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Research on the Public's Intention to Use Shared Autonomous Vehicles: Based on Social Media Data Mining and Questionnaire Survey

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Abstract: While the emergence of shared autonomous vehicles can be an effective solution to improve transport issues and achieve sustainable development, the benefits associated with shared autonomous vehicles can only be realized when the public intends to use them. Therefore, it is necessary to conduct an in-depth study on the public's intention to use shared autonomous vehicles and identify the key influencing factors. This study mined social media data to obtain real public perceptions. A qualitative exploratory analysis was used to identify thematic variables regarding social media data on shared autonomous vehicles, from which a research model of the public's intention to use SAVs was proposed. Then, a questionnaire survey was conducted, and the structural equation model and Bayesian network were used to analyze the questionnaire data quantitatively. The findings reveal how perceived risk, social information, trust, perceived usefulness, and personality traits affect the public's intention to use shared autonomous vehicles, and how to enhance the public's intention to use them. This study will enrich the research on traveler psychology in the context of intelligent travel and provide theoretical basis and decision support for future policies to promote shared autonomous vehicles.

Keywords: shared autonomous vehicle; sustainable development; intention to use; data mining; structural equation model; Bayesian network



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1. Introduction

With the rapid development of society, advanced technologies such as autonomous driving technology and the rise of the sharing economy are important topics shaping the future of smart cities. As a part of the sharing economy, shared travel has great potential. In recent years, ride-sharing methods such as shared bicycles, shared electric vehicles, and shared cars have achieved great development and alleviated many traffic problems [1]. Autonomous vehicles (AVs), without the intervention and control of the driver, can reduce the number of accidents caused by human error, and reduce emissions by easing traffic congestion, which can also bring many benefits to road traffic.

However, in the early stage of new technology development, AVs are expensive due to high research and development costs. Additionally, the study by Anas et al. [2] noted that the decline in GDP per capita also affects the public's intention to use AVs, and those potential users will not consider purchasing AVs in the short term, preferring to use SAVs. In this context, shared autonomous vehicles (SAVs), which combine the features of autonomous vehicles and sharing economy, will be more popular among travelers [3]. And many scholars point out that SAVs are a revolutionary way of traveling [4].

The arrival of the era of shared autonomous driving can also solve the waste of resources caused by the long-term vacancy of some private cars to a certain extent. Because

of its shared characteristics, it can reduce people's intention to buy private cars. Moreover, due to its driverless characteristics, it can also prevent the occurrence of unanswered orders and improve people's travel efficiency [5]. The emergence of SAVs will contribute to sustainable development.

SAVs, as an early and easily promoted mode of travel for the application of autonomous driving technology, have developed rapidly in recent years. The rapid development of SAVs is reflected not only in the huge investments made by transportation network companies (e.g., Uber and Lyft) in the development of SAVs systems, but also in the changes in the business models of traditional automakers. Manufacturers including Ford and Volkswagen envision fully autonomous vehicle systems for on-demand mobility in the next few years [6].

But for SAVs to be widely used, public perception is crucial. The influence of social media on public perception is huge, and with the promotion of SAVs on social media, the public's awareness of SAVs continues to deepen. If the benefits of SAVs are publicized through the media, the public will be more willing to use them, which will promote the commercialization process of SAVs. However, even if the public recognizes the benefits of SAVs, their willingness to use them is not high. Haboucha et al. [7] found that 25% of people refused to use SAVs even though they cost nothing to use. Marvin [1] also pointed out that the private car is seen by most people as a comfortable, convenient, and flexible way of getting around, and it is unclear whether SAVs can break this preconceived concept. Therefore, it is important to research the public's intention to use SAVs, find out the potential rules of the public's intention to use SAVs, and propose measures to improve the public's intention to use SAVs.

Based on the above content, this study attempts to use mixed methods to analyze and explain the public's intention to use SAVs. Due to the information age, social media has an increasing influence on the public and the huge amount of information on social media platforms. Therefore, this study mined the social media data and qualitatively extracted some thematic variables from the public comments about SAVs to obtain the factors that influence the public's intention to use SAVs. Then, based on the extracted theme variables, a research framework of SAV use intention was proposed, a questionnaire was designed, and an empirical investigation was carried out to analyze the key factors and action mechanisms that affect public use intention. The research conclusions will help provide ideas for policymakers to introduce relevant policies, and automobile manufacturers can carry out targeted product design and promotion, improve the public's intention to use SAVs, and promote the further development of SAVs.

The structure of this paper is as follows: Section 2, Literature Review. Section 3, Experimental Design, introduces the process of research model construction and the results of the questionnaire survey. Section 4 describes the methodology and results of the model analysis and proposes some measures to increase public intention to use SAVs. Section 5 summarizes the significance, limitations, and future prospects of this study.

2. Literature Review

The literature review is divided into the following three parts: We first reviewed the current research on SAVs usage intentions (see Section 2.1). On this basis, the data collection and analysis methods used in studies to survey the public's intention to use AVs and SAVs were reviewed (see Sections 2.2 and 2.3).

2.1. Research on the Intention to Use SAVs

As the process of urbanization accelerates, the rise of advanced technologies such as autonomous driving and the sharing economy is an important part of shaping the structure of future smart cities. In this case, shared travel, as a market segment of the sharing economy, has disruptive potential [8]. Especially in recent years, car sharing has been included in the solution of traffic problems in many cities and has achieved great development. This shift from ownership to shared services will fundamentally change

people's travel behavior in the future, and with the launch of SAVs, this shift is also becoming more interesting.

During the process of SAVs from the laboratory to the market, the public's intention to use them is an important premise that has a great impact on the promotion of SAVs. Many scholars have explored the factors that affect users' intention to use SAVs. Marvin [1] conducted statistics on these studies and found that there were 119 psychological factors involved. For example, Li et al. [9] found that users' acceptance and choice of autonomous buses are based on the public's perceived usefulness and perceived ease of use of the product. Yuen et al. [5] found that attitude, subjective norms, and perceived behavioral control all promote the public's willingness to use SAVs. Hongyun et al. [10] proposed that external environment and personal attributes affect people's intention to use SAVs. The external environment includes policy support, media propaganda, and social norms. Regarding personal attributes, studies have analyzed the influence of gender, age, occupation, and other factors on the use of SAVs by individuals [11,12]. However, personality traits, as one of the stable attributes of individuals, are not mentioned in these studies.

As research has progressed, studies have investigated the influence of consumers' personality traits on their willingness to use AVs. The results demonstrated that personality traits can influence consumer acceptance of AVs, either directly or indirectly through factors such as trust [13]. A study by Neil et al. [14] also found that personality traits influence consumers' intention to use AVs. In contrast, Kyriakidis et al. [15] concluded that personality dimension variables were not associated with public perceptions of AVs. The limited research and inconsistent findings suggest that the influence of personality traits on the public's intention to use AVs needs more research and attention. And the influence of personality traits has been largely ignored in the research on the intention to use SAVs.

2.2. Data Collection Methods

In the field of studying intention to use, researchers often use questionnaires to collect data. Because questionnaire surveys can help deeply understand the consumer market and consumer psychology, and this method is simple to operate, this method has been widely used. In investigations related to autonomous driving, Carina et al. [16] investigated the influence of people's intention to use public AVs, and they analyzed a total of 435 questionnaires. Krueger et al. [11] designed a questionnaire to investigate Australian residents from three aspects, including their demographic characteristics, frequency of using transport modes, and preference for SAVs. As a common data collection method for empirical analysis, a questionnaire survey can help researchers understand the needs, behaviors, and attitudes of specific groups, and its effect has been verified by a large number of studies.

However, the data obtained by using only questionnaires have certain limitations. First, designing questionnaires relies on the knowledge of researchers or their focus on the topic, and it is difficult to fully reflect the public's perception. Secondly, a questionnaire survey requires respondents to answer the questions under the supervision of surveyors, and their answers are limited to the questions in the questionnaire, so they cannot express themselves freely [17]. However, on social media platforms, the public can speak freely and express their real thoughts in their own time, and social media can provide a huge amount of data for researchers to analyze.

In recent years, studies have emerged to analyze public perceptions of AVs through social media data. However, there are fewer studies on SAVs. Yue et al. [18] investigated social media users' perceptions of AVs through 696,835 Twitter datasets. Das et al. [19] collected the 15 most viewed videos on YouTube videos about AVs and analyzed 38,746 comments to deepen the understanding of public attitudes toward AVs and potential concerns. Jacelyn et al. [20] obtained 1164 tweets to assess people's intention to accept and use AVs. The results of the existing studies suggest that public comments on AVs posted on social media platforms can reflect their perceptions and intentions to use this new product. However, this approach has some limitations in that it lacks statistical correlation between influential factors related to the public's intention to use AVs.

Therefore, for SAVs, if we want to explore people's intention to use them more deeply, it is not enough to analyze them only by questionnaire data or social media data; we need to combine the questionnaire data and social media data to investigate the user's psychology in depth.

