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Effect of autonomous vehicles on car-following behavior of human drivers: Analysis based on structural equation models

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ABSTRACT

Road traffic will experience a transition towards a mixed traffic flow, consisting of both autonomous vehicles (AVs) and human-driving vehicles (HVs), scenarios where HV drivers follow AVs will inevitably arise. This necessitates a comprehensive and in-depth exploration of driver behavior in such contexts, particularly focusing on the changes in their following behavior. To investigate the factors that influence the following behavior of HV drivers when following AVs in a human-machine mixed driving environment. Specifically, this study examines the impact of four variables on following intentions and following distance: driver's understanding of AV performance, safety trust, tolerance for slow driving, and the driver's perception of traffic flow conditions. To this end, a model framework is constructed that captures the relationships among these factors. A total of 376 valid samples were obtained through a survey. After verifying the internal consistency and reliability of the data, a structural equation model was utilized to conduct path analysis and mediation effect analysis to examine the relationships among the influencing factors. The results indicate that safety trust has a significant positive impact on following intentions, while traffic environmental perception has a significant negative impact. Safety trust has a significant negative impact on following distance, while tolerance for slow driving has a significant positive impact. Environmental perception and understanding of vehicle performance only indirectly influence following distance through their effects on safety trust and tolerance for slow driving. Among all factors, safety trust has the greatest impact on both following intentions and following distance. The results of this study can serve as a foundation for analyzing vehicle interactive behavior in human-machine mixed driving environments and as a basis for parameter calibration of car-following models.

1. Introduction

In recent years, many countries and regions around the world have enacted laws and regulations to permit the operation of autonomous vehicles (AVs) on public roads within designated areas. For instance, in February 2021, Germany issued the "Autonomous Driving Act," which allows Level 4 (L4) AVs to operate on public roads within specified areas under the supervision of remote operators [1]. Similarly, in December 2022, Japan passed the "Amendment to the Japanese Road Traffic Management Act," permitting L4 AVs to

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provide transportation services and utilize automated delivery robots starting from April 1, 2023 [2]. In June 2022, Shenzhen in Guangdong Province of China issued the "Regulations on the Management of Intelligent and Connected Vehicles in Shenzhen Special Economic Zone," allowing AVs of L3 level and above to operate on public roads starting from August 1, 2022 [3]. Furthermore, in March 2023, Shanghai Pudong in China issued the "Implementation Rules for the Promotion of Driverless Intelligent and Connected Vehicle Innovation Applications in Pudong New Area, Shanghai," which permits L4 AVs to operate on the roads [4]. In August 2023, the California Public Utilities Commission (CPUC) approved Cruise and Waymo to provide round-the-clock RoboTaxi services in San Francisco [5]. Furthermore, at the World Intelligent Connected Vehicles Conference (WICV 2023) in September 2023, representatives from global automakers and industry organizations jointly released the "Consensus on Promoting the Commercial Application of Global Intelligent Connected Vehicles (Beijing)", which further advanced the legalization and commercialization of AVs on the road [6].

Compared to Human-Driving Vehicles (HVs), the development of AVs has the potential to offer numerous benefits [7], such as alleviating traffic congestion [8], improving traffic flow stability [9], reducing accident rates [10], decreasing parking demand [11], reducing greenhouse gas emissions and minimizing energy consumption [12]. However, these potential benefits can only be fully realized when AVs become widespread and affordable to the public between 2040 and 2060 [13]. The transition from a pure HV traffic system to a pure AV traffic system may take many years, and for a period of time in the future, AVs will have to share the road network with human drivers [14].

Existing research indicates that the coexistence of AVs and HVs will significantly change the following behavior between vehicles [15], and the recognizability of AVs due to their appearance may impact driver behavior [16–18]. To ensure traffic safety in human-machine mixed driving environments, some regions require AVs on the road to be equipped with prominent recognizable signs or devices to provide clear safety cues to other vehicles and pedestrians. For example, the "Directive of the European Parliament and of the Council of 27 November 2019 on the deployment of cooperative intelligent transport systems (C-ITS)" mandates that AVs must indicate their autonomous driving mode [19]. In Shenzhen, Guangdong Province, China, automobile manufacturers are required to equip vehicles with external indicators for autonomous driving mode [3]. In Shanghai Pudong, China, AVs are required to display temporary license plates and vehicle identification signs when on the road [4]. The survey questionnaire in this study was designed based on the recognizability of AVs to investigate the behavioral intentions of respondents when following AVs.

In addition to the recognizability of AVs, a driver's own characteristics (Sociodemographic, physiological, and psychological) can also lead to variations in their following behavior toward AVs [20]. However, these changes in following behavior can have a negative impact on traffic safety and increase the severity and frequency of traffic accidents [21,22]. To ensure the safety of drivers and promote effective coordination between AVs and HVs, it is necessary to study the factors influencing driver behavior when following AVs in human-machine mixed driving environments, as well as the relationships between these factors. This research is significantly important for future studies on human-machine mixed driving traffic flow.

The main contributions of this study are as follows:

(1) A survey questionnaire was developed to investigate the behavioral intentions of HV drivers when following AVs, considering factors such as driver's understanding of AV performance, safety trust, tolerance for slow driving, and perception of traffic environment.
(2) A structural equation model was constructed based on the survey questionnaire to analyze the factors influencing driver behavior when following AVs and quantitatively assess their impact on following behavior.
(3) The study identified the degree of influence of each factor on following behavior: Safety trust is the most significant factor affecting both following intentions and following distance. Tolerance for slow driving has a significant direct impact on following distance. Perception of traffic environment and understanding of AV performance indirectly affect following distance through their effects on safety trust and tolerance for slow driving.

This research paper is organized into five sections. Section 1 introduces the research topic, outlines the research objectives, highlights the contributions of the study, and presents the structure of the paper. Section 2 provides a comprehensive review of the relevant literature. Section 3 formulates hypotheses and presents the model framework. Section 4 details the methodology employed in the study, including the design of the questionnaire and the data collection process. Section 5 presents a thorough analysis of the research results. Finally, Section 6 concludes the paper and discusses prospects for research in this area.

2. Literature review

Scholars both domestically and internationally have employed a variety of methods, including simulation experiments, field experiments, and real-world datasets, to study variations in driving behavior. The primary focus of these studies is on examining changes in safety gaps (following distance and time headway), time to collision (TTC), vehicle speed, acceleration, and deceleration fluctuations of HVs when encountering AVs.

