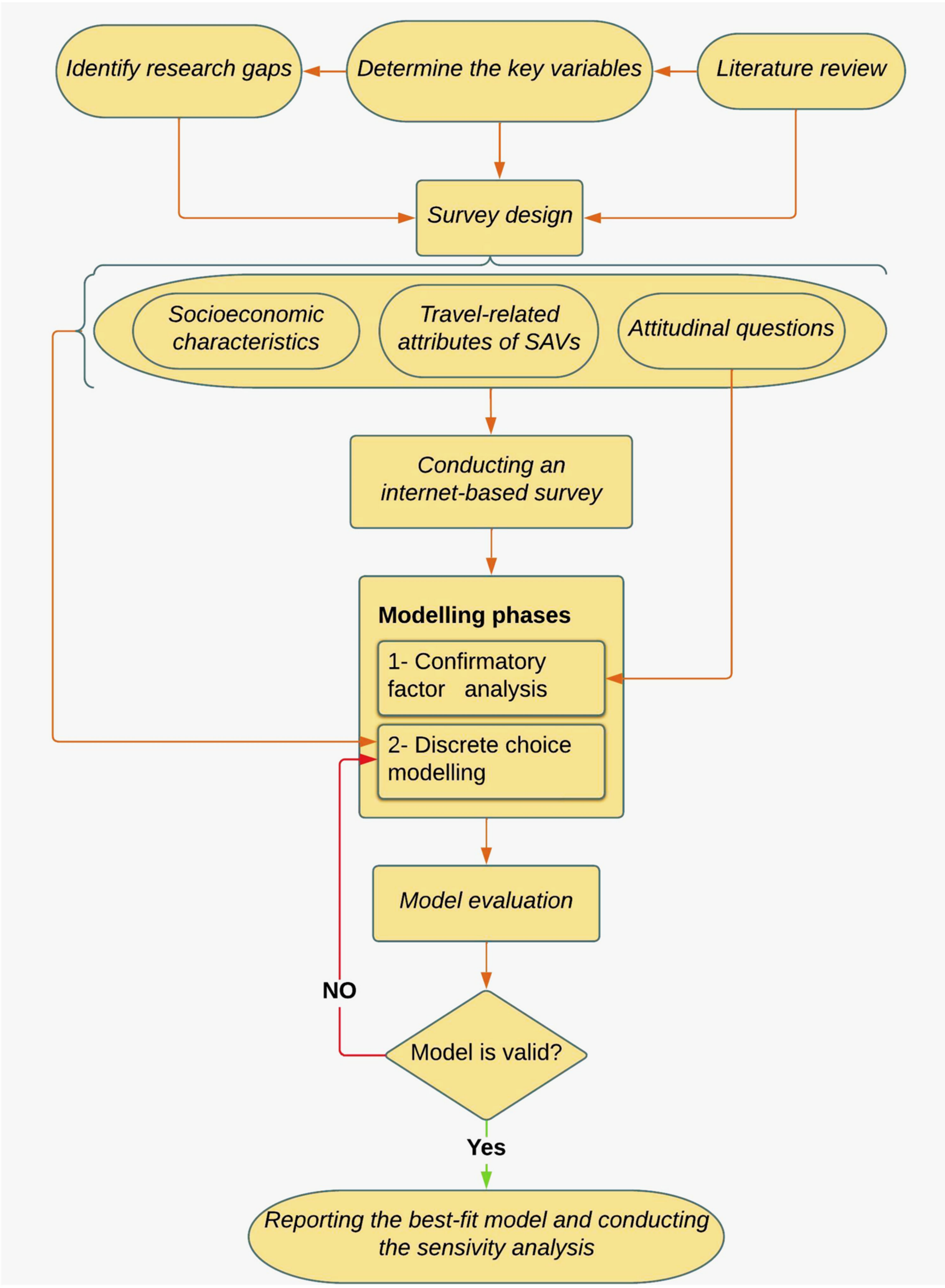

Figure 2. Research methodology flowchart.

3.1. Survey Design and Choice Experiment Design

In our conjoint survey, a choice set consisting of hypothetical alternatives based on a combination of different attributes of a service or product was presented to the respondents, and they were asked about their preference for the alternatives [53]. In this research, due to the absence of SAVs in Tehran, a stated preference (SP) survey was designed to determine the preferences of various users, including private cars, buses, and subways, toward a modal shift to SAVs. Moreover, due to the discrete and dichotomous nature of our dependent variable (shifting/not shifting to SAVs), we used the binary logit model. This method has been used in many previous studies when the respondents have to choose an option from a set of alternatives [54]. It should be noted that, although this method has been used extensively in prior studies, the choice set in this model was limited and restricted individuals' responses to only two outcomes. The adequate sample size was determined using Equation (1) proposed by Cochran [55].

$$n_0 = \frac{pqz^2}{e^2} \tag{1}$$

where the sample size is n_0, the standard error at the considered significance level is z, the proportion of the population with the attribute in question is p, q is 1-p, and the acceptable sample error is e.