2.3. Methods of Analysis

In the field of intention to use automated driving technology, the earliest methods used are mainly descriptive statistics, factor analysis, analysis of variance, etc., in which most of the studies used descriptive analysis methods to analyze the data initially [21,22].

As the research progresses, researchers are beginning to use more advanced quantitative analysis models to identify the key factors influencing people's intention to use AVs and the underlying mechanisms.

As the study progressed, researchers began to use more advanced quantitative analytical models to clarify the key influences and the intrinsic mechanisms at work on the intention to use automated driving technologies. Among them, structural equation modeling (SEM) has been widely used to assess the influence of latent variables that cannot be directly observed on intention to use. Hang et al. [23] constructed an SEM of the public's intention to use SAVs and fitted the parameters to 367 questionnaires. Kenesei et al. [24] used perceived risk as a mediator to explore the direct and indirect paths of trust on the willingness to use AVs and tested the model using SEM. Lee et al. [25] used SEM to examine how each psychological latent variable affects the influences on the intention to use AVs. Numerous studies have demonstrated the good fit of SEM.

Although SEM is widely used to analyze user psychology, Long et al. [26] pointed out that SEM can analyze the intrinsic relationship between variables and confirm whether the effect of the independent variable on the dependent variable is significant, but it is not able to explain the priority of importance of the independent variable and predict the degree of impact of changes in the independent variable on the dependent variable. In contrast, Bayesian networks (BNs) represent the strength of the relationship between variables based on the digitization of probability distributions and can automatically calculate and output the probability of change in the target variable brought about by a change in the independent variable. Therefore, BN is combined with SEM, thus enabling more accurate interpretation and prediction. Delphine et al. [27] used a BN to analyze the probabilistic interrelationships between various aspects of AVs and revealed the safety potential of AVs to reduce traffic injuries and fatalities. Dorde et al. [28] investigated the differences in the willingness of people with disabilities to accept AVs and used a Bayesian linear regression model to analyze this, and the model worked well.

Overall, SEM and BN complement each other, and a combination of these two methods can more accurately quantify the relationship between the factors influencing the intention to use SAVs.

3. Experimental Design

3.1. Social Media Data Mining

SAVs in this study refer to consumer-oriented AVs that can provide shared services, where the user submits an order via his/her electronic device, the system automatically matches the nearest vehicle and selects the optimal route, the vehicle arrives at the user's location and delivers it to the destination, and payment is made via the Internet upon arrival. "Shared" here is mainly to emphasize the difference from "private" AVs and does not consider the issues of car sharing and traditional shared car rental.

In this section, the public's real concerns about SAVs were explored by mining public comments on social media platforms, and then the results of the TF-IDF algorithm and sentiment analysis were used to match the variables of the quantitative analysis as the basis for the questionnaire design.

3.1.1. Data Collection

TikTok is one of the most popular social apps in the world, with over 750 million daily active users, and in 2023, TikTok topped the ranking of monthly active user size in China's mobile video segment. It is a platform developed for all age groups where users can discuss social issues and express their opinions freely [29]. So, the comments of TikTok were selected to be investigated and analyzed in this study.

In this study, we searched for "shared autonomous vehicles" in TikTok and selected popular science videos, i.e., videos that introduced the product, to ensure that the commenters have a certain understanding of the product before posting comments to the greatest extent possible. The comment data of the five most viewed videos about the introduction of SAVs posted on the TikTok platform were collected through web crawler technology, and a total of 23,315 comments were obtained. In order to obtain more accurate analysis results next, the acquired data were preprocessed. To obtain more accurate analysis results in the next step, the acquired data were pre-processed. Considering the improper use of words by users, network delays, and other reasons, many high-frequency words and multiple words may come from the same user when extracting data within a short period continuously, and if too much of this type of datum is captured, it will affect the extraction of keywords as well as the analysis of the final data. Therefore, duplicates were first removed based on user name and text. Secondly, comments with insufficient information were cleaned up, comments with insufficient word count were filtered, and messages with a total word count of less than 5 were mandated to be deleted. And meaningless content (such as emoticons, links, and special characters) was deleted, resulting in 20,833 data.

3.1.2. Results of TF-IDF Calculation and Sentiment Analysis

The TF-IDF algorithm (term frequency–inverse document frequency) is a weighting algorithm that is currently widely used, mainly for text data feature extraction.

In the subsequent data processing, the TF-IDF algorithm can obtain the feature word weight of each comment; the larger the TF-IDF value, the higher the weight of the word. And the feature weight of a consumer in a certain aspect can reflect their attention to this aspect; the higher the weight, the higher the attention.

As the network review data are relatively scattered, it is difficult to directly see the focus of consumer attention, so it is necessary to structure the network review data into weights under each feature. This lays the foundation for the subsequent establishment of the indicator system of influencing factors on the willingness to use SAVs.

The number of topics has a significant impact on model performance; too many topics may result in meaningless topics and too few may mask the qualities of the topics [30,31]. After analyzing and discussing this study, four topics were identified to explain the public's intention to use SAVs, which are the factors influencing the public's use of SAVs. The steps for matching the variables are as follows:

Step 1: The comment data were processed by word segmentation to obtain a high-frequency word list. The extraction of clustering of comment topic words was achieved based on the TF-IDF method. Each topic word is a keyword with the top ten TF-IDF values, i.e., the words with the highest probability of occurrence.

Step 2: After collecting and reading the relevant literature, we collected the latent variables and their definitions from the widely used behavioral theoretical frameworks (e.g., technology acceptance model, theory of planned behavior, unified theory of acceptance and use of technology) and identified the research variables with the characteristics of Chinese consumers.

Step 3: Based on the existence of a many-to-one relationship between the subject terms and the characteristics of the influencing factors, the subject terms were assigned to topics with consistent content, and then the names of the latent variables from each theory were assigned to a topic as a label.

The summarized thematic terms became the basis for hypothesis development: trust, perceived risk, social influence, and perceived usefulness. The results of the thematic labels

and the definitions of the associated latent variables are presented in Table 1. In addition, the data were imported into the SnowNLP library, and the text of each comment was taken and analyzed for affective sentiment tendency to derive a value between 0 and 1. If the sentiment score is greater than 0.5 it means that the sentiment polarity of this comment is on the positive side, while a sentiment score of less than 0.5 indicates that the sentiment polarity is on the negative side.

Table 1. Results of labels and definitions of latent variables.

Top Ten Keywords with the Highest Probability of the Topic	Comments Example	Labels for Topics	Original Variable Definition	References
Accident, system, driverless, liability, danger, driving, unemployment, driver, steering wheel, control, life	As long as it's a machine, it's going to malfunction, and there's no telling when it's going to be dangerous.	Perceived Risk	Consumers anticipate the possible negative outcomes of using new technologies	[24,32,33]
Believe, safe, worry, reassure, safety officer, technology, high-tech, experience, dare to ride, scary	I'll sit because I believe in Chinese technology	Trust	Trust related to system functionality and predictability	[13,24]
Useful, drink, sleep, work, make money, driving licence, cheap, passengers, smart, taxi	Because of this technology, I'll feel more comfortable drinking outside in the future.	Perceived Usefulness	The convenience and benefits that consumers perceive the service or product to provide	[32,33]
Impact, promotion, national, social, development, trends, Tesla, Didi, Baidu, life, heard	AI intelligence is the future.	Social Influence	Individuals change their attitudes and behaviors as a result of the information they receive, the people around them, and the environmental influences	[13,34]

The distribution of the sentiment analysis results is shown in Figure 1. It can be seen that the public's comments on SAVs are more widely distributed below 0.5. It shows that based on the text analysis of the comments on the TikTok platform, the public currently had a poorer evaluation of SAVs, and there were more negative sentiment evaluations, indicating that the public had a more negative attitude towards SAVs.

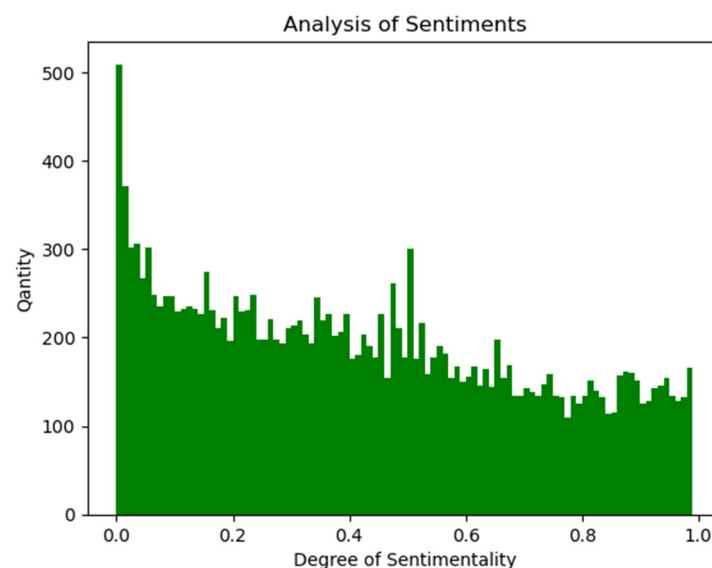


Figure 1. Distribution of the results of the sentiment analysis.