Several domestic and foreign scholars have utilized simulation experiments to investigate changes in the following behavior of HVs when encountering AVs in different traffic environments, such as the presence of AVs, AV platoons, and AV dedicated lanes. For example, De Zwart et al. [15] found that when AVs were present, drivers adopted smaller safety gaps and exhibited larger acceleration when passing through traffic signals. Reddy et al. [18] investigated the influence of two types of AV driving modes (aggressive and conservative) on the acceptable gaps for HVs to follow. Their results showed that in a traffic environment with identifiable aggressive AVs, HVs exhibited significantly larger acceptable gaps compared to a traffic environment with identifiable conservative AVs. Gouy et al. [23] studied variations in time headway of following vehicles under three conditions: following an AV platoon with small time headway, following an AV platoon with large time headway, and not following any platoon. They found that drivers reduced their time headway when driving alongside an AV platoon with smaller time headway. Aramrattana et al. [24] arrived at similar conclusions, further discovering that drivers felt unsafe and uncomfortable interacting with AV platoons, leading to increased mental exertion. Razmi Rad et al. [25], Schoenmakers et al. [26], and Chen et al. [27] conducted simulation experiments and discovered that drivers maintained significantly smaller safety gaps when driving near AV dedicated lanes. Sohrabi et al. [28] found through simulation experiments that narrow AV-dedicated lanes can have a negative impact on drivers traveling alongside these lanes. Some scholars have used simulation experiments to investigate changes and differences in driving behavior among drivers with different driving styles when following AVs. For instance, Ma and Zhang [29] studied the behavioral changes of three types of drivers (aggressive, neutral, and defensive) when following AVs. They found that compared to following HVs, aggressive and neutral drivers felt more anxious and uncomfortable and were more likely to exhibit aggressive behavior when following AVs, while no such differences were observed for defensive drivers.

Several scholars have conducted field experiments to compare and analyze the differences between following HVs and AVs, and to study changes in driving behavior when HVs follow AVs. For example, Soni et al. [30] found that compared to following HVs, drivers maintained significantly shorter time headways when following AVs. Furthermore, when positive information about AVs was provided to drivers, their trust in AVs increased, leading to a further reduction in the following gaps. Mahdinia et al. [17] and Rahmati et al. [31] studied behavioral differences between drivers following AVs or HVs through field experiments and found that drivers following AVs exhibited lower fluctuations in speed and acceleration. Some scholars have also investigated differences in the following distance during AV following among drivers with varying levels of trust in AV technology through field experiments. For instance, Zhao et al. [32] studied three types of drivers (AV believers, AV skeptics, and AV non-sensitive individuals) and analyzed changes in speed and following gaps when following AVs. They found that when AVs were recognizable to drivers, believers maintained smaller gaps while skeptics maintained larger gaps, indicating that drivers' behavioral responses to AVs depend on their subjective trust in autonomous driving technology.

Some scholars have utilized real-world datasets such as the Waymo dataset, Lyft Level 5 dataset, and NGSIM dataset to study changes in driving behavior when HVs follow AVs. For example, Sinha et al. [33], Huang et al. [34], and Wen et al. [35]conducted research and analysis using the Waymo dataset. Huang et al. [34] and Wen et al. [35]found that drivers exhibited lower driving fluctuations in terms of speed and acceleration when following AVs and maintained higher Time to Collision (TTC) values. Zhang et al. [36] used the NGSIM and Lyft Level 5 datasets to investigate whether the presence of AVs affects drivers' following behavior. They found statistically significant differences in drivers' following behavior when following AVs, characterized by a decrease in both the mean and variance of time headways. Different scholars also compared and analyzed differences in following behavior under different following combinations. For instance, Sinha et al. [33] examined behavioral differences between two following combinations (HV-AV and AV-HV) and found that AVs maintained larger following gaps than HVs when driving at higher speeds on main roads and at lower speeds on highways. Li et al. [37] studied three following combinations (HV-HV, AV-HV, and HV-AV) using the Lyft Level 5 dataset. They observed significant differences between HV-HV and the other two combinations, indicating that HV behavior changed (i.e., became less aggressive and safer) after the introduction of AVs in traffic, and the average TTC values of drivers increased significantly.

The aforementioned scholars have revealed changes in HV following behavior in human-machine mixed driving environments, as well as variations among drivers with different characteristics. Some conclusions also indicate that changes in driving behavior are related to driver characteristics such as trust in AVs and subjective perceptions. However, these studies have not explored the underlying factors that contribute to these behavioral changes. Since the structural equation model (SEM) is a generalized multivariate statistical model, it is a common method for multivariate data analysis to test theoretical hypotheses, which allows for a more comprehensive study of the relationships between variables and enhances predictive power and interpretability of the model. Therefore, previous scholars have mostly used SEM to analyze the influencing factors of driver behavior in traditional traffic flow, focusing on defensive driving behavior, competitive driving behavior, aggressive driving behavior, safe driving behavior, and speeding behavior [38–42]. Many of them have applied the theory of planned behavior (TPB) [43] for analysis. However, relying solely on a single TPB model may have certain limitations. Therefore, many scholars have expanded the research scope by incorporating additional influencing factors based on their research objectives. For example, Li et al.[38], Zhang et al.[39], Armitage et al. [40], Ding et al. [41] and others have pointed out that social environment, perceived behavioral control, beliefs (behavioral beliefs, normative beliefs, control beliefs), moral norms, descriptive norms, anticipated regret, Type A personality, risk perception, and driving habits are also influential factors in driver behavior in traditional traffic flow.

In recent years, scholars have considered the impact of the introduction of AVs on drivers and analyzed the psychological factors and interactions among these factors that contribute to changes in driver behavior intentions in human-machine mixed driving environments. For example, Li et al. [44] based on the extended theory of planned behavior, established an SEM to analyze the correlation between drivers' following intentions towards connected automated vehicles (CAV) and their influencing factors. Cui et al. [45] constructed an SEM of the driver's intention for risky behavior based on questionnaire survey results, explaining the intention for risky behavior when interacting with CAV. Building upon this, scholars have quantified the impact of AVs on drivers for mixed traffic flow modeling research. For instance, Li et al. [14], Chen et al. [46], and Zhu et al. [47] have quantified drivers' cognitive behavior characteristics, drivers' acceptance of CACC, and driver personality differences through questionnaire surveys. These quantified factors are incorporated into the car-following model [48] and lane-changing model to study the impact of driver behavior changes caused by AVs on traffic flow.

In summary, domestic and foreign scholars have mainly focused on the impact of AVs on the driver following behavior but have been unable to accurately analyze the reasons and influencing factors behind changes in HV following behavior in human-machine mixed driving environments. Only a few scholars have used SEM to explore the psychological factors and interactions contributing to changes in the driver behavior intentions in human-machine mixed driving environments. However, the considered influencing factors are not comprehensive, and research on driving behavior has not addressed changes in following distance. Therefore, this study introduces four influencing factors: driver's understanding of AV performance, safety trust, tolerance for slower speeds, and driver's perception of traffic environment. This study establishes a relationship model for the influencing factors of driver following behavior, develops a questionnaire based on the model framework, and conducts a survey. A structural equation model is then constructed and the effectiveness of the model and relationships between variables are analyzed using SPSS and AMOS software.

