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Initial trust formation on shared autonomous vehicles: Exploring the effects of personality-, transfer- and performance-based stimuli

Min Wu, Kum Fai Yuen *

School of Civil and Environmental Engineering, Nanyang Technological University, Singapore

A R T I C L E I N F O

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A B S T R A C T

Building initial trust is critical for the acceptance of shared autonomous vehicles (SAVs). Initial trust determines whether this emerging mobility solution will be accepted when it is available in the market. This study examines the initial trust formation process in the context of SAVs using the elaboration likelihood model and trust transfer theory. It investigates the effects of different personality-based, transfer-based, and performance-based factors on initial trust and adoption intention. A structural equation modelling is conducted in Singapore based on valid survey design principles, sampling protocols, and data analysis procedures. Results show that among three trust-building paths, the performance-based factors which include SAV capability and interaction quality are the most important. The transfer-based (i.e., trust in shared mobility) and personality-based factor (i.e., trust propensity) rank second and third, respectively. Six moderators such as covid history and shared mobility experience are also tested to investigate significant differences in the results. Based on these findings, this study offers theoretical and policy implications for scholars and practitioners.

1. Introduction

Shared autonomous vehicles (SAVs) can be seen as a new type of transportation that blends autonomous vehicles and car/ride sharing, which enables both in-vehicle freedom and shared mobility (Fagnant et al., 2015; Hao and Yamamoto, 2018; Zhang et al., 2015). Fig. 1 depicts the relationship between shared autonomous vehicles, autonomous vehicles, and shared mobility.

The adoption of SAVs will create numerous benefits to both the user and society. From the user perspective, SAVs can provide improved traffic safety and travel experience, and reduced travel time and travel cost (Fagnant and Kockelman, 2015; Iacobucci et al., 2018; Liu et al., 2018). From the society perspective, SAVs have the potential to reduce traffic congestion, parking demand, and carbon emissions (Jones and Leibowicz, 2019; Menon et al., 2019; Zhang et al., 2015). Some specific disadvantages should also be mentioned, such as high initial cost (Jones and Leibowicz, 2019), unintended shifts in model choice (from mass transportation to SAVs) (Pakusch et al., 2018), security issues (Narayanan et al., 2020), machine errors (Fridman, 2018), job losses and some other moral machine dilemmas (Milakis et al., 2017). Overall, there are obvious potentials to incorporate this new mobility solution into the existing transportation infrastructures to provide more accessible, efficient, and eco-friendly transport for the general public.

However, as an emerging transportation mode, SAVs are not available in the market. Therefore, initial trust, which is established without any prior knowledge, experience and interactions about the trustee, is considered a prerequisite for initial interaction and

* Corresponding author.
E-mail address: kumfai.yuen@ntu.edu.sg (K.F. Yuen).

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essential for public adoption (Aljaafreh et al., 2014; Kim et al., 2009; McKnight et al., 1998). Some studies such as Merat et al. (2017), Gkartzonikas and Gkritza (2019), and Paddeu et al. (2020a) have explored the relation between trust and adoption in the context of SAVs and identified some factors influencing trust. Nevertheless, these studies apply either two broad or too narrow definition of trust and do not distinguish between initial trust and cumulative trust, which may hinder accurate interpretation of the trust formation process of SAVs. Given that SAVs are still not available in the market, cumulative trust which is developed on knowledge, experience, and iterative interactions may not exist. Therefore, at the current stage, it appears more appropriate to concentrate on the early stage: the initial trust formation toward SAVs.

Differing from previous studies, this study will focus on initial trust to provide a more realistic fine-grained analysis of trust antecedents and the trust-adoption relation. Based on the elaboration likelihood model and trust transfer theory, initial trust can be established through three paths: personality-based, transfer-based, and performance-based path. Thus, this study (a) identifies personality-based, transfer-based, and performance-based factors that are considered in the process of initial trust formation using the elaboration likelihood model and trust transfer theory, (b) examines how these factors contribute to initial trust and adoption intention in the context of SAVs, and (c) ranks the importance of the three trust-building paths by comparing their path coefficients. In theory, this study contributes to the understanding of the early trust formation process of SAVs, reflecting more closely to the reality. In practice, this study supports policy makers, SAV operators, and manufacturers in facilitating public trust and acceptance towards SAVs from an early stage, through demonstrating the importance of different trust-building paths.