3.2. Model Construction and Research Hypotheses

Four variables were obtained in the previous section; combined with the review of current research on SAV use intention in Section 2.1, personality is an influencing factor worth discussing, so this study introduced the personality variable to extend the research model and make the model more explanatory. The SAV use intention model constructed in this research is presented in Figure 2.

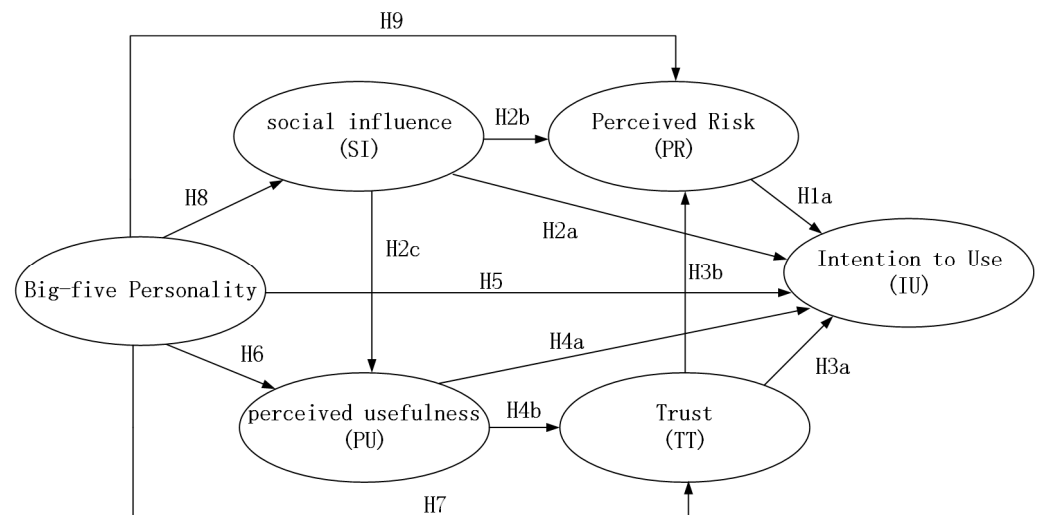


Figure 2. Model diagram of SAV use intention.

The model consists of six main components: perceived risk, social influence, trust, perceived usefulness, five personalities, and intention to use. Based on the research background and research model, combined with the related literature, this study proposed some hypotheses and verified them. This section describes the rationale for all the variables in this model and presents the hypotheses.

3.2.1. Perceived Risk

Perceived Risk (PR) arises because people have concerns about whether the goals they set for themselves will meet their own requirements [35]. SAVs are a new technology, despite a large body of research suggesting that they are safer and more efficient than traditional manual driving. However, many surveys have shown that whilst respondents recognize the potential benefits of automated driving technologies, they also express great concern about the risks associated with their use [36]. Peng's study found that perceived risk was a major barrier to individuals' use of AVs [37]. The results of a questionnaire survey conducted by Peng et al. [38] in Tianjin also confirmed this finding. Therefore, the following hypotheses were proposed in this study:

H1a. *Perceived risk has a significant negative effect on the public's intention to use SAVs.*

3.2.2. Social Influence

Social influence (SI) is a psychosocial phenomenon prevalent in social life. With the rapid changes in society, the behavior of individuals in society will naturally change due to the information in the social environment. Social influence is the process of obtaining opinions or information from those around a person as a basis for decision-making and changing one's initial thoughts based on the behavior of others.

In 2000, Bansal et al. [39] suggested that the information people obtain and the opinions of those around them change their perceptions of autonomous vehicles. The study by Ling et al. [40] also showed that the more information consumers receive from within the group before making a decision, the more influence it will have on the consumer's

decision. The reason why consumers are easily influenced by information from other groups is that consumers always tend to make decisions on the premise of having enough information about the product. In the study of autonomous vehicles as a consumer object, Zhang et al. [13] also verified the viewpoint that the greater the perceived informational influence, the higher the public acceptance of autonomous driving technology, and that social influence also positively affects perceived usefulness. Therefore, the following hypotheses are proposed in this study:

H2a. *Social influence has a significant positive effect on the public's intention to use SAVs;*

H2b. *Social influence has a significant negative effect on the public's perceived risk;*

H2c. *Social influence has a significant positive effect on the public's perceived usefulness.*

3.2.3. Trust

Trust (TT) refers to the extent to which users perceive SAVs as trustworthy despite uncertainty and risk. It has been noted that sufficient trust is an important prerequisite for autonomous vehicles to be used [41]. If consumers do not trust the technology, they are unlikely to use it. In the early stages of the marketization of new technology, it is important to create sufficient trust in consumers to overcome perceptions of risk and thus develop positive attitudes towards the new technology [37]. Kenesei et al. [24] conducted a study based on the public's trust/risk/intention to use AVs and found that trust positively affects the public's intention to use (IU) AVs and also has a significant negative effect on perceived risk. Li et al.'s [9] study on self-driving buses is also consistent with this. Therefore, this paper makes the following hypotheses:

H3a. *Trust has a significant positive effect on the public's intention to use SAVs;*

H3b. *Trust has a significant negative effect on the public's perceived risk.*

3.2.4. Perceived Usefulness

Perceived usefulness (PU) is one of the important variables in the technology acceptance model, which argues that perceived usefulness positively influences behavioral intention [23]. Since then, some scholars have also empirically demonstrated that public perceived usefulness positively influences people's intention to use [33]. Xiaowei et al. [42] explored the factors affecting users' intention to use SAVs, and Lingbo et al. [32] explored the public's intention to use driverless taxis, and all of their findings verified the influence of perceived usefulness on the willingness to use SAVs.

Trust in SAVs is relative to what the user wishes to achieve. To establish consumer trust in SAVs, they must prove themselves helpful to the user. The significant role of perceived usefulness in trust can be explained in terms of the facilitation and benefits that the traveler perceives that the mode of travel can bring to the trip or to society. A study by Dikmen et al. [43] found that the user's initial trust in Tesla's Autopilot system was positively correlated with perceived usefulness. Therefore, the following hypotheses are proposed in this study:

H4a. *Perceived usefulness has a significant positive effect on the public's intention to use SAVs;*

H4b. *Perceived usefulness has a significant positive effect on public trust.*

3.2.5. Personality

Personality, a system of traits and the most enduring characteristic that an individual possesses, promotes the behavior of an individual to exhibit characteristics with the same tendencies. The Big Five model of personality is the most influential and widely recognized

theoretical model of personality [13]. It suggests that a person's personality traits consist of five dimensions: openness to new things, conscientiousness, extraversion, agreeableness, and neuroticism. Conscientiousness describes an individual's cognitive style and openness to new things; the higher the openness, the more they like to pursue changes and are more creative. Conscientiousness describes an individual's way of controlling and regulating their impulses and shows the qualities of being responsible, prudent, reliable, and organized. Extroversion describes an individual's ability to socialize and express their emotions confidently and boldly. Agreeableness describes an individual's attitude towards other people: those with high agreeableness value interpersonal harmony more, are closer and friendlier to people, and trust others easily. Neuroticism reflects an individual's process of regulating emotions and emotional instability, and those with high scores on this dimension have more anxious and depressed moods [34].

In 2008, Devaraj et al. [44] first combined the Big Five personality model with a model of technology acceptance to explore how personality traits affect willingness to use technology. The results showed a strong correlation between the Big Five personality model and intention to use. Perceived usefulness was negatively correlated with neuroticism and positively correlated with agreeableness, while conscientiousness mediated the relationship between perceived usefulness and intention to use. Since then, scholars have explored the relationship between personality and intention to use. The study of Svendsen et al. [45] indicated that personality traits indirectly affect intention to use through perceived usefulness, and that extroversion is significantly and positively correlated with intention to use.