3. Hypotheses

To examine the predictive validity of the four considered influencing factors, namely Traffic Environment Perception (TEP), Performance Understanding (PU), Safety Trust (ST), and Tolerance for Slow Driving (TSD), in relation to Following Intention (FI) and Following Distance (FD), a review of the relevant literature on these influencing factors are presented below. This review provides a comprehensive analysis of the existing research on these factors and their impact on driver behavior in human-machine mixed driving environments. By examining the existing literature, this study aims to provide a solid foundation for our investigation into the predictive validity of these factors in relation to following behavior.

3.1. Traffic environment perception

The driving task of a driver can be formalized into a control task, consisting of two main stages: the perception process and the response process. The perception process involves transforming the perceived environment into stimuli that are input to the response process [49]. During the perception process, drivers are easily influenced by both the traffic environment (such as traffic conditions, weather, and lighting conditions) [50,51] and personal attributes (such as psychological state, driving skills, and performance understanding) [52]. In a human-machine mixed driving environment, drivers' behavior near AVs takes into account not only the influence of the traffic environment and personal attributes but also considers interference from AVs [36]. Therefore, it is necessary to consider drivers' traffic environment perception ability in a human-machine mixed driving environment.

Based on this, the following hypotheses are proposed:

H_{a1}. : TEP positively influences ST.

H_{a2}-H_{a4}. : TEP negatively influences TSD (H_{a2}), FI (H_{a3}), and FD (H_{a4}).

H_{m1}-H_{m2}. : TEP indirectly influences FD through ST (H_{m1}) and TSD (H_{m2}).

H_{m5}. : TEP indirectly influences FD through ST and TSD.

3.2. Performance understanding

When individuals have relevant information about a particular technology and are familiar with its usage, they may modify their evaluation of the technology, leading to changes in their behavior [53]. Existing research indicates that public understanding of AVs directly influences their acceptance of autonomous driving technology [54,55], and studies suggest that drivers' trust in AVs is largely influenced by their knowledge and information about AVs [30]. Therefore, it is necessary to consider drivers' understanding of AV performance when dealing with this emerging technology. This understanding can provide valuable insights into drivers' behavior and acceptance of AVs in human-machine mixed driving environments.

Based on this, the following hypotheses are proposed:

H_{b1}. : PU positively influences ST.

H_{b2}-H_{b4}. : PU negatively influences TSD (H_{b2}), FI (H_{b3}), and FD (H_{b4}).

H_{m3}-H_{m4}. : PU indirectly influences FD through ST (H_{m3}) and TSD (H_{m4}).

H_{m6}. : PU indirectly influences FD through ST and TSD.

3.3. Safety Trust

Trust is a crucial factor in human-machine interaction, and its role is equally applicable in human-machine mixed driving environments [56]. Several scholars have considered the role of trust in the acceptance of AVs and have highlighted its significance in determining whether the public accepts AVs [57–59]. Building upon this foundation, researchers have also found that drivers' behavior towards AVs is primarily influenced by their level of trust [17,30,36]. Therefore, in this study, the research factors identified by previous studies are adopted and the impact of drivers' trust in the safety of AVs on their following behavior is considered. By examining the role of trust in human-machine mixed driving environments, this study aims to provide valuable insights into drivers' behavior and acceptance of AVs.

Based on this, the following hypotheses are proposed:

H_{c1}-H_{c2}. : ST positively influences TSD (H_{c1}) and FI (H_{c2}).

H_{c3}. : ST negatively influences FD.

3.4. Tolerance for slow driving

To interact with other road users, AVs must establish a set of rules to govern and guide the interaction process, referred to as driving strategies. Existing driving strategies include defensive, competitive, negotiated, and cooperative driving strategies [60]. Negotiated and cooperative driving strategies require the vehicle to be equipped with V2V and V2X communication systems, while competitive driving strategies can lead to excessive competition and potential dangers for AVs [61]. These issues are challenging to address in the early stages of AV deployment. On the other hand, defensive driving strategies prioritize the safety of the AV itself, increasing driving safety [62] while reducing discomfort for other vehicle drivers [63]. Therefore, in the early stages of AV deployment, defensive driving strategies are commonly adopted to ensure safety. However, the lower driving speed and larger following distance maintained by AVs using this strategy can affect traffic efficiency [60]. To account for situations where drivers follow AVs adopting a defensive driving strategy, it is necessary to consider the driver's tolerance for slow driving.

Based on this, the following hypothesis is proposed:

H_{d1}. : TSD positively influences FD.

3.5. Following intention

In the Theory of Planned Behavior (TPB), it is posited that individual behavior is determined by individual behavioral intentions (BI). Many scholars have applied TPB to the study of driver behavior, as summarized in Section 2 [38–42], where the influence of BI on subsequent individual behavior is considered. Building upon these previous research factors, this study considers the impact of drivers' following intentions towards AVs on their following behavior. Furthermore, it examines the influence of drivers' following intentions on their tolerance for slow driving. By incorporating these factors into the analysis, this study aims to provide a comprehensive understanding of the factors that influence driver behavior in human-machine mixed driving environments. Based on this, the following hypotheses are proposed:

H_{e1}—H_{e2}. : FI positively influences TSD (H_{e1}) and FD (H_{e2}).

Based on the aforementioned analysis, a model framework is proposed for the factors influencing driver following behavior, incorporating traffic environment perception, performance understanding, safety trust, and tolerance for slow driving. The model framework is illustrated in Fig. 1, where elliptical variables represent latent variables and rectangular variables represent measured variables. This framework provides a comprehensive understanding of the factors that influence driver behavior in human-machine mixed driving environments and serves as a foundation for further analysis and investigation.

