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Modeling public acceptance of private autonomous vehicles: Value of time and motion sickness viewpoints

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ABSTRACT

Autonomous vehicles (AVs) offer the opportunity to achieve safe, efficient, accessible, affordable and productive transportation, while also enhancing the mobility of vulnerable groups. Nevertheless, the benefits associated with AVs can only be realized when the mass public have the intention to make use of this technology. This study aims to examine the impacts of several factors on general acceptance of AVs including perceived AV motion sickness, willingness to use time more efficiently in an AV, perceived value of time and perceived risk using private SAE Level-5 AVs, as well as the interrelationships between these factors. Using a sample of 1,418 respondents, partial least squares structural equation modeling (PLS-SEM) was used to test the proposed structural model. Results revealed that perceived value of time, perceived risk and willingness to use time more efficiently in an AV significantly affected the behavioral intention. Results from multi-group analysis showed that participant age also played a role in behavioral intention via the perceived value of time. It is hoped that the findings of this study can help AV policymakers and developers better understand the role that the studied factors play in shaping public intentions to use AVs.

1. Introduction

Autonomous vehicles (AVs)—as the product of the deep integration of the automobile industry with artificial intelligence, the Internet of Things, high-performance computing and other new generation information technologies—are expected to revolutionize mobility systems in the near future (Balasekaran et al., 2021). Developing this technology has become a strategic goal for a growing number of countries.

SAE International (2018) issued its recommended standards for the classification of AVs and the definitions of relevant terms. According to SAE's definition, driving automation is divided into six levels: Level 0 is No Driving Automation, Level 1 is Driver Assistance, Levels 2–4 are Partial, Conditional and High Driving Automation, and finally Level 5 (Full Driving Automation) which is self-driving without any human intervention and will be the subject of this work.

AVs are expected to improve road safety, reduce pollution and enhance traffic management, while also freeing up parking space in major cities and providing the level of comfort necessary for users to engage in other activities while travelling (Rouse et al., 2018; Isaac, 2016). The last aspect may hold special potential for changing the way that people perceive time spent travelling in cars, leading to a reduction in value of time in terms of willingness to pay for saving travel time (Kolarova et al., 2018). The benefit of an AV

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compared to conventional human-driven vehicles (HVs) is proportional to travel time, since one of the potential advantages of an AV in this respect is the more comfortable in-vehicle experience and the ability to work while on the move (Seo and Asakura, 2017). However, similar to Singleton (2019), we advocate that further studies on the impact of AVs regarding the value of time (VOT) and its follow-on effects on the use of commuting time are needed.

Despite the positive progress made with public attention and interest, news and reports of AVs involved in traffic crashes have emerged (DMV, 2021), and these crashes might harm the safety reputation and erode the public acceptance of AV technology (Othman, 2021). Therefore, it remains to be seen how public perceived risk of AVs will be shaped under the current circumstances. In addition, the potential negative impacts of AVs include job losses, increased urban sprawl, congestion, vehicle-miles travelled (VMT), and car sickness (Rouse et al., 2018; Isaac, 2016). Of these, increased congestion and greater VMT also mean longer travel times, highlighting the importance of understanding the VOT for AVs, with car sickness would be an obstacle for large-scale AV development. As AV occupants do not need to watch the road, vehicle designers may come up with much more flexible in-vehicle seating arrangements than today which potentially increase the tendency of motion sickness. This could emerge as an important barrier to the widespread adoption of AVs (Jones et al., 2019; Iskander et al., 2019).

It is also worth noting that the process of introducing new technologies is not always smooth. The main obstacles to the mass adoption of AVs in transportation systems include not only technical issues, but also issues related to legal frameworks, psychological factors and public acceptance (Shariff et al., 2017; Nordhoff et al., 2016). Similar to other emerging technologies, public acceptance of AVs is heterogeneous to a certain extent, meaning that people have varying perceptions and degrees of sensitivity to different attributes of AVs. Understanding levels of acceptance of AVs and how related factors affect their acceptance can provide a basis and reference for the wide application of AVs in the transportation market in the future. Therefore, public acceptance is a key driving force for the development and deployment of AVs. Carrying out research on public acceptance of AVs will help government departments, manufacturers and travel service providers make better-informed decisions, promoting the healthy development and introduction of AVs.

To address this issue a survey was conducted in this work and a model was developed to investigate the factors that influence AV adoption. By incorporating *perceived AV sickness*, *perceived risk*, *perceived value of time* and *willingness to use time more efficiently in an AV*, this study aims to investigate how these factors influence the AV acceptance.

2. Literature review

Acceptance is an important measure of the success of technology implementation, and can also guide further development and technological progress. With the future commercialization of AVs, increasing attention is being paid to public perception and acceptance. Existing studies of AV acceptance have been based on theories of human behavior, with the three most common being the technology acceptance model (TAM) (e.g., Zhang et al., 2020; 2019; Lee et al., 2019; Panagiotopoulos and Dimitrakopoulos, 2018; Xu et al., 2018), theory of planned behavior (TPB) (e.g., Chen and Yan, 2019; Buckley et al., 2018) and unified theory of acceptance and use of technology (UTAUT) (e.g., Kaye et al., 2020; Madigan et al., 2017). A variety of factors have been studied, with special attention paid to perceived ease of use, perceived usefulness and trust (Jing et al., 2020; Keszey, 2020). As for specific research findings, in a survey study of 647 drivers extending the TAM to include social and personal factors, Zhang et al. (2020) found that social influence and initial trust played the most important roles in AV acceptance, with the original TAM still being valid for explaining AV acceptance. In another study based on TAM, Lee et al. (2019) introduced factors for AV use in a survey of 313 respondents, finding that perceived usefulness, self-efficacy, perceived risk and psychological ownership were significant factors affecting intention to use AVs.

Several recently published reviews on AV acceptance can be found (Alawadhi et al., 2020; Jing et al., 2020; Keszey, 2020; Harb et al., 2021; Zhang et al., 2021). More specifically, Alawadhi et al. (2020) conducted a systematic review of 85 journal articles and identified a total of 14 factors influencing the adoption of autonomous driving. These were sorted into four readiness categories: technology, infrastructure, legal and user acceptance. In another systematic review based on 75 pieces of AV acceptance literature by Jing et al. (2020), the authors extracted, sorted and summarized psychological variables and AV attributes affecting AV acceptance based on seven factors related to behavioral theories (e.g., perceived ease of use, attitude and social norm) and six other factors (e.g., safety, performance-to-price value and mobility). Keszey (2020) conducted a systematic review of 27 papers examining AV adoption, finding that behavioral intention to use (BIU) AVs was influenced by variables related to personality traits, emotional states, perceptions of AVs, social environment and descriptive variables. In a review by Harb et al. (2021), the authors identified 27 papers exploring acceptance and intention to adopt automation technology, as well as the factors (e.g., perceived benefits and risks) that influence these decisions. This study also identified three key research methods for exploring this topic: driving simulators, virtual reality and survey studies. Finally, Zhang et al. (2021) conducted a *meta*-analytic review and quantitatively synthesized existing literature, with results suggesting that trust was the most significant contributing factor to AV acceptance, followed by perceived usefulness and perceived risk. While numerous studies have been conducted, there is little research examining the effects of *perceived AV sickness*, *perceived value of time* and *willingness to use time more efficiently in an AV* on behavioral intention to use AVs, as well as their interrelationships. Based on a review of existing research, this study focuses on these factors and proposes a new theoretical research model, with details provided in **Section 3**.

3. Hypotheses and research model

3.1. Behavioral intention

Acceptance is “the degree to which an individual incorporates the system in his/her driving, or, if the system is not available, intends to use it” (Adell et al., 2014, p. 18), while in the Theory of Reasoned Action (TRA), behavioral intention refers to “a person’s subjective probability that he will perform some behavior" (Fishbein and Ajzen, 1975, p. 288), and is the ultimate predictor of the actual behavior (Agudo-Peregrina et al., 2014). Using behavioral intention (to use AVs) as the dependent variable, instead of actual usage, is particularly useful for examining the acceptance of technological systems at an early stage (Choi and Ji, 2015).

Adapted from Liu et al. (2019b), behavioral intention was assessed using "I intend to use AVs in the future," "I intend to buy AVs in the future," and "I will recommend family members and friends to use AVs," all based on a five-point Likert scale (strongly disagree to strongly agree).