An extensive range of questions (Figure A1) about attitudes, travel attributes, and socioeconomic characteristics were asked in five main sections. Participants were initially assured of the survey's objective as well as the anonymity and confidentiality of their responses. In the first section, respondents' travel behaviors including the frequency of using different modes of transportation, driving experience, accident experience in the past five years, and reasons for satisfaction with internet taxis were asked. Moreover, their last trip characteristics such as travel mode, trip purpose, departure and arrival times, waiting times, travel costs, and parking space availability were also asked. In the second section, due to the absence of SAVs in Tehran, a short video clip along with SAVs' operational designed was shown to respondents to enable them to better perceive this technology's features. Afterwards, we asked the respondents to state their level of familiarity with SAVs, ranging from "1 = not familiar at all" to "4 = very familiar and having comprehensive information". Moreover, based on respondents' last trip characteristics, 18 orthogonal scenarios were designed using four three-level attributes of SAVs, including travel time, travel costs, waiting time, and the number of passengers sharing the SAV. The levels of considered attributes for private car and transit users are presented in Table 2. Considering time limitations and preventing respondents' confusion, a fractional factorial design (FFD) approach was used to design scenarios. Moreover, the choice experiments were divided into three six-scenario blocks and presented to respondents randomly, and their willingness to shift toward SAVs was asked (Table 3).

Table 2. Stated preference attributes and their levels across private car and transit users.

Attribute	Trip Mode	Level		
		1	**2**	**3**
Travel time change (%)	Private car	0	+15	+25
	Transit	0	−15	−30
Travel cost (1000 IRR [1] per 5 min)	Private car/Transit	10	15	20
Waiting time (min)	Private car/Transit	2	5	8
Number of travelers in SAV	Private car/Transit	1	2	3

[1] IRR is the unit of money in Iran and each 1000 IRR is equivalent to 0.024 USD (29 November 2022).

Table 3. An example of conjoint format of the modal shift to SAVs for private car users.

Travel Time (Min)	Travel Cost (1000 IRR)	Waiting Time (Min)	Number of Travelers in SAV	Would You Shift to SAV?	
				Yes	No
1.15 × TT *	TT/5 × 20	8	2	☐	☐
1.25 × TT	TT/5 × 20	5	1	☐	☐
1.25 × TT	TT/5 × 10	5	3	☐	☐
1.15 × TT	TT/5 × 15	8	3	☐	☐
TT	TT/5 × 15	2	2	☐	☐
TT	TT/5 × 10	2	1	☐	☐

* TT stands for travel time.

In the fourth section, psychological factors such as sharing attitude, ecological awareness, consumer innovativeness, perceived risk, and perceived usefulness were also assessed using a 5-point Likert scale ranging from (1) strongly disagree to (5) strongly agree. Finally, socio-economic characteristics of the respondents were asked, including their gender, age, education, occupation, household car ownership status, driving license status, and income.

3.2. Featuring the Selected Sample

3.2.1. Socioeconomic and Household Characteristics

A web-based survey was designed and administered in October 2021 in Iran for two months due to the pandemic. As a pilot survey, 30 questionnaires were filled out in order to test the clearness of the questions. Various social media platforms were used to distribute the questionnaire. The return rate of the survey was 20%. A random representative sample of 645 individuals from Tehran, Iran, was obtained. Following refinement of the data, 607 valid samples were evaluated for further analysis. The average time to complete the survey was 15 min, with a standard deviation of 5 min, indicating that participants carefully filled in the questionnaire. A frequency analysis of socioeconomic characteristics of respondents (Table 4) showed that more than half (61.3%) of the sample were males, which is due to the higher income and car ownership status of men in Iran compared to women [56]. Regarding respondents' age, approximately half were between 25 and 34 years old. Nearly half of the respondents held a master's degree. In terms of driving experience, approximately 41% of individuals had less than five years of experience. Considering the increasing trend of car ownership in Tehran [56], only 5% of the sample did not own a car in their household. Moreover, about 6% of the households did not have a driving license. Our sample indicates an approximately balanced distribution of household income levels: 40.5% middle-income, 25.7% high-income, and 23.6% low-income.

Table 4. Frequency analysis of explanatory variables: Socio-Demographic and Household Related Characteristics.