In addition, personality can also be used to predict the intention to use autonomous vehicles. A study by Neil et al. [14] found that people with higher levels of conscientiousness were less eager to adopt autonomous vehicles, but that conscientiousness moderated the relationship between subjective norms and the intention to use the technology, and that neuroticism was negatively correlated with the perceived usefulness of the new technology. Based on the definition of the Big Five personality traits and the findings of related research, the following hypotheses are proposed in this study:

H5a. *Openness have a significant positive effect on the public's intention to use SAVs;*

H5b. *Conscientiousness have a significant negative effect on the public's intention to use SAVs;*

H5c. *Extroversion have a significant positive effect on the public's intention to use SAVs;*

H5d. *Agreeableness have a significant positive effect on the public's intention to use SAVs;*

H5e. *Neuroticism have a significant negative effect on the public's intention to use SAVs.*

H6a. *Openness have a significant positive effect on the public's perceived usefulness;*

H6b. *Conscientiousness have a significant negative effect on the public's perceived usefulness;*

H6c. *Extroversion have a significant positive effect on the public's perceived usefulness;*

H6d. *Agreeableness have a significant positive effect on the public's perceived usefulness;*

H6e. *Neuroticism have a significant negative effect on the public's perceived usefulness.*

H7a. *Openness have a significant positive effect on the public's trust;*

H7b. *Conscientiousness have a significant negative effect on the public's trust;*

H7c. *Extroversion have a significant positive effect on the public's trust;*

- H7d.** *Agreeableness have a significant positive effect on the public's trust;*
- H7e.** *Neuroticism have a significant negative effect on the public's trust.*
- H8a.** *Openness have a significant positive effect on the public's social influence;*
- H8b.** *Conscientiousness have a significant negative effect on the public's social influence;*
- H8c.** *Extroversion have a significant positive effect on the public's social influence;*
- H8d.** *Agreeableness have a significant positive effect on the public's social influence;*
- H8e.** *Neuroticism have a significant negative effect on the public's social influence.*
- H9a.** *Openness have a significant negative effect on the public's perceived risk;*
- H9b.** *Conscientiousness have a significant positive effect on the public's perceived risk;*
- H9c.** *Extraversion have a significant negative effect on the public's perceived risk;*
- H9d.** *Agreeableness have a significant negative effect on the public's perceived risk;*
- H9e.** *Neuroticism have a significant positive effect on public's perceived risk.*

3.3. Questionnaire

The questionnaire used in this study consisted of four parts: an introduction to shared autonomous vehicles, respondents' personal attributes (including age, gender, education, and driving experience), a Big Five personality scale, and an SAV use intention scale.

A simplified Big Five personality scale was used in this study. The original Big Five personality scale has 44 items and with the advancement of time. Too many questions will reduce the respondent's concentration, thus reducing the authenticity of the obtained data. And, as researchers are also faced with limited time for assessment, personality questionnaires are trending toward being shorter and shorter. Thus, Rammstedt et al. [46] shortened the Big Five personality scale to 10 items. The overall relevance, reliability, and construct validity of the new scale were tested, which proved the feasibility of the 10-item Big Five personality scale. The investigation of Carciofo et al. [47] proved that the Chinese version of the Big Five personality scale had good convergent validity and effectiveness. So, this version of the Big Five personality scale was chosen for the investigation of this study.

The question items covered in this paper are from well-established scales that have been validated in research. Among them, social influence was referred to the scales developed by Jung et al. [48] and Zhang et al. [13], trust was measured using the scales designed by Zhang et al. [49] and Peng et al. [37], perceived usefulness was measured using the questions designed by Bansal et al. [39] and Xiaowei et al. [42], and perceived risk and intention to use SAVs were measured using the scale developed by Xiaowei et al. [42] (see Appendix A for detailed question pieces). The psychological latent variable question items were on a five-point Likert scale (from 1 "Strongly Disagree" to 5 "Strongly Agree").

The formal survey was distributed from 17 January 2023, to 30 January 2023, and the formal survey was mainly conducted online using Questionnaire Star, with a total of 1080 questionnaires distributed. Before the survey began, the investigators informed the respondents of the purpose of this study and obtained their consent. We cannot obtain the personal identity information of the participants during or after the investigation.

After excluding the invalid questionnaires with contradictory answers and answers that were all in agreement with the options, 988 questionnaires were finally obtained, and the validity rate of the questionnaires was 91.48%. The demographic characteristics of the respondents are shown in Table 2.

Table 2. Descriptive statistical analysis of the sample.

Demographic Variable	Value Set	Frequency	Proportion (%)
Gender	Male	576	58.30%
	Female	412	41.70%
Age	18–25	102	10.32%
	26–30	359	36.34%
	31–40	352	35.63%
	41–50	78	7.89%
	51–60	67	6.78%
	Over 60	30	3.04%
Education level	Below associate degree	106	10.73%
	Associate degree	212	21.46%
	Bachelor’s degree	558	56.48%
	Postgraduate degree	88	8.91%
	Doctoral degree	24	2.43%
Actual driving experience	No driving experience	70	7.09%
	Less than 2 years	212	21.46%
	2–5 years	250	25.30%
	5–10 years	349	35.32%
	More than 10 years	107	10.83%

In the questionnaire sample of this survey, males accounted for 58.30% of the respondents, and females accounted for 41.70%, the number of males was slightly higher than the number of females, and the overall gender distribution was relatively even. 46.67% of the respondents were under 30 years old, and 53.33% of the respondents were over 30 years old. In terms of the education of the respondents, 32.19% of the respondents had less than a bachelor’s degree, and 67.81% had a bachelor’s degree or above. Overall, the respondent group had a high level of education and a certain degree of cognitive ability in SAVs. Respondents with less than 10 years of driving experience were more numerous, accounting for about 90% of the total number of respondents. Detailed results are in Supplementary Dataset S1.

4. Results

4.1. Analysis of Structural Equation Modeling

Structural equation modeling (SEM) is an effective method that enables the study of relationships between variables that are difficult to observe directly. It includes measurement modeling and structural modeling, which can test the relationship between observed variables and latent variables, and latent variables and latent variables, respectively.

In this paper, in order to explore the factors and underlying patterns that influence consumers’ intention to use SAVs, none of the psychological latent variables involved can be directly measured. At this time, SEM is very suitable for testing the relationship between the influencing factors and the intention to use SAVs.

The parameter estimation of SEM is commonly used by maximum likelihood estimation (ML) and partial least squares (PLS). The PLS-SEM parameter estimation results are more stable, which can solve the problems of measurement error and non-normality of variables and improve the empirical capability of the model. So, this study chose using SmartPLS 3.0 for the PLS-based parameter estimation.

4.1.1. Model Testing

Model testing usually involves assessing the internal consistency and reliability, convergent validity, and discriminant validity of the model. Table 3 shows that the alpha values of all latent variables were greater than 0.7, which were all acceptable, indicating that the internal consistency of the sample data was good, and the data were relatively authentic and reliable. The factor loadings of all factors were greater than 0.8, which means that the selected research variables were reasonable. The CR values of all latent variables were greater than 0.8 and the AVE values were greater than 0.7, which proved that the factors were more interpretable with each other; the measurement error was within a reasonable range; and the convergence was excellent. The evaluation of discriminant validity is shown in Table 4, and all AVE square roots were greater than other structural correlation coefficients, which can reflect a good discriminant validity. Overall, the valid sample data was suitable for further research with model fitting.

Table 3. The results of statistical analysis and confirmatory factor analysis.

Constructs	Item	Mean	SD	FL	α	CR	AVE
Social influence (SI)	SI1	3.55	1.17	0.831	0.86	0.905	0.704
	SI2	3.72	1.144	0.845			
	SI3	3.66	1.151	0.838			
	SI4	3.63	1.143	0.844			
Trust (TT)	TT1	3.39	1.157	0.829	0.861	0.905	0.705
	TT2	3.6	1.17	0.854			
	TT3	3.53	1.183	0.848			
	TT4	3.5	1.167	0.828			
Perceived usefulness (PU)	PU1	3.51	1.128	0.831	0.872	0.913	0.723
	PU2	3.68	1.133	0.847			
	PU3	3.63	1.127	0.862			
	PU4	3.63	1.14	0.861			
Perceived risk (PR)	PR1	2.46	1.166	0.846	0.873	0.913	0.725
	PR2	2.29	1.186	0.851			
	PR3	2.34	1.188	0.862			
	PR4	2.4	1.16	0.846			
Intention to use (IU)	SY1	3.51	1.161	0.825	0.812	0.888	0.726
	SY2	3.69	1.148	0.877			
	SY3	3.59	1.151	0.853			
Extraversion (E)	E1	3.64	1.151	0.87	0.713	0.874	0.777
	E2	3.76	1.158	0.893			
Agreeableness (A)	A1	3.82	1.142	0.904	0.766	0.895	0.811
	A2	3.72	1.142	0.897			
Conscientiousness (C)	C1	3.81	1.135	0.873	0.719	0.877	0.781
	C2	3.77	1.138	0.894			
Openness (O)	O1	3.86	1.146	0.875	0.717	0.876	0.779
	O2	3.76	1.148	0.891			
Neuroticism (N)	N1	2.3	1.136	0.886	0.728	0.88	0.786
	N2	2.25	1.172	0.887			

SD = standard deviation; FL = factor loading; α = Cronbach's alpha; CR = composite reliability; AVE = average variance extracted.

Table 4. Results of discriminant validity test.