3.2. Perceived value of time

The value of time (or value of travel time; VOT) is defined as "the marginal tradeoff between travel time and unearned income that would leave the traveler indifferent" (Small, 2012), and it has been shown that conducting onboard activities reduced VOT on the train (Molin et al., 2020). In the context of AVs, these autonomous driving systems also allow users to conduct other in-vehicle activities such as working and studying, thereby reducing VOT (Harb et al., 2021; Jing et al., 2020) and making them especially attractive for longer-distance commuters (Haboucha et al., 2017). In a survey study of 1,881 respondents by Zhong et al. (2020), the authors found that riding in a private AV reduced commuters' VOT by 18–32% when compared to conventional driving. If users perceive a reduction in VOT thanks to using their time more efficiently in AVs, they may have higher intentions to use AVs. Therefore, in line with previous research, the following hypothesis is posited:

H1: Perceived value of time has a negative effect on behavioral intention.

Adapted from Lavieri and Bhat (2019), perceived value of time was assessed using the item, "AVs are appealing because they will allow me to use my travel time more efficiently (e.g., work or study in the car) even if the travel time might be longer," on a scale ranging from 1 (strongly agree) to 5 (strongly disagree).

3.3. Willingness to use time more efficiently (for work or study) in an AV

Another important factor that needs to be considered for AV adoption is public willingness to use time more efficiently (for work or study) in an AV. While AVs allow drivers to free up time traditionally spent focusing on the road and enable its use for work or study in a comfortable in-vehicle environment (Haboucha et al., 2017), user willingness remains a prerequisite for adoption. Such willingness may reduce the perceived value of time and contribute to intention to use AVs. Thus, the following hypotheses were suggested:

H2: Willingness to use time more efficiently in an AV has a negative effect on perceived value of time.

H3: Willingness to use time more efficiently in an AV has a positive effect on behavioral intention.

Assessment of willingness to use time more efficiently in an AV used the item, "Are you willing to use your time more efficiently (for work or study) in an AV?", and a five-point scale ranging from 1 (very unwilling) to 5 (very willing).

3.4. Subjective evaluation of commute time

It is said that "demand determines the market," and AVs have the potential to allow people to work or study while transiting, making more efficient use of their time. However, a demand for these products is essential (i.e., demand based on time wasted during commutes), meaning it is critical to gather subjective evaluations of (current) commute times. For example, in a survey study of 656 commuters in the U.S. by Singleton (2018), the author made use of subjective evaluations of commute times for different modes of commuting, finding that up to 50% of car drivers considered their commutes were wasted time, followed by car passengers (23%) and transit commuters (17%). In China, a report by the China Academy of Urban Planning and Design (2020) looked at data for 36 major cities and found that only 76% of commuters had commutes within 45 min, while more than 10 million people (13%) had commutes longer than one hour. This suggests both potential negative physical and mental effects and significant time wasted. For research subjects who express feeling that their time is being wasted commuting, they may have a desire to improve their time utilization, and AVs offer the possibility of working and studying in a comfortable environment. Thus, the following hypothesis was proposed:

H4: Inefficient use of current commuting time has a positive effect on willingness to use time more efficiently in an AV.

In this study, inefficient use of current commuting time was assessed using the item, "Do you think your current commute time is being efficiently used?", and a five-point scale ranging from 1 (fully used) to 5 (totally wasted).

3.5. Perceived AV sickness

In this study, perceived AV sickness is defined as "the degree to which the potential adopter believes that using an AV would cause car sickness". As mentioned above, in comparison to passengers, drivers of conventional vehicles have been shown to be less prone to motion sickness, as they are an integral part of the control loop of a vehicle's motion (Salter et al., 2019). One of the main benefits of AVs is that they allow time that would otherwise be spent driving to be used for economically-productive (non-driving) activities such as working and studying. However, the threat of experiencing motion sickness may decrease willingness to use the time spent travelling in AVs more efficiently, meaning that a key benefit of this technology may not be capitalized on and user acceptance may be negatively impacted (Diels and Bos, 2016; Green, 2016; Iskander et al., 2019). Therefore, it was hypothesized that:

H5: Perceived AV sickness has a negative effect on willingness to use time more efficiently in an AV.

H6: Perceived AV sickness has a negative effect on behavioral intention.

In this study, perceived AV sickness was assessed using “AVs would cause car sickness” and a five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree). Note that the question is more in general terms.

3.6. *Car sickness susceptibility*

Motion sickness produces varying degrees of discomfort, from dizziness through nausea up to vomiting (Murdin et al., 2011). Car sickness, as a form of motion sickness that occurs in road vehicles, still affects about two thirds of passengers, with the highest incidence of car sickness being reported in China (compared to Brazil, Germany, UK and USA) (Schmidt et al., 2020). With the introduction of AVs, motion sickness is likely to become more prevalent, with those people previously susceptible becoming more so due to the increased range of seating positions and the possibility of undertaking more activities with eyes focused away from the road (Iskander et al., 2019). In other words, susceptibility to motion sickness caused by conventional vehicles may be “transferred” to AVs, meaning that people who regard themselves as susceptible to carsickness may perceive that AVs can cause motion sickness as well. Furthermore, motion sickness is known to be more susceptible for passengers in the vehicle than its driver (Salter et al., 2019) which will now become relevant to those people using AV who used to drive. The following hypothesis was proposed:

H7: Car sickness susceptibility has a positive effect on perceived AV sickness.

Adapted from the motion-sickness-susceptibility questionnaire (Golding, 1998), car sickness susceptibility was assessed using the item, “Do you regard yourself as susceptible to car sickness?”, on a four-point scale ranging from 1 (not at all) to 4 (very much so).

3.7. *Perceived risk*

Although AVs have been promoted as enhancing road safety by removing human error from drivings (Yuen et al., 2020; Diels and Bos, 2016), users still have serious concerns about the potential risks of AVs. This perceived risk may be a critical obstacle to achieving widespread acceptance (Zhu et al., 2020). For example, Lee et al. (2019) conducted a survey study of 313 respondents and found that perceived risk significantly negatively affected intention to use AVs. Similarly, in another survey study of 1,355 participants, Liu et al. (2019a) found that perceived risk was a negative predictor of willingness to pay for AV technology. Additionally, if people perceive AVs as being unsafe, they may be unable to concentrate on working or studying, hindering user willingness to use time more efficiently in an AV. Therefore, the following hypotheses were offered:

H8: Perceived risk has a negative effect on willingness to use time more efficiently in an AV.

H9: Perceived risk has a negative effect on behavioral intention.

Following Choi and Ji (2015) and Zhang et al. (2019), perceived risk was assessed using four items: “AVs might not perform well and create problems,” “Using AVs would be risky,” “I am worried that failures or malfunctions of AVs may cause accidents,” and “I am worried about the general safety of AVs.” All were based on a five-point Likert scale (strongly disagree to strongly agree).

In summary, Fig. 1 shows all the factors and hypothetical relationships proposed in this study. The significance of these hypotheses is examined through partial least squares structural equation modeling (PLS-SEM; Hair et al., 2017).

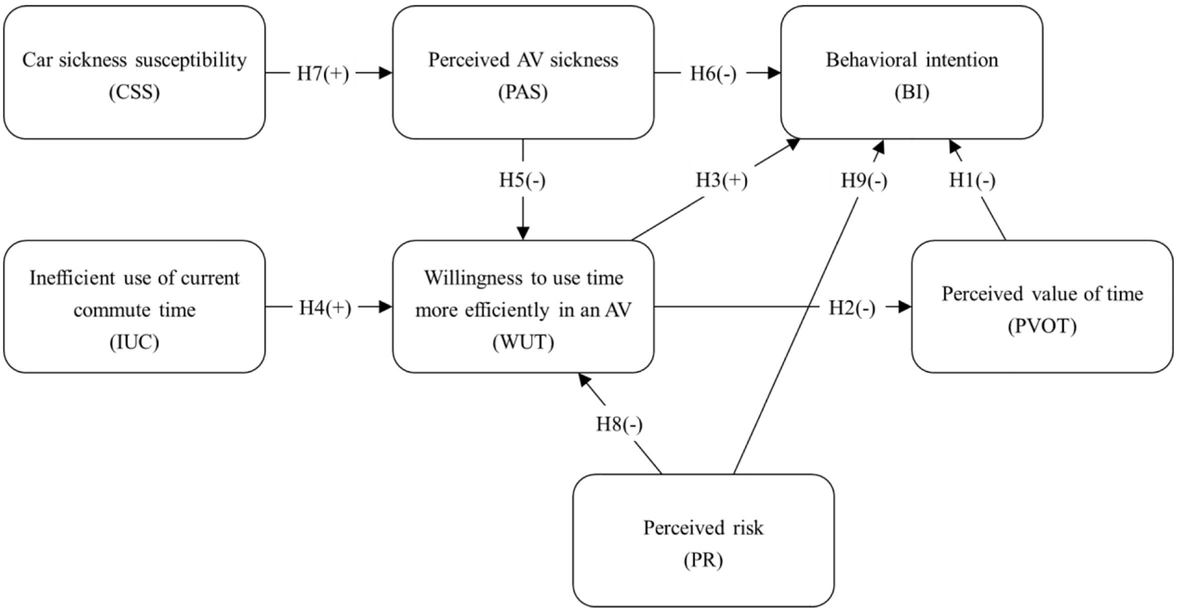

Fig. 1. Proposed research model.