Variable	Category	Frequency	
		Count	Percentage (%)
Gender	Female	235	38.7
	Male	372	61.3
Age (years)	18–24	145	23.9
	25–34	318	52.4
	35–44	85	14
	45–64	49	8.1
	>64	10	1.6
Marriage status	Single	420	69.2
	Married	187	30.8

Table 4. *Cont.*

Variable	Category	Frequency	
		Count	Percentage (%)
Education	At most apprenticeship diploma	57	9.4
	Bachelor	193	31.8
	Master	306	50.4
	PhD	51	8.4
Number of cars in household	0	34	5.6
	1	295	48.6
	2	199	32.8
	3+	79	13
Number of driving licenses in household	0	40	6.6
	1	181	29.8
	2	166	27.3
	3	145	23.9
	4+	75	12.4
Driving experience (years)	0	68	11.2
	1–5	181	29.8
	6–10	181	29.8
	11+	177	29.2
Income level	Very low	42	6.9
	Low	143	23.6
	Medium	246	40.5
	High	156	25.7
	Very high	20	3.3

3.2.2. Socioeconomic and Household Characteristics

Figure 3 provides an overview of the stated preferences of respondents regarding the modal shift to SAVs at different levels of explanatory variables. According to individual characteristics, there is not much difference in the shift to SAVs between males and females. Respondents with PhDs had a lower tendency to modal shift to SAVs owing to their higher income as well-educated respondents. Respondents under 18 and over 65 showed the highest and lowest willingness to shift to SAVs, respectively. When taking into account household characteristics, the modal shift increased in proportion to the size of the household. Increasing household car ownership was associated with a significant decrease in the modal shift to SAVs, which could be an indication of car dependency. Households with at least three private cars were the most reluctant to shift to SAVs. Since SAVs have lower travel costs due to being shared, households with very low incomes had the greatest tendency to shift to them, and a decreasing trend is evident as income increases. SAVs were more commonly used by those without a driving license, as a result of increased mobility. More experienced drivers were less likely to use SAVs due to their reliance on their own experience. People who had been involved in an accident had a lower willingness to shift to SAVs because of their lower trust in technology. Those who used internet taxis were more inclined to shift to SAVs due to their greater level of innovation. The most likely groups to shift to SAVs were those who were moderately or highly familiar with SAVs.

