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Exploring the Factors Affecting Mode Choice Intention of Autonomous Vehicle Based on an Extended Theory of Planned Behavior—A Case Study in China

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Abstract: Autonomous vehicle (AV) is an innovative transport option that has the potential to disrupt all industries tied to transportation systems. The advent of AV technology will bring a novel on-demand mobility pattern such as shared autonomous vehicle (SAV). To promote AV technology, it is important to understand which factors influence travelers' intention to use AVs and SAVs. This paper collected literature from databases such as Scopus, Web of Science and ScienceDirect, and made a systematic review. The study aims to explore the determinants that influence travelers' behavioral intentions towards use AVs and SAVs based on an extended version of the theory of planned behavior, which incorporates knowledge and perceived risk. This study was tested empirically using a valid survey sample collected from 906 respondents in China. Structural equation model was conducted to investigate the predictors of intentions to use AVs and SAVs. Results showed that knowledge about AV technology and perceived risk are the two main potential obstacles for travelers to use AVs and SAVs. Attitude significantly affects AVs and SAV choice intentions. Subjective norm is the most critical factor affecting the travelers' intention to use AVs. Perceived behavioral control potentially stymie the travelers' intention to use SAVs. The findings will enhance the understanding of travelers' choice motivation from psychological and service perspectives, and provide data support for governments and companies in improving travel management strategies and product services.

Keywords: autonomous vehicle; shared autonomous vehicle; travel mode choice; behavior intention; theory of planned behavior; sustainable transportation

1. Introduction

Traffic safety and congestion are major transportation issues in many areas around the world. Driver errors remain the primary cause of vehicle collisions, and the increasing number of private vehicles is worsening traffic congestion. With progress in advanced vehicular technologies, the emergence of AV provides travelers with an alternative, safer and more sustainable transportation mode. AV (also known as driver-less and self-driving) is defined as a motor vehicle capable of sensing its environment and navigating entirely without human driver's active input [1,2]. AV technology has received considerable attention in major car manufacturers and IT companies. Under the background of the sharing economy, the advent of AV technology will bring a novel mobility pattern such as SAV, which could transform vehicles from an owned product to an on-demand service [3–5]. SAVs can drive to pick up passengers autonomously without moving to a waiting spot. It can provide a service comparable to that of a taxi without driver, rather than searching for and walking long distances to an available vehicle. Without the need for a driver, acquisition, insurance, travel, and parking costs could be lower than those of personal vehicles. In addition, several variable costs such as depreciation, maintenance and cleaning could also be reduced to a certain extent, and could be shifted to the entity vehicle. One of the largest costs of vehicle ownership is the depreciation cost, the value of the car could be lost over time. Although it will be years before widespread adoption of AV technology, some studies suggested clearly that AV technology will have a devastating impact on traditional transportation systems. On the one hand, AV technology could effectively reduce traffic accident and provide a better solution for road safety, traffic congestion and energy consumption by avoiding unnecessary brake and maintaining the best headway [6–10]. On the other hand, AVs and SAVs could also increase trip number and travel distance by eliminating driving burden and making motorized travel more accessible (to senior citizens and persons with disabilities, for example), which will lead to an increase in the number of AVs or SAVs on the road and the further aggravation of road traffic congestion [11]. In the early stage of AV technology, traffic congestion might not be improved and even worsened due to congestion-inducing effects of shared fleets of AVs and mixed traffic fleet condition [12,13]. In the long term, with the popularity of AV technology and the increase in AV penetration on the road, AVs and SAVs could dramatically reduce congestion caused by human driving behavior and improve the road transportation efficiency [10,14,15]. The impact of AV technology on transportation system, especially whether it can alleviate traffic congestion and reduce traffic accidents, depends to a large extent on travelers' mode choice. Understanding travel mode choice is significant since it affects the daily travel efficiency and AV technology industry development prospects. Furthermore, the analysis of travelers' choice is also an important issue for policymakers, who might decide to implement specific interventions to stimulate the diffusion of innovative and sustainable technology. This circumstance requires a more comprehensive understanding of the factors that influence the intentions of travelers to use AVs and SAVs.

Existing research on AV mainly focuses on macro-level analysis, including policy issues [7,16], legislative supervision [17], SAV dispatch optimization [5,18,19] and the impact on traditional transportation system [5,20,21]. In the study of user behavior at the micro-level, individuals' travel mode choice behavior in AV and SAV mobility behavior has already become a hot research topic and recently get more attention. However, the travel mode model used in the study of AV choice behavior mainly regards socioeconomic attribute and travel mode attribute as the explanatory variables of the model [19,22–26], while ignoring the intrinsic influence brought by the individual's preference heterogeneity. In recent years, only a few studies have focused on psychological factors such as safety, technology interest, or environmental concern [13,27,28]. However, most of these studies only considered attitudinal factors. To our best knowledge, AVs and SAVs use intention behavior has so far not been studied based on a rigorous theoretical background. When attempting to interpret behavior intention, theory-based model provides a more systematic approach to identifying relevant determinants of the specific behavior, and thereby allows a deeper understanding of it. Recent work in choice models has also emphasized the importance of the explicit treatment of psychological factors which affect decision-making [29]. Especially for research that ultimately aims to implement and change behavior, theory-based approach is more effective for formulating and designing specific measures and interventions [30].

One theory that has been more widely adopted by researchers seeking to explain general travel mode choices is the theory of planned behavior (TPB), which was first proposed by Ajzen [31] based on the Theory of Reasoned Action [32]. This theory seeks to capture the highly complicated reality of travel mode choice making in a framework consisting of attitudes, subjective norm, and perceived behavioral control. In addition, two external factors are added to the TPB model namely: knowledge and perceived risk. We intend to develop an extended TPB theoretical framework to explore the determinants of travelers' choice intention to use AVs or SAVs and to fill the research gap by examining a broader range of factors that could influence individuals' intentions in China. China is selected as the study area for analysis, as it is the largest developing country with a rather high motorization level and huge automobile market potential [33,34]. The understanding of the basic issues related to travel mode choice for AVs and SAVs remains insufficient in China because the existing research mainly focuses on Western countries. The analysis can provide some insights into the factors that may encourage travelers' adoption of AVs or SAVs, and thereby on the design of transportation policies.

The remainder of this paper is organized as follows. Section 2 provides a further review of the literature on AV and SAV mode choice. Section 3 describes the theoretical framework and research hypotheses used in this analysis. Section 4 presents survey questionnaire design and data collection. Data analysis and model result are described in Section 5. Section 6 discusses the key findings from this analysis and potential policy implications. Finally, conclusions and further research area are discussed.