4. Materials and methods

4.1. Survey design and administration

The online questionnaire, comprising 3 sections, started with an explanatory statement and consent form to introduce the participants to the motivation and objective of the study, and to ask their consent to participant in the research. The second section starts with an introduction to AVs that included a diagram of all the SAE levels of driving automation, as well as a brief definition of AVs at the SAE level 5 (or full automation) to ensure that the participants have a common understanding of the level of AVs when completing the survey questionnaire. Following the definition were questions about the respondent's demographic information, such as age, gender, education, place of living and income.

As the survey was conducted in China using the Chinese-version questionnaire translated by a NAATI certified translator.[1] A pilot was also conducted to test the questions in the questionnaire and measure the time required to answer them.

After receiving ethical approval from the Monash University Human Research Ethics Committee, this survey was conducted in December 2020 via WJX (also known as Sojump)[2]. A minimum of 300 responses was considered desirable, since most AV-acceptance studies have used sample sizes higher than 300 (Zhang et al., 2021; Keszey, 2020). A total of 1,588 completed surveys were received. Following logic and consistency checks, 170 responses were removed, leaving a total of 1,418 valid surveys.

4.2. Demographics of respondents

Most (83%) of respondents reside in inner urban areas (Fig. 2), and <3% reside in rural areas. It should be noted that this is far below the proportion of the country's rural population in 2020 (36%) (National Bureau of Statistics of China, 2021). Demographic and driving-related data for respondents are shown in Table 1. More than half of respondents were female (55%), slightly higher than the proportion of females in China in 2020 (49%) (National Bureau of Statistics of China, 2021). More than half of respondents were between the ages of 25–34 (56%), and possessed at least a bachelor's degree (76%), indicating a high overall level of education among respondents. This is compared with 2020 census data showing that just 15% of the population had a college diploma or greater (National Bureau of Statistics of China, 2021). The vast majority (86%) of respondents work full-time, followed by students (5%) and self-employed workers (4%), while of the four respondents who selected "other", two are freelancers, one a full-time mother, and one is preparing for a postgraduate entrance exam.

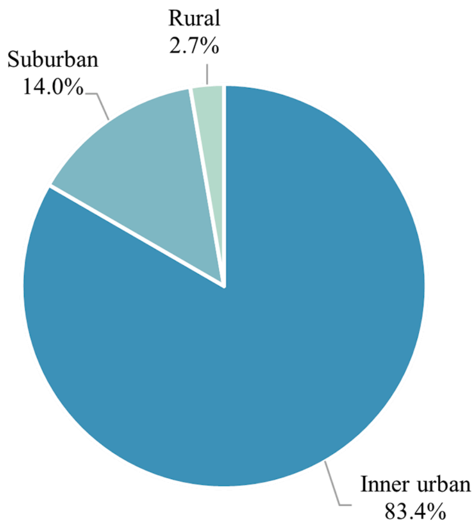

Fig. 2. Distribution of residential locations.

1 https://www.naati.com.au/information-guides/descriptors-for-translating.
2 www.wjx.cn.

Table 1
Summary of demographic and driving related information (n = 1,418).

Variable	Frequency	Percentage	Cumulative percentage
Gender			
Male	638	45.0%	45.0%
Female	780	55.0%	100.0%
Age			
18–24	155	10.9%	10.9%
25–34	799	56.4%	67.3%
35–44	343	24.2%	91.5%
45–54	95	6.7%	98.2%
55–64	22	1.6%	99.7%
65 and older	4	0.3%	100.0%
Educational level			
Less than high school degree	20	1.4%	1.4%
High school degree	60	4.2%	5.6%
Some college but no degree	266	18.8%	24.4%
Bachelor’s degree	911	64.3%	88.7%
Master’s degree	148	10.4%	99.1%
Doctoral degree	13	0.9%	100.0%
Employment status			
Full-time employment	1219	86.0%	86.0%
Part-time employment	45	3.2%	89.1%
Self-employed	55	3.9%	93.0%
Unemployed/Looking for work	14	1.0%	94.0%
Unemployed/Not looking for work	4	0.3%	94.3%
Student	65	4.6%	98.9%
Retired	12	0.9%	99.7%
Other	4	0.3%	100.0%
Annual household income (before taxes)			
< ¥30,000	43	3.0%	3.0%
¥30,000 – 59,999	93	6.6%	9.6%
¥60,000 – 89,999	127	9.0%	18.6%
¥90,000 – 119,999	156	11.0%	29.6%
¥120,000 – 149,999	209	14.7%	44.3%
¥150,000 – 179,999	181	12.8%	57.1%
¥180,000 – 209,999	142	10.0%	67.1%
¥210,000 – 239,999	145	10.2%	77.3%
¥240,000 – 269,999	117	8.3%	85.5%
¥270,000 – 300,000	86	6.1%	91.6%
> ¥300,000	119	8.4%	100.0%
Driving license			
Yes	1310	92.4%	92.4%
No	108	7.6%	100.0%
Driving frequency			
Rarely/never	192	13.5%	13.5%
<4 days per month	145	10.2%	23.8%
One day a week	84	5.9%	29.7%
2–3 days a week	278	19.6%	49.3%
4 or more days a week	402	28.4%	77.6%
Daily	317	22.4%	100.0%
Weekly driving kilometers			
< 20 km	306	21.6%	21.6%
[20 – 100] km	472	33.3%	54.9%
(100 – 200] km	318	22.4%	77.3%
(200 – 300] km	190	13.4%	90.7%
(300 – 400] km	89	6.3%	97.0%
(400 – 500] km	26	1.8%	98.8%
greater than 500 km	17	1.2%	100.0%

4.3. Data analysis

Partial least squares structural equation modeling (PLS-SEM; Hair et al., 2017) was performed using SmartPLS 3 (Ringle et al., 2015). PLS-SEM is a nonparametric method that makes no distributional assumptions. The reason why PLS-SEM is an appropriate approach for this study is that the goal is to predict a target construct (i.e., *behavioral intention*) or to identify key "driver" constructs (e.g., *perceived risk*, *perceived AV sickness*, and *perceived value of time*), and that it can handle single-item constructs, with no identification problems (Hair et al., 2017). In addition, multi-group analysis (MGA) in PLS-SEM is useful for exploring differences among groups (e.g., age, gender, and income) in terms of intention to use AVs. Previous studies have also shown that PLS-SEM is effective in investigating technology acceptance in various research areas such as Chatbots (Kasilingam, 2020), wearable health monitoring technology (Binyamin and Hoque, 2020), virtual reality technology (Kwok et al., 2021), and AVs (Chen and Yan, 2019).

The data were analyzed in two stages: first the reliability and validity of the measurement model, then the hypothesis testing and analysis. Path significance was estimated using a complete bootstrapping re-sampling method with 5,000 sub-samples (Hair et al., 2017).

5. Results

In this section, the results of the descriptive, measurement-model and structural-model analyses are discussed.

5.1. Descriptive analysis

As shown in Fig. 3, "car (as driver)" was the most commonly used mode of transport for commuting (71% of respondents), far more than the second-most used – "train/metro" (36%), and the third-most used – "bus/bus rapid transit" (33%).

Fig. 4 shows that nearly half (46%) of respondents find their commutes to be time wasted. When asked about the barriers to working or studying while commuting (Fig. 5), "I am the driver" topped the list, followed by "unsmooth driving" and "unstable internet". Nine respondents selected "other", specifying barriers that include walking, carsickness, time being too short, and fear of having her privacy compromised.