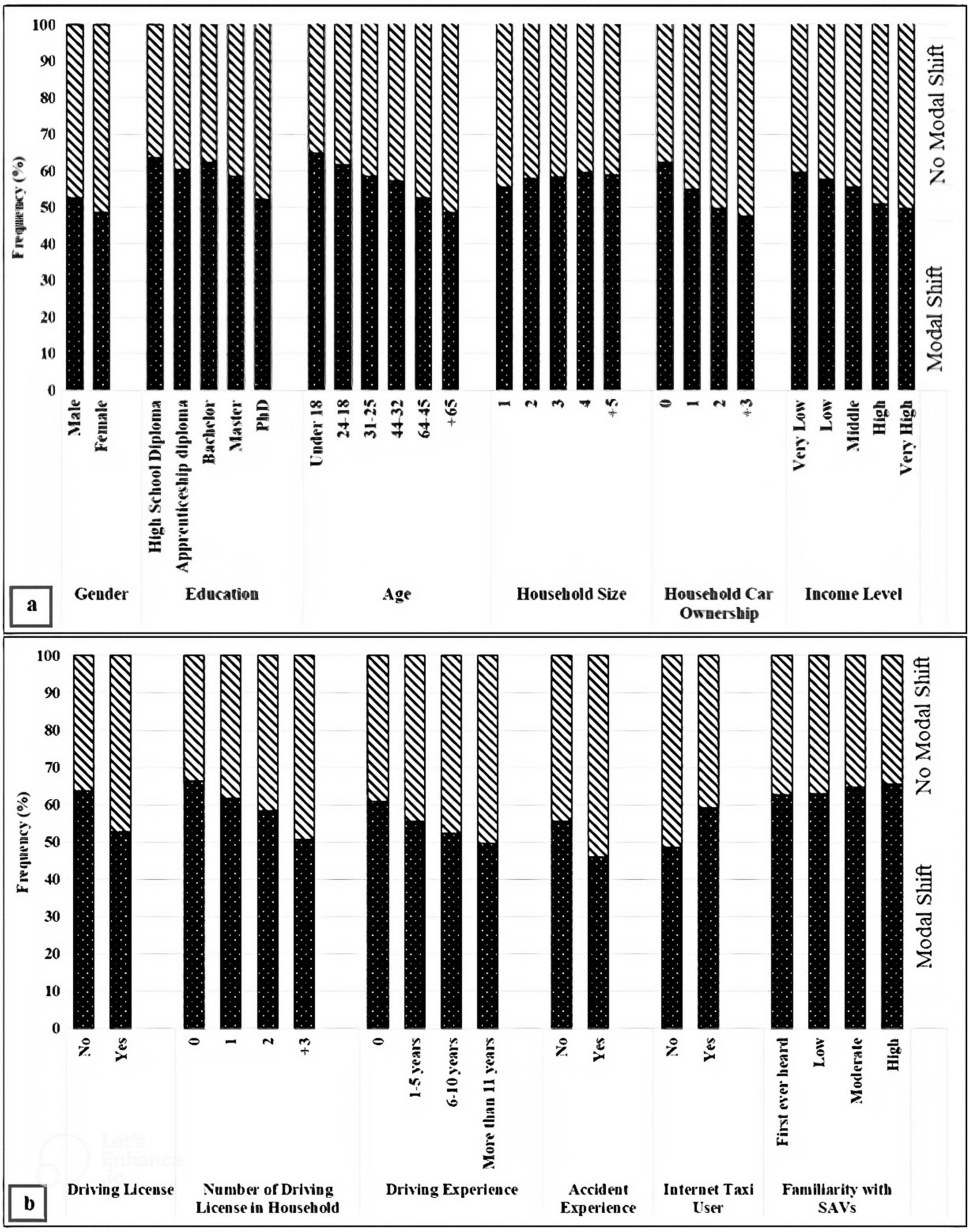

Figure 3. Frequency analysis of the modal shift preference to SAVs by (**a**) socio-economic characteristics and (**b**) travel-related factors.

4. Estimation Results and Discussion

In the following subsections, we discuss a confirmatory factor analysis (CFA) that was conducted to determine the significant indicators of each latent construct affecting modal shift behavior (Section 4.1). Following that, binary logit models are discussed (Section 4.2) as a discrete choice modeling approach, and critical discussions are made on the estimation results (Sections 4.2.1–4.2.3). Lastly, several recommendations for policy and practice (Section 4.3) are provided in an effort to increase the likelihood of a modal shift to SAVs.

4.1. Confirmatory Factor Analysis

In this section, we discuss the results of a CFA conducted using Amos v.24 software [57] to determine the relationships between the indicators and latent constructs. The estimation results of the CFA, including factor loadings, means, and other goodness of fit measures as well as validity and reliability indices, are presented in Table 5. In terms of the validity of latent constructs, because the items were derived from the literature, the content validity was supported. In addition, measures were also evaluated based on converging and discriminant validity [58]. Item reliability, average variance extracted (AVE), and composite construct reliability (CR) were used to examine the convergent validity. According to Hair et al. [59], the convergent validity test for AVE and CR requires values greater than 0.5 and 0.7, respectively [60]. Factor loading associated with latent constructs was used to assess item reliability. A Cronbach's alpha (CA) of 0.8 or higher is considered excellent, but an alpha of 0.5–0.7 can be considered acceptable. The measurement model was rerun after indicators with factor loadings below 0.6 were excluded from the model. All the values of CR and CA ranged from 0.721 to 0.887 and 0.720 to 0.885, respectively, indicating acceptable internal consistency [61]. Moreover, AVE values ranged from 0.504 to 0.797. These all exceeded 0.5, indicating acceptable convergence validity [59]. In terms of discriminant validity (Table 6), this refers to the fact that constructs differ from one another. The square root of AVEs (bold font) ranged from 0.710 to 0.893, which exceeded the correlation coefficient between constructs, indicating that the discriminant validity test was satisfied [58]. As part of our model goodness of fit evaluation, we used model identification indices, such as chi-square (χ^2), normed chi-square (CMIN/df), normed fit index (NFI), comparative fit index (CFI), and root mean square error of approximation (RMSEA), to determine whether each relationship in the hypothetical model was supported by the data. Based on Hair et al. [59], if NFI, CFI, TLI, and IFI values exceeded 0.90, we would consider the model fit to be acceptable, whereas RMSEA values of 0.01, 0.05, and 0.08 would indicate excellent, good, and acceptable model fit, respectively. Based on the aforementioned confirmation, the data were well-fitted, and the validity and reliability of the latent constructs were confirmed.

Table 5. Evaluation of the reliability and validity of the CFA model.

Construct	Item	Mean	Factor Loadings	CA	CR	AVE	Source
Sharing attitude	I think participating in collaborative consumption/sharing will be positive	4.04	0.860	0.885	0.887	0.797	[22]
	I think participating in collaborative consumption/sharing will be fun	3.98	0.920				
Consumer innovativeness	I think advancement in technology is generally a positive thing	4.25	0.660	0.798	0.801	0.504	[62]
	I am excited about the possibilities offered by new technologies	4.31	0.790				
	I have a positive attitude toward innovations	4.35	0.740				
	In general, I will not be hesitant to try out UAMs	4.13	0.640				
Ecological awareness	SAVs are more environmentally friendly than conventional cars	4.12	0.880	0.808	0.813	0.686	[63]
	SAVs can reduce air pollution	3.25	0.821				
Perceived usefulness	Using SAVs will relieve my stress of driving	4.26	0.763	0.769	0.725	0.569	[64]
	SAVs can reduce traffic congestion, thereby shortening the riding time	4.11	0.746				
Privacy concern	SAVs are secure and would not be hacked	2.85	0.770	0.720	0.721	0.564	[38,65]
	I am assured that SAVs will not use my personal information for other purposes without my authorization	2.92	0.740				

χ^2 = 87.156, df = 29, $p < 0.01$; RMSEA = 0.051; CFI = 0.980; NFI = 0.970; CMIN/df = 3.005.