2. Literature Review

Although AV technology is not available to the public yet, several literatures have observed and analyzed the potential impact of the emerging AVs or SAVs on travel mode choice, as well as travel behavior shift. Table 1 summarizes some relevant representative studies on AVs or SAVs travel mode choice, in terms of research object description, influence factors summary and research methods. One of the major concerns in studying the travel mode choices behavior is to understand key factors affecting AV or SAV mode choice behavior intention. Early research mainly illustrated how travelers' perceptions along with their demographic factors influencing their intended use of AVs or SAVs. Many factors have been investigated to examine their influence on AV or SAV choice intention, including age, gender, income, education level and so on. These findings indicate that those that are young, well-educated, of moderate-income, and living in an urban environment tend to be positive about using this innovative travel mode [35–37]. Another strand of research that is relevant to our study uses stated-preference (SP) methods to examine travelers' responses to attributes of the travel mode choice alternatives such as travel time, travel cost, etc. Krueger et al. [24] conducted a stated choice experiment in Australian, participants were asked to make mode choices for a reference trip. The alternatives in this experiment include shared and non-shared AVs, as well as the originally chosen mode used in the reference trip. The alternatives were specified by three travel attributes including travel cost, travel time and waiting time. Shared and non-shared automated mobility showed to be perceived as two distinctive modes by the participants. In addition to the above travel attribute variables, walking time, travel time and time to find parking spot were added in Winter et al. [22] to examine free-floating carsharing services and SAVs mode choice based on a stated choice experiment conducted among the Dutch. Furthermore, Levin et al. [26] and LaMondia et al. [25] anticipates the potential effect of AV on transit demand and long-distance travel choices respectively based on a modified four-step planning model. Scheltes et al. [23] and Liu et al. [19] explored the potential AVs and SAVs mode choice through the agent-based simulation experiment. However, the experiment data was limited to assumption or previous travel survey, and AV technology information was not included, so the models built were not accurately calibrated or validated.

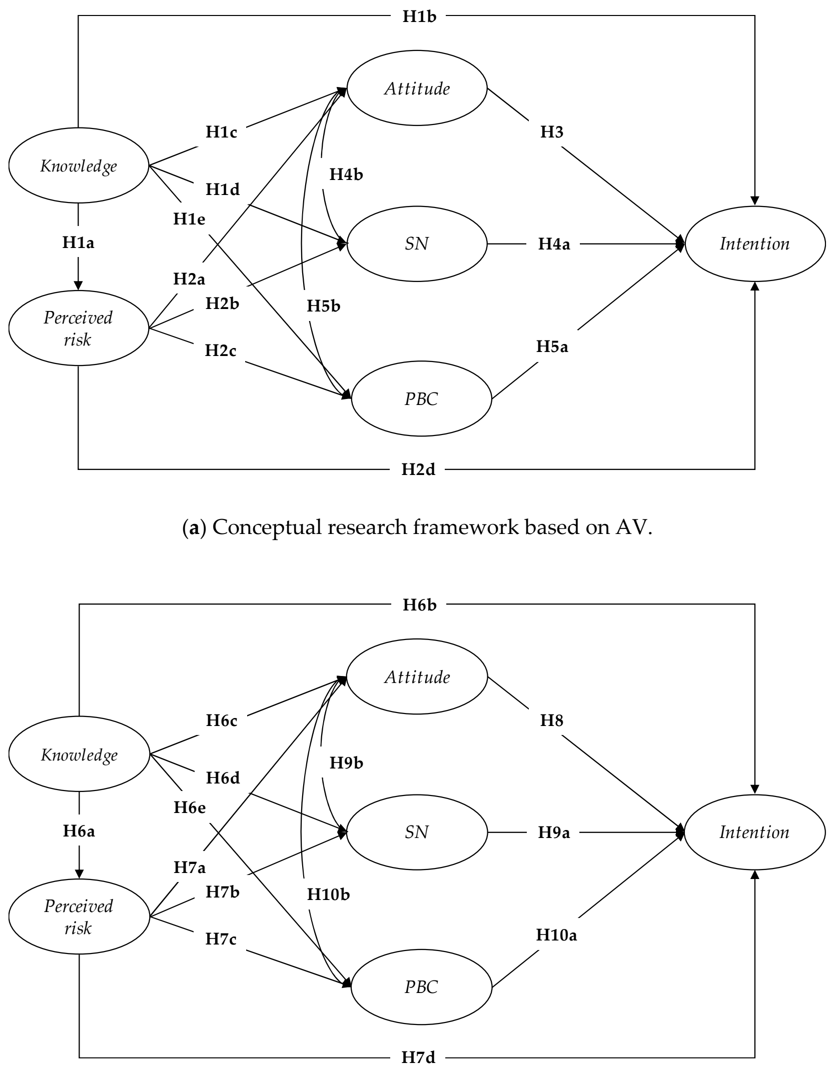
In addition, several additional psychological factors also might influence mode choice intention. Haboucha et al. [13] conducted a stated preference questionnaire survey across Israel and North America. On the basis of the socioeconomic attributes and current commuting characteristics, five attitudinal variables are extracted to explore the individuals' intention to own and use AVs. The result shows that enjoy driving, environmental concern, and Pro-AV attitude played a significant role in estimating the travel mode choice decision. Another dimension of travel mode choice behavior explored in the 2016 survey by MD Yap et al. [28] was the impact of AV on the last mile public transport travel in the Netherlands, which incorporated instrumental attributes, socioeconomic variables and attitudinal indicators in a stated choice experiment. More than 20 attitudinal indicators were provided in the survey to measure the intention to use AVs as last mile transport. This study finds that attitude regarding trust and sustainability can play an important role in the choice of travelers to use AVs as last mile transport. AVs were further subdivided into automated gasoline vehicle and automated electric vehicle by Shabanpour et al. [27] to estimate respondents' vehicle choice behavior. Several opinion-based variables related to AVs were included in a stated preference survey in Chicago. This result shows that those who concern safety and environment were more willing to purchase these types of vehicles. Three latent attitudes were organized in a stated preference survey by Nazari et al. [38] to study Washington travelers' insight into shared and private mobility. Results indicate that green travel pattern and mobility-on-demand savviness promote interest in SAVs, whereas safety concern hinders public choice intention of SAVs. From the discussion, much of the previous work on AVs and SAVs has focused on the descriptive, univariate analysis of demographics and travel attribute solely of users based on survey data samples. This paper aims to build on the existing body of literature by examining a statistical sample containing psychological latent variables. In doing so, this study provides an analysis of the travel mode choice intention differences in demographics and psychological latent variables.

Table 1. Summary of the relevant studies on the real-time traffic management problem.