As shown in Fig. 6, up to 79% of respondents expressed a willingness to use their time more efficiently for work or study in AVs. As for households surveyed based on income (Fig. 7), more respondents from high-income households (84%) were willing to use their time more efficiently in AVs than respondents from low-income households (74%). Note that the average wage of employed persons in urban units is ¥90,501 in 2019 (National Bureau of Statistics of China, 2020), so those households making less than ¥180,000 were placed in the low-income group, and those earning ¥180,000 or higher were placed in the high-income group (assuming that there are

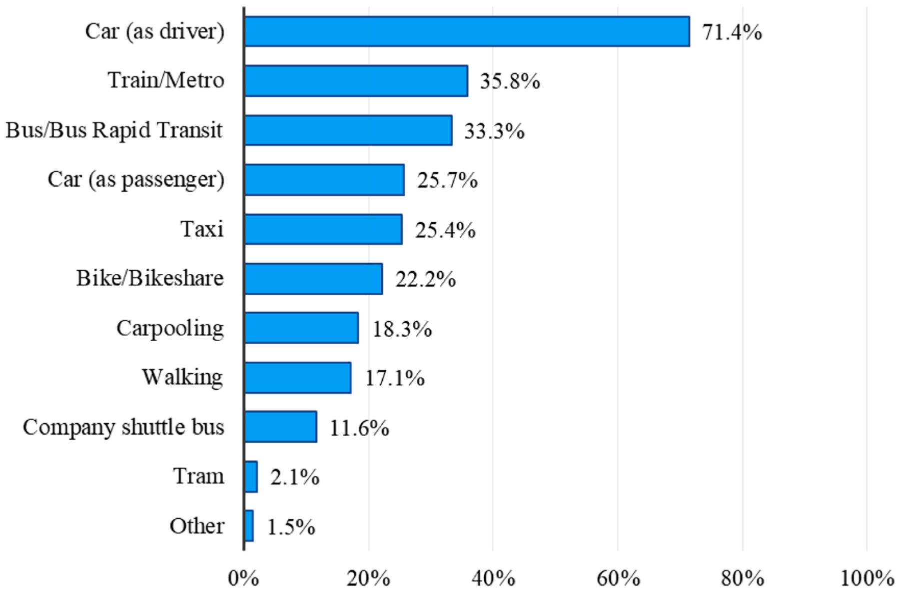

Fig. 3. Distribution of the most commonly used mode/modes of transport for commuting. Note: The question, based on Correia et al. (2019), is multiple choice. The percentage refers to the proportion of respondents who chose this option.

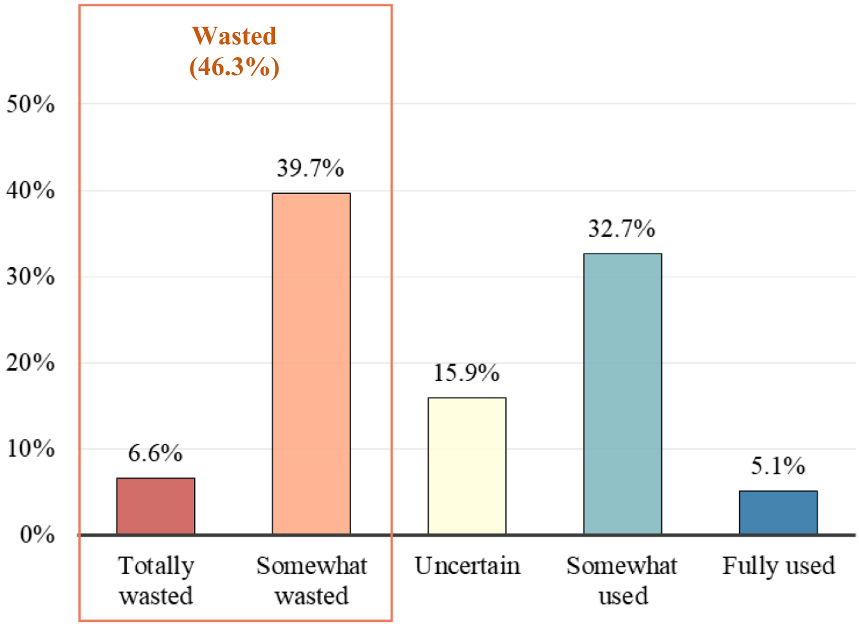

Fig. 4. Subjective evaluation of current commute time.

two employees in a household).

As shown in Fig. 8, driving is the leading in-vehicle activity of a commuter of this survey. In accordance with the findings in (Fig. 5), being the driver is the main barrier to working or studying while commuting, and "watching vehicle/road/traffic" comes second, as an activity concomitant with driving. However, for traveling in an AV (Fig. 9), "working/handling official business" becomes the primary activity, indicating that respondents look forward to being able to work in an AV so that they can use their time more efficiently. "Communicating: by phone, email, etc." comes second, which is easy to understand, since it is an important part of most modern jobs and social activities.

As shown in Fig. 10, "smooth driving" is the most important prerequisite for working or studying in an AV, and necessary for

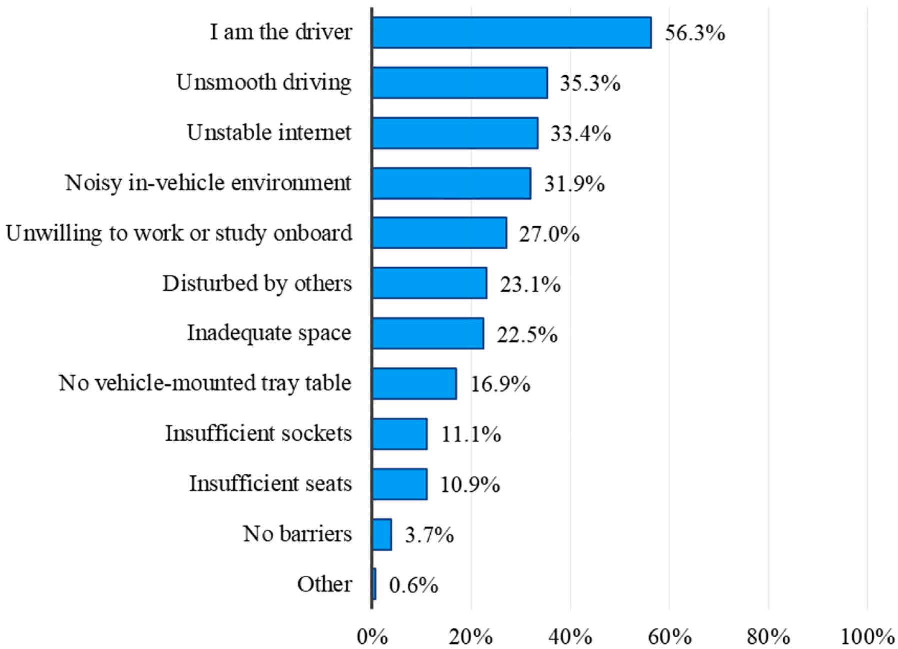

Fig. 5. Barriers to working or studying while commuting. Note: The question, developed based on Tang et al. (2018), is multiple choice.

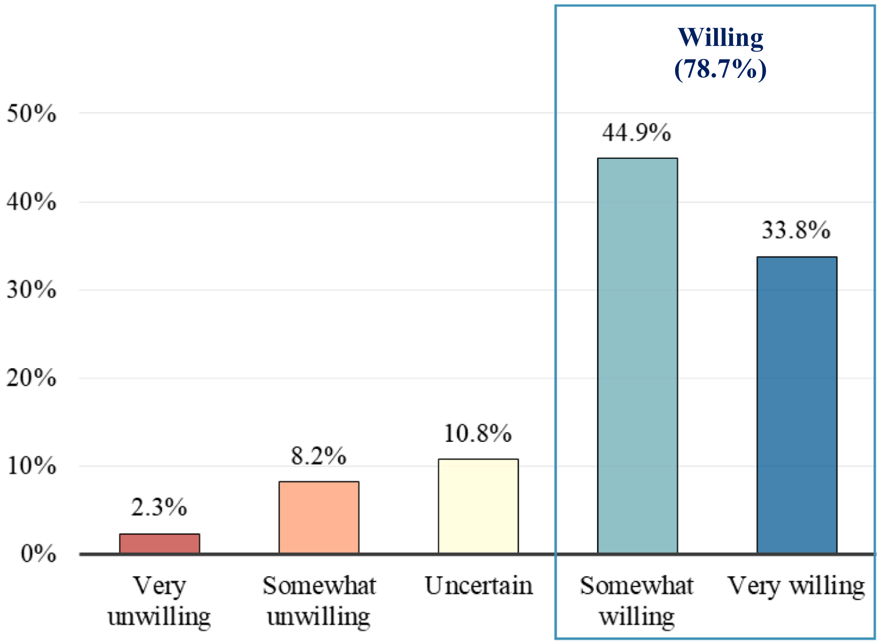

Fig. 6. Willingness to use time more efficiently (for work or study) in an AV.

comfort and for preventing carsickness. "Good internet connectivity" ranks second, since it is indispensable for most work, while third is the "quiet in-vehicle environment" needed for good concentration. Six respondents selected "other", specifying adequate lighting and mental preparation".