	SI	TT	PU	PR	IU	E	A	C	O	N
SI	0.839									
TT	0.405	0.84								
PU	0.377	0.376	0.85							
PR	−0.445	−0.42	−0.421	0.851						
IU	0.435	0.407	0.429	−0.463	0.852					
E	0.391	0.35	0.346	−0.459	0.402	0.881				
A	0.385	0.366	0.358	−0.455	0.41	0.753	0.9			
C	0.348	0.351	0.341	−0.432	0.406	0.733	0.736	0.883		
O	0.391	0.377	0.378	−0.473	0.411	0.74	0.729	0.726	0.883	
N	−0.366	−0.327	−0.318	0.441	−0.38	−0.732	−0.725	−0.722	−0.731	0.887

SI = social influence; TT = trust; PU = perceived usefulness; PR = perceived risk; IU = intention to use; E = extraversion; A = agreeableness; C = conscientiousness; O = openness; N = neuroticism.

4.1.2. Path Analysis

Based on the path coefficients and T-values, it can be determined whether the assumptions about the latent variables in the test model are valid (see Table 5 and Figure 3). As shown in Table 5, the effects of each psychological latent variable on intention to use and the interactions between the variables were highly significant. As for the effects of personality, only conscientiousness significantly and negatively affected intention to use; extraversion, agreeableness, and openness had a significant positive effect on social influence; agreeableness and openness had a significant positive effect on trust; openness had a significant negative effect on perceived risk and a significant positive effect on perceived usefulness; and neuroticism did not have a significant effect on any of the variables. The results of the hypothesis testing in Table 5 are presented in Figure 4, and all paths shown in the figure are those for which the hypotheses are valid.

Table 5. Results of hypothesis testing.

Hypotheses	Path	Path Coefficients	T-Values (T)	Supported?
H1a	PR→IU	−0.172 ***	4.968	Yes
H2a	SI→IU	0.167 ***	5.288	Yes
H2b	SI→PR	−0.221 ***	6.688	Yes
H2c	SI→PU	0.254 ***	8.618	Yes
H3a	TT→IU	0.132 ***	4.541	Yes
H3b	TT→PR	−0.195 ***	6.237	Yes
H4a	PU→IU	0.176 ***	6.152	Yes
H4b	PU→TT	0.254 ***	7.9	Yes
H4a	Openness→IU	0.022	0.471	No
H4b	Conscientiousness→IU	−0.093 *	2.004	Yes
H4c	Extraversion→IU	0.024	0.49	No
H4d	Agreeableness→IU	0.049	1.046	Yes
H4e	Neuroticism→IU	−0.008	0.179	No
H5a	Openness →PU	0.165 **	3.263	Yes
H5b	Conscientiousness→PU	−0.067	1.419	No
H5c	Extraversion→PU	0.03	0.554	No

Table 5. Cont.

Hypotheses	Path	Path Coefficients	T-Values (T)	Supported?
H5d	Agreeableness→PU	0.091	1.643	No
H5e	Neuroticism→PU	0.032	0.638	No
H6a	Openness→TT	0.127 *	2.412	Yes
H6b	Conscientiousness→TT	−0.063	1.261	No
H6c	Extraversion→TT	0.046	0.9	No
H6d	Agreeableness→TT	0.1 *	2.105	Yes
H6e	Neuroticism→TT	−0.001	0.019	No
H7a	Openness→SI	0.151 **	2.796	Yes
H7b	Conscientiousness→SI	0.005	0.088	No
H7c	Extraversion→SI	0.14 **	2.65	Yes
H7d	Agreeableness→SI	0.126 *	2.548	Yes
H7e	Neuroticism→SI	−0.064	1.23	No
H8a	Openness→PR	−0.125 *	2.619	Yes
H8b	Conscientiousness→PR	0.035	0.76	No
H8c	Extraversion→PR	−0.084	1.763	No
H8d	Agreeableness→PR	−0.068	1.517	No
H8e	Neuroticism→PR	0.069	1.485	No

SI = social influence; TT = trust; PU = perceived usefulness; PR = perceived risk; IU = intention to use. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

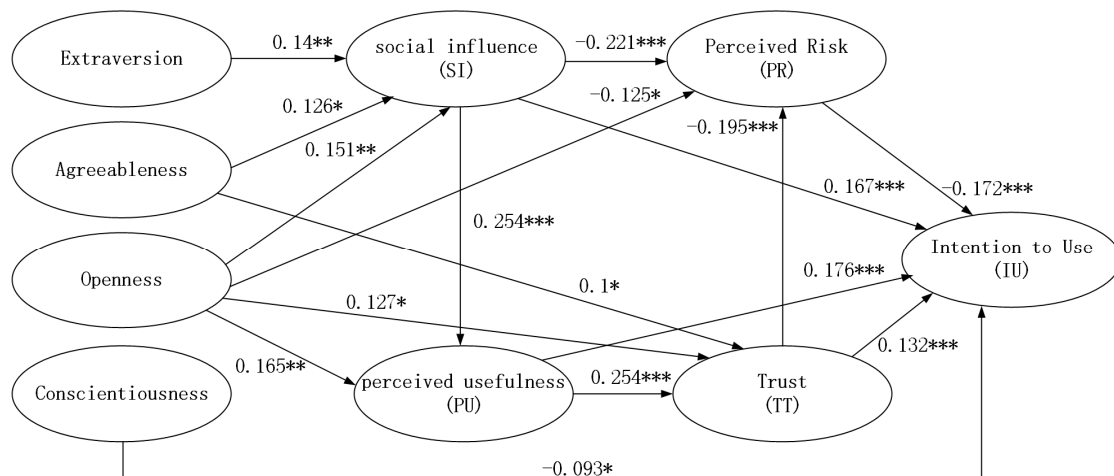


Figure 3. Results of the path test of the public's intention to use shared autonomous vehicles. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

4.2. Bayesian Network Analysis

The modeling approach of SEM is based on theoretical knowledge. The relationship between multiple variables is assessed through causality, with information from the observed data. However, SEM analysis may reduce the accuracy of the prediction results if there is a nonlinear relationship between the independent and dependent variables. Thus, this study uses a Bayesian network (BN), which is capable of handling nonlinear relationships, for the analysis. The BN can also calculate the magnitude of the probability of changes in other variables that follow when the target variable is affected. This enables the effective identification of important determinants of the public's intention to use SAVs,

thus providing reliable evidence of inferential knowledge for SEM when dealing with uncertain relationships.

The results of the SEM analysis in Section 4.1 revealed the key variables that affect people's intention to use SAVs, and this section, using a BN, shows how these factors shape individual behavioral intentions by graphically explaining the causal relationships between the variables.

4.2.1. Theoretical Foundations of Bayesian Networks

The BN is a graphical model that expresses the correlation of probabilities between variables [50]. Nodes represent latent variables and directed edges represent dependencies between nodes.

The BN consists of a network structure S and network parameters P , where the network structure represents the qualitative description and the network parameters represent the quantitative description, which can be expressed as follows:

$$BN = (S, P) \quad (1)$$

The network structure S is a directed acyclic graph, consisting of a set of node variables $V (V = \{V_1, V_2, \dots, V_n\})$ and a set of directed edges $L (L = \{V_i V_j | V_i, V_j \in V\})$, which can be represented as follows:

$$S = (V, L) \quad (2)$$

The network parameter P is the probability of the magnitude of the correlation between the different node variables, responding to the conditional probability relationship between the corresponding parent nodes of each node:

$$P = \{P(V_i | V_1, V_2, \dots, V_{i-1}), V_i \in V\} \quad (3)$$

Further, a Bayesian network may be represented as follows:

$$BN = (S, P) = (V, L, P) \quad (4)$$

Denoting with V_{pi} the set of parent nodes of the variable V_i , the joint distribution of the node values can be written as the product of the local distribution of each node with its parent node, and the joint probability distribution of Z is denoted as follows:

$$P(V) = P(V_1, V_2, \dots, V_n) = \prod_{i=1}^n P(V_i | V_{pi}) \quad (5)$$

4.2.2. Model Construction and Validation

Structure learning and parameter learning are the two most important steps in developing a BN [51]. In this study, a Bayesian topology was used to construct the network based on structures that have been tested by structural equation modeling. Before parameter learning, all variables need to be discretized into relevant number of classes. SmartPLS 3.0 derived the scores of each latent variable corresponding to PLS-SEM, performed K-means clustering, and discretized them into three states: "Low", "Medium", and "High". Since the network nodes constructed in this study were latent variables, the expectation maximization (EM) method was used to calculate the conditional probabilities.

Figure 4 shows the BN model after learning with Netica parameters, and the results show that the probability of "high" intention to use in the surveyed samples was about 42.2%, and the probability of "medium" intention to use was about 30.8%. Among the psychological latent variables that had a significant effect on willingness to use, social influence had the highest probability of being at a high level in the sample data, at 44.8%; high perceived usefulness, at 29.7%; high trust, at 34.2%; and high perceived risk, at 34.5%. Responsible personality, which had a negative and significant effect on intention to use, had the highest probability of being at the "medium" level in the sample data, at 59.6%.