Author	Country/Area	Research Object	Influence Factors	Method
Nazari et al., 2018 [38]	USA	carsharing, ridesourcing, and ridesharing with AVs	latent variable	SP experiment
Haboucha et al., 2017 [13]	Israel/North America	current car, private AV and SAV	demographic variable travel attribute latent variable	SP experiment
Winter et al., 2017 [22]	Netherlands	free-floating carsharing services and SAV	demographic variable travel attribute	SP experiment
Liu et al., 2017 [19]	Austin, USA	human-driven vehicle, SAV, and transit	travel attribute	Agent-based simulation
Scheltes et al., 2017 [23]	Netherlands	AV, walking/bicycle and transit	travel attribute	Agent-based simulation
Shabanpour et al., 2017 [27]	Chicago, USA	non-automated gasoline vehicle, non-automated electric vehicle, automated gasoline vehicle, and automated electric vehicle	demographic variable travel attribute opinion-based variable	SP experiment
Krueger et al., 2016 [24]	Australia	SAV, SAV without ride-sharing and public transit	demographic variable travel attribute	SP experiment
MD Yap et al., 2016 [28]	Netherlands	AV, bus/tram/metro, and bike	demographic variable travel attribute latent variable	SP experiment
LaMondia et al., 2016 [25]	USA	AV, personal vehicle and air	travel attribute	Four-step planning model
Levin et al., 2015 [26]	USA	AV with parking or repositioning, and transit	travel attribute	Four-step planning model

3. Theoretical Framework and Research Hypotheses

TPB model has achieved a considerable reputation for predicting and explaining human behavior intention [31,32]. According to TPB model, individual's behavioral intentions are explained as a consequence of attitudes, subjective norm and perceived behavioral control. The TPB has been used in a wide range of environmental protection, green behavior, commodity purchases and travel choice behaviors. Most studies have shown that the TPB has good explanatory power for behavioral intentions. This paper attempts to apply TPB to AV and SAV travel mode choice intentions and to explore the key influencing factors. Figure 1 displays the proposed conceptual model hypotheses based on the TPB framework.



(**a**) Conceptual research framework based on AV.

(**b**) Conceptual research framework based on SAV.

Figure 1. Conceptual research framework.

3.1. Knowledge about AVs (KN)

Knowledge is an important construct in behavioral research. It plays a crucial role in individuals' choice decision making [39]. Behavior-related knowledge means knowing how to perform the intended behavior, to determine responsibility for the intended act and to evaluate the perceived effectiveness of the behavioral act [40]. If consumers have a better understanding of the characteristics and attributes of a product, it will not only improve the accuracy of consumers in behavior decision-making, but also reduce the risk of decision-making. A large number of studies have shown that individuals' knowledge of a product plays a crucial role in their attitudes and intentions to choose and use the product [40–42]. Simsekoglu et al. [43] found that the lack of knowledge of e-bikes may be a potential obstacle to residents' use of e-bike in Norway. The research of Barth et al. [44] and Krause et al. [45] have showed that knowledge of electric vehicle can significantly improve the acceptance of electric vehicle, whereas the lack of knowledge can be an obstacle to use electric vehicle. In this study, knowledge will be defined as the product attribute or product knowledge. The product knowledge will include the performance attribute and the advantages of AVs. Based on the above analysis, it can be inferred that travelers' knowledge and experience of AV technology play an important role in regulating and influencing the formation of choice intention. In the context of AV technology, travelers' knowledge of

AVs is also important to promote AV technology development and affect travelers' choice. If a traveler knows less about AV technology, they may have some security concerns when choosing this mode to travel, which means that knowledge about AVs is negatively associated with individuals' perceived risk. Furthermore, if the travelers know more about AV technology, such as the performance attributes of AVs (e.g., operation process, driving comfort, mileage, cost) and the advantages of AVs (such as improving safety and easing traffic congestion), they might be more likely to use AVs with positive attitude and intention. In addition, the lack of knowledge about AVs will further affect the individual's pursuit of important people. Similarly, when travelers know more about the performance attributes and advantages of AVs, they may think that they have the perceived control ability to operate and drive AVs easily. In contrast, travelers are reluctant to use AVs due to the lack of knowledge and experience in AVs. As a result, the traveler's perceived control on AVs is low, which may prevent the choice behavior of AVs directly. Based on the above viewpoints, this study proposes the following hypotheses:

Hypothesis 1a (H1a): *Knowledge about AVs is negatively associated with individuals' perceived risk.*

Hypothesis 1b (H1b): *Knowledge about AVs is positively associated with individuals' intention to adopt AVs.*

Hypothesis 1c (H1c): *Knowledge about AVs is positively associated with individuals' attitude towards AVs.*

Hypothesis 1d (H1d): *Knowledge about AVs is positively associated with individuals' subjective norm of AVs.*

Hypothesis 1e (H1e): *Knowledge about AVs is positively associated with individuals' perceived behavior control to adopt AVs.*

3.2. Perceived Risk (PR)

Perceived risk refers to the expected negative effects of consumers when they purchase a particular product or service. Perceived risk is a multidimensional variable, including time, function, physical, financial, social and psychological risks [46]. Relevant studies have shown that perceived risk has a negative impact on consumers' attitude and intention to use innovative products or services [47–49]. The risk perception is very crucial as it could affect directly to the purchase and purchasing intention. In the context of AV technology, these views are equally applicable to the study of AV choice intention. Perceived risk may be the main barrier for individuals to use AVs and SAVs. In fact, perceived risk is often originated from the lack of knowledge and information about AVs and SAVs. In addition, according to market research reports related to AVs, the potential risks of AV technology are regarded as a key factor affecting the acceptance of AVs. The research of Menon et al. [50] and Zmud et al. [51] show that perceived risk is one of the reasons why the public is unwilling to accept AVs, and the most important one is the potential safety risk of AVs. In the present study, risk perception is defined in terms of the travelers' perceptions of the uncertainty and adverse consequences of using AVs and will be investigated from the view of physical attributes of AVs, financial, and physical (health issue) approach. As an innovative technology product, AVs may have some security and reliability problems [15,52,53], such as the failure of self-driving system (e.g., radar and camera), the paralysis of communication system or hacker attack, which may cause travelers' concerns about safety problems. Therefore, they may have a negative attitude and be unwilling to choose this mode when travelers realize the potential risks of using AVs. In addition, perceived risk has a negative impact on individual's subjective norm and perceived behavior control [54,55]. When travelers realize the potential risks of AVs, they may doubt whether their friends and relatives will support them to use AVs and whether they can learn to use AVs easily. Based on the above viewpoints, this study proposes the following hypotheses:

Hypothesis 2a (H2a): *Perceived risk is negatively associated with individuals' attitude towards AVs.*