Fig. 11 illustrates that 84% of respondents expressed feeling that undertaking some or all of their regular job/study in an AV would be possible. From a practical point of view, this is a great opportunity for AV developers to explore ways to allow people to finish some or all of their work or study while traveling in AVs, including through enhanced interior layouts and better control of vehicle motion dynamics.

Of the 1,418 respondents, 139 were not willing to undertake some or all of their regular work or studies in an AV, with lack of safety and carsickness being the top two reasons (Fig. 12). For example, they stated:

> "I can't confirm that I'm safe in the vehicle. Autonomous vehicles are still a concept, and are yet to be realized. When they really appear, and have been verified to be safe and reliable, I will be willing to do some of my routine work and studying in it."

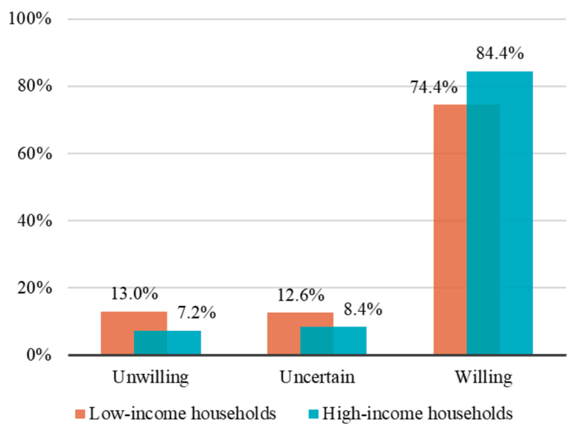

Fig. 7. Willingness to use time more efficiently (for work or study) in an AV (by annual household income).

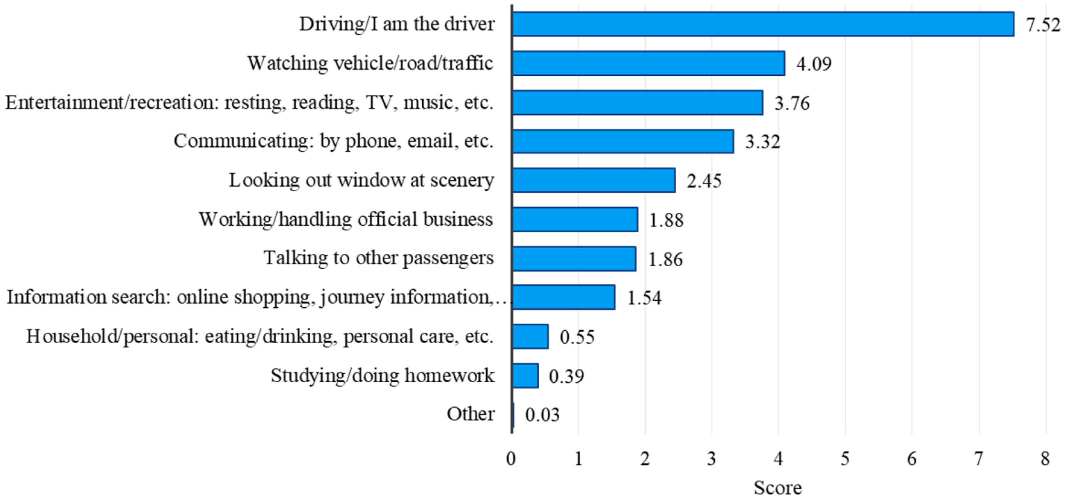

Fig. 8. Scores of current main in-vehicle activities during commute time. Note: The question is developed based on Zhong et al. (2020) and Koppel et al. (2019). In the question, participants can click 1–3 options (in order of priorities). The maximum score is 11, with higher scores indicating more important (refer to **Appendix A** for the calculation of scores).

> "I am afraid of the safety of automatic driving, and will always observe whether the driving is safe and be on tenterhooks, making me unable to concentrate on my work."
>
> "Looking at a computer or a phone gives me car sickness."

Please note that the question for Fig. 12 (i.e., Would you be willing to undertake some or all of your regular job/study in an AV?) is a yes–no question, differing from the question for Fig. 6 (i.e., Are you willing to use your time more efficiently for work or study in an AV?), which uses a 5-point Likert scale and puts greater emphasis on the more efficient use of time. Of the 139 respondents who chose no (unwilling) in the former question, 36 chose "somewhat willing" to use time more efficiently for work or study in an AV (the latter question), while 33 chose "uncertain," meriting further exploration.

As shown in Fig. 13, if travel costs were the same for both conventional and autonomous vehicles, 94% of respondents would accept a 5-min travel-time increase in AVs, as long as the AV allowed them to make more efficient use of travel time (such by working or studying), while 70% of respondents would accept a 10-min increase, showing that people consider AVs to be less wasteful of their time than HVs, and the value of time when using AVs (VOT_{AV}) is small than that of using HVs (VOT_{HV}) under these conditions. However, when the travel time increases by 15 min, the difference between those who accept and those who do not is much less, and when the travel time increases by 20 min, most (69%) of respondents do not accept it.

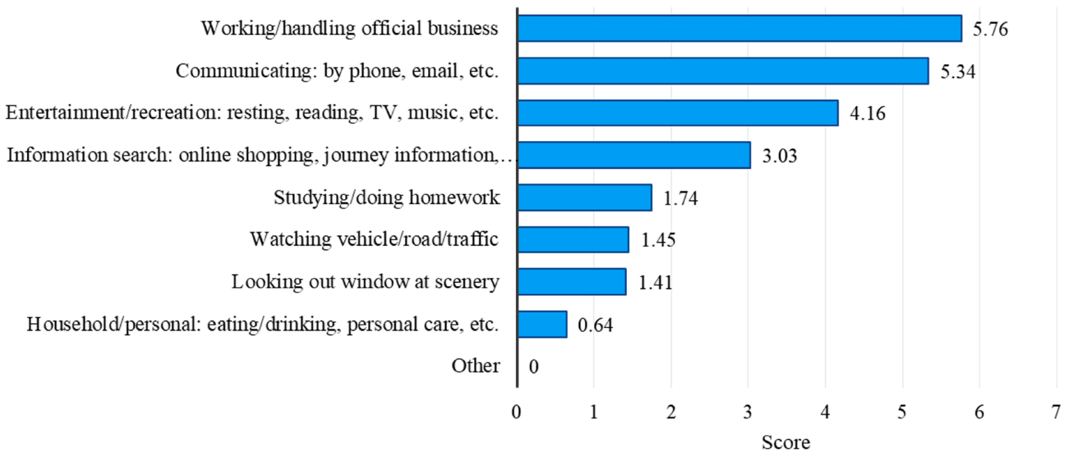

Fig. 9. Scores of main in-vehicle activities respondents are likely to do when traveling in an AV. Note: The question is developed based on Zhong et al. (2020) and Koppel et al. (2019). The question type and the calculation of scores are the same as those in Fig. 8. The maximum score is 9, with higher scores indicating more important.

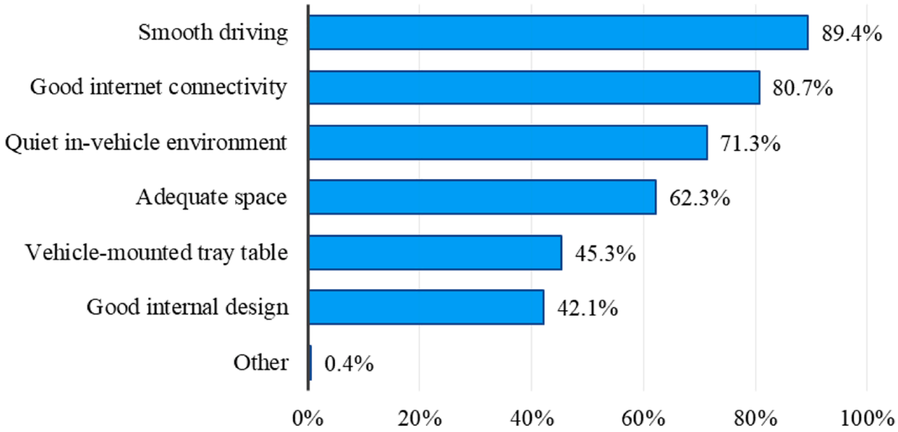

Fig. 10. Necessary conditions to work/study in an AV. Note: The question, developed based on Tang et al. (2018), is multiple choice, with multiple categories able to be selected.