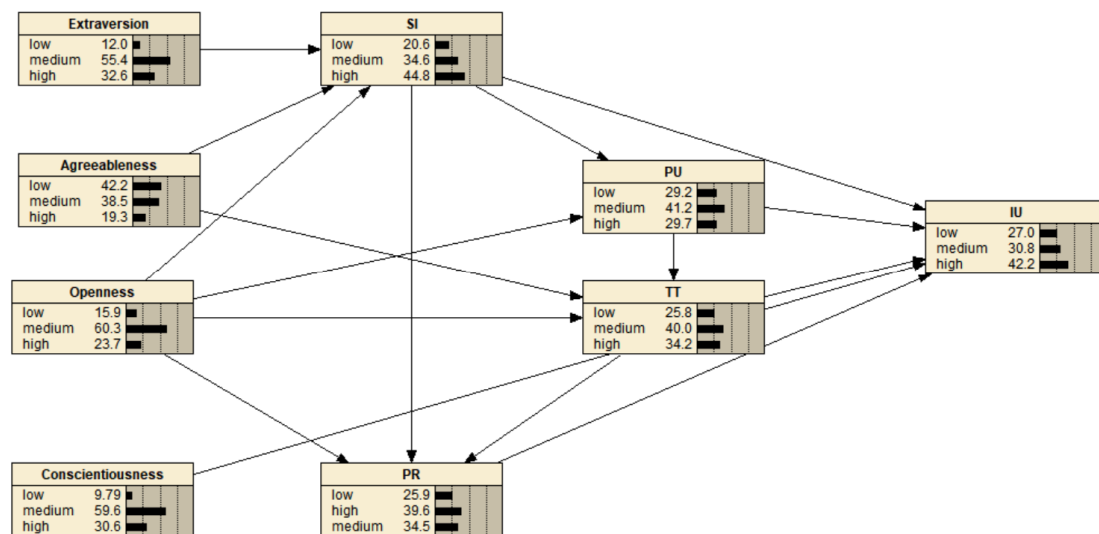


Figure 4. Bayesian network model after parameter learning. SI = social influence; PR = perceived risk; PU = perceived usefulness; TT = trust; IU = intention to use.

After determining the structure of the BN model, calculations were made to assess the robustness of the model based on the original dataset. In this study, the accuracy of the constructed model used to predict the public's intention to use shared autonomous vehicles was validated by the error rate. In this study, 70% of the survey data was randomly selected as a training set and the remaining 30% of the sample was used as a test set to assess the model performance. The overall prediction of the intention to use node reached 93.56% correctly, and it can be concluded that the BN model constructed in this study had a good prediction ability for exploring the public's intention to use SAVs.

4.2.3. Results of Bayesian Network Analysis

The BN quantifies and predicts influences through inference and diagnosis, mainly by estimating the probability of behavioral intentions based on changes in the state probabilities of each variable. Figure 5 presents the Bayesian inference of the public's intention to use SAVs. When the three states of social influence, trust, and perceived usefulness changed, the intention to use in the high state showed an upward trend. When the state of perceived usefulness changed from "low" to "high", the probability of a high level of intention to use increased the most, from 28.9% to 55.6%, an increase of 26.7%, indicating that perceived usefulness had the most significant effect on the intention to use. In addition, the probability of a high level of intention to use showed an increasing and then decreasing trend when the three states of perceived risk and conscientiousness personality were changed.

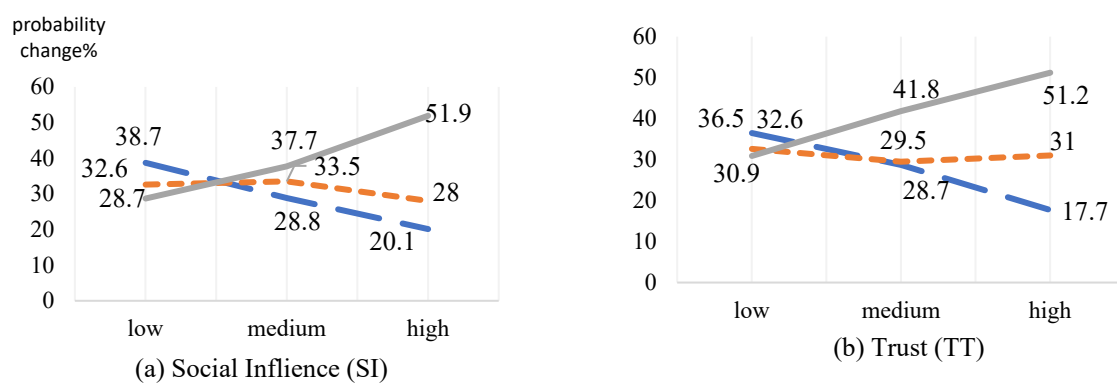


Figure 5. Cont.

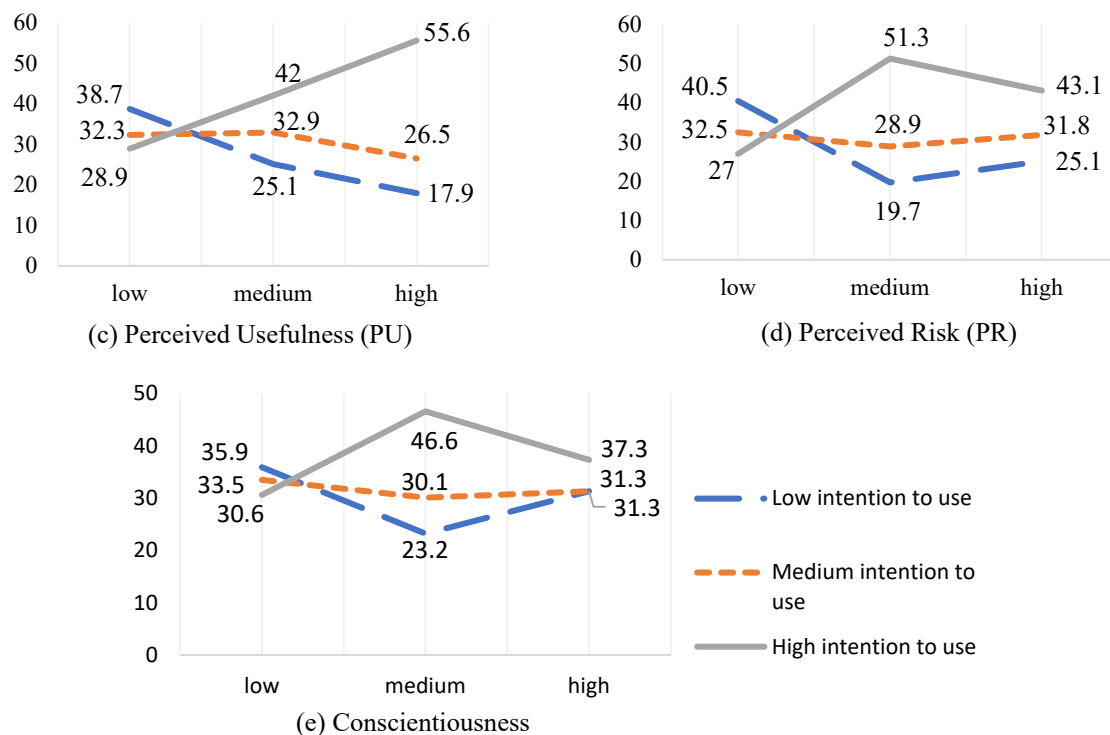


Figure 5. Results of forward reasoning for intention to use.

Table 6 shows the new conditional probabilities of the variables in the “low”, “medium”, and “high” states when the intention to use was high. It can be seen that the high state of social influence and trust had the largest increase in probability compared to the pre-diagnostic state, from 44.8% to 55.1% and 34.2% to 41.5%, respectively. In contrast, none of the changes in personality were significant.

Table 6. Bayesian inference of high behavioral intentions for public intention to use SAVs.

High Intention to Use	Social Influence		Trust		Perceived Usefulness		Perceived Risk		Extraversion		Agreeableness		Openness		Conscientiousness	
	PCP	NCP	PCP	NCP	PCP	NCP	PCP	NCP	PCP	NCP	PCP	NCP	PCP	NCP	PCP	NCP
Low	20.6	14	25.8	18.8	29.2	20	25.9	16.5	12	10.9	42.2	41.2	15.9	12.1	9.79	7.1
Medium	34.6	30.9	40	39.6	41.2	40.9	39.6	48.2	55.4	57.6	38.5	41.1	60.3	66.7	59.6	65.9
High	44.8	55.1	34.2	41.5	34.2	39	34.5	35.2	32.6	32	19.3	17.6	23.7	21.3	30.6	27

PCP = prior conditional probability; NCP = new conditional probability.