Hypothesis 2b (H2b): *Perceived risk is negatively associated with individuals' subjective norm of AVs.*

Hypothesis 2c (H2c): *Perceived risk is negatively associated with individuals' perceived behavioral control to AVs.*

Hypothesis 2d (H2d): *Perceived risk is negatively associated with individuals' intention to AVs.*

3.3. Attitudes toward Behavior (ATT)

According to the TPB, the main determinant of behavioral intention is attitude. Attitudes toward behavior is a psychological tendency which refers to an individual's favorable or unfavorable evaluations of a particular object or a specific behavior under consideration [31]. A person who believes that positively valued outcomes will result from performing the behavior will have a positive attitude towards such behavior. As a result, attitude can be considered as an important factor in predicting and describing human behavior. On the basis of TPB analytical framework, individual's attitudes are valid predictive variables affecting travel mode choice behavioral intentions [31,56]. Liu et al. [57] pointed out that there was a significant positive impact between travelers' attitudes towards low-carbon travel and choice intention. Stark and Hössingerb [58] found that attitudes have the highest explanatory power for travel-related intention.

Applied to AVs that function as a way to satisfy travelers' need for travel multiformity and convenience. In this study, the behavioral attitude of travelers to AVs reflects the traveler's general evaluation and inclination toward this behavioral intention. The empirical evidence makes it reasonable to assume that if the travelers believe that the AVs would gain a positive outcome associated with the personal aspirations, the more likely would they be to have a favorable attitude toward AVs. Based on the above viewpoints, this study proposes the following hypotheses:

Hypothesis 3 (H3): *Individuals' behavioral attitude is positively associated with intention to AVs.*

3.4. Subjective Norm (SN)

Subjective norm is a social factor that refers to individual's perceived social pressure to engage or not to engage a particular behavior [31]. Subjective norm reflects the influence of salient individuals or groups that have an influence on an individual's behavioral decisions. According to the TPB, subjective norm is a predictor of specific behavior via behavioral intention. However, there are usually not consistent results whether subjective norm was main predictor of travel-related behavior intention. Several studies have shown that subjective norm indeed has a significant and positive influence on behavioral intention, which indicated that pressure from salient individuals or groups motivate or obstruct individuals to perform a specific behavior [59–61]. Subjective norm was found to have the greatest impact on consumers' intention to adopt hybrid electric vehicles in China [61]. The study of Pan et al. [62] found that subjective norms had a positive impact on passengers' travel intention of using low-cost carriers in China. Furthermore, collectivism has a relatively dominant position in many aspects of people's daily life in the context of Chinese rationalizations, thus social pressure may play an important role in influencing people's choice intention [63,64]. In this study, people are not willing to take the lead in choosing this mode with their concerns and wait-and-see attitudes when AVs enter the market in the future. The ideas and practices of the people they matter most in their life may have an important impact on travelers' choice intention. Based on the above viewpoints, this study proposes the following hypotheses:

Hypothesis 4a (H4a): *Subjective norm is positively associated with individuals' intention to AVs.*

Hypothesis 4b (H4b): *Subjective norm is positively associated with individuals' attitude towards AVs.*

3.5. Perceived Behavioral Control (PBC)

Perceived behavioral control refers to the perceived ease or difficulty of a particular behavior performance [31]. The more resources and opportunities individuals believe they possess, the fewer obstacles they anticipate, and the greater perceived control over the behavior. These resources and opportunities may be divided into internal and external factors, including internal to the individual, such as skills, abilities, knowledge and awareness, or external, such as time, opportunity or the cooperation of other people. Perceived behavioral control has the same ability as actual behavioral control, which will have a direct impact on behavioral intention. Related research have shown that perceived behavioral control is strong determinants of intentions to purchase new energy vehicles [54,65]. With regards to AVs, several constraints do exist. Among the most important control factors that influence travelers' behavior intention include knowledge, price/cost, and convenience/availability. On the one hand, people have expressed a certain degree of concerns about AV technology cost [66]. On the other hand, as an innovative technology, accessibility and operation may be more complex than regular vehicle, which makes individuals doubt whether they can access and drive AVs easily. In this study, travelers are more willing to use AVs when they think that the AVs are easier to use and less expensive than private vehicle or taxi under the same conditions. Based on the above viewpoints, this study proposes the following hypotheses:

Hypothesis 5a (H5a): *Perceived behavioral control is positively associated with individuals' intention to AVs.*

Hypothesis 5b (H5b): *Perceived behavioral control is positively associated with individuals' attitude towards AVs.*

4. Methods

Given that AVs and SAVs have not yet made their way into the marketplace, and revealed preference survey data does not offer valuable insights on individuals' mode choice behavior. To study travel mode choice preferences for AVs and SAVs, revealed preference and stated preference were designed to measure individuals' preferences.

4.1. Survey Design

The questionnaire was formulated based on the research framework and hypotheses mentioned above. To determine the impact of AVs or SAVs on individual travel mode choice, a stated preference experiment was designed to collect basic data on respondents' response to AVs or SAVs since currently no real AVs or SAVs exist on the market in China. The online survey was conducted through 'SoJump' (https://www.sojump.cn/), a professional online questionnaire survey platform which allows to specify a variety of different question types, store the collected answers and handle the data. The questionnaire survey consisted of two main parts.

In the first part of the survey, the respondents were asked to report their age, gender, income level, education level, driver's license possession, and other demographic information. The second part probed the psychological factors that influenced respondents' travel mode choice decisions. Those latent variable items based on TPB according to the suggestion by Azjen [31] were used to measure their intention to use AVs or SAVs. Each psychological construct was measured by three items on a five-point Likert scale (1 = strongly disagree; 5 = strongly agree), with 3 serving as neutral [67]. To obtain a better understanding of the respondents' attitudes, 3 or 4 statements were provided for each of the expected latent variables, as presented in Table 2 (Table 2 lists only the measuring items of AV, and those of SAV are similar.). Among the constructs, attitudes consisted of items that aimed to explore the respondents' evaluations of the usefulness of AV. Subjective norm comprised of items that measured the respondents' perceptions of the societal responses to their decision of using adopting AVs (e.g., approval from the most important persons in their lives). Perceived behavioral control contained items that expected to reveal the respondents' perceptions of the ease or difficulty related to adopting AVs (e.g., availability and affordability of AVs in the future); perceived risk comprised of items that aimed to measure the respondents' potential perceived risk regarding AVs. Knowledge contained items that expected to measure the respondents' interpretation of AV technology. Intention included items that aimed to measure the respondents' planned behaviors regarding AVs (e.g., use of AVs in the future instead of regular vehicle).