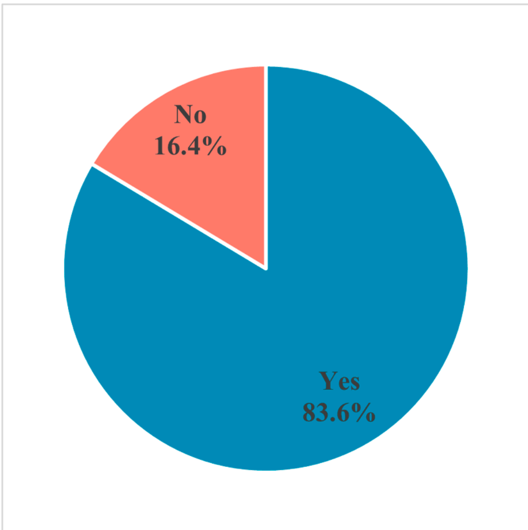

Fig. 11. Responses to the possibility of working or studying in an AV. Note: The questions are developed based on Correia et al. (2019).

Our results indicate that when the AV's *travel time* increases by 15 min, the probability of perceiving a smaller *total travel cost* using AV is approximately the same as that of HVs among all the respondents. This implies that there is no dominant opinion within the surveyed respondents, and that the difference between the total travel costs using HVs and AVs is in fact very small. For this reason, Equation (1) states that the total travel costs using either type of vehicles (HV or AV) is deemed to be the same when AV's travel time is 15 min longer.

$$VOT_{HV} \times T = VOT_{AV} \times (T + 15) \quad (1)$$

$$\mathrm{VOT_{AV}} < \mathrm{VOT_{HV}} \quad (2)$$

It should be noted that according to the China Academy of Urban Planning and Design (2020), the average commute time in 36 major Chinese cities is 36 min; in our study, 83.4% of the participants resided in inner urban areas, and<3% in rural ones. From this, it can be assumed that the length of the reference trip for answering this question is likely to be around 36 min. Additionally, it is worth noting that this equation is based on the respondents in this study and might not represent the general population, as well as their various travel patterns.

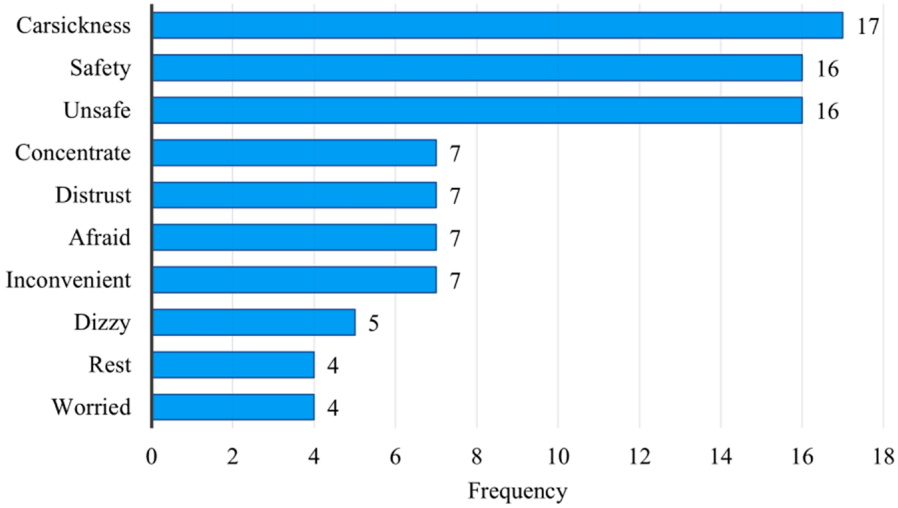

Fig. 12. Word frequencies of reasons for not willing to undertake (some or all of) regular job/study in an AV.

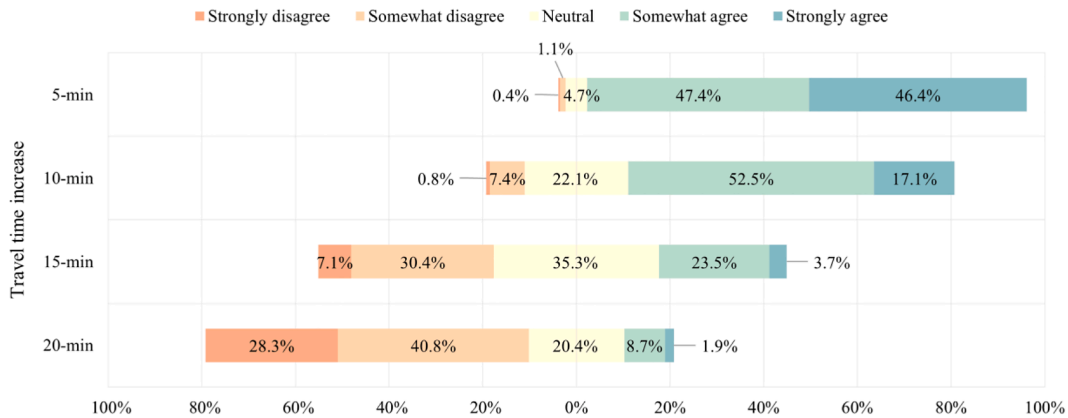

Fig. 13. Responses to "If an AV allows you to make more efficient use of your travel time (such as working or studying in it), how acceptable would you be if your travel time increased by using an AV (compared to that of a conventional vehicle; travel costs are the same for both)?". Note that this question provides an additional context to the results by evaluating the level of acceptance of different increases in AV's travel time while allowing more efficient use of this time.

5.2. Measurement model analysis

Following the guidelines suggested by Hair et al. (2017, p. 122; 2019), the results of the measurement model were assessed. As shown in Table 2, all the values for outer loadings, Cronbach's alpha, and composite reliability (CR) were above the 0.70 threshold, showing that indicator reliability and internal consistency reliability were achieved, while the average variance extracted (AVE) values were well above the required minimum level of 0.50, indicating high levels of convergent validity. Discriminant validity was assessed using the Fornell-Larcker criterion and Heterotrait-Monotrait ratio-of-correlations (HTMT) (see Table 3). Results of the Fornell-Larcker criterion show that the square-root values of AVE, in diagonal, were higher than the inter-construct correlation, thus establishing the discriminant validity of the measurement models. All the HTMT values were below the 0.85 threshold, further establishing discriminant validity for the model. Note that "by convention, single-item measures are included as reflective in a PLS path model" (Hair et al., 2014, p. 58).

Table 2
Construct reliability and validity.

Construct	Item	Outer loadings	Cronbach's alpha	CR	AVE
Car sickness susceptibility	CSS1	1.000	1.000	1.000	1.000
Perceived AV sickness	PAS1	1.000	1.000	1.000	1.000
Inefficient use of current commute time	IUC1	1.000	1.000	1.000	1.000
Willingness to use time more efficiently in an AV	WUT1	1.000	1.000	1.000	1.000
Perceived value of time	PVOT1	1.000	1.000	1.000	1.000
Perceived risk	PR1	0.832	0.859	0.903	0.700
	PR2	0.854			
	PR3	0.835			
	PR4	0.825			
Behavioral intention	BI1	0.877	0.814	0.890	0.729
	BI2	0.854			
	BI3	0.830			

Note: CR = composite reliability; AVE = average variance extracted.

Table 3
Discriminant validity.

Latent variable	BI	CSS	IUT	PAS	PR	PVOT	WUT
Fornell-Larcker criterion							
BI	0.854						
CSS	−0.031	1					
IUC	0.046	0.013	1				
PAS	−0.146	0.311	−0.016	1			
PR	−0.259	0.127	0.034	0.282	0.837		
PVOT	−0.439	0.018	−0.099	0.079	0.052	1	
WUT	0.338	−0.035	0.165	−0.098	−0.080	−0.383	1
Heterotrait-Monotrait ratio (HTMT)							
BI							
CSS	0.034						
IUC	0.051	0.013					
PAS	0.160	0.311	0.016				
PR	0.301	0.140	0.036	0.297			
PVOT	0.483	0.018	0.099	0.079	0.053		
WUT	0.372	0.035	0.165	0.098	0.083	0.383	

5.3. Structural model analysis

All the inner variance-inflation-factor (VIF) values were<3 (Table 4), meaning that collinearity was not an issue (Hair et al., 2019). The standardized root mean square residual (SRMR) value for the estimated model was 0.066 (<0.08), indicating a good fit (Hair et al., 2017). The R^2 values for behavioral intention and perceived value of time were 0.278 and 0.147 respectively, larger than the cutoff value of 0.10 (Falk and Miller, 1992), suggesting acceptable explanatory power.

