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Usage Intention of Shared Autonomous Vehicles with Dynamic Ride Sharing on Long-Distance Trips

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Abstract: Technology advancements have paved the way for public access to shared autonomous vehicles (SAVs), but there is still no travel survey examining how SAVs with dynamic ride sharing (DRS) affect long-distance (LD) trips. Given the growth in these trips and the higher importance of travel time and cost on LD trips, assessing potential impacts of SAVs could be a vital tool in planning for a sustainable transportation system. This paper examines the impact of various attitudinal, sociodemographic, and travel-related characteristics on the usage intention of SAVs with DRS on LD trips. We have designed and conducted a web-based survey for this purpose and based on a representative sample of 723 individuals in 2021, a Generalized Ordered Logit model is estimated. Estimation results highlight the key importance of following psychological factors in a descending order: price evaluation, perceived usefulness, consumer innovativeness, sharing attitude, and privacy concern. Further, key factors among sociodemographic and travel-related characteristics are gender, education level, driving license, household car ownership, generational element, and crash history. These findings provide crucial insights into the likely effects of SAVs with DRS on LD trip behavior, based on which a number of practical implications are proposed for facilitating policy-making.

Keywords: shared autonomous vehicle; dynamic ride sharing; long-distance trip; generalized ordered logit; intention to use; psychological factors

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1. Introduction

Autonomous vehicle (AV) technologies are actively being developed by many well-known automobile manufacturers and technology firms [1]. Nearly half of the states in the United States have adopted legislation regarding AVs, and they are already being used experimentally in many cities. However, AVs are still being met with considerable uncertainty in terms of their social acceptance. Several studies have shown that new technologies do not immediately appeal to consumers, and their attitudes towards AVs may vary significantly [2]. Moreover, in any country or context, public perception will be subject to regular fluctuations until AVs are widely available in market at an affordable price [3]. Hence, field surveys can contribute to the valuable implications for policy and practice in various transportation-related organizations. There are many potential benefits of AVs such as safety enhancement [4], a reduction in car ownership and urban sprawl, a better network performance [5,6], and an improvement in public health [7]. However, there are still many concerns associated with AVs such as their safe operation, security, privacy, and design [8–10]. For instance, locations of users can be recorded using GPS on their smartphones, and internet-based services can match advertisements to users interests. On other hand, private cars are the most preferred transportation mode in Tehran, accounting for over 43% of all trips [11,12]. Given the challenges associated with the increase in personal car use and the car ownership pattern which is significantly increasing from 175 private car per 1000 capita in 2010, and it is estimated to be 679 in 2030 [13], authorities are thinking about the introduction of a new, sustainable transportation mode. Among the available alternatives, AVs would increase travel distance, which is not in line with sustainable transportation policies despite the likelihood that AV prices would be higher than conventional cars [3,14,15]. Therefore, this type of motorized alternative might not be widely supported by policymakers and it is likely that shared autonomous vehicles (SAVs) will become more popular. One of the shared mobility services is ride-sourcing that riders can arrange on-demand or pre-arranged rides using their smartphones [16]. Travelers reduce travel costs by sharing rides with strangers through dynamic ride sharing (DRS), a service that has many potential benefits [17–19]. Many studies believe that the integration of SAVs with ridesharing services would have many benefits, particularly on long distance (LD) trips that are more affected by travel time and cost than short-distance trips [20].

Passenger trips over long distances contribute significantly to congestion, air and noise pollution, severe collisions and traffic volume in most nations. LD trips are a special category of trip, since they are rare (with exception of extended commuters) while involve a high mileage traveled [21]. In light of the exhausting and tedious nature of LD driving, using autonomous cars might be an appealing option for this type of trips. By reducing the responsibility of drivers, AVs may lead to a better and safer travel experience for everyone. Those traveling for business or commuters, for instance, may consider working en-route, whereas family and friends on vacation may enjoy better quality interactions on the way, along with more flexibility in departure times and perhaps lower travel costs [22].

Determine factors that encourage people to use technologies and reduce their resistance to change is a critical component of ensuring the successful deployment of any policies. To the best of the authors' knowledge, there is still no travel survey targeting inter-regional SAVs with DRS impacts on LD trips. Thus, this paper aims to investigate how various attitudinal, sociodemographic, and travel-related characteristics affect the usage intention of SAVs with DRS on LD trips.

This paper is structured as follows: previous studies will be reviewed in Section 2. Section 3 introduces the methodological approach including model, survey design and data processing. Data analysis and results are presented in Section 4. Main findings are critically discussed in Section 5 along with some recommendations for policy and practice. The conclusion as well as some future research suggestions are provided in Section 6.

2. Literature Review

There are a limited number of studies that have focused on the usage intention of SAVs on LD trips. As shown in Table 1, we provide a brief overview of previous studies investigating the use of different types of AVs for a variety of purposes. For example, in a study of LD travel mode choice by LaMondia et al. [20], it was forecasted that 25% of airline trips under 500 miles will be shifted to AVs. After estimation of a binary logistic regression model, their findings highlighted the significance of general travel time and travel cost. One of the main limitations of this study was the absence of attitudinal factors and the consideration of the travel time and travel cost as generic, not a mode-specific variable because of limitation in data. In a study by Kolaroca and Steck [21], the value of travel time saving (VTTS) on LD trips has been studied using the stated preference survey in Germany. The estimation results of the mixed logit model highlighted the importance of trip purpose, travel cost, travel time, waiting time, and access time in VTTS in the presence of AVs. Not taking into account socioeconomic and attitude variables was the main limitation of their study. Bansal and Kockelman [23,24] examined the willingness of respondents to use AVs on LD trips as part of their study. Descriptive analysis of respondents' answer shows that a large share of respondents (37.2%) intended to use AVs for LD trips with one-way distances between 100 and 500 miles. In addition, after purchasing an AV, people also anticipate increasing the number of LD trips they make, by an average of 1.3 trip per month. The limitations of their study on LD trips were not estimating a model and considering a limited number of variables. Moreover, in the study of Kim et al. [25], over 3000 Georgians were asked to respond to a survey about 16 potential changes that AVs may bring. More than half of the respondents were interested in changing their activity patterns due to AVs, particularly for increasing the frequency of leisure as well as LD trips. Gurumurthy and Kockelman [3] investigated the mode choice preference of Americans on LD trips as part of their study. Estimation results of MNL model highlight the impact of trip purpose, car ownership, house size, age, driving license, number of children, income, etc. Their study on LD trips was limited by focusing on only socioeconomic characteristics. Maleki et al. [26] conducted a survey among transportation experts and they found a positive correlation between LD trips and using AVs on leisure trips. Studies have shown that AVs have the potential to make significant changes in the market structure and the decision of travelers in mode choice [27,28]. Previous studies have mainly focused on classic features such as travel time and travel cost to evaluate travelers' preference between different types of AVs including private AVs and SAVs [29,30]. Moreover, travel distance have been evaluated in travelers' mode choice in the study by Arentze and Molin [31]. However, most of the studies focused on short-distance trips and less attention has been paid to LD trips [28,29]. In some other studies, authors have shown that other factors, such as psychological characteristics have the potential to affect individuals' willingness to use AVs [28,30,32]. Psycho-social latent constructs are particularly useful for studies examining the adoption and usage of current and emerging mobility services, not only for improving prediction fit, but also for developing proactive strategies for creating equitable, safe, and community-driven AV systems [22]. Therefore, in this study, along with socioeconomic, household, and travel-related characteristics, we try to explain the respondents' usage intention of SAVs on LD trips by taking into account six latent constructs including privacy concern (PC), attitude toward sharing (ATS), consumer innovativeness (CI), price evaluation (PE), perceived usefulness (PU), and car dependency (CD).

Table 1. An overview of previous studies in use of AVs in LD trips.

Author	Variable			Mode	Model [3]
	Demographic	Travel-Related [1]	Attitudinal [2]		
LaMondia et al. [20]	✓	-	-	AV	BLR
Kolarova & Steck [21]	-	TC; TT; WT	-	AV	MXL
Bansal and Kockelman [23]	✓	-	-	AV	DA
Bansal and Kockelman [24]	✓	-	-	AV	DA
Kim et al. [25]	✓	TP	CI, PNCM, TL; RA	AV	FA & KM
Gurumurthy and Kockelman [3]	✓	-	-	AV & SAV	MNL
Maleki et al. [26]	✓	-	-	AV	CA

Abbreviations: [1]: Travel cost (TC); Travel time (TT); Waiting time (WT); Trip purpose (TP). [2]: Perceived Risk (PR); Privacy concern (PC); Relative advantage (RA); Travel liking (TL); Pro non-car mode (PNCM); Consumer Innovativeness (CI). [3]: Mixed logit model (MXL); Multinomial Logit (MNL); Binary Logistic Regression (BLR); Correlation Analysis (CA); Ordered Probit (OP); Factor Analysis (FA); K-means clustering algorithm (KM); Descriptive Analysis (DA).

In terms of privacy concern, since passengers are typically forced to share their personal information with social networks, it affects individuals' decision-making behaviors [14,25,33]. According to perceived risk theory, consumers perceive risk when they are faced with uncertainty and likely unwanted outcomes. [34]. Several studies have confirmed that privacy concerns significantly decrease usage intention of AVs [14,33,35]. Consumer innovativeness is defined as the willingness of consumers to purchase/use recently released products more frequently and more quickly than others [36]. Therefore, based on previous studies, it can be considered to be an influential factor in usage intention of SAVs among potential users [14,37]. Price evaluation refers to consumer's subjective assessment of a service's perceived benefits against its monetary cost [38]. Nastjuk et al. [39] and Yuen et al. [40] reported an association between price evaluation and usage intention for new products. Choosing whether or not to use SAVs is dependent on how people perceive this technology usefulness to meet their mobility requirements [41]. Moreover, several studies have highlighted the key role of PU in shaping consumers' intention to use of AVs [42–44]. Car dependent refers to the people who rely on their private cars to complete their trips on a daily basis [45]. There are many reasons for this, including inappropriate transit system, urban sprawl, psychological factors, and the lack of a safe pedestrian infrastructure [12,46,47]. Several studies found that it is more likely that those who are pro-car ownership/use will desire private AVs. While a positive attitude toward public transportation and sharing is associated with higher use of shared mobility/transit services [33,48]. Attitude toward sharing/collaborative consumption refers to the exchange of goods and services between participants, either directly or by means of intermediaries, through which consumers "obtain" or "provide" resources or services both temporarily or permanently [49]. As a form of consumption, collaborative consumption does not require ownership of assets or products. The product can instead be booked and accessed as needed by members of a community. Since SAVs are a form of shared mobility which is equipped with autonomy technology, it is anticipated that people who have a positive attitude toward sharing are more inclined to use SAVs [48].

Based on the aforementioned studies, it can be concluded that although rapid advancements in technology have opened up the possibility of SAVs for public use, there is still no travel survey targeting inter-regional SAVs with DRS impacts on LD trips. In other words, a number of studies have been conducted regarding the factors affecting the intention to use AVs, specifically on LD trips. However, there are still gaps which this paper attempts to fill partially and contribute to the existing literature. For instance, most of the related literature on LD trips focus on AVs, whereas shared AVs with DRS have not receive much attention, despite supporting sustainable transportation development. Additionally, most studies have emphasized socioeconomic and travel-related characteristics and have less focused on psychological constructs, which are significantly influential in travel mode choice and technology adoption. Lastly, most previous studies have been conducted in developed countries, and to the best of our knowledge, there have been no studies in developing countries on this topic. Thus, it seems critical for a wide range of purposes, especially policymaking, to understand how SAVs impact travel behavior, given the major implications of these vehicles. Therefore, considering the outbreak of pandemic, people may only prefer private transportation modes over shared mobility services, the survey we have designed and administered exclusively for our study (Section 4), addresses how SAVs impact respondents' usage intention on LD trips.

3. Generalized Ordered Logit Model

Considering the ordinal scale of intention to use measurement levels (1: Low, 2: Moderate, and, 3: High), we used ordered logit model (OLM). Despite accounting for categorical properties of dependent variable, unordered discrete choice models, such as multinomial logit models, neglect the ordered properties. Moreover, unordered models are restricted by their lack of closed-form likelihoods and independence of irrelevant alternatives (IIA) [50]. The parallel regression assumption (or parallel assumption) is one of the key constraints of the OLM, since it implies that associated coefficients are consistent across levels of intention. In the case that at least one of the included coefficients varies across the intention levels, this assumption may be violated. By ignoring this issue, marginal effects and parameter estimations can be biased [48,49]. To verify if a proportional odds assumption is valid, Brant [50] proposed a test whose null hypothesis is $H_0 : \beta_i = \beta$. If the test has not been significant, the estimated coefficients vary across intention levels and OLM results may be biased.

According to typical ordered response models, an unobserved continuous intention propensity is assumed as a linear function (Equation (1)):

$$U_{in} = \beta_i' X_{in} + \varepsilon_{in} \tag{1}$$

where U_{in} is a function determining usage intention level i, for individual n,$\beta_i's$ are a set of unknown parameters for usage intention level i, X_{in} is a vector of explanatory variables affecting usage intention level i for individual n; and ε_{in} is an error term accounting for unobserved factors (those not included in vector x), whose distribution is assumed to be standard logistic or Gumbel. Equation (2) is a method to calculate the conditional probability that an ambition is at a given level of intention.

$$\begin{aligned} &P(I=0) = \varphi(-\beta' X) \\ &P(I=1) = \varphi(\mu_1 - \beta' X) - \varphi(-\beta' X) \\ &P(I=2) = \varphi(\mu_2 - \beta' X) - \varphi(\mu_1 - \beta' X) \\ &\ldots \\ &P(I=j) = 1 - \varphi(\mu_{j-1} - \beta' X) \end{aligned} \tag{2}$$

Each intention level is predicted with a probability ranging from 0 to 1. Moreover, μ_is are threshold parameters that should be estimated and $\varphi(\cdot)$s are the standard cumulative logistic distribution function.

If the parallel regression assumption is violated, Generalized Ordered Logit (GOL) should be calibrated which allows the threshold parameters to vary across observations, thereby relaxing the parallel-lines assumption. Hence, the new thresholds in GOL are as Equation (3).

$$\mu_{in} = \overline{\mu_i} + X' k_i \tag{3}$$

where a threshold value for observation n and intention level i is given by μ_{in}, a constant term is given by $\overline{\mu_i}$, and an influence parameter for the explanatory variables is given by k_i.

The marginal effects are commonly reported after the model coefficients are calculated, which make the results more informative. As an explanatory variable increases by one unit, marginal effect shows the change in intention probabilities, while all other variables held constant. For continuous variables, it shows the immediate change given that the unit may be very small. For binary variables the change is from 0 to 1 [51]. Using Equation (4), the marginal effect for each explanatory variable on specific level of usage intention can be calculated.

$$\frac{(\partial P(I=j)}{\partial X} = [\varphi(\mu_{j-1} - \beta' X) - \varphi(\mu_j - \beta' X)]\beta \tag{4}$$

4. Survey Design and Data Processing

An online survey was designed and conducted in Tehran in September 2021 in order to provide quantitative aspects of our proposed model. It also aimed to understand factors that may influence people's intentions to use SAVs on LD trips. A random sample of 723 Iranians was taken from the population of the city of Tehran. To determine the clarity and comprehensibility of the questions, 30 pilot questionnaires were administered based on which the main survey was modified. The survey was designed after reviewing well-known papers in the literature and consulting experts in the field of AVs. The designed questionnaire consisted of three sections after a brief explanation of the survey objectives and confidentiality and anonymity of individuals' responses. The first section of the survey asked about the respondents' dominant travel mode, driving experience, experience of accidents and the severity, experience on using internet taxis (like Uber) and their level of satisfaction/dissatisfaction. The second section was then devoted to the preparation of a short video clip which introduced and showed the features of SAVs with DRS to fill the gap of the absence of this technology in Tehran, Iran. Using a 5-point Likert scale (1: very low to 5: very high), people were surveyed regarding their intention to use SAVs with DRS on LD trips which we classified the respondents into three categories based on their intention, including: Low, Moderate, and High. Moreover, using a 5-point Likert scale ranging from (1) strongly disagree to (5) strongly agree, psychological factors including PC, ATS, CI, PE, PU, and CD were measured. Thirdly, socioeconomic characteristics had been asked, such as gender, marital status, age, education level, income, household size and private car ownership.

Sample Description

A descriptive analysis of socioeconomic characteristics (Table 2) shows that a balanced proportion of men and women participated in the survey (50.8% vs. 49.2%). In terms of age, the millennial generation accounted for 60% of the respondents. In terms of marital status, 411 (56.8%) of the respondents were single and the remaining were married. There were 240 (33.2%) people with master's degree among the respondents. The household car ownership level shows that 373 (51.6%) of the respondents own only one private car. According to familiarity with SAVs, 384 respondents (53.1%) had never even heard of this technology before the survey. Finally, half of respondents reported having an average income. By comparing the age, gender, and household size distributions of the collected sample with Tehran census data, it can be concluded that the sample is representative of the Tehran population [52].

Table 2. Frequency analysis of individuals and households demographic characteristics.

Characteristic/Variable	Count (Relative %)	Characteristic/Variable	Count (Relative %)
Gender		**Household car ownership**	
Female	356 (49.2)	0	72 (10.0)
Male	367 (50.8)	1	373 (51.6)
Generation		2	221 (30.6)
Z (lower than 21)	63 (8.7)	3^+	57 (7.9)
Millennial (22–37)	438 (60.6)	**Household size**	
X (38–53)	150 (20.7)	1	22 (3.0)
Baby Boomer (54–72)	49 (9.5)	2	78 (10.8)
Silent (more than 73)	3 (0.4)	3	245 (33.9)
Marital Status		4	240 (33.2)
Single	411 (56.8)	5^+	138 (19.1)
Married	312 (43.2)	**Income level**	
Education level		Very low	17 (2.4)
Did not complete high school	40 (5.5)	Low	201 (27.8)
High school diploma	182 (36.3)	Average	363 (50.2)
Bachelor	214 (29.6)	High	124 (17.2)
Master	240 (33.2)	Very high	18 (2.5)
Doctorate	47 (6.5)	**Familiarity with SAVs**	
Driving Experience		First ever heard	384 (53.1)
No driving license	123 (17.0)	Low	210 (29.0)
1–5 years	125 (17.3)	Moderate	105 (14.5)
6–10 years	190 (26.3)	High	24 (3.3)
11–15 years	128 (17.7)		
More than 15 years	157 (21.7)		

At different levels of explanatory variables (Figure 1), the usage intention of SAVs with DRS on LD trips indicates that, due to the increase in mobility, those without a driving license have a higher intention of using this technology. SAVs are additionally less likely to be used by more experienced drivers on LD trips because they rely more on their own experience than on technology. In terms of respondents' crash history, people who experienced more accidents are less inclined to use SAVs. Users who are more satisfied with internet taxis have a higher usage intention of SAVs, which is due to higher level of innovation among them. Users who are moderately or highly familiar with SAVs have the highest usage intentions for this technology on LD trips. In addition, men are slightly more likely than women to use SAVs. Low educated (under high school) individuals have the least intention of using SAVs in comparison with other educational levels. As household car ownership level increases, the usage intention of SAVs decreases. This could be attributed to the higher level of car dependency among these households with a greater number of private cars. SAVs are least likely to be used by households with lower income levels. Additionally, when comparing the intentions for using SAVs among different generations, it is evident that people's intentions decline with age, with baby boomers and Z generation having the least and most usage intentions, respectively.

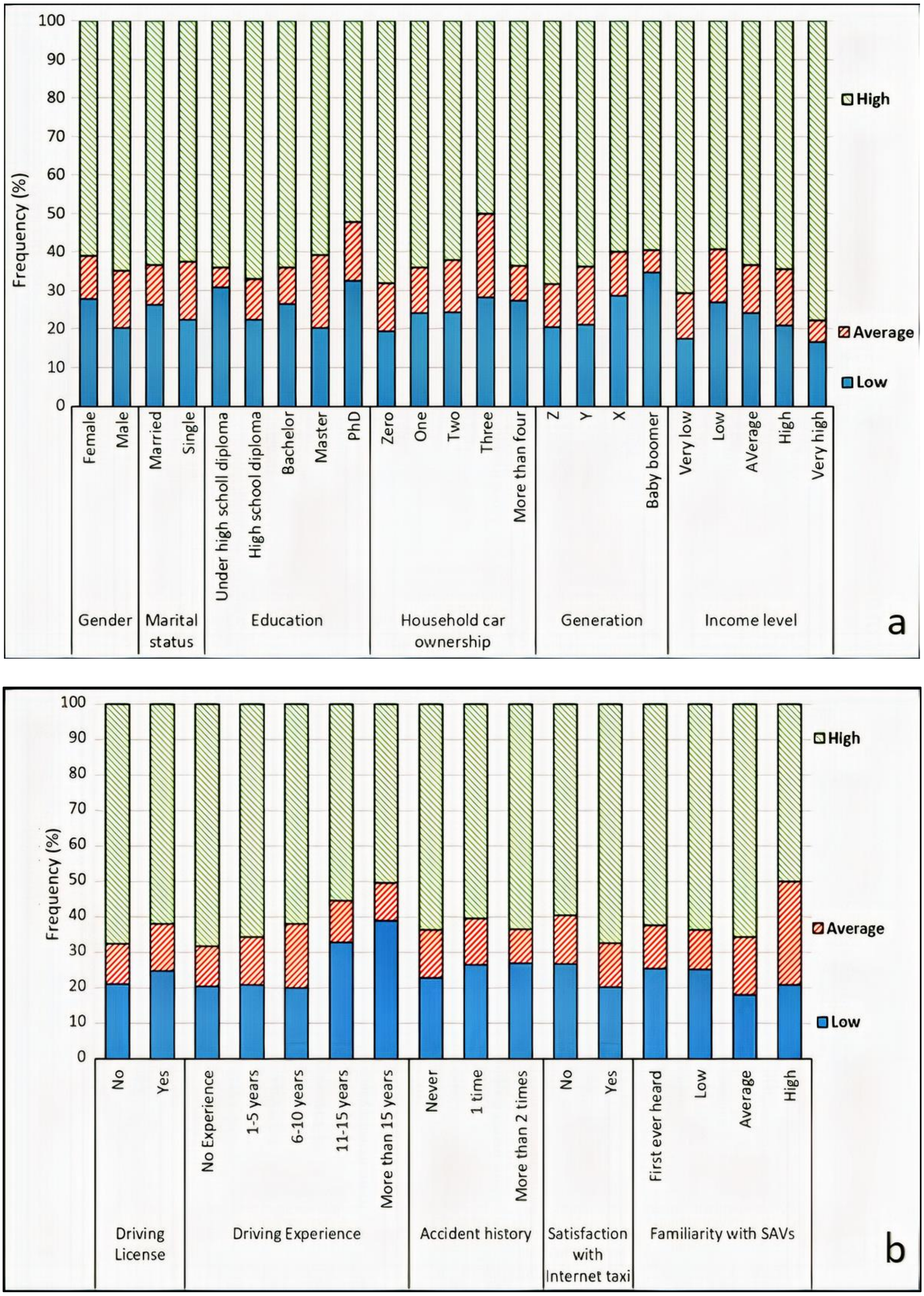

Figure 1. Stacked histogram of the usage intention of SAVs on LD trips by (**a**) Socio-economic characteristics, and (**b**) Travel behavior.

5. Estimation Results

5.1. Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) is a multivariate statistic technique which is frequently used for estimating the structure of instruments by evaluating the extent to which the measured variables represent the number of latent constructs. Researchers can use CFA to test the hypothesis that observed variables are related to their latent constructs [53]. Besides content validity, converging validity and discriminant validity are used to evaluate a measure's validity [54,55]. Since the items/indicators are taken from previous studies, the content validity is supported. Convergent validity is assessed based on three indices including item reliability, average variance extracted (AVE) with the greater value of 0.5, and composite construct reliability (CR) with the greater value of 0.7 [54,55]. Table 3 presents the mean value, factor loading, T-value, AVE, CR, and Cronbach's alpha (CA) to measure convergent validity and reliability of latent constructs. We test the reliability of individual items by cross- and factor-loading associated with corresponding latent constructs. We exclude items with low factor loadings from the analysis. Consequently, we only include all significant items ($p < 0.01$) have loadings above 0.50 on their corresponding constructs [56]. Furthermore, as shown in Table 3, all of the CR and AVE values of latent constructs exceed the recommended thresholds. Cronbach's alpha is also used to evaluate the questionnaire's reliability. There is acceptable reliability with an alpha of 0.6–0.7, but excellent reliability will achieve with an alpha of 0.8 or higher. A discriminant validity test is also conducted to determine whether latent constructs are distinct (Table 4). It can be concluded from Table 4 that all square roots of the AVEs exceed the correlation coefficients in the corresponding columns and rows, which indicates that the discriminant validity criteria is supported [55]. During the evaluation of model goodness of fit, we determine whether the data supports each relationship in the hypothetical model using model identification indices such as Normed Chi-square (CMIN/df), Normed Fit Index (NFI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA). According to Hair et al. [54], an NFI, CFI, TLI, and IFI value in excess of 0.90 indicates a model with acceptable fit, whereas RMSEA values of 0.01, 0.05, and 0.08 indicate a model with excellent fit, moderate fit, and acceptable fit, respectively. According to the above mentioned confirmation, the data has been fitted very well and the validity and reliability of latent constructs are acknowledge.

Table 3. Results of reliability and validity of the latent factors.

Construct	Item	Mean	Factor Loading	CA	CR	AVE	Source
Attitude toward sharing	I can save money by participating in collaborative consumption/sharing	3.69	0.842	0.71	0.88	0.66	[57]
	I think participating in collaborative consumption/sharing will be fun	3.42	0.717				
	Ride-sharing is a good way to reduce fuel consumption.	4.02	0.828				
	Ride-sharing is a good way to reduce pollutant emission.	3.10	0.847				
Car dependency	I like driving a car.	3.83	0.799	0.70	0.76	0.52	[33]
	A private car makes me feel safe.	3.86	0.656				
	I'm worried about losing the pleasure of driving when using SAVs.	3.06	0.692				
Personal innovativeness	I have a positive attitude toward innovations	4.08	0.736	0.75	0.81	0.69	[37]
	Among my peers, I am usually the first to try out new technologies	3.54	0.914				
Price evaluation	I could save money by using SAVs	4.12	0.698	0.75	0.86	0.56	[40]
	SAVs would offer better value for money	3.25	0.821				
	The benefits of an autonomous car will justify the price	3.82	0.724				
Perceived usefulness	SAVs can reduce air pollution.	4.06	0.762	0.83	0.86	0.51	[42]
	Using SAVs will relieve my stress of driving.	3.56	0.655				
	SAVs will reduce emissions.	3.61	0.686				
	SAVs can reduce traffic accidents.	3.26	0.733				
	SAVs can reduce traffic congestion, thereby shortening the riding time.	3.80	0.637				
	Overall, SAVs is useful and advantageous.	2.97	0.745				
Privacy concerns	I believe that using SAVs would threaten my privacy.	3.27	0.830	0.84	0.84	0.64	[14,33]
	I am concerned that SAVs will collect too much personal information from me.	3.41	0.821				
	I am concerned that SAVs will use my personal information for other purposes without my authorization	3.52	0.754				
Model fit: $\chi^2 = 135.498$, $df = 55$, $p < 0.001$; $CMIN/df = 2.464$; $RMSEA = 0.045$; $CFI = 0.977$; $NFI = 0.963$.							

Table 4. Correlation matrix and discriminant validity.

	Construct	1	2	3	4	5	6
1	Attitude toward sharing	**0.81** [1]					
2	Car dependency	−0.05	**0.72**				
3	Personal innovativeness	0.56	0.11	**0.83**			
4	Price evaluation	0.53	0.05	0.72	**0.75**		
5	Perceived usefulness	0.35	0.24	0.64	0.57	**0.71**	
6	Privacy concern	−0.34	0.08	−0.32	−0.35	−0.22	**0.80**

[1] Note: bold numbers represent square root of AVE.

5.2. Generalized Ordered Logit Model Estimation Results

Firstly, an ordered logit model (OLM) is estimated to examine the effect of various explanatory variables on intention to use SAVs with DRS on LD trips (Table 5). In order to facilitate interpretation of the influential factors in different intention levels, marginal effects are also calculated and reported in this Table. The model goodness of fit is assessed using pseudo R^2 proposed by McKelvey and Zavonia [58]. The OLM estimation result highlights the positive influence of attitude toward sharing, perceived usefulness, inverse of perceived risk, experiencing a severe accident, not owning a driving license, being a pro-transit user and belonging to baby boomer generation on higher usage intention of SAVs on LD trips. However, inverse of consumer innovativeness and price value, women who holding PhD and households with high car ownership level are negatively associated with higher usage intention of SAVs. An OLM can be checked for parallel odds by performing the Brant test as a Wald test. Brant tests are also computed for each coefficient individually in addition to all coefficients based on the estimated coefficients and their variances. According to Brant test result, it rejects the proportional odds hypothesis. As a result, one or more variables reject the hypothesis. Therefore, using a GOL model, we respecify the OLM model, allowing each outcome of the endogenous variable to have a separate coefficient (see Table 6).

Table 5. Estimation results of OLM of intention to use SAVs with DRS on LD trips.

Variable	Coefficient	$P > \|z\|$	Marginal Effect		
			Low	Moderate	High
Attitude toward Sharing	1.336	0.000	−0.219	−0.089	0.308
Perceived Usefulness	1.728	0.038	−0.479	−0.196	0.675
$\frac{1}{(Perceived\ Risk)^2}$	0.048	0.078	−0.008	−0.003	0.011
$\frac{1}{Consumer\ Innovativeness}$	−2.385	0.030	0.391	0.159	−0.550
$\frac{1}{Price\ Value}$	−4.482	0.001	0.735	0.298	−1.033
Pedestrian experienced a severe crash (dummy variable)	1.740	0.033	−0.168	−0.108	0.276
No driving license (1 if true; otherwise 0)	0.314	0.073	−0.051	−0.021	0.072
Women with PhD	−1.188	0.025	0.252	0.036	−0.288
Households owning at least three private cars (1 if true; otherwise 0)	−0.517	0.074	0.095	0.029	−0.124
Public users during COVID-19 (1 if true; otherwise 0)	0.331	0.094	−0.052	−0.022	0.074
Baby boomer (1 if true; otherwise 0)	2.726	0.041	−0.191	−0.135	0.326
Threshold, μ_1	−0.692				
Threshold, μ_2	0.080				
Model statistics					
Number of observation	723				
Log-likelihood at convergence	−568.008				
Restricted log-likelihood	−650.324				
Pseudo R^2	0.127				

Table 6. Estimation results of GOL model of intention to use SAVs with DRS on LD trips.

Variable	Moderate Intention		High Intention		Marginal Effect		
	Coefficient	$P > \|z\|$	Coefficient	$P > \|z\|$	Low	Moderate	High
Attitude toward Sharing	1.682	0.000	1.142	0.000	−0.279	0.022	0.257
Perceived Usefulness	1.268	0.089	1.968	0.073	−0.904	0.135	0.769
$\frac{1}{(Perceived\ Risk)^2}$	0.059	0.076	0.046	0.095	−0.009	−0.001	0.010
$\frac{1}{Consumer\ Innovativeness}$	−2.070	0.081	−2.886	0.018	0.344	0.308	−0.652
$\frac{1}{Price\ Value}$	−4.299	0.003	−4.300	0.002	0.715	0.257	−0.972
Pedestrian experienced a severe crash (dummy variable)	1.759	0.113	1.703	0.038	−0.293	−0.093	0.386
No driving license (1 if true; otherwise 0)	0.237	0.250	0.351	0.052	−0.039	−0.040	0.079
Women with PhD	−0.784	0.233	−1.547	0.015	0.130	0.219	−0.349
Households owning at least three private cars (1 if true; otherwise 0)	−0.352	0.301	−0.633	0.038	0.058	0.085	−0.143
Public users during COVID-19 (1 if true; otherwise 0)	0.301	0.208	0.328	0.105	−0.050	−0.024	0.074
Baby boomer (1 if true; otherwise 0)	1.451	0.056	3.135	0.078	−0.422	0.095	0.327
Constant	0.324	0.736	0.478	0.608	-	-	-
Model statistics							
Number of observation			723				
Log-likelihood at convergence			−560.002				
Restricted log-likelihood			−650.324				
Pseudo R^2			0.1389				

5.3. Discussion

Based on estimated coefficients, a series of sociodemographic, travel related and psychological factors are significantly associated with the intention to use SAVs with DRS on LD trips. Table 7 summarizes the impact of each explanatory variable on the usage intention of SAVs on LD trips. According to the GOL model estimation results, psychological factors are the most important factors in intention to use SAVs on LD trips. Based on the marginal effect values, the most critical factors in shaping the high intention level of respondent in using SAVs on LD trips in a descending order are price evaluation, perceived usefulness, consumer innovativeness, attitude toward sharing, and perceived risk, respectively. Regarding psychological factors, respondents who assess SAVs' services more beneficial were found to result in high intention of using this technology which is in line with Nastjuk et al. [39] findings. According to marginal effects, if inverse of PV increases by one unit, the probability of high intention decreases by 97.2%, whereas the likelihood of moderate and low intention increases by 25.7% and 71.5%, respectively. Perceived usefulness also positively correlated with high and moderate usage intentions of SAVs on LD trips which is in accordance with Yuen et al. [44] finding. Based on marginal effects, if perceived usefulness increases by one unit, the likelihood of high and moderate usage intentions of SAVs increases by 76.9% and 13.5%, respectively, while the probability of low usage intention decreases by 90.4%. Consumer innovativeness, as another examined latent factor, shows that as an individual has a better attitude toward technology, it is more likely to has a higher intention level of using SAVs on LD trips which is in line with Zhang et al. [14] findings. When inverse of CI increases by one unit, there is a 65.2% decrease in the probability of high usage intention based on marginal effects, however, the likelihood of low and moderate usage intentions increases by 34.4% and 30.8%, respectively. As the next influential unobserved construct, it is found that, attitude toward sharing (ATS) has a significant increasing impact on increasing the intention level of respondents. In other hand, as ATS increases, the likelihood of using SAVs with DRS on LD trips will also increase which is in accordance with Acheampong et al. [48] findings. Furthermore, according to marginal effects, one unit increase in the attitude toward sharing increases the likelihood of both high and moderate intention levels of using SAVs on LD trips by 25.7% and 2.2%, respectively. Many studies have found that SAVs could decrease car usage and ownership. For instance, the results of a study showed that an SAV can be replaced by 11 private cars [59]. Apart from reducing car usage, the use of SAVs also has environmental benefits, such as reducing fuel consumption, GHG emissions, and air pollutants [6,57]. In these vehicles, the possibility of optimal use of fuel increases through ridesharing and autonomy technologies. Investigation of automation's impact on fuel efficiency had already been studied and can be seen in Figure 2. Based on the "Base" scenario (where the penetration rate of AVs increases annually and reaches 100% in 2040), the estimated fuel consumption reaches a maximum around 2020, then decreases from 2020 to 2036 before remaining flat for the rest of the decade after 2036, at approximately 87 billion gallons. In addition, it can be seen that automation can reduce fuel consumption on average by 38% in comparison with the "No AVs" case and this effect increases as AV market share increases [60]. Moreover, as the indicators of attitudes toward sharing, we asked respondents about potential advantages of SAVs in terms of fuel consumption and pollutant emissions (Table 3). An analysis of the opinions of the respondents highlighted that they were in agreement with the potential advantages of SAVs in reducing fuel consumption (on average 4.02 out of 5) and pollutant emissions (3.10 out of 5). In light of the positive impact of sharing attitudes on the usage intention of SAVs on LD trips, it is recommended that policy makers present reports of the reduction of fuel consumption and pollution emissions to stimulate people's sense of sharing. We also examine the effect of perceived risk on intention to use SAVs which is negatively associated with the intention level of respondents. Due to a better model specification, we use a squared inverse of PR. In accordance with previous studies [14,25,33], it can be concluded that lower perceived risk is associated with higher intention level of using SAVs on LD trips. Moreover, based on marginal effects, one unit increase in squared inverse of perceived risk is associated with 1% increase in the high intention of using SAVs on LD trips. Due to the higher safety level offered by AVs [39], pedestrian who experienced a severe accidents are more likely to use SAVs on their LD trips.

Table 7. An overview of the variables affecting the usage intention of SAVs on LD trips.

Variables	Usage Intention		
Attitude toward Sharing	L* (−)	M (+)	H (+)
Perceived Usefulness	L (−)	M (+)	H (+)
$\frac{1}{(Perceived\ Risk)^2}$	L (−)	M (−)	H (+)
$\frac{1}{Consumer\ Innovativeness}$	L (+)	M (+)	H (−)
$\frac{1}{Price\ Value}$	L (+)	M (+)	H (−)
Pedestrian experienced a severe crash (dummy variable)	L (−)	M (−)	H (+)
No driving license (1 if true; otherwise 0)	L (−)	M (−)	H (+)
Women with PhD	L (+)	M (+)	H (−)
Households owning at least three private cars (1 if true; otherwise 0)	L (+)	M (+)	H (−)
Public users during COVID-19 (1 if true; otherwise 0)	L (−)	M (−)	H (+)
Baby boomer (1 if true; otherwise 0)	L (−)	M (+)	H (+)

* L—Low, M—Moderate, H—High; (+) means increasing the likelihood of a specific intention level, (−) means decreasing the likelihood of a specific intention level.

Further, when the respondent is a pedestrian who experienced a severe accident, the likelihood of high intention of using SAVs on LD trips increase by 38.6%. It is therefore recommended to the designers of autonomous vehicles that they take into account the safe performance of SAVs when they are in close proximity to pedestrians, given that pedestrians are the most vulnerable road users and accidents involving pedestrians are a major concern both for their number and severity [61,62]. SAVs provide a significant advantage to people without a driving license, and the results of the study show that they are more willing to use SAVs on LD trips than individuals with driving license. In other word, individuals without a driving license have a higher intention level of using SAVs on LD trips which is in line with Liu et al. [7] findings. Furthermore, according to marginal effects, when the respondent has a driving license, the probability of both low and moderate intention level of using SAVs on LD trips decreases by 3.9% and 4%, respectively. However, not owning a driving license increases the likelihood of high usage intention by 7.9%. Due to lower safety perception of Iranian women, particularly in the shared mobility services because of fear of abuse, imaginary harassment, gender social halo, and family norms [63], they are less likely to use shared mobility. Based on the estimation result, it can be concluded that women with PhD have a lower intention of using SAVs on LD trips because of higher income and lower safety perception of shared mobility services. Moreover, according to marginal effects, when respondent is a women who holding PhD degree, the probability of high intention level of using SAVs on LD trips decreases by 34.9%, while the likelihood of low and moderate usage intention increases by 13% and 21.9%, respectively. Those households that rely on private vehicles for their daily mobility needs, prefer to limit their travel mode to their private cars. Therefore, compared with other households with lower level of car ownership, households owning at least three private cars have a lower intention of using SAVs on LD trips which is in line with Garidis et al. [33] findings. Further, marginal effects show that owning at least three private cars decreases the likelihood of high intention of using SAVs on LD trips by 14.3%, however, the likelihood of low and moderate usage intentions of SAVs among households with lower car ownership level, increases by 5.8% and 8.5%, respectively. It was found in a study by Acheampong et al. [48] that people prefer to use SAVs and alternative public transportation when they have a positive attitude toward it. In our study, people who are a pro-transit user during the pandemic, have a higher intention of using SAVs on LD trips compared with non-transit users. Marginal effect values indicate that when a respondent is a transit user during the pandemic, the likelihood of high intention of using SAVs on LD trips increases by 7.4%. Although, their low and moderate usage intention decreases by 5% and 2.4%, respectively. With the growth of technology, Y generation, known as baby boomers, are becoming technology immigrants compared to millennial, who are technology natives [64]. In addition to technology perspective, SAVs have the potential to increase mobility for Y generation. Therefore, individuals who belonging to baby boomer generation have a higher intention of using SAVs on LD trips which is in line with Arbib and Seba [65] findings. Furthermore, according to marginal effects, when the respondent belonging to baby boomer generation, the probability of both high and moderate intention levels of using SAVs on LD trips increases by 32.7% and 9.5%, respectively.

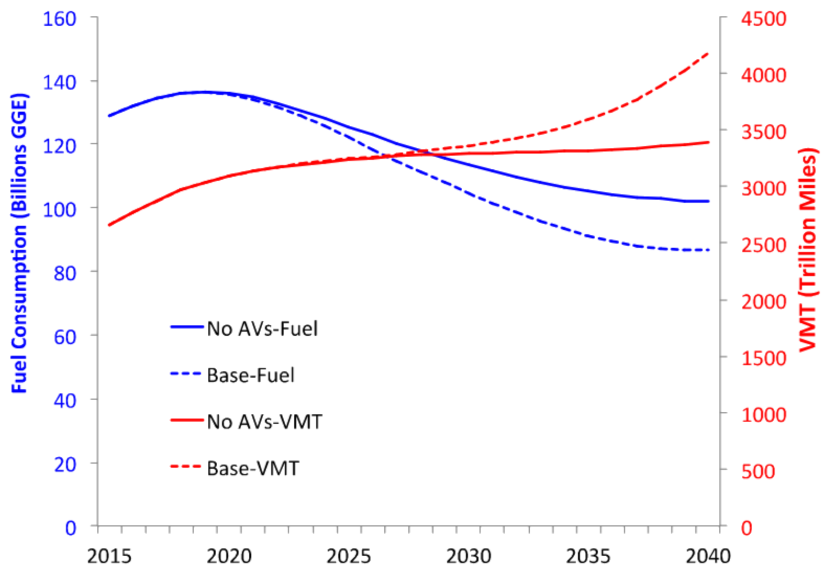

Figure 2. Comparison of the fuel consumption between "No AVs" and "Base" scenarios [60].

5.4. Practical Implications

Intentions to use SAVs on LD trips are significantly influenced by potential users' price evaluation. Accordingly, authorities should consider this factor to enhance the price evaluation of SAVs among the public. Government and automobile manufacturers can also develop educational campaigns to educate consumers about the benefits of SAVs such as reduction in congestion, accidents, fuel consumption, and greenhouse gas emissions. Many consumers compare SAVs to their prior travel modes they have used. Therefore, when the above benefits are enhanced, customers are more likely to have a positive attitude toward SAVs [40]. The second most critical factor influencing individuals' usage intention of SAVs with DRS is perceived usefulness. Perceived usefulness reveals improvements in fulfilling individual transportation needs. Furthermore, it is recommended to present citizens with information about the benefits and advantages of SAVs to increase consumers' usage intentions. Further, consumer innovativeness is the third most influential latent variable that is positively correlated with the intention of using SAVs with DRS on LD trips. Policymakers might be able to encourage people to use SAVs by inspiring a sense of innovation in them. First-time users can be encouraged to use the service by promoting policies such as free trials. This will increase their desire to keep using the service in the future. In terms of psychological factors, sharing attitude is the fourth most influential latent variable that is positively associated with usage intention of SAVs with DRS on LD trips. We might be able to encourage people to use SAVs by inspiring a sense of collaborative consumption in them. For instance, service providers could offer more subsidies for travelers who prefer to share their rides with more strangers. Moreover, informing the benefits of collaborative consumption in terms of lower congestion, travel costs, fuel consumption, and pollutant emissions could have a significant effect on increasing the sharing attitude of potential users. The last critical psychological factor is privacy concern among the potential users. Governments should ensure that service providers protect citizens' personal information in order to address citizen concerns about privacy. Another practical implication which could encourage travelers, particularly women to use SAVs on LD trips would be providing special services for them. For instance, women-only SAVs or using closed-circuit televisions (CCTVs) to increase the safety perception of women, leading to increase their intention to use SAVs.

6. Conclusions and Future Research

6.1. Findings and Inferences

Technology adoption has been the subject of numerous discussions in a wide variety of fields. It is crucial to determine the influential factors that will encourage people to adopt emerging technologies to ensure the successful deployment of an intended technology. On the basis of the above-mentioned experience, this study aims to identify the factors influencing usage intentions for SAVs on long distance trips. Therefore, the influence of psychological, travel behavior, and sociodemographic variables has been examined in this study by using a GOL model. Based on the findings, SAVs with DRS usage intentions were significantly influenced by the following unobserved and observed variables including: price evaluation, perceived usefulness, consumer innovativeness, sharing attitude, perception of risk as latent constructs, and gender, accident experience, driving license status, education level, household car ownership, transit user, and generation as observed variables. Marginal effect values at different usage intention levels (low, moderate, and high) illustrated that price evaluation, perceived usefulness, and consumer innovativeness were the most influential factors in increasing the likelihood of high usage intention for SAVs on LD trips, respectively. However, a reduction in perceived usefulness and price evaluation as well as being a baby boomer increased the likelihood of lower usage intentions for SAVs on LD trips. Also, among different factors contributing to moderate usage intentions for SAVs, consumer innovativeness, price evaluation, and women with PhDs were the most influential. In order to promote the usage intention of SAVs with DRS on LD trips, these results are useful to transportation planners, policymakers, and autonomous vehicle operators.

6.2. Limitations and Recommendations for Further Research

By filling previous gaps, this study contributes to the body of usage intention literature on SAVs with DRS on LD trips. While this study provided insight and knowledge about SAVs, it also raised some new questions that require further study.

Using psychological, sociodemographic, and travel-related variables, this study attempted to establish a framework for analyzing factors associated with usage intention of SAVs. However, the model could not consider some travel-related attributes of stated preference scenarios for SAVs such as travel time, waiting time and travel cost. Therefore, it is recommended to assess these variables' impact on usage intention SAVs in future research.

It is also limited by the fact that the study was conducted in Tehran, a congested and polluted city in Iran. Consequently, generalizing findings is challenging due to differences in travel behaviors, culture, and other context-related factors. Nonetheless, this model can be used to determine how individuals will use SAVs on LD trips in other contexts.

Concerning the potential benefits of SAVs in reduction of environmental issues, it is recommended to determine the impacts of SAVs on fuel consumption and pollutant emission in future studies.

Finally, this study used the GOL model to determine the effect of various factors associated with usage intention of SAVs on LD trips. However, it is recommended to consider Random-Effect GOL (REGOL) as another extension of the OLM, which takes into account unobserved heterogeneity in respondents' behavior.

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