Table 6. Correlation matrix and discriminant validity results.

	Construct	1	2	3	4	5
1	Ecological awareness	**0.828** *				
2	Perceived risk	0.279	**0.751**			
3	Consumer innovativeness	0.4	0.129	**0.71**		
4	Shared attitude	0.546	0.286	0.448	**0.893**	
5	Perceived usefulness	0.463	0.157	0.429	0.542	**0.754**

* Bold numbers are the square root of AVE.

4.2. Discrete Choice Modelling

In Tables 7 and 8, the best fit binary logit models are presented to indicate the key factors in the modal shift preference of private car and transit users toward SAVs separately. The proposed models employ a wide range of variables in order to enhance their explanatory power. For instance, to examine the existence of any probable systematic heterogeneity in the respondents' behavior, interaction variables have also been used in addition to independent variables. It is worth noting that Nlogit5.0 [66] software was used for model estimation. All explanatory variables in the models were evaluated based on t-values at different confidence levels. Accordingly, all explanatory variables in the proposed models were significant at a confidence level greater than 90%. Moreover, in order to determine the most influential factors, marginal effects were also calculated [67]. In the following subsections, we discuss the influence of factors that have been categorized into three groups, namely, travel features and behavior characteristics, travel-related attributes of SAVs, and attitudinal and demographic factors.

Table 7. Estimation results of binary logit model of modal shift preference of transit users.

Variable	Definition	Coef.	M. E.
Constant	Intercept	−9.339 ***	-
	Travel Features and Behavior Characteristics		
NuseT	Weekly frequency of using transit	−0.158 *	−0.032
LnTT	Natural logarithm of transit travel time	5.928 ***	1.221
Diss1	Satisfaction with internet taxis (1 if true; 0 otherwise)	0.466 **	0.091
NotUseC	Not using a private car due to the lack of ability to drive (1 if true; 0 otherwise)	0.974 ***	0.200
	Travel-related Attributes of SAVs		
WTS	SAVs' waiting time (min)	−0.065 **	−0.013
LnTTS	Natural logarithm of SAVs' travel time	−3.423 ***	−0.705
Tcs	SAVs' travel cost	−0.183 ***	−0.038
	Attitudinal and Demographic Factors		
NUITEC	Consumer innovativeness among users who frequently use internet taxis	0.172 **	0.035
Shattitu	Sharing attitude	0.470 ***	0.097
EnviFem	Ecological awareness among females	−0.090 **	−0.018
EXDPR	Privacy concern among low-experienced drivers	−0.196 **	−0.040
PUKNOW1	Perceived usefulness among respondents who never heard of SAVs	0.249 ***	0.167
	Number of observations	696	
	Log-likelihood at convergence (LL(β))	−406.93	
	Log-likelihood at zero (LL(0))	−482.43	
	ρ_0^2	0.156	

***, **,*: significance at 1%, 5%, and 10% levels, respectively.

Table 8. Estimation results of binary logit model of modal shift preference of car users.

Variable	Definition	Coef.	M. E.
Constant	Intercept	0.936 **	-
	Travel Features and Behavior Characteristics		
Nuses	Weekly frequency of using internet taxis	0.133 **	0.030
Nusecar	Weekly frequency of using private car	−0.059 **	−0.127
Trpur_1	Work trip (1 if true; 0 otherwise)	0.139 *	0.031
Ttkoli	Private car total travel time (min)	0.049 ***	0.011
Diss9	Lower use of car-sharing services because of COVID outbreak (1 if true; 0 otherwise)	−0.339 *	−0.076
Injr-1	Experiencing an injury-causing accident (1 if true; 0 otherwise)	−0.166 *	−0.037
	Travel-related Attributes of SAVs		
Wts	SAVs waiting time (min)	−0.040 **	−0.096
Wtstts	Ratio of waiting time to travel time in SAVs	−1.284 ***	−0.290
Tts	SAVs travel time (min)	−0.026 ***	−0.089
Tcs	SAVs travel cost	−0.062 ***	−0.014
Nps	Number of passengers sharing their ride	−0.501 ***	−0.113