The smallest Q^2 value in this study was 0.036 (PAS = 0.095, WUT = 0.036, PVOT = 0.144, BI = 0.200), which is larger than zero (Hair et al., 2017), so the predictive accuracy of the path model was deemed acceptable. Results of the estimated structure model are presented in Fig. 14, with significant paths appearing as solid lines and non-significant paths appearing as dotted lines. A summary of path coefficients (β) and results of hypotheses testing is shown in Table 4. With the exception of H3 (PAS → BI), all of the proposed hypotheses were supported. Specifically, it was found that *car sickness susceptibility* had a positive effect on *perceived AV sickness* (β = 0.311, $p < 0.001$) in support of H1. *Perceived AV sickness* was a significant negative predictor of *willingness to use time more efficiently in an AV* (β = -0.077, $p < 0.01$), but did not directly affect *behavioral intention* (β = -0.039, $p = 0.123$). Therefore, H2 was supported, while H3 was not. However, it was found that *perceived AV sickness* indirectly affected *behavioral intention* via *willingness to use time more efficiently in an AV* and *perceived value of time*, with total indirect effects of −0.024 ($p = 0.010$).

Inefficient use of current commute time had a significant positive effect on *willingness to use time more efficiently in an AV* (β = 0.166, $p < 0.001$), supporting H4. Both H5 and H6 were supported, as *willingness to use time more efficiently in an AV* was shown to have significant effects on *perceived value of time* (β = -0.383, $p < 0.001$) and *behavioral intention* (β = 0.180, $p < 0.001$). As for proposed hypotheses related to *perceived risk* (H7 and H8), both were supported, given that *perceived risk* had significant negative effects on *willingness to use time more efficiently in an AV* (β = -0.064, $p = 0.029$) and *behavioral intention* (β = -0.215, $p < 0.001$). Finally, *perceived value of time* was found to be a reliable predictor for *behavioral intention* (β = -0.355, $p < 0.001$), meaning H9 was supported by the data.

Table 4
Summary of hypothesis testing.

Hypothesis	Inner VIF	Path coefficient (β)	p value	Supported?
H1: PVOT → BI	1.174	−0.355***	**<0.001**	**Supported**
H2: WUT → PVOT	1.000	−0.383***	**<0.001**	**Supported**
H3: WUT → BI	1.181	0.180***	**<0.001**	**Supported**
H4: IUC → WUT	1.002	0.166***	**<0.001**	**Supported**
H5: PAS → WUT	1.087	−0.077**	**0.008**	**Supported**
H6: PAS → BI	1.095	−0.039	0.123	Rejected
H7: CSS → PAS	1.000	0.311***	**<0.001**	**Supported**
H8: PR → WUT	1.088	−0.064*	**0.029**	**Supported**
H9: PR → BI	1.090	−0.215***	**<0.001**	**Supported**

Note: VIF = variance inflation factor; CSS = Car sickness susceptibility; PAS = Perceived AV sickness; IUC = Inefficient use of current commute time; WUT = Willingness to use time more efficiently in an AV; PR = Perceived risk; PVOT = Perceived value of time; BI = Behavioral intention; ***p < 0.001; **p < 0.01; *p < 0.05.

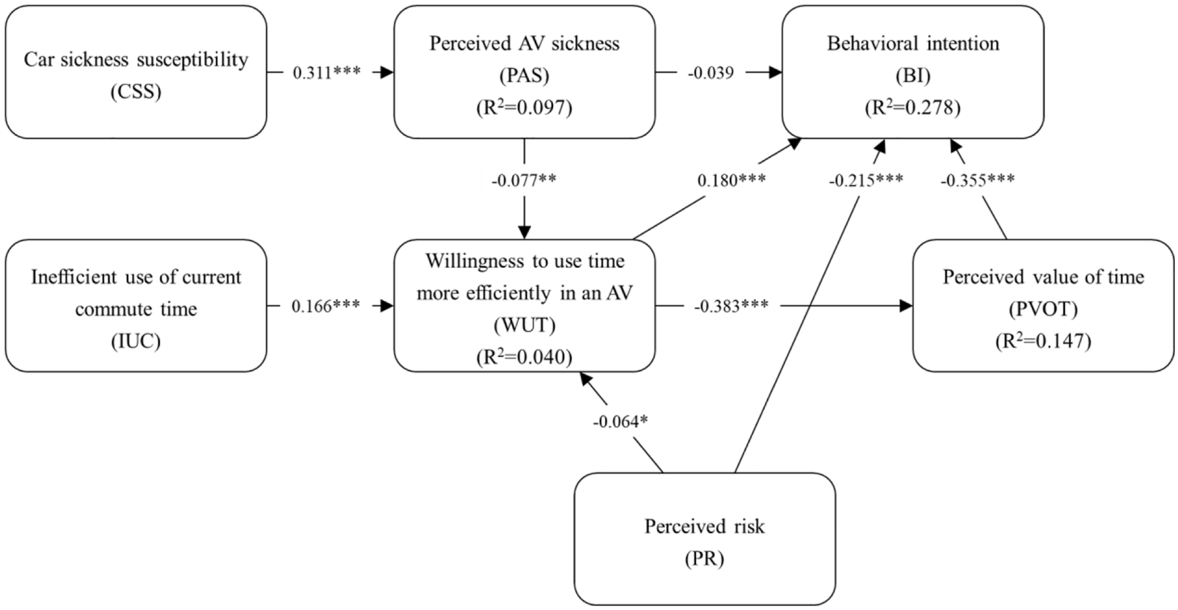

Fig. 14. Results of the structural equation model. Note: ***p < 0.001; **p < 0.01; *p < 0.05.

Table 5
Division of groups.

Factor	Group	Range	N	%
Age	Younger	18–34	954	67.3%
	Middle-aged and senior	35 and older	464	32.7%
Annual household income(before taxes)	Low	<¥180.000	809	57.1%
	High	≥¥180.000	609	43.0%

5.4. Multi-group analysis

The age and annual household income of the respondents were used as control variables in the multi-group analysis. For each of the variables, the data set was split into two groups. Respondents aged 18 to 34 were assigned to the young group, while those 35 and older were assigned to the middle-aged and senior group. In terms of annual household income, the division is the same as in Fig. 7. Details about this split are provided in Table 5.

Before running MGA, establishing configural and compositional invariance (i.e., partial measurement invariance) is required (Hair et al., 2017). Following the measurement invariance of composite models (MICOM) procedure (Henseler et al., 2016) with 5,000 permutations, the assessment of partial measurement invariance was conducted, with results being provided in Table 6 and Table 7. It can be seen that all the original correlations are greater than or equal to the 5% quantile, while permutation p-values are all greater than 0.05, establishing compositional invariance. Note that when running MICOM in SmartPLS, configural invariance is automatically

Table 6
Assessment results of partial measurement invariance – age groups.

Construct	Compositional invariance			Partial measurement invariance
	Original correlation	5.0%	Permutation *p*-values	
BI	1	0.999	0.382	Established
CSS	1	1	0.237	Established
IUC	1	1	0.149	Established
PAS	1	1	0.198	Established
PR	0.998	0.995	0.429	Established
PVOT	1	1	0.068	Established
WUT	1	1	0.376	Established

Note: CSS = Car sickness susceptibility; PAS = Perceived AV sickness; IUC = Inefficient use of current commute time; WUT = Willingness to use time more efficiently in an AV; PR = Perceived risk; PVOT = Perceived value of time; BI = Behavioral intention.

Table 7
Assessment results of partial measurement invariance – income groups.

Construct	Compositional invariance			Partial measurement invariance
	Original correlation	5.0%	Permutation *p*-values	
BI	1	0.999	0.362	Established
CSS	1	1	0.117	Established
IUC	1	1	0.600	Established
PAS	1	1	0.427	Established
PR	0.999	0.995	0.471	Established
PVOT	1	1	0.507	Established
WUT	1	1	0.427	Established

Note: CSS = Car sickness susceptibility; PAS = Perceived AV sickness; IUC = Inefficient use of current commute time; WUT = Willingness to use time more efficiently in an AV; PR = Perceived risk; PVOT = Perceived value of time; BI = Behavioral intention.

confirmed (Cheah et al., 2020).

The results of the PLS-MGA show that there are significant group differences (note *diff* below represents path coefficient difference):

- For the *Age* groups, H9 (PVOT → BI) differed significantly (*diff* = 0.142, $p = 0.015$), showing a greater negative effect of *perceived value of time* on *behavioral intention* for the *middle-aged and senior* group (β = -0.453, $p < 0.001$) than the *younger* group (β = -0.311, $p < 0.001$).
- Meanwhile, for the *Income* groups, H5 (WUT → PVOT) differed significantly (*diff* = 0.114, $p = 0.032$), meaning there was a greater negative effect of *willingness to use time more efficiently in an AV* on *perceived value of time* for the high-income (β = -0.452, $p < 0.001$) than the low-income group (β = -0.338, $p < 0.001$).