Furthermore, one of the main obstacles in collecting valid data we encountered was that many respondents did not have enough information about AVs and SAVs to offer a fully formed opinion. Introduction photo and video of AV technology were integrated with the second part to ensure that respondents had an idea of these vehicles.

Table 2. Sources of constructs and items used in the study.

Variables	Measuring Item	Source
	Attitude (ATT)	
av_att1 *av_att2* *av_att3*	For me, adopting an AV is unfavorable/favorable. For me, adopting an AV is negative/positive. For me, adopting an AV is undesirable/desirable.	Azjen [31]
	Subjective Norm (SN)	
av_sn1 *av_sn2* *av_sn3*	People who are important to me expect that I should use an AV in the future. People who significant to me (such as relatives and friends) support my use of AVs. If people around me use AVs, I will also use AVs.	Azjen [31] Donald et al. [68]
	Perceived Behavioral Control (PBC)	
av_pbc1 *av_pbc2* *av_pbc3*	I have enough opportunity to use an AV when traveling. Whether or not I use an AV when traveling is completely up to me. I have enough resources (money) to use an AV when traveling.	Azjen [31] Lanzini et al. [69]
	Perceived risk (PR)	
av_pr1 *av_pr2* *av_pr3*	I am worried about bring me and my family certain risks when using AVs. I am afraid of suffering financial and time losses when using AVs. I am worried that the function and the system cause me trouble when using AVs.	Mitchell and Vincent-Wayne [47] Wang et al. [70]
	Knowledge (KN)	
av_kn1 *av_kn2* *av_kn3*	I am familiar with the performance of AVs (such as operating procedures, driving comfort, and driving distance). I am familiar with the cost of using AVs. I know the advantages of AVs over traditional cars (such as improving safety and easing traffic congestion).	Parkins et al. [71] Liao et al. [72]
	Intention (INT)	
av_int1 *av_int2* *av_int3* *av_int4*	I might use an AV when AVs enter the market. I plan to use an AV when AVs enter the market. I try to use an AV when AVs enter the market. I give priority to using AVs if I need to use a car when AVs enter the market.	Azjen [31] Lanzini et al. [69]

4.2. Sample and Data Collection

Two pre-tests were conducted before carrying out the formal questionnaire survey: the first pre-test was a pen and pencil version of the questionnaire which was randomly distributed to 45 college students. According to the comments and feedback, errors in terms of wording, phrasing and sequencing of questions were corrected and the questionnaire was edited online. A second pre-test was conducted by an online survey in order to obtain further feedback on this questionnaire. Data collection was started after correcting the remaining errors and misunderstanding item sources. A total of 1143 questionnaires were collected between 14 January and 5 February 2018, in Zhenjiang, China. 906 valid questionnaires were obtained after eliminating and cleaning the same answers, logical errors and invalid questionnaires. The validity rate of the questionnaires was 79.27%. To prevent repeatedly submitting questionnaires by the same person, the questionnaire submitted by IP address is limited to once.

5. Analysis and Results

5.1. Demographics and Descriptive Findings

Table 3 summarizes the socio-demographic characteristics of the overall sample participating in this survey. Among the surveyed respondents, 53.75% were male and 46.25% were female. The average age was 33.65 years old. The education level was relatively high; more than half of respondents had Bachelor's degrees. The majority of personal monthly income was less than 2000 RMB (32.23%), followed by 2001–4000 RMB (28.70%), 4001–6000 RMB (20.09%),6001–8000 RMB (8.50%), and more than 8000 RMB (10.48%). In addition, the majority of respondents did not know much about AV technology.

Table 3. Summary of respondents' demographic information (N = 906).

Variables	Frequency	Percentage (%)
Gender		
Male	487	53.75%
Female	419	46.25%
Age		
18–25	272	30.02%
26–35	261	28.81%
36–45	164	18.10%
>45	209	23.07%
Education		
Junior school and below	58	6.40%
High school	131	14.46%
College	238	26.27%
Bachelor	424	46.80%
Master or above	55	6.07%
Income		
<2000	292	32.23%
2001–4000	260	28.70%
4001–6000	182	20.09%
6001–8000	77	8.50%
>8000	95	10.48%
Awareness of AV technology		
Strongly Agree	91	10.04%
Agree	270	29.80%
Undecided	401	44.26%
Disagree	112	12.36%
Strongly Disagree	32	3.54%

5.2. The Reliability and Validity of the TPB Questionnaire

IBM SPSS v21.0 and AMOS v21.0 were used to test the models and hypotheses proposed in the study. The fitness of the model should be tested before performing the hypothesis test. Confirmatory factor analysis (CFA) was applied to examine the measurement model's reliability and validity. Cronbach's alpha and Composite reliability (CR) were used to check the internal consistency of the items in each construct. Taking AV model as an example, Table 4 shows that the minimum value of Cronbach's alpha was 0.892, and all values were higher than the recommended minimum value of 0.70 [73]. Therefore, the data was tested to have a good reliability and stability. The CR values of the 6 latent variables were between 0.893 and 0.939, which were all above the recommended minimum value of 0.7 [74], indicating a high degree of internal consistency among the latent variables. In addition, convergent validity of the model was tested by the construct's standardized factor loading and the average variance extracted (AVE). The result shows that the standardized factor loadings of the 19 observed variables were between 0.726 and 0.969, all values were higher than the standard of 0.5 [75], indicating that each observed variable had a high explanatory power for their respective latent variable. The AVE values of all the latent variables were between 0.553 and 0.860, which were all above the recommended minimum value of 0.5 [74]. Hence, all variations of the observed variables explained by their latent variable were greater than the variations explained by their errors, indicating that the average explanatory power of each item in the construct was evident. In summary, the above results show that the measurement model has a good performance on structural reliability, convergence validity and discriminant validity. Table 5 displays the results of discriminant validity test. All AVE values are greater than the inter-construct correlations, indicating the constructs have good convergent and discriminant validity. The measurement model was validated and ready for structural model analysis.

Table 4. The results of statistical analysis and confirmatory factor analysis.