Table 8. *Cont.*

Variable	Definition	Coef.	M. E.
	Attitudinal and Demographic Factors		
Techm	Inverse of consumer innovativeness	−1.342 *	−0.303
Shattitu	Sharing attitude	0.135 *	0.030
Envicon	Ecological awareness	0.206 **	0.046
Perrifem	Privacy concern among women	−0.072 **	−0.106
PUINC3	Perceived usefulness among middle-income respondents	0.317 **	0.103
	Number of observations		2946
	Log-likelihood at convergence (LL(β))		−1897.78
	Log-likelihood at zero (LL(0))		−2042.01
	ρ_0^2		0.071

***, **,*: significance at 1%, 5%, and 10% levels, respectively.

4.2.1. Travel Features and Behavior Characteristics

There is a positive association between the frequency of using (as well as satisfaction with) internet taxi services and the likelihood of a modal shift to SAVs among private car and transit users. Based on the marginal effect values, the probability of a modal shift to SAVs among private car users increased by 3% with a one-unit increase in the frequency of weekly usage of internet taxis. Meanwhile, the satisfaction of transit users with internet taxis increased the likelihood of a modal shift to SAVs by 9%. This is due to the many similarities between how SAVs and internet taxis are requested, as well as the higher familiarity of internet taxi users with technology, as found by Kim et al. [68]. Further, there is a significant negative relationship between the likelihood of a modal shift to SAVs and the weekly frequency of using cars and transit. By increasing one unit in the frequency of weekly use of a private car, the probability of a modal shift to SAVs decreased by 12.7%, which is due to the critical influence of car dependency. This finding is in line with Acheampong et al.'s [23] findings. In addition, the probability of a modal shift to SAVs decreased by 3.2% among public transportation users when the frequency of weekly transit use increased by one unit. As can be seen, the marginal effect of car use is four times greater than the marginal effect of transit use. This finding is also in accordance with several studies that have indicated that transit users are more inclined to use SAVs, whereas people who rely on a car are more inclined to own a private AV [23,28,69].

Increasing the travel time in private cars and transit has a significant and positive impact on the willingness of passengers to undergo a modal shift to SAVs. According to marginal effect values, we can conclude that increasing the travel time of private cars and using a private car on work trips increases the probability of a modal shift to SAVs by 1.1% and 3.1%, respectively. Due to regular work schedules, commuters prefer to take advantage of shared transportation services to reduce travel time, especially during rush hours. Furthermore, Malichová et al.'s [70] results indicate that most people prefer ridesharing for their working trips as opposed to other types of travel.

As well, Azimi et al.'s [33] research indicates that the decision to shift to ridesharing is strongly influenced by cost and travel time among transit users. According to this study, if the logarithm of travel time in transit is increased by one unit, there will be an increase of 122.1% in the probability of a modal shift to SAVs. This is due to the fact that, by using SAVs, transit users will not only save time in traveling but will also share their trips with fewer travelers and will be able to travel in greater comfort.

It has been found that among private car users, those who have used shared services less frequently due to the outbreak of COVID-19 are less likely to shift to SAVs, which is in line with Nickkar et al.'s [71] findings. The marginal effect value indicates that this variable will reduce the likelihood of a modal shift to SAVs by 7.6%.

Based on accident experience, private car users who have experienced an injury-causing accident are less likely to shift to SAVs, which is in accordance with Liu et al.'s [72] findings. Experiencing such an accident will reduce the probability of a modal shift by

3.7% because individuals have less trust in this emerging technology. Since SAVs have many advantages in terms of increasing mobility for individuals without a driving license or those who are elderly, transit users who are unable to drive a car will be 20% more likely to shift to SAVs. Various studies such as those by Harper et al. [73] and Fagnant and Kockelman [74] have found similar results.

4.2.2. Travel-Related Attributes of SAVs

An increase in the waiting time of SAVs is associated with a reduction in the likelihood of modal shift behavior among private car and transit users, which is consistent with Krueger et al.'s [28] findings. Based on the marginal effect, the probability of a modal shift among private car and transit users decreased by 9.6% and 1.3%, respectively, when the waiting time of SAVs was increased by one unit. This finding indicates the higher sensitivity of private car users to the waiting time of SAVs.

Travel time and travel cost are the main factors that influence the choice of SAVs [26]. In our study, the travel cost of SAVs had a significant and decreasing effect on the likelihood of transit and private car users' shifting behaviors. A one-unit increase in the SAVs' travel cost was associated with a 1.4% and 3.8% reduction in the likelihood of a modal shift from private cars and transit to SAVs, respectively, indicating that transit users are more sensitive to travel costs. In terms of SAVs' travel time, an increase of one unit in their travel time reduced the probability of private car modal shift behavior, on average, by 8.9%. On the other hand, among transit users, an increase of one unit in the logarithm of SAVs' travel time significantly reduced the probability of modal shift by 70%. Further, a one-unit increase in the ratio of waiting time to travel time for SAVs reduced the likelihood among private car users shifting to SAVs by 29%. Our aforementioned findings are in line with Farzin et al.'s [32] findings.