4. Methodology

4.1. Survey design

The questionnaire is divided into three parts. The first part collects basic sociodemographic information, including respondents' gender, age, years of driving experience, and sources of information about AVs. The second part investigates respondents' self-reported

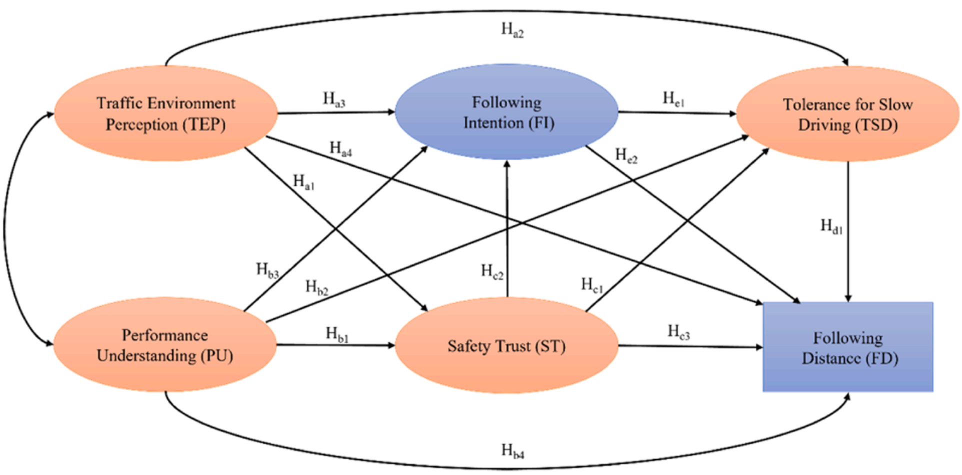

Fig. 1. Driver following behavior research model.

performance understanding and behavioral intentions toward AVs, consisting of six dimensions: Traffic Environment Perception (TEP), Performance Understanding (PU), Safety Trust (ST), Tolerance for Slow Driving (TSD), Following Intention (FI), and Following Distance (FD). Except for "Following Distance," which is assessed using categorical options and subjective questions, the other dimensions are measured using a 5-point Likert scale, ranging from "1" (strongly disagree) to "5" (strongly agree). The specific design of the questions for each dimension is as follows: (1) TEP: Assesses respondents' perception of traffic conditions and consists of four items, such as "I can accurately judge the traffic conditions around the vehicle." (2) PU: Assesses respondents' understanding of AV performance and consists of four items, such as "I understand the performance and sensor parameters of connected automated vehicles." (3) ST: Measures respondents' level of trust in AV safety and includes five items, such as "Connected automated vehicles will not pose a danger due to loss of control." (4) TSD: Measures respondents' tolerance for slow driving behavior of AVs and includes three items, such as "Even if the connected automated vehicle in front is driving too slowly, I would not attempt to overtake." (5) FI: Assesses changes in following intention influenced by AVs and consists of four items, such as "Driving behind a connected automated vehicle makes driving easier." In addition, two categorical items are included to investigate changes in following distance (FD) influenced by AVs. For example, "On the highway, how would you adjust your following distance when the vehicle in front changes from a regular vehicle to a connected automated vehicle?" (Following distance will significantly decrease, Keep the same distance, Following distance will significantly increase).

The third part investigates respondents' actual understanding of AVs by focusing on five aspects: driving characteristics, advantages, disadvantages, and sensor features. It includes five multiple-choice questions designed to validate the self-reported level of understanding in the scale.

It should be emphasized that the traffic scenarios in the questionnaire are all ideal weather conditions. The complete questionnaire is provided in Appendix A and Appendix B.

4.2. Data collection

The survey was conducted using an online method through the Wenjuanxing platform, targeting non-professional motor vehicle drivers. A total of 379 questionnaires were collected in the formal survey. Invalid questionnaires, including those with response times less than 3 min or greater than 20 min, and cases where multiple items were answered with the same choice, were excluded. Finally, 376 valid samples were obtained, meeting the requirement of having a sample size at least 5–10 times the number of observed items in the scale questions[64–66].

5. Results

5.1. Descriptive statistical analysis

The sociodemographic characteristics of the sample are presented in Table 1. In this survey, male respondents accounted for 52.39% of the sample, while female respondents accounted for 47.61%, indicating a balanced gender distribution. The majority of respondents were aged between 25 and 40 years, representing approximately 85.90% of the sample. In terms of driving experience, the majority of respondents had between 2 and 10 years of experience, accounting for 81.39% of the sample, indicating a certain level of driving proficiency. Over 90% of respondents had no firsthand experience with AVs and acquired knowledge about them through news, the internet, or acquaintances.

In the questionnaire survey, the understanding of AV performance by drivers was assessed based solely on subjective self-reporting, which may only represent their perceived level of understanding to a certain extent. At the same time, drivers' behavior towards AVs in traffic flow is based on their self-reported level of understanding. If there is a significant discrepancy between their self-reported understanding and actual understanding, it can create traffic hazards and affect traffic flow safety. To mitigate the impact of any

Table 1
Sociodemographic characteristics of the sample.

Variable	Category	Frequency	Percentage
Gender	Male	197	52.39%
	Female	179	47.61%
Age	< 24	28	7.45%
	25–32	207	55.05%
	33–40	116	30.85%
	41–49	18	4.79%
	> 50	7	1.86%
Driving experience	< 1 year	21	5.59%
	2–5 year	169	44.95%
	6–10 year	137	36.44%
	> 10 year	49	13.03%
Information source	News and internet	252	67.02%
	Relatives and friends	96	25.53%
	Personal experience	27	7.18%
	Others	1	0.27%

mismatch between self-reported understanding and actual understanding, a series of questions related to the actual understanding of AV performance were included in the survey to test respondents' performance understanding. The scores obtained were used to calculate drivers' actual understanding of AV performance, aiming to validate the correlation between self-reported and actual understanding. By comparing the scores of the 5 multiple-choice questions representing drivers' actual understanding of AVs with the scores of the 4 Likert scale questions representing their self-reported understanding, and after standardization, the scatter plot of self-reported versus actual understanding is shown in Fig. 2.

In Fig. 2, darker-colored points indicate a higher number of drivers with equivalent levels of understanding regarding the performance of AVs. The larger the diameter of the points, the closer the ratio between self-reported performance understanding and actual performance understanding is to 1. The Pearson correlation analysis was subsequently conducted to examine the correlation between the two. The correlation coefficient for the Pearson correlation analysis method is defined as follows:

$$\rho_{XY} = \frac{\mathrm{Cov}(X, Y)}{\sqrt{\mathrm{D}(X)}\sqrt{\mathrm{D}(Y)}} \tag{1}$$

In the above equation, ρ_{XY} is the Pearson correlation coefficient, X is the driver's self-reported understanding score with AV, Y is the driver's actual understanding score with AV, $\mathrm{Cov}(X, Y)$ is the covariance, $\sqrt{\mathrm{D}(X)}$ and $\sqrt{\mathrm{D}(Y)}$ is the standard deviation.

The results indicated a correlation coefficient of 0.565, which was found to be significant at the 0.01 level. From this, it can be generally concluded that drivers' self-reported performance understanding can represent their actual understanding of AV performance.

Correlation analysis of the questionnaire revealed that the variables of FI and FD had low correlation with age, gender, driving experience, and information source. The correlation coefficients between FI and information source were significant at the 0.05 level but small (0.089), and between FD and age were significant at the 0.05 level but small (0.086), except for these, there was no significant effect of FI and FD with any other sociodemographic characteristics variables. Whereas FI and FD are significantly correlated with TEP, PU, ST, and TSD with a p-value of 0. Therefore, this study will mainly consider these seven influential variables in the model construction and analysis.