Based on the results of the BN’s reasoning and diagnosis, in order to explore measures to better enhance the public’s intention to use SAVs, this study assumed the following two scenarios:

Scenario 1: Suppose that the media vigorously conducts the official popularization of science about SAVs and the benefits that SAVs bring to everyone, and the government enacts relevant policies at the same time. This may lead to a rise in the public’s perceived usefulness and social impact of SAVs (i.e., a high state of perceived usefulness and social impact). As shown in Figure 6, the results of the BN analysis at this point show that the public’s high intention to use SAVs rose from 42.2% to 60.6%.

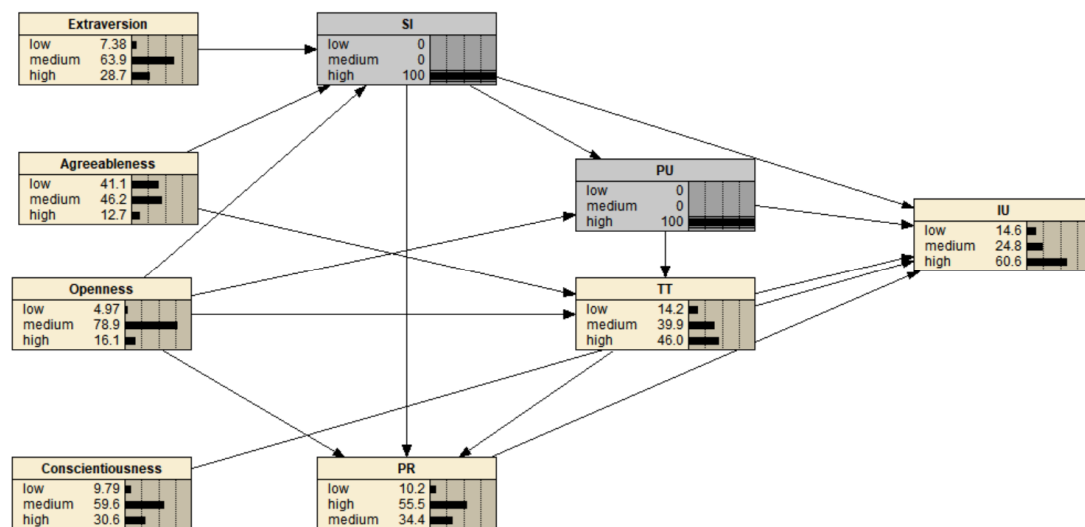


Figure 6. Scenario 1: Impact of increased positive publicity about SAVs on intention to use. SI = social influence; PR = perceived risk; PU = perceived usefulness; TT = trust; IU = intention to use.

Scenario 2: If the security of SAVs is not improved, it may lead to a decrease in public trust and an increase in perceived risk (i.e., low status of trusted nodes and high status of perceived risk nodes). As shown in Figure 7, the results of the BN analysis show that in this scenario, the public's high intention to use SAVs decreases from 42.2% to 30.4%.

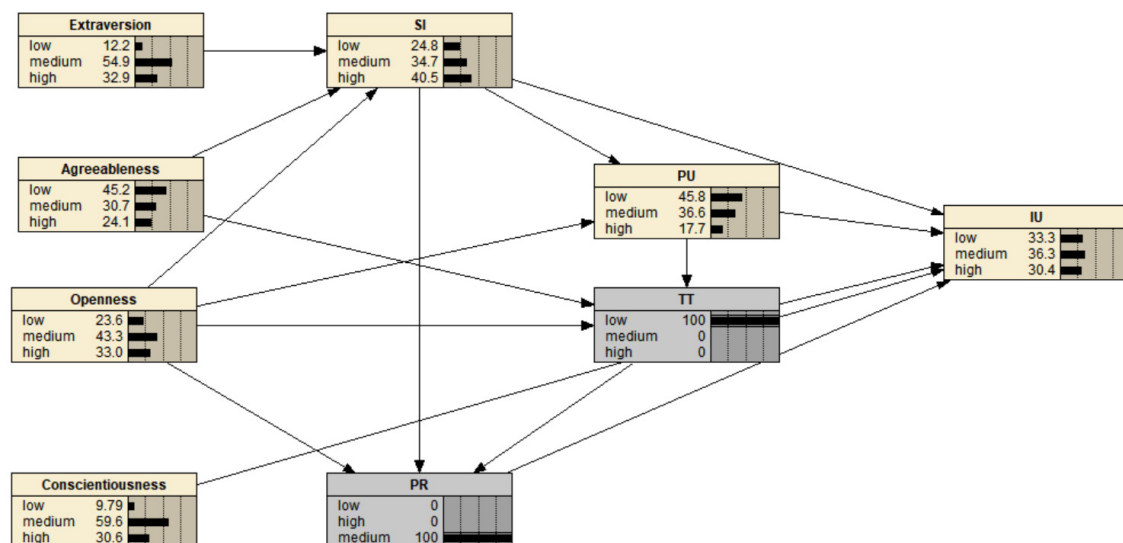


Figure 7. Scenario 2: The effect of no change in SAVs safety on intention to use. SI = social influence; PR = perceived risk; PU = perceived usefulness; TT = trust; IU = intention to use.

4.3. Discussion

This research aimed to survey the mechanisms influencing the Chinese public's intention to use SAVs to increase their trust and acceptance of SAVs. This section discusses our main findings and suggests appropriate countermeasures based on the analysis.

4.3.1. Analysis of Findings

A total of 988 valid questionnaires were obtained in this study through an empirical survey. The questionnaires and data used in this study were tested and proved to be credible and valid. Based on this, the PLS-SEM model was established, which was significantly valid, and finally, a Bayesian network with latent variables as the core was established. Combining SEM with a BN to identify key variables and quantify the degree of influence,

provides a reference for the future development of policy measures to promote the use of shared autonomous vehicles. The conclusions of the main factors influencing people's intention to use SAVs are as follows:

(1) Feature word extraction from the collected online review data found that public concerns about SAVs can be collapsed into four feature variables: social impact, trust, perceived usefulness, and perceived risk. The results of sentiment analysis found that the current public attitude towards the product is on the negative side.

(2) The results analyzed by the PLS-SEM model found that social influence, perceived usefulness, and trust significantly and positively affect the intention to use, and perceived risk significantly and negatively affects the intention to use.

Social influence has a significant positive effect on perceived usefulness, perceived usefulness has a significant positive effect on trust, and social influence and trust have a significant negative effect on perceived risk. Consistent with the findings of Zhang et al. [13], who explored the factors affecting the public's intention to use AVs, the greater the positive influence of perceived usefulness and social influence on the intention to use, the greater the intention of people to use SAVs; Jing et al. [52] found that perceived risk significantly negatively influences an individual's intention to use SAVs; Hang's [23] study found that social influence had a significant positive effect on perceived usefulness; Peng et al. [33] found that trust in the elderly had a significant positive effect on AVs acceptance and trust had a significant negative effect on perceived risk. These findings are consistent with the findings of this paper.

In addition, this study found that conscientiousness personality significantly negatively affects intention to use, and extraversion, agreeableness, and openness indirectly affect intention to use. Extraversion, agreeableness, and openness had significant positive effects on social influence, and openness also had significant positive effects on perceived usefulness and trust, and significant negative effects on perceived risk. Consistent with the findings of Neil et al. [14], people with more conscientious personalities are more conformist and less eager to use SAVs. Inconsistently, the present study found that neurotic personality had no significant effect on intention to use.

(3) From the analysis of the BN model, it is found that the probability of the public's intention to use in a high state is about 42.2% from the learning of the BN parameters. When social influence, trust, perceived usefulness, perceived risk, and conscientiousness are switched from "low" to "high" status, the change in the status of the perceived usefulness node has the greatest impact on intention to use compared to other variables. When perceived usefulness switched from "low" to "high", the growth rate of intention to use in the high state reached 26.7%. The BN diagnosis revealed that the probability of social influence and trust increased the most in the high state, and the change in personality was not significant. Hypothesizing two scenarios about SAVs found that more media publicity about the benefits of SAVs and the introduction of government policies would significantly increase the public's willingness to use SAVs. However, if the safety of SAVs is not improved, the public's intention to use SAVs will decrease significantly.

4.3.2. Recommendations

(1) Based on the above research findings, the following recommendations are proposed: Shape the relative advantages of SAVs to improve the public's perceived usefulness. Currently, both online comments and questionnaire data showed that public attitudes towards SAVs are relatively negative. As in Hypothetical Scenario 1 in Section 4.2.3, if the media vigorously carries out the official popularization of science about SAVs, and the government enacts relevant policies at the same time, the public's perceived usefulness and social impact of SAVs rises, and the intention to use them consequently rises. Therefore, the following are important: enhance publicity on the role of SAVs, such as reducing road congestion and traffic accidents and promoting sustainable social development, to increase public perception of the positive influence of SAVs on society; maintain early users and

stimulate more potential users to use SAVs; and improve relevant laws and regulations to reduce users' concerns.