The structure of the rest of the paper is as follows. Section 2 provides a review of the relevant literature and proposes the theoretical model and hypotheses. Section 3 introduces the research process, data sources, and analytical methods. Section 4 presents the results and discussion. Section 5 summarizes the findings of this paper and suggests the direction of future research.

2. Literature review

2.1. Elaboration likelihood model

Elaboration likelihood model (ELM) is a dual process theory developed by Petty and Cacioppo (1986) which describes how people process stimuli and how these stimuli alter their attitudes and consequently, behaviors. According to ELM, a level of "elaboration" occurs when an individual is presented with stimuli. Here, "elaboration" refers to the level of effort required for the individual to process and evaluate the stimuli received, and then follow through with a call to action. Both positive stimuli and negative stimuli can be captured by ELM. There are two major routes of stimulus motion: the central route which reflects a high level of elaboration and the peripheral route which reflects a low level of elaboration. Under the central route, individuals' attitudes are affected by their careful and thoughtful consideration of the relevant information and comparative advantage provided by the stimuli. Under the peripheral route, the change in attitude is prompted by superficial cues in the stimulus or by simple reasoning based on the stimulus (Miller, 2005).

Up to now, ELM has been used by researchers from varied domains, including consumer behavior (Chang et al., 2020; Hu et al., 2021; Teeny et al., 2017), health care (Cao et al., 2017; Li et al., 2021; Susmann et al., 2021; Yoo et al., 2020), media (Ahmad Rizal et al., 2022; Molina and Jennings, 2018; Petty et al., 2009), politics (Kulkarni, 2017; Shahin et al., 2021) and so on. Based on previous studies, it can be found that ELM is a useful theory when examining the fundamental processes that drive individuals' cognition and

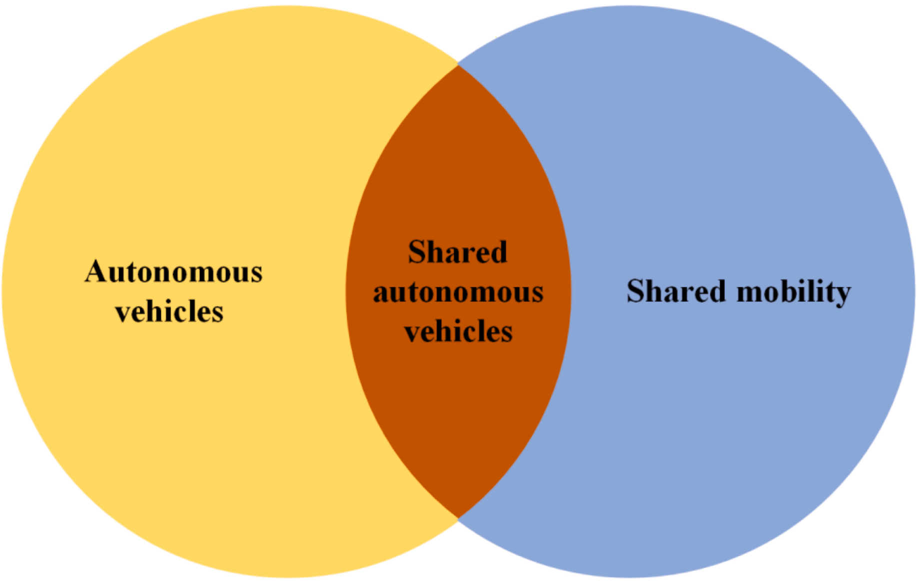

Fig. 1. The relationship between shared autonomous vehicles, autonomous vehicles, and shared mobility.

behavior.

In addition, ELM has also been widely used in studies of initial trust. For example, Zhou (2012) uses ELM to investigate consumers' initial trust in mobile banking. Silic and Ruf (2018) apply ELM to identify major factors which positively affect