Descriptive statistics, including skewness and kurtosis, were calculated using SPSS 26.0 software. The absolute values of skewness ranged from 0.002 to 0.92, and the absolute values of kurtosis ranged from 0.006 to 1.093. Referring to the standards proposed by Bentler and Bonett [67], data can be considered normally distributed if the absolute value of skewness is less than 2 and the absolute value of kurtosis is less than 5. In this study, all variables met these criteria, providing a solid foundation for subsequent model quality testing using the maximum likelihood method.

5.2. Reliability and validity assessment

The reliability of the questionnaire scale data was rigorously evaluated using the SPSS 26.0 software. In addition, the validity of the questionnaire scale data was thoroughly assessed through the utilization of both SPSS 26.0 and Amos 26.0 software. The results of these reliability and validity tests are presented in Table 2, providing a comprehensive overview of the robustness of the data collected through the questionnaire scale.

Initially, a comprehensive reliability test was conducted. As illustrated in Table 2, the corrected item-total correlation (CITC) of all items ranged from 0.383 to 0.684, with all values being close to or exceeding the threshold of 0.4, indicating a high degree of correlation among the items. Furthermore, the overall Cronbach's alpha coefficient for the questionnaire was determined to be 0.886,

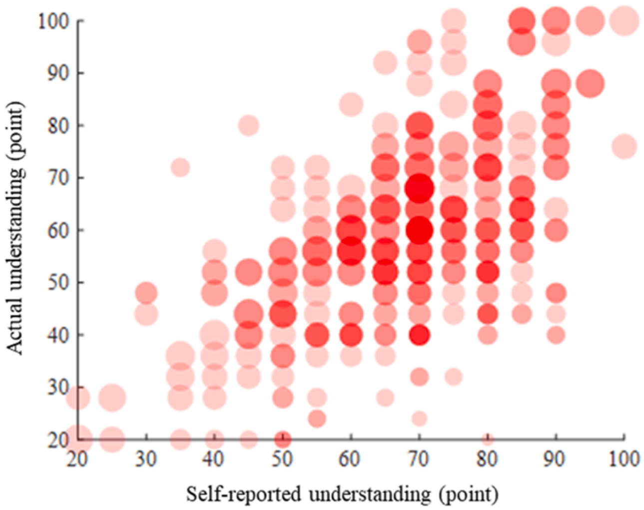

Fig. 2. Consistency test of performance understanding.

which exceeds the commonly accepted threshold of 0.7, indicating good internal consistency. The Cronbach's alpha coefficients for each latent variable were found to range from 0.661 to 0.816, all close to or exceeding the threshold of 0.7, indicating that the questionnaire design met the necessary requirements and that the structural arrangement achieved an acceptable level of reliability.

Subsequent to the satisfactory reliability results, the collected data were rigorously examined for suitability for factor analysis. As depicted in Table 2, the results of the Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity indicated that the overall KMO value for the scale was 0.901, exceeding the threshold of 0.7, and that the KMO values for each latent variable ranged from 0.679 to 0.828, all being close to or exceeding the threshold of 0.7. Additionally, the Sig values for both the overall scale and individual latent variables were all determined to be less than 0.05, indicating that the scale data were suitable for factor analysis. Furthermore, it was found that the variance explained ratio for the five factors was 60.906%, exceeding the threshold of 60%, indicating that these five factors were able to effectively extract information from the items.

Finally, a thorough validity test was conducted. As presented in Table 2, it was determined that the factor loadings for each variable ranged from 0.640 to 0.8838, all exceeding the threshold of 0.5. The average variance extracted (AVE) values for each latent variable were found to range from 0.507 to 0.649, all exceeding the threshold of 0.5. The composite reliability (CR) values for each latent variable ranged from 0.804 to 0.881, all exceeding the threshold of 0.7. These results indicated that there was good convergence between measurement items and their respective constructs, demonstrating good convergent validity of the scale. To verify the distinctiveness among measurement items, a test of discriminant validity was also conducted and its results are presented in Table 3.

As indicated in Table 3, it was determined that the square roots of the average variance extracted (AVE) values for each factor were greater than the correlation coefficients between that factor and other constructs. This result demonstrates that there is differentiation among the measurement items on different constructs, indicating that the discriminant validity of the scale is good. This further supports the robustness of the scale and its ability to effectively measure the constructs of interest.

5.3. Model Evaluation

The initial SEM was constructed using the Amos 26.0 software and was evaluated using the Maximum Likelihood Estimation method. The results of the goodness-of-fit indices indicated that AGFI and NFI were close to 0.9, while the other seven indices were determined to be above 0.9. Referring to the recommendations by Bentler and Bonett [67] regarding acceptable values for goodness-of-fit indices, it can be concluded that the SEM constructed in this study exhibits a good fit. The specific values for each index are presented in Table 4.

5.4. Path analysis

A path analysis was rigorously conducted using the Amos 26.0 software in order to examine the significance of the regression coefficients between the factors in SEM and to determine whether the hypotheses stated in Section 2 were supported. The results of this initial path analysis are presented in Table 5, providing a detailed overview of the relationships among the factors in SEM.

As indicated in Table 5, the results of the path analysis revealed the following:

a. The initial hypotheses H_{a1}, H_{a2}, H_{a3}, and H_{b1} were supported, while H_{b2} and H_{b3} were not supported. This suggests that PU does not have a significant effect on TSD and FI. However, both TEP and PU were found to have a positive significant effect on ST, with path

Table 2
Results of the reliability and validity assessment.

Latent variable	Measured variable	CITC	Factor loading	Cronbach's Alpha	KMO and Sig values	variance explained ratio	AVE	CR	Overall reliability and validity
PU	PU1	0.606	0.801	0.761	KMO:0.771	19.622%	0.5858	0.850	Cronbach's Alpha:0.886
	PU2	0.591	0.791		Sig:0.000				KMO:0.901
	PU3	0.553	0.760						Sig:0.000
	PU4	0.497	0.706						Cumulative variance
ST	ST1	0.598	0.802	0.792	KMO:0.828	12.430%	0.5534	0.860	explained ratio:60.906%
	ST2	0.642	0.782		Sig:0.000				
	ST3	0.494	0.766						
	ST4	0.526	0.696						
	ST5	0.620	0.664						
TEP	TEP1	0.510	0.761	0.661	KMO:0.694	10.816%	0.5074	0.804	
	TEP2	0.383	0.756		Sig:0.000				
	TEP3	0.402	0.685						
	TEP4	0.507	0.640						
FI	FI1	0.684	0.838	0.816	KMO:0.800	9.954%	0.6487	0.881	
	FI2	0.619	0.833		Sig:0.000				
	FI3	0.674	0.790						
	FI4	0.580	0.758						
TSD	TSD1	0.534	0.801	0.712	KMO:0.679	8.084%	0.6363	0.840	
	TSD2	0.536	0.799		Sig:0.000				
	TSD3	0.527	0.793						

Table 3
Results of the test for factor discriminant validity.