(2) Integrate multiple communication channels to promote scientific and effective publicity of SAVs: There are some problems with the current media reports, and one-sided accident reports can easily trigger public panic. For example, before the matter is clarified, some media use the title "autonomous vehicles traffic accidents" to attract public attention, which strengthens the public's negative perception of autonomous driving technology. In this regard, various media channels should be integrated and reported objectively. To create a branding effect, when promoting SAVs, include officially certified content, as well as statements from ordinary people who have experienced them, to increase users' trust and sense of immersion. The government should also be responsible for verifying relevant information and formulating relevant policies to guide the positive dissemination of this product.

(3) Focus on improving the security of the technology to build public trust in SAVs. As in Hypothetical Scenario 2 in Section 4.3.2, if the security of SAVs is not upgraded, it leads to a decline in public trust and a rise in perceived risk, reducing the public's intention to use it. Therefore, SAVs developers should continue to enhance the research on the security performance of SAVs and explore more application experience scenarios. More pilot projects can be promoted in the future, and people can be invited to visit SAVs to reduce their worries when using SAVs. Secondly, streamline the process for users to take SAVs and encourage the public to form the habit of intelligent traveling.

5. Conclusions

SAVs are a great driving force for the future development of the automotive industry with the potential to bring several benefits to the country and society. Studying the public's perception and intention to use SAVs before launch will help the product to develop better.

This study focused on analyzing the current public's intention to use SAVs, i.e., how the public's psychological factors and personality traits affect their intention to use. Based on online review data, research latent variables were identified to model the public's intention to use SAVs. An empirical survey was conducted to analyze the key factors and mechanisms affecting the public's intention to use SAVs in combination with the SEM and BN models.

Qualitative analyses showed that social influence, trust, perceived usefulness, and perceived risk are the factors that the public really cares about; quantitative analyses showed that social influence, trust, and perceived usefulness significantly and positively affect the intention to use; and perceived risk and conscientious personality significantly and negatively affect the intention to use.

Overall, these findings can help R&D organizations to design products that better meet users' needs, help social media to promote SAVs to consumers' personalities, and provide a reference for future governmental supportive policies on SAVs to promote the further development of SAVs. The theoretical and practical implications of this study are presented below.

5.1. Theoretical Significance

In the context of the gradual commercialization of SAVs, people's intention to use them and the factors influencing them are undoubtedly hot topics today. However, relevant research in China started later than in Western countries such as Europe and the United States. In this paper, a questionnaire was designed based on online review data, which is more authentic and reliable. The reliability test of the obtained questionnaire met the requirements, which indicates that the questionnaire designed in this study is reasonable, and this questionnaire can provide a reference for the subsequent research on the public's intention to use SAVs.

Also, this study validated the past research results in a new research context and further explored the influence of personality traits on the intention to use SAVs. Taking

the “Big Five personality” as a new research perspective, this study analyzed its influence on the intention to use SAVs in depth, enriched the explanation of the mechanism of the influence of personality traits on human behaviors, provided a research basis for a comprehensive understanding of the public’s intention to use SAVs, and opened up new ideas for subsequent research.

Second, the quantitative methods of past theoretical models have some shortcomings; they fail to truly reflect the public’s concerns about shared autonomous vehicles. This paper combined quantitative and qualitative analyses to overcome the subjective judgment of the questionnaire designer and obtain more realistic findings, providing researchers with more comprehensive insights into public perceptions of SAVs.

In addition, SEM analyses are often used in traditional research on intention to use when exploring the interactions between variables, but it is difficult to quantify the degree of influence of the independent variables on intention to use. This study combined SEM with BN to achieve an in-depth exploration of the degree of influence of latent variables on intention to use and to further predict the trend of intention to use with latent variables. In this study, the latent variable scores were processed to achieve a consistent causal relationship in PLS-SEM and BN to achieve a better combination and obtain more accurate analysis results. Moreover, this study understood consumers’ perceptions of SAVs and made scenario assumptions before the commercialization of SAVs, which provides theoretical support for the development and promotion of SAVs in the future. Future research may explore the factors that influence consumers’ use of SAVs after the commercialization of SAVs to investigate the changes in consumer intention to use SAVs before and after commercialization.

5.2. Practical Implications

SAVs, as an emerging product, can bring great opportunities to the country and society. The development of SAVs is closely related to the public’s intention to use them. Therefore, exploring the public’s intention to use the product is very important for commercializing SAVs to a certain extent. In this paper, a qualitative and quantitative study was conducted based on the public’s online comments on SAVs to better understand the public’s real concerns about SAVs. This will help relevant R&D organizations to design products in a targeted manner, which will be an important guide for the future development of SAVs.

This research is an advanced study before the full promotion of shared autonomous vehicles. When SAVs are commercialized in the future, consumers will be faced with the choice of using them or not, and if we find measures to increase the public’s use of SAVs ahead of time, we can reduce the cost of future rollout. Similar to new energy vehicles, the field also conducted a lot of research on the public’s willingness to use them before they were available, which is one of the reasons why they have gained popularity from the moment they were commercialized. Therefore, this study has certain practical significance.

Finally, by analyzing the influence of different personality traits on the willingness to use SAVs, it helps automobile manufacturers to understand the psychological needs of users and give more personalized promotion and services according to individual personality trait difference, as well as enhance the user experience, and on this basis, explore the marketing strategy and management strategy to promote SAVs in order to achieve their commercialization.

5.3. Research Limitations and Prospects

There are still some limitations in this study that can provide directions for future research, and the outlook of this study is as follows:

(1) Although the survey method of mining online review data and questionnaires ensures the authenticity of the acquired data to a large extent, the analysis still does not guarantee that the themes and variables are perfectly matched. Future studies could explore better methods to combine qualitative and quantitative research.

(2) This study combined PLS-SEM with the BN model to deeply explore the reasons affecting the public's intention to use SAVs. However, this analysis is limited to the psychological level, and in the future, the public's psychology can be combined with their behaviors to analyze how the intention to use specifically affects their actual use behaviors.

(3) The source of data collection can be more comprehensive. The vast majority of the surveyed population had no experience in using SAVs. In the future, people who have used SAVs can be interviewed, and the influencing factors obtained will be more realistic. Survey forms such as face-to-face interviews and semi-structured in-depth interviews can also be combined to follow up on the public's intention to use them. Moreover, the online comment data used in this paper mainly come from the TikTok platform, but there are also related discussions on other platforms; the comments collected in this study are not comprehensive enough, and public comment data can be collected from more platforms in the future. Finally, the respondents in this study were younger and more educated. In the future, the questionnaire collection method can be improved to expand the scope of the study and collect more effective data.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su16114462/s1>, Dataset S1. Questionnaire data from respondents.

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Appendix A. Items of Measurement Scales

Constructs	Items	Contents
Personality	Openness	O1 I have a very fertile imagination.
		O2 I'm a person who's not very interested in art.
	Conscientiousness	C1 I'm a thoughtful person.
		C2 I'm a rather lazy person.
	Extraversion	E1 I am a more introverted person.
		E2 I am an outgoing and sociable person.
	Agreeableness	A1 I am easily trusting of others.
		A2 I am strict with others.
	Neuroticism	N1 I am an easy-going person who can cope well with external pressures.
		N2 I am an easily anxious person.

Appendix A. Cont.

Constructs	Items	Contents
Social influence (SI)	SI1	Getting information about SAVs by following news media reports affects my attitude towards SAVs.
	SI2	Information about SAVs obtained from friends with relevant experience will affect my attitude towards SAVs.
	SI3	My attitude towards SAVs will be influenced by information about SAVs released by automobile companies.
	SI4	My attitude towards SAVs is influenced by information about SAVs obtained through social media.
Trust (TT)	TT1	I think SAVs are trustworthy.
	TT2	I think SAVs are reliable.
	TT3	I think travelling with SAVs is very safe.
	TT4	Overall, I can trust SAVs.
Perceived usefulness (PU)	PU1	While using SAVs, I will have more time to do other things in the car (e.g., rest, recreation, etc.).
	PU2	SAVs can improve the mobility of people who are unable to drive (e.g., old, sick, drunk, etc.).
	PU3	SAVs can improve the efficiency of my journeys.
	PU4	SAVs can reduce the cost of my journeys.
Perceived risk (PR)	PR1	I am concerned that SAVs will not be able to adapt to complex environments and terrains.
	PR2	I am concerned that SAVs will be more prone to equipment or system failure.
	PR3	I am concerned that SAVs will make it easier to compromise my travelling privacy.
	PR4	I am concerned that irregular operation of SAVs may threaten my personal safety.
Intention to use (IU)	IU1	When the SAVs hit the market, I would choose to use them.
	IU2	I will use SAVs frequently in my future travels when they are available on the market.
	IU3	I would recommend my friends and family to use SAVs.

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