Construct	Measures	Means	*SD*	Cronbach'α	Standardized Factor Loading	CR	AVE
ATT	*av_att1*	3.82	0.791	0.940	0.944	0.939	0.836
	av_att2	3.81	0.813		0.930		
	av_att3	3.71	0.811		0.867		
SN	*av_sn1*	3.58	0.750	0.892	0.880	0.893	0.736
	av_sn2	3.57	0.749		0.851		
	av_sn3	3.56	0.740		0.842		
PBC	*av_pbc1*	3.65	0.732	0.908	0.969	0.916	0.786
	av_pbc2	3.66	0.768		0.726		
	av_pbc3	3.62	0.732		0.945		
PR	*av_pr1*	2.45	0.704	0.936	0.895	0.936	0.829
	av_pr2	2.47	0.745		0.912		
	av_pr3	2.48	0.745		0.924		
KN	*av_kn1*	3.51	0.946	0.928	0.920	0.928	0.811
	av_kn2	3.48	0.997		0.863		
	av_kn3	3.46	1.029		0.918		
INT	*av_int1*	3.61	0.779	0.939	0.876	0.935	0.782
	av_int2	3.64	0.795		0.883		
	av_int3	3.58	0.776		0.883		
	av_int4	3.57	0.749		0.895		

Table 5. Results of discriminant validity test.

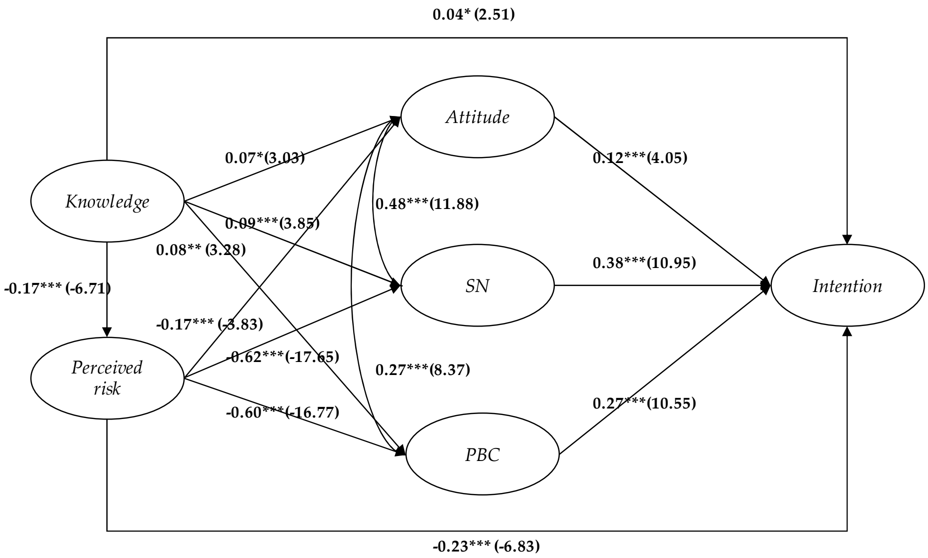
	ATT	SN	PBC	PR	KN	INT
ATT	**0.836**					
SN	0.703	**0.736**				
PBC	0.623	0.691	**0.786**			
PR	−0.554	−0.598	−0.538	**0.829**		
KN	0.278	0.254	0.222	−0.235	**0.811**	
INT	0.692	0.712	0.727	−0.669	0.296	**0.782**

Note: Values along diagonal (in bold) are AVEs of the constructs. Values below diagonal are the correlations between two constructs. ATT: Attitude; SN: Subjective norm; PBC: Perceived Behavioral Control; PR: Perceived Risk; KN: Knowledge; INT: Intention.

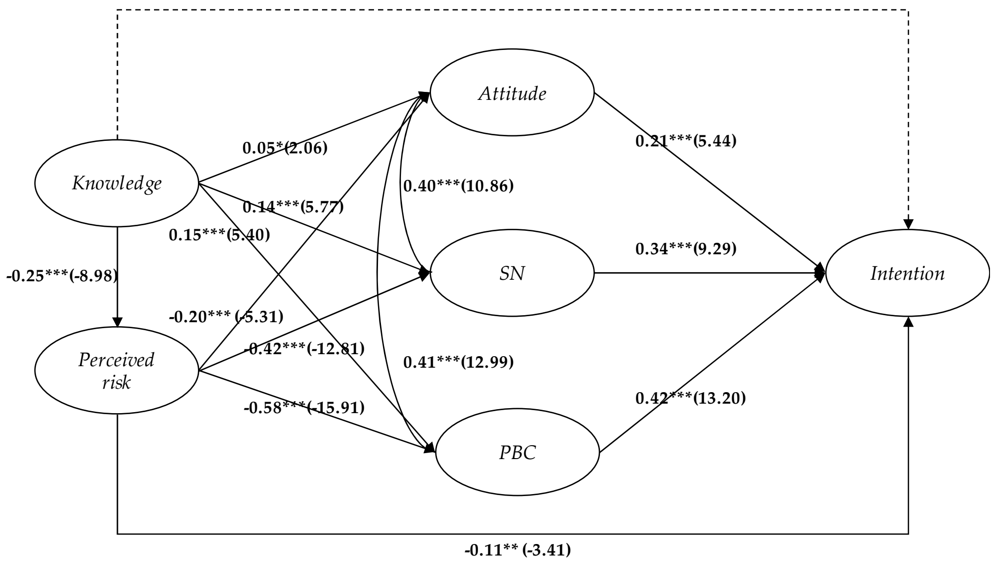
5.3. Structural Model and Hypothesis Tests

The structural equation model was employed to explore the interrelations among constructs and the model fitting situation is often evaluated by sample size independent fit indices such as chi-square/degree of freedom (χ^2/df), the comparative fit index (CFI), the Tucker-Lewis index (TLI), the root mean squared error of approximation (RMSEA) and Standardized Root Mean Square Residual (SRMR). According to the rule of thumb, the χ^2/df value is between 1 and 3 (this value can be between 1 and 5 if the sample size is more than 500), CFI and TLI values are greater than 0.90, RMSEA and SRMR values are smaller than 0.08, the overall model was regarded as acceptable and excellent. Taking AV model as an example, the related model fit indices of the model in this research was excellent (χ^2/df = 3.719; CFI = 0.978; TLI = 0.970; RMSEA = 0.055; SRMR = 0.068).

Figure 2 presents the path coefficients and the hypothesis testing results of the proposed model with significant paths as solid lines and non-significant paths as dotted lines among variables. The supporting condition of the hypothesis is that the absolute z-value should be above 1.96 that is, $p < 0.05$. Specifically, it was found that knowledge about AVs showed a positive effect on attitude, subjective norm, perceived behavior control and intention to use AVs, which supported hypothesis H1b, H1c, H1d, and H1e. Knowledge had a negative effect on perceived risk ($\beta = -0.17$, $p < 0.001$), which supported hypothesis H1a. However, the knowledge about SAVs had no significant impact on behavioral intention to use SAVs, which was inconsistent with hypothesis H6b. Therefore, knowledge was not significant predictors of behavioral intention in the SAV model. Among the proposed hypotheses related to perceived risk, perceived risk had a significant negative effect on attitude, subjective norm, perceived behavior control and intention to use AVs and SAVs. Thus, those hypotheses H2a, H2b, H2c, H2d, H7a, H7b, H7c, and H7d were supported. Knowledge of AVs and SAVs had a positive effect on perceived risk, which supported H1a and H6a. Furthermore, attitude towards using AVs and SAVs showed a positive effect on behavioral intention to use (β = 0.12, p < 0.001; β = 0.18, p < 0.001), which supported H3 and H8. Subjective norm and perceived behavior control were also main significant positive predictors of behavioral intention, which supported H4a, H5a, H9a and H10a by the data.