	PU	ST	TEP	FI	TSD
PU	0.586				
ST	0.520**	0.553			
TEP	0.408**	0.416**	0.507		
FI	0.399**	0.701**	0.287**	0.649	
TSD	0.374**	0.556**	0.192**	0.509**	0.636
the square roots of AVE	0.765	0.744	0.712	0.805	0.798

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

Table 4
SEM goodness-of-fit indices before correction.

Measure	Reference Standard	Initial value	Result
$\chi 2/df$	1–3	2.158	Good
RMSEA	0–0.08	0.056	Good
SRMR	0–0.08	0.052	Good
GFI	0.9–1.0	0.912	Good
AGFI	0.9–1.0	0.884	Acceptable
NFI	0.9–1.0	0.858	Acceptable
IFI	0.9–1.0	0.927	Good
TLI	0.9–1.0	0.911	Good
CFI	0.9–1.0	0.926	Good

coefficients of 0.267 and 0.502, respectively. Additionally, TEP was found to have a negative significant effect on both TSD and FI, with path coefficients of − 0.162 and − 0.155, respectively.

b. The initial hypotheses H_{c1} and H_{c2} were supported, while H_{e1} was not supported. This suggests that FI does not have a significant effect on TSD. However, ST was found to have a positive significant effect on both TSD and FI, with path coefficients of 0.823 and 0.958, respectively.
c. The initial hypotheses H_{c3} and H_{d1} were supported, while H_{a4}, H_{b4}, and H_{e2} were not supported. This suggests that TEP, PU, and FI do not have a significant effect on FD. However, TSD was found to have a positive significant effect on FD, with a path coefficient of 0.216, while ST was found to have a negative significant effect on FD, with a path coefficient of − 0.731.

It is worth noting that although the hypothesis H_{a3} (FI ← TEP) did not reach significance in the initial model, it did reach significance in the revised model. This is reasonable because in the initial model there may have been multicollinearity among variables which could mask or weaken the influence of certain variables (such as TEP) on other variables (such as FI) [68]. When certain paths are removed from the model, the issue of multicollinearity among variables is addressed and the hypothesis H_{a3} (FI ← TEP) reaches significance.

After a rigorous process of sequentially removing non-significant paths from the model and re-evaluating its quality, it was determined that all goodness-of-fit indices of the revised model met the necessary standards. The SEM with revised paths is depicted in Fig. 3, providing a visual representation of the relationships among the variables in the model according to the results presented in

Table 5
Results of path analysis.

Hypotheses	Path relationship	Initial significance		Significance and path coefficients after correction		
		P-value	Result	P-value	Estimate	S.E.
H_{a1}	ST←TEP	0.001**	Supported	0.001**	0.401	0.267
H_{a2}	TSD←TEP	0.034*	Supported	0.047*	-0.193	-0.162
H_{a3}	FI←TEP	0.081	Rejected	0.019*	-0.250	-0.155
H_{a4}	FD←TEP	0.973	Rejected	Deleted path	——	——
H_{b1}	ST←PU	***	Supported	***	0.559	0.502
H_{b2}	TSD←PU	0.487	Rejected	Deleted path	——	——
H_{b3}	FI←PU	0.146	Rejected	Deleted path	——	——
H_{b4}	FD←PU	0.448	Rejected	Deleted path	——	——
H_{c1}	TSD←ST	0.004*	Supported	***	0.653	0.823
H_{c2}	FI←ST	***	Supported	***	1.031	0.958
H_{c3}	FD←ST	0.026*	Supported	***	-0.395	-0.731
H_{d1}	FD←TSD	0.046*	Supported	0.025*	0.148	0.216
H_{e1}	TSD←FI	0.819	Rejected	Deleted path	——	——
H_{e2}	FD←FI	0.391	Rejected	Deleted path	——	——

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$, S.E. (Standardized estimate).

Table 5.

Based on the results of the model modification and testing, the relationships among the latent variables can be described as follows:

$$FD = 0.216TSD - 0.731ST \tag{2}$$

$$FI = 0.958ST - 0.155TEP \tag{3}$$

$$TSD = 0.823ST - 0.162TEP \tag{4}$$

$$ST = 0.267TEP - 0.502PU \tag{5}$$

5.5. Mediation analysis

Based on the results of the path analysis presented in Section 4.4, it can be observed that TEP has a significant effect on ST and TSD, but not on FD. As such, it is possible that ST and TSD may act as full mediators between TEP and FD (hypotheses H_{m1} and H_{m2}). Similarly, ST and TSD may also act as full mediators between PU and FD (hypotheses H_{m3} and H_{m4}). The path analysis results indicate a significant positive influence of ST on TSD, suggesting the presence of serial mediation between ST and TSD in the relationships between TEP and FD, as well as between PU and FD (hypotheses H_{m5} and H_{m6}).

To rigorously test the mediating effects, the Bootstrap method [69] and the user-defined estimands feature in the Amos 26.0 software were utilized. The code was written to perform the mediation analysis with a sample size of 2000 bootstrap samples and a bias-corrected confidence interval of 90%. The criterion for establishing the presence of mediating effects was whether the confidence interval of the total effect estimate included zero. The results of this mediation analysis are presented in Table 6 for further reference.

As indicated in Table 6, it can be observed that hypotheses H_{m1}, $H_{m2,}$ and H_{m3} are supported, suggesting that TEP has a significant indirect effect on FD, with ST and TSD serving as full mediators between TEP and FD. Additionally, hypotheses H_{m5} and H_{m6} are also supported, indicating that PU has a significant indirect effect on FD, with ST and TSD acting as full mediators between PU and FD. However, for hypotheses H_{a4}, H_{b4}, and H_{m4}, the confidence intervals were found to include zero, indicating the absence of a mediating effect and thus these hypotheses are not supported.