This study contributes to the existing literature by examining how people's modal shift behavior is affected by the number of people sharing their rides in SAVs. An increase in the number of passengers sharing rides will reduce the probability of a modal shift of private car users by 11.3%. This finding is consistent with Pakusch et al. [69] and Acheampong et al.'s [23] findings.

4.2.3. Attitudinal and Demographic Factors

Both private car and transit users' modal shift preferences are positively impacted by consumer innovativeness. As the inverse of consumer innovativeness increased by one unit, the probability of shifting to SAVs decreased by 30.3% among private car users. Nevertheless, systematic heterogeneity was observed among transit users regarding attitudes toward technology. It was found that with the increase of one unit of attitude towards technology among users who frequently use internet taxis, the likelihood of a modal shift increased by 3.5%. As Chan and Lee [75] found, innovative consumers are more likely to adopt emerging technologies. Our findings are in accordance with Golbabaei et al. [43] and Keszey's [44] results.

The likelihood of a modal shift to SAVs is positively associated with sharing attitudes among both private car and transit users. As the sharing attitude increased by one unit, the likelihood of shifting from private cars and transit to SAVs increased by 3% and 9.7%, respectively. Therefore, transit users exhibit a higher sharing attitude, which is consistent with the findings of Acheampong et al. [23].

Private car users with a higher level of environmental awareness are more likely to shift to SAVs by 4.6%, as SAVs align better with sustainable transportation [23]. Moreover, there is systematic heterogeneity among transit users in this variable, as a result of which, with a one-unit increase in environmental concern among male transit users, the likelihood of shifting to SAVs decreases by 1.8%, since many studies indicate that SAVs increase vehicle miles traveled [37].

The perception of risk is systematically heterogeneous among private car and transit users. The likelihood of female private car users shifting to SAVs decreased by 1.6% when perceived risk was increased by one unit, which is consistent with the findings of Lee and Hess [76] and Yeganeh et al. [77]. The likelihood of transit users shifting to SAV decreased by 4% when perceived risk increased by one unit among less experienced drivers.

Among public transit and private car users, there is systematic heterogeneity in perceived usefulness. As a result of an increased perception of SAVs' usefulness by one unit among middle-income private car users and transit users who have never heard of SAVs, the likelihood of modal shift increased by 10.3% and 16.7%, respectively. This finding implies that respondents who find SAVs' services more beneficial are more likely to shift to SAVs, which is consistent with Wadud and Huda's [48] findings.

4.3. Implications for Policy and Practice

A key factor in ensuring the successful deployment of revolutionary technology is identifying factors that encourage people to use it and reduce their resistance to change. Based on the proposed models, consumer innovation, the ratio of waiting time to travel time of SAVs, perceived usefulness, the weekly frequency of using private cars, the number of passengers sharing their rides, and privacy concerns can serve as the most critical variables (with marginal effect values of at least 0.10 in the transit/car model) that can be used for policymaking.

The strongest latent construct positively correlated with the likelihood of shifting to SAVs is consumer innovativeness. A sense of innovation might be invoked in people by policymakers in order to encourage them to use SAVs. It may be possible to promote policies such as free trials in order to encourage first-time users to take advantage of this service.

The second most important factor is the ratio of waiting time to travel time for SAVs. In light of the higher value of travel time among private car users compared to transit users, the marginal effect of waiting time on travel time is nearly eight times greater for private car users. In terms of policy and practice, a tradeoff between waiting time and travel cost could be offered to users who tend to experience lower waiting times in order to increase the utility of using SAVs [78].

Another factor that contributes to the shifting preferences of transit and car users is perceived usefulness. Increasing the likelihood of a modal shift to SAVs can be achieved by presenting their benefits and advantages through various social and mass media.

The fourth influential factor is the weekly frequency of using cars, which is negatively associated with the likelihood of shifting to SAVs. Travel demand management (TDM) policies such as congestion pricing and parking management are recommended to decrease the dependence on private cars and encourage car users to use SAVs.

As the number of passengers sharing their rides increases, it will also negatively affect car users' willingness to shift to SAVs. Due to the higher level of comfort of a private car over shared mobility services, it is recommended that policymakers provide passengers with the option of selecting the preferred number of people to share the trip at various levels of travel cost.

Lastly, privacy concerns play a critical role in the shifting preferences of transit and car users. Travelers should be assured that the information they provide will be protected by the service provider in order to satisfy their concerns regarding privacy. The provision of special services to women, in particular, could be another practical implication that could encourage travelers to use SAVs. Closed-circuit television (CCTV) or women-only SAVs, for instance, would increase women's safety perception, which would increase their willingness to shift.