(**a**) Results of the structural model based on AV.



(**b**) Results of the structural model based on SAV.

Figure 2. Results of the structural model. Note: *** p < 0.001; ** p < 0.01; * p < 0.05.

6. Discussion and Implications

This study has attempted to understand the travelers' behavior intention to use AVs and SAVs and the key influence factors of behavior intention in the Chinese context. This research established a socio-psychological model to examine AV and SAV choice intentions. Based on the original TPB theoretical framework, this study also attempted to extend the TPB by incorporating two additional psychological variables: knowledge and perceived risk. This paper broadens the TPB application to AV research. The TPB model, despite being extensively used in studies of human behaviors, has only limited use in the AV technology context. The extend TPB models used in this study successfully explained travelers' AV and SAV choice intentions. Overall, the findings suggest that most travelers in China have positive attitudes towards the notion of AVs and SAVs, although they were relatively unfamiliar with specific AV technology. The standard path coefficient in Tables 6 and 7 indicated the degree of correlation between the two variables of this path. Both the TPB components and external factors were assessed for their influence on AVs and SAVs choice intentions.

Table 6. Standardized path coefficients and significance level of AV model.

Hypotheses	Path	Standardized Estimate	C.R.	P	Supported (p < 0.05)
H1a	PR ← KN	−0.17	−6.71	***	Yes
H1b	INT ← KN	0.04	2.51	0.012	Yes
H1c	ATT ← KN	0.07	3.03	0.002	Yes
H1d	SN ← KN	0.09	3.86	***	Yes
H1e	PBC← KN	0.08	3.28	0.001	Yes
H2a	ATT ← PR	−0.17	−3.83	***	Yes
H2b	SN ← PR	−0.62	−17.65	***	Yes
H2c	PBC← PR	−0.60	−16.77	***	Yes
H2d	INT ← PR	−0.23	−6.83	***	Yes
H3	INT ← ATT	0.12	4.05	***	Yes
H4a	INT ← SN	0.38	10.95	***	Yes
H4b	ATT ← SN	0.48	11.88	***	Yes
H5a	INT ← PBC	0.27	10.55	***	Yes
H5b	ATT ← PBC	0.27	8.37	***	Yes

Note: *** p < 0.001.

Table 7. Standardized path coefficients and significance level of SAV model.

Hypotheses	Path	Standardized Estimate	C.R.	P	Supported (p < 0.05)
H6a	PR ← KN	−0.25	−8.98	***	Yes
H6b	INT ← KN	0.03	1.34	0.179	No
H6c	ATT ← KN	0.05	2.06	0.040	Yes
H6d	SN ← KN	0.14	5.77	***	Yes
H6e	PBC← KN	0.15	5.40	***	Yes
H7a	ATT ← PR	−0.20	−5.31	***	Yes
H7b	SN ← PR	−0.42	−12.81	***	Yes
H7c	PBC← PR	−0.58	−15.91	***	Yes
H7d	INT ← PR	−0.11	−3.41	***	Yes
H8	INT ← ATT	0.21	5.44	***	Yes
H9a	INT ← SN	0.34	9.29	***	Yes
H9b	ATT ← SN	0.40	10.86	***	Yes
H10a	INT ← PBC	0.42	13.20	***	Yes
H10b	ATT ← PBC	0.41	12.99	***	Yes

Note: *** p < 0.001.

6.1. Perceived Risk, Knowledge and Their Implications

Perceived risk is conceptualized in various studies according to different study background. In behavior-relative research, perceived risk is mainly associated with a distinct product or product attribute. Three items about perceived risk had higher standardized factors in the confirmatory factor analysis (see Table 4). In the extended TPB model, it was observed that perceived risk has a significant relationship with behavioral intention to use AVs (β = −0.23, z = −6.83 at significant level $p < 0.001$) and intention to use SAVs (β = −0.11, z = −3.41 at significant level $p < 0.001$). The beta coefficient value of perceived risk is negative, which implies that risk results in a negative impact on behavioral intention. In terms of knowledge, the result shows that knowledge about AV have a statistical relationship with intention to use AVs (β = 0.04, z = 2.51 at significant level $p < 0.05$). In the AV structure equation model, knowledge about AV not only have an impact on travelers' behavioral intentions directly, but also have an influence on behavioral intentions through attitudes, subjective norm and perceived behavioral control indirectly. It should be noted that knowledge has no significant impact on behavioral intention in the SAV model (β = 0.03, z = 1.34 at significant level $p > 0.05$), which is consistent with previous research [76]. It is suggested that knowledge related to specific behaviors may be not enough to make decisions in some behavioral studies, and the variables such as potential attitudes and beliefs related to behaviors may be more important than knowledge.

Specifically, travelers' lack of knowledge and potential perceived risks associated with using AVs and SAVs often lead to travelers produce negative attitudes and further prevent them from traveling by this mode. Therefore, in order to further encourage travelers to use AVs and SAVs in China, special attention should be paid to raising the knowledge about AV technology and reducing the potential perceived risks. Individuals' awareness of AV technology can be improved by advertising the benefits of using AVs and SAVs through both online and offline media campaigns. Additionally, AV companies can also provide users the opportunity directly to experience AVs and SAVs, because such an experience can improve knowledge about AV technology effectively. SAV companies can purchase insurance and provide security for users to reduce perceived risk and to increase perceived trust. Furthermore, it is also necessary for companies to regularly inspect and maintain the vehicles to eliminate the potential safety hazards of vehicles.

6.2. Attitude and Its Implications

Several studies have confirmed that attitude was the main predictor of behavior intention in the social as well as travel-relative behavior context [31,60,62,68]. Parallel to studies in the field of social science and travel behavior, the present study also shown that attitude is one of main predictors of intention. This study supports that the impact of attitude was highly significant on behavior intention to use AVs (β = 0.12, z = 4.05 at significant level $p < 0.001$) and also on behavior intention to use SAVs (β = 0.21, z = 5.44 at significant level $p < 0.001$).