6. Discussion and conclusion

The primary objective of this study is to utilize SEM to investigate the impact of traffic environment perception, performance

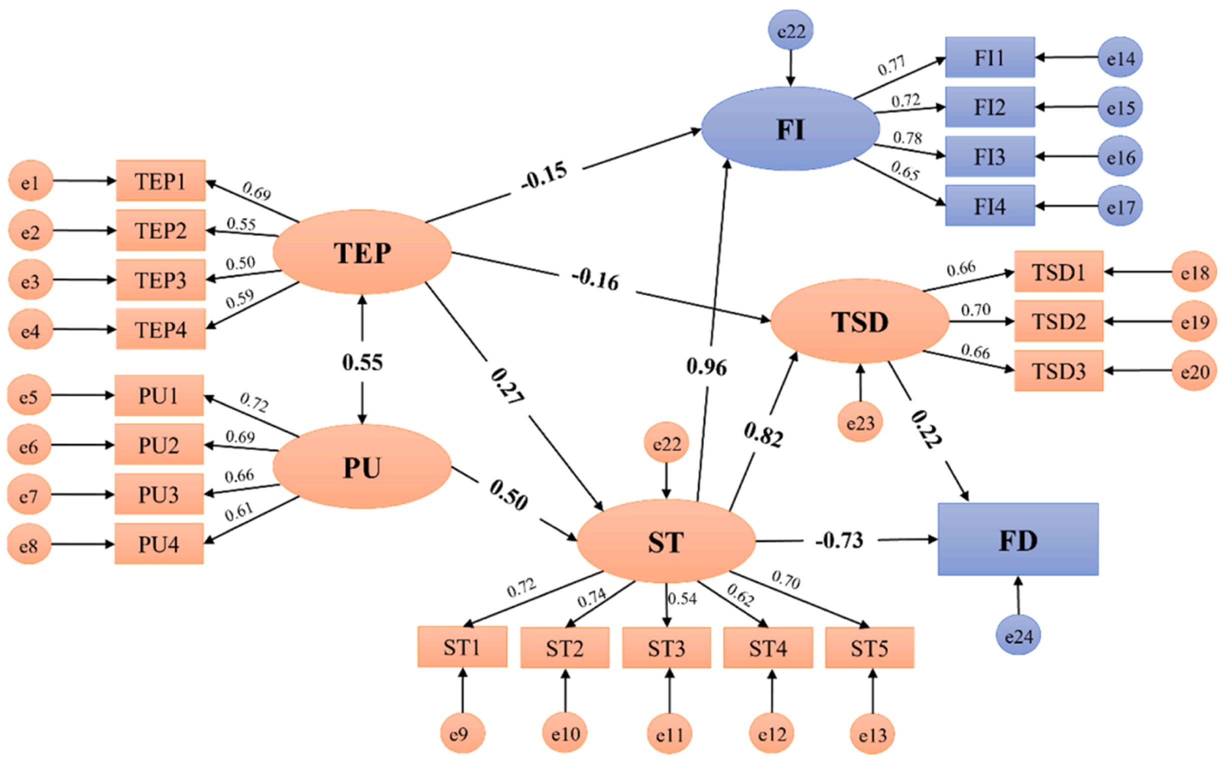

Fig. 3. Driver following behavior revised SEM.

Table 6
Result of mediation analysis.

Types of effects.	Hypotheses	Path relationship	S.E.	Estimate	95% Confidence interval		P-value	Result
					Lower	Upper		
Direct effect	H_{a4}	FD←TEP	0.095	0.037	-0.115	0.181	0.755	Rejected
Indirect effect	H_{m1}	FD←ST←TEP	0.085	-0.222	-0.370	-0.092	0.005**	Supported
	H_{m2}	FD←TSD←TEP	0.039	-0.051	-0.131	-0.010	0.011*	Supported
	H_{m5}	FD←TSD←ST←TEP	0.033	0.049	0.013	0.120	0.007**	Supported
Direct effect	H_{b4}	FD←PU	0.100	0.106	-0.071	0.264	0.324	Rejected
Indirect effect	H_{m3}	FD←ST←PU	0.096	-0.445	-0.626	-0.304	0.001**	Supported
	H_{m4}	FD←TSD←PU	0.028	0.020	-0.010	0.086	0.229	Rejected
	H_{m6}	FD←TSD←ST←PU	0.053	0.099	0.031	0.205	0.007**	Supported
Total mediation effect			0.055	-0.406	-0.493	-0.313	0.001**	

Note: *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$, S.E. (Standard error).

understanding, safety trust, and tolerance for slow driving on drivers' following intention and distance. Through rigorous analysis of the research data, several noteworthy results have been identified that warrant further discussion and practical application. These findings provide a solid theoretical foundation for the development of future measures related to human-machine mixed traffic flow in practice.

6.1. *Effect of variables*

Based on the results of the path analysis of the model, the following findings regarding the following intention variable have been obtained:

1) Traffic environment perception was found to have a significant negative impact on following intention. This suggests that as drivers become more aware of changes in the surrounding traffic environment while following an AV, their intention to continue following the AV decreases. This finding indicates that drivers, with an understanding of the surrounding traffic conditions, prefer to assert their driving autonomy and are less willing to follow AVs.
2) Safety trust was found to have a significant positive impact on following intention. This indicates that the higher the level of safety trust drivers have in AVs, the more inclined they are to follow behind them. After the introduction of AVs, increasing drivers' trust in their safety can enhance their willingness to follow them, thereby avoiding unnecessary lane-changing behaviors caused by the reluctance of HVs to follow AVs. This promotes a harmonious and cooperative coexistence of HVs and AVs in human-machine mixed traffic flow.

Based on the results of the path analysis and mediation analysis of the model, the following findings regarding the following distance variable have been obtained:

1) Safety trust was found to have a significant negative impact on following distance. This suggests that as drivers' trust in AVs increases, the following distance between HVs and AVs decreases. This finding indicates that drivers with low levels of safety trust maintain an additional safety distance while following AVs, while drivers with high levels of trust shorten their safety distance. However, it is important to note that there is an upper limit to the change in following distance. Data from real-world experiments on human-machine mixed traffic flow conducted both domestically and internationally indicate that changes in following distance due to the presence of AVs mostly remain within 15 m. As such, this conclusion can be used to calibrate the following distance when HVs follow AVs, providing a basis for parameter calibration in human-machine mixed traffic flow following models.
2) Tolerance for slow driving was found to have a significant positive impact on following distance. This suggests that the higher a driver's tolerance for the low-speed driving of AVs, the greater the following distance between HV and AV. The higher the tolerance for slow driving of AVs, the lower the driver's expected driving speed and the significantly reduced lane-changing behavior motivated by speed gain. A more conservative driving style leads to a larger following distance when driving behind AVs.
3) Traffic environment perception and performance understanding were found to indirectly influence following distance through the mediating variables of safety trust and tolerance for slow driving. This indicates that the stronger a driver's perception of traffic conditions and understanding of the performance of AVs, the higher their trust in the safety of AVs and the lower their tolerance for slow driving. Consequently, this leads to a reduction in following distance. In future human-machine mixed driving environments, if drivers have insufficient or inaccurate understanding of AVs, extreme driving behaviors such as keeping a distance from or closely following AVs may occur. These behaviors can reduce traffic efficiency and safety. Therefore, future traffic management authorities need to provide comprehensive education to drivers about autonomous driving to ensure that they have a correct understanding of the advantages and limitations of AVs. This will enable HVs to safely and reasonably coexist with AVs in a human-machine mixed driving environment, thereby improving the overall operational efficiency of the road system.