5. Summary and Conclusions

5.1. Conclusions and Inferences

Automated, connected, and shared mobility is often seen as the key to a sustainable mobility future for metropolises. The integrated use of automation and on-demand ride-sharing services may cause significant changes to urban transportation and people's travel behavior. The key to achieving a successful deployment of emerging technologies is to identify the factors that will affect potential users' behavior. Accordingly, this paper contributes to the existing body of literature pertaining to modal shift preferences by examining how attitudinal, travel-related attributes, and demographic variables affect the shifting behavior of private car and transit users to SAVs with dynamic ridesharing (DRS).

The estimated binary logit coefficients show a significant difference in the modal shift behavior of transit and private car users. Shifting behaviors of private car users are significantly influenced by consumer innovativeness and privacy concerns as attitudinal factors, the number of passengers sharing a trip and the ratio of waiting time to travel time of SAVs as travel-related attributes, and car dependency as travel behavior features. Transit users' modal shift preferences, however, are affected by a number of attitudinal factors, including their intention to share and perceived usefulness as attitudinal factors, the travel cost of SAVs as a travel-related attribute, and transit travel time as a trip characteristic. Further, the waiting time and travel cost of SAVs and sharing attitudes have been simultaneously significant in the shifting preference of both transit and private car users to SAVs. While the travel cost of SAVs and sharing intentions were more critical factors in determining transit users' modal shift likelihood, private car users were more sensitive to the waiting time of SAVs.

5.2. Limitations and Further Research Recommendations

By filling previous gaps, this study contributes to the body of modal shift behavior literature on SAVs with DRS. While this study provides insight and knowledge about SAVs, because of our research limitations, it has also raised some new questions that require further study. This study was undertaken in a rather crowded and polluted city as a case study that cannot be generalized to other contexts due to differences in travel behavior, cultures, and other environmental factors. However, this model can still be applied to other contexts in order to predict how people will shift to SAVs. Further, the dichotomous dependent variable used in this study can be further extended to a multiscale, such as the 5-point Likert scale. Lastly, this study examined the effect of the number of travelers sharing a ride on the shifting likelihood of respondents. This factor sheds light on the sharing intentions of respondents. However, it is recommended to ask about the preferred place to sit in the vehicle too, in future studies.

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Appendix A. Questions of Survey

Please specify the following information

Gender	☐ Male	☐ Female	☐ Prefer not to say		
Age	------------				
Marital status	☐ Married	☐ Single			
Education Level	☐ At most high school		☐ Bachelor	☐ Master	☐ PhD
Number of cars in your household			------------		
Number of driving license in household			-----------		
Your driving experience (years)			------------		

Your income level compare to the average income of Tehran	☐ Very low	☐ Low	☐ Medium	☐ High	☐ Very high

Weekly usage frequency of your dominant travel mode		------------		
Your familiarity with SAVs	☐ Never heard of SAVs	☐ Low	☐ Moderate	☐ High
Experiencing an accident	☐ No	☐ Yes, please specify the severity level:- ---------		

Consider your last trip and respond to the following questions

Travel mode	Departure time	Waiting time	Arrival time	Egress time	Travel cost	Purpose

Suppose the following condition, please specify that are you willing to shift to SAVs?

Travel Time (min.)	Travel Cost (1000 IRR)	Waiting Time (min.)	Number of travelers in SAV	Would you shift to SAV? Yes	No
1.15×TT *	TT/5×20	8	2	☐	☐
1.25×TT	TT/5×20	5	1	☐	☐
1.25×TT	TT/5×10	5	3	☐	☐
1.15×TT	TT/5×15	8	3	☐	☐
TT	TT/5×15	2	2	☐	☐
TT	TT/5×10	2	1	☐	☐

* TT stands for travel time.

Please specify your agreement level with the following statements (1: Strongly disagree to 5: Strongly agree)

	1	2	3	4	5
I think participating in collaborative consumption/sharing will be positive	☐	☐	☐	☐	☐
I think participating in collaborative consumption/sharing will be fun	☐	☐	☐	☐	☐
I think advancement in technology is generally a positive thing	☐	☐	☐	☐	☐
I am excited about the possibilities offered by new technologies	☐	☐	☐	☐	☐
I have a positive attitude toward innovations	☐	☐	☐	☐	☐
In general, I will not be hesitant to try out UAMs	☐	☐	☐	☐	☐
SAVs are more environmentally friendly than conventional cars.	☐	☐	☐	☐	☐
SAVs can reduce air pollution.	☐	☐	☐	☐	☐
Using SAVs will relieve my stress of driving.	☐	☐	☐	☐	☐
SAVs can reduce traffic congestion, thereby shortening the riding time.	☐	☐	☐	☐	☐
SAVs are secure and would not be hacked.	☐	☐	☐	☐	☐
I am assured that SAVs will not use my personal information for other purposes without my authorization	☐	☐	☐	☐	☐

Figure A1. The research questionnaire.

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