6. Discussion

6.1. Theoretical implications

This study fills an important gap in the literature on public acceptance of AVs by integrating *perceived AV sickness*, *willingness to use time more efficiently in an AV*, and *perceived VOT*, to understand the factors influencing public acceptance of AVs.

Unsurprisingly, as seen in Fig. 7, more respondents from high-income households (84%) than low-income households (74%) showed a willingness to use time more efficiently. The negative effect of *willingness to use time more efficiently in an AV* on *perceived value of time* was greater for higher-income households, as they tended to place greater value on their time, spend more time driving, do more driving for business-related reasons, and therefore benefit more from the more productive use of their time AV could provide (Wadud, 2017).

In line with the results of prior studies (Zhu et al., 2020; Lee et al., 2019), this study found that *perceived risk* significantly affected behavioral intention to use AVs. In addition, *perceived risk* was found to have an indirect effect of −0.014 ($p < 0.05$) on *behavioral intention* via *willingness to use time more efficiently in an AV*. Therefore, improving behavioral intentions will require taking measures (such as education, training and experience) to reduce *perceived risk*.

Willingness to use time more efficiently in an AV was also found to directly affect *behavioral intention*, in addition to contributing to a reduction in *perceived value of time*, and thus having an indirect effect of 0.136 ($p < 0.001$) on *behavioral intention* via *perceived value of time*. Although *perceived AV sickness*, *perceived risk* and *inefficient use of current commute time* all exerted significant effects on *willingness* *to use time more efficiently in an AV*, its explanatory power ($R^2 = 0.04 < 0.10$) was very weak. Therefore, there is a need for further research examining the determinants of *willingness to use time more efficiently in an AV*.

Perceived AV sickness was found to not affect *behavioral intention* directly, but indirectly through *willingness to use time more efficiently for work or study in an AV*. A possible explanation for this is that reading a book or staring at a screen for work or study would be more likely to cause motion sickness (due to head downward inclination) (Iskander et al., 2019), leading to a rejection of AVs. This was also reflected in the comments of respondents' as to why they would be unwilling to undertake some or all of their regular job or study in an AV. For example: "Looking at a screen may cause car sickness"; "Looking at a computer or mobile phones will make me carsick"; or "Reading will make me carsick."

As for *Age* groups, a greater negative effect of *perceived value of time* on *behavioral intention* was found with the middle-aged and senior group than with the younger group. Some possible explanations for these results include the increased time constraints, higher incomes and greater responsibilities of middle-aged respondents (it should be noted that only four respondents were 65 or older). In this way, this group showed more intention to use AVs if their perceived value of time could be reduced through conducting in-vehicles activities such as handling official business.

6.2. Practical implications

The findings of this study can help AV developers, stakeholders and policymakers determine better practices for the design and implementation of AVs. The results of descriptive analysis revealed that more than 40% of respondents considered "smooth driving," "good internet connectivity," "quiet in-vehicle environment," "adequate space," "vehicle-mounted tray table," and "good internal design" to be necessary conditions for engaging in work or study in an AV. Therefore, AV developers have an opportunity to improve their technology based on these aspects. The possibility of customized vehicle spaces may also lead to substantially enhanced comfort and productivity during commutes. Such improvements may affect perceptions of travel-time costs, especially for those who spend substantial amounts of time traveling (Zhong et al., 2020).

Perceived value of time exhibited the strongest effects on *behavioral intention* to use AVs, implying that reducing the user's *perceived value of time* (by using his or her time more efficiently in an AV) should be a significant part of AV promotion. One possible strategy, according to our model, would be to increase their *willingness to use time more efficiently in an AV* ($p < 0.001$). This implies that developers should design AVs for comfort, safety and convenience, and promote them in these terms, to enhance the *willingness of use time more efficiently in an AV*, and thus reduce the *perceived value of time*.

When it comes to reducing *perceived risk* and minimizing its negative effects on intention to use AVs, policymakers and manufacturers can make use of social media tools, public events showcasing AVs, and test drives, as well as the development of natural human–computer interaction such as verbal interaction, gesture interaction and system-initiative interaction. This not only has the potential to improve the driving experience, but also accelerate the process of AV commercialization (Hu et al., 2019). It is particularly important to show the public how AVs are able to operate in complex driving environments and highly hazardous situations, while also promoting public awareness of the limitations of AV technology (Dikmen and Burns, 2016).

Although *perceived AV sickness* was not found to have a direct effect on *behavioral intention*, it did have an indirect effect via *willing to use time more efficiently in an AV*. As can be seen in Fig. 12, feeling unsafe and fearing carsickness are the top two reasons for not being willing to work or study in an AV. The importance of safety, and potential measures to reduce perceived risk, have already been discussed, and AV developers should explore ways to mitigate or avoid motion sickness to enable passengers to work or study comfortably in an AV, such as through enhanced interior layout (e.g., with book stands and displays at eye level) or better control of vehicle motion dynamics (e.g., by maintaining a constant speed) (Iskander et al., 2019). In addition, in reality it may end up being the case that AV designers are able to provide users with the opportunity to control the acceleration/deceleration profile of their vehicle as they wish, with passengers either choosing to travel using relatively smooth acceleration/deceleration profiles, or using more "aggressive" profiles (Le Vine et al., 2015). This will allow users to choose the profile they are most comfortable with and may also increase their usage intention.

7. Conclusions, limitations and future work

This study has proposed and empirically tested an AV-acceptance model that integrates *perceived AV sickness*, *willingness to use time more efficiently in an AV*, *perceived risk*, and *perceived value of time*. The results of this study show that *willingness to use time more efficiently in an AV* has a significant positive impact on intention to use, while *perceived value of time* and *perceived risk* have significant negative effects on it. Moreover, the negative effect of *perceived value of time* on *behavioral intention* is greater for those middle-aged and older.

Several limitations should be considered when interpreting the results of this study, with the first being the generalizability of the findings. As the survey was China-based, generalizing the findings in the context of other countries and cultures would need to be explored further. Therefore, the impact of cross-cultural differences needs to be considered. An additional limitation is the fact that the sample is not evenly distributed by age, with an especially low number of older respondents. Additionally, most (83%) of participants lived in inner urban areas, meaning that responses may show some geographical specificity. The sample profile is not entirely representative of the wider population in the the studied country. In contrast with national demographics, survey respondents were better-educated, much more likely to reside in inner urban areas, and comprise a higher proportion of females. Additionally, note that regarding the item used to assess inefficient use of current commuting time (in **Section 3.4**), respondents may have had varying opinions about what in-vehicle activities could be considered as efficient use of time. The study also focused on private fully AVs (AVs with zero human input and for personal use), and the results are not necessarily generalizable to other levels of automation or shared AVs.

To improve the model's usefulness and explanatory power, additional potential influencing factors, such as comfort and reliability, are worthy of further exploration. In addition, it is possible that there are other links among the factors used in this study, and that other factors related to value of time and motion sickness or that influence them could also be added to the model in future studies. Furthermore, as some of the constructs are measured by single items, the development and use of multiple items may enhance predictive validity. Additionally, given growing familiarity with AV technology via the internet, television, or direct experience with AVs, factors such as perceived risk are expected to change over time. Therefore, longitudinal studies to further clarify how these factors and their effects on AV acceptance evolve should be examined. Finally, the study focuses on general acceptance of AVs, and more research is required to examine public acceptance and subsequent behavior when using and interacting with an AV in specific scenarios, as well as various travel and commute patterns.

Appendix A. The calculation of scores[3]

Higher scores indicate a higher overall ranking, with the equation being:

$$Score = \frac{\sum Frequency \times Weight}{N}$$

where *Frequency* is the number of times an option was selected, *N* is the number of respondents, and *Weight* is determined by the position of options. For example, if there were 3 options in the ranking, the first position would have a weight of 3, the second position would have a weight of 2, and the third position would have a weight of 1. Please note that the calculation of weights would not be affected by the number of options that respondents are allowed to select.

For example, there are 11 options in Fig. 8. "Studying/doing homework" ranked first 22 times ($weight = 11$), second 24 times ($weight = 10$), and third 8 times ($weight = 9$), meaning that the score of "studying/doing homework" $= (22 \times 11 + 24 \times 10 + 8 \times 9)/1418 = 0.39$.

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