6.2. Limitations and future work

This study still has some limitations. First, the fundamental assumption of this study is that road traffic is currently in the transition period from purely HV to purely AV. During this transitional phase, the driver's levels of understanding, acceptance, and safety trust towards AVs approximately follow a normal distribution. However, as AVs become more widely adopted in society, variables such as performance understanding are likely to undergo significant changes. As such, it is necessary to conduct further investigations to validate the validity of the model during the widespread adoption phase of AVs. Therefore, in future research, we will consider the characteristics of drivers at different stages of the commercialization of AV, such as with the increase in the number of drivers who have been personally exposed to AVs, we can increase the sample size of this type of drivers, and compare and analyze whether having been personally exposed to AVs affects the driver's following behavior in the face of AVs, so as to improve the model of this study.

Second, since the questionnaire was randomly distributed on the online platform, the final sample data may not be comprehensive enough, e.g., the sample may not include the sample of drivers who are not proficient Internet. Therefore, in future research, the distribution of the questionnaire can be considered as a combination of online and offline, or more diversified data collection methods (e.g., driving simulation, real vehicle experiments, etc.) can be used to improve the reliability and accuracy of the survey results. In addition, different questionnaires can be designed separately to target different categories of drivers (e.g., classified according to driver's personality and driving style, etc.) in terms of changes in following behavior when facing AVs, so as to increase the diversity of the samples, and multiple questionnaire surveys can be carried out to optimize and calibrate the structural equation model of this study.

Finally, when conducting the questionnaire design, we only considered four factors: traffic environment perception, performance understanding, safety trust and tolerance for slow driving, and some external factors that were not considered, such as traffic conditions, road status and weather conditions, which may not be comprehensive enough. Therefore, in future research, we will consider the influence of the above mentioned external factors on drivers' following behavior, and on this basis, we will consider the research on the influencing factors of AV on the change of drivers' lane changing behavior to further improve the existing model.

CRediT authorship contribution statement

Xia Li: Conceptualization, Project administration, Writing – review & editing, Supervision. **Zhijian You:** Investigation, Writing – original draft, Writing – review & editing, Validation. **Xinwei Ma:** Project administration, Writing – review & editing, Supervision. **Xiaomin Pang:** Investigation, Validation, Data curation, Formal analysis. **Xuefeng Min:** Funding acquisition. **Hongjun Cui:** Project administration, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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Appendix A. Questionnaire Part I & II

Item	Description
Sociodemographic characteristics	
1	What is your age?
2	What is your gender?
3	How many years of driving experience do you have?
4	What is your source of information about connected automated vehicles?
Traffic Environment Perception (TEP)	
1	I can accurately sense the speed of the vehicle in front of me.
2	I can accurately detect the omens of traffic accidents in time.
3	I can accurately identify road signs and other traffic information.
4	I can accurately judge the traffic conditions around the vehicle.
Performance Understanding (PU)	
1	I understand the performance and sensor parameters of connected automated vehicles.

(*continued on next page*)

(*continued*)

Item	Description
2	I understand how connected automated vehicles operate and how they work.
3	I understand the advantages and disadvantages of the current situation of connected automated vehicles.
4	I understand the history and development prospects of the connected automated vehicles industry.
Safety Trust (ST)	
1	The safety level of connected automated vehicles is significantly high.
2	Connected automated vehicles will not pose a danger due to loss of control.
3	Concentration on the road environment is not required while following a connected automated vehicle.
4	Driving with a connected automated vehicle induces relaxation and happiness.
5	Connected automated vehicles possess a higher likelihood of avoiding traffic hazards compared to human drivers.
Tolerance for Slow Driving (TSD)	
1	Even if the connected automated vehicle in front is driving too slowly, I would not attempt to overtake.
2	Even if the connected automated vehicle in front is driving slowly, it does not affect my driving speed.
3	Even if there is a connected automated vehicle in front of me, I maintain a high level of patience.
Following Intention (FI)	
1	Driving behind a connected automated vehicle makes driving easier.
2	Driving behind a connected automated vehicle reduces the risk factor.
3	Driving behind a connected automated vehicle is my preference.
4	When following behind a connected automated vehicle, I maintain the same distance as I would with a regular vehicle, if not less.
Following Distance (FD)	
1	On the highway, how would your following distance change when the vehicle in front changes from a regular vehicle to a connected automated vehicle, if you are currently following at a closer distance?
2	On the highway, how would your following distance change when the vehicle in front changes from a regular vehicle to a connected automated vehicle, if you are currently following at a higher distance?

Appendix B. Questionnaire Part III

Item	Description	Answer
Actual performance understanding of AVs		
1	What do you agree about the driving characteristics of connected automated vehicles?	Different connected automated vehicles can communicate with each other. Connected automated vehicles can communicate with road infrastructure. The transition of power in connected automated vehicles is smoother than in regular vehicles. The extreme acceleration performance of connected automated vehicles is stronger than that of regular vehicles. Connected automated vehicles have more precise control when overtaking and changing lanes than regular vehicles.
2	What do you agree about the advantages and disadvantages of connected automated vehicles?	Connected automated vehicles can better adapt to different groups of people. Connected automated vehicles rely on stable specific spectrum signals. Connected automated vehicles rely on clear road markings for driving. Connected automated vehicles can handle emergency situations better than regular vehicles. Connected automated vehicles can pay better attention to blind spots while driving than regular vehicles.
3	What do you agree about radar sensors for connected automated vehicles?	Radar sensors include lasers, millimeter waves, ultrasonic waves, infrared rays, etc. Severe weather can disperse or block the laser beam of radar sensors. Millimeter-wave radar has strong penetration and can pass through rain, snow, and dust. Laser radar can be used to draw a 3D map of surrounding obstacles. The radar used for reversing is an ultrasonic radar.
4	What do you think is the difference between radar and camera sensors for connected automated vehicles?	Camera technology is mature and has low cost. Cameras are easy for users to understand and interact with. Radar sensors generally play an auxiliary role. Radar is more susceptible to interference from other vehicles than cameras. Cameras can provide higher pixel and color resolution than radar.
5	Do you agree with the following information about connected automated vehicles?	Pure electric vehicles are more suitable for carrying connected automated driving systems. Connected automated vehicles rely more on high-precision maps. The response of connected automated vehicles is more sensitive than that of ordinary vehicles. Connected automated vehicles will plan the subsequent path in real-time during operation. The calculation of road information by connected automated vehicles needs to be executed locally.

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