In the original paradigm of TPB model, attitude is a positive influence on behavioral intentions which shows that travelers rely on their thoughts and feelings. In this study, attitude was determined by beliefs related to the behavior attitude in survey question. In other words, the travelers have that a positive attitude of AVs and SAVs, are more likely to plan to choose this mode. This finding is consistent with prior research; attitude is an efficient predictor of AV and SAV choice intention [13,27,28]. Hence, more efforts should be made to enhance traveler's comprehensive evaluation of choice behavior in the future. Improving the acceptance and recognition of AV technology can significantly enhance the travelers' intention to travel by this mode. Therefore, the government should positively take corresponding measures to emphasize the benefits of AV technology on transportation system, and the positive impact on society/environment benefits. In particular, it is necessary to emphasize the benefits individuals choose AVs and SAVs for personal travel convenience, which enhances individual's accept attitude of AVs and SAVs.

6.3. Subjective Norm and Its Implications

Several studies have found that subjective norm is the weakest indicator of behavior intention in original TPB framework [31,77], some other studies also confirmed that subjective social pressure is a significant and powerful predictor of intention [59,60]. However, three items used to measure subjective norm in this study had very high factor loadings and appeared to be highly internally consistent (Cronbach's alpha = 0.892 for AV model and 0.881 for SAV model). In addition, the present study results also show that subjective norm is the most critical factor affecting the travelers' intention to use AVs (β = 0.38, z = 10.95 at significant level $p < 0.001$). Moreover, the direct effect of subjective norms on intentions to use SAVs reached 0.34 at significant level $p < 0.001$. This finding may provide a new understanding of traveler intentions in the emerging AV markets. On the one hand, compared with Western individuals, Chinese people are influenced by traditional collectivism education. Besides, social pressure has an important impact on the individual's intention to act [78–80]. Individuals are more willing to follow people who are important to them. The thoughts or opinions from friends and family around them are important determinants of personal choice intentions. On the other hand, since AV is an innovative travel mode in the future and travelers' understanding of AV is limited, the most travelers may be unwilling to take the lead in using AVs. Travelers may seek suggestion or advice from their family and friends about traveling by this mode. Therefore, perceived social pressure may be a highly salient factor in this context. For the government, it is possible to start with the formulation of policies or regulations and to promote the enthusiasm of users with positive advocacy, thus generating the use intention of AVs. For AV companies, free trial driving and test driving should be conducted to make some people have the willingness to use AVs, then using the word-of-mouth effect to publicize and affect more people's willingness to travel by the mode.

6.4. Perceived Behavior Control and Its Implications

Perceived behavioral control was defined in this study as assessing their self-perception of eases/difficulties in AV or SAV use intention. The perceived behavioral control has been also criticized as a significant predictor of behavioral intention in TPB model [54,62,65]. In the study, three items used to measure perceived behavior control had high factor loadings and appeared highly internal reliability (Cronbach's alpha = 0.908 for AV model and 0.907 for SAV model). Furthermore, the significant correlation was verified with perceived behavioral control and both behavior intention to use AVs (β = 0.27, z = 10.55 at significant level $p < 0.001$) and behavior intention to use SAVs (β= 0.42, z = 13.20 at significant level $p < 0.001$).

In this study, it is found that attributes such as cost, convenience, and availability are significant indicators of perceived behavior control. This finding suggests that travelers in China have a need for perceived control over external resources when choosing AVs as a travel mode. A possible explanation for the importance of perceived behavior control in this study may be related to financial and service control, which may be important aspects of perceived control. Therefore, governments and companies need to take appropriate measures to improve the level of perceived behavior control in the future. The government should focus on infrastructure platform construction and preferential policy formulation, such as providing a certain degree of subsidies and tax benefits to individual consumers. SAV companies should pay more attention to the service design and management provided such as configuring rationally the number of vehicles based on user data, optimizing system and mobile APP design to provide the real-time power, mileage fee information, so that travelers can easily access SAV service.

7. Conclusions and Limitations

New forms of mobility mode are entering the market, which will have a huge impact on travel mode choice in the future transportation system. This calls for a thorough understanding of travelers' intentions to use AVs and SAVs in China, which has so far received little research attention. In this paper, we carried out an empirical research on the influencing factors of psychological latent variable on AV technology mode choice intention. The main findings are as follows. By incorporating knowledge and perceived risk, this study has proposed and empirically tested an extended TPB model to understand traveler' behavioral intention to use AVs and SAVs. From a theoretical view, this research implies that the TPB model also has good applicability and validity in the context of AV technology. Knowledge and perceived risk provide another more potential important way to explain other factors that influence travelers to use innovative technologies with uncertainty. From an empirical view, these research findings suggest that in order to promote AV technology choice intention, relevant organizations should focus on improving the credibility of AV to reduce the perceived risk. In addition, travelers' understanding of AV technology will also increase the intention to choose this mode. As a result, car manufacturers and governments can publicize the benefits of AV technology (such as, easing congestion and increasing mobility) to increase travelers' intention of choosing AVs and SAVs. Finally, considering the critical positive effects of SN and PBC on AV and SAV choice intentions separately, the role of SN and PBC should also be emphasized. This means that free trial driving and test driving make some people have the willingness to use AV technology and improving the potential ability of travelers' behavior control, which is useful for facilitating travelers to use AVs and SAVs.

This study can be improved in several aspects concerning its limitations; these require further research efforts. The first limitation is that most respondents did not have actual experience with AV technology. The behavioral intention discussed in this study is based on the initial intention of the respondents' knowledge about AV technology gained from new media such as the Internet or television. As AVs enter the market, individuals will be more familiar with AV technology, and their behavioral intentions and their antecedents will be changed in the future. Therefore, a longitudinal tracking study is recommended to further clarify the evolution of behavioral intentions after having more interaction with AV technology [81]. This would be an interesting next research topic. The second limitation is that this research investigated only general SAV mode choice behavior intention; research motivation mechanisms on specific SAV (SAV can be classified from different standpoint, such as SAV with ridesharing or non-ridesharing) mode choice behavior or comparing behaviors may obtain more exciting new findings. The third limitation is that the research sample only comprised Zhenjiang (China) survey data. Therefore, future studies can aim at generalizing and comparing our findings to explore choice intentions in cross-province or different countries. The fourth limitation is that online survey method was adopted in this survey, which may lead to limited sampling and respondent availability. These respondents mainly include the elderly and people who reside in remote areas. Moreover, future studies should explore the role of other factors such as trust, safety, reliability, and driving habits. A more complex structural model with a network of interrelationships among factors can be developed to further study the behavioral intentions to use AVs and SAVs in China. Finally, this paper focused on the relationships between predicting factors and traveler intentions, future research could expand the model to explore the potential relationship between intention and actual behavior in the AV technology context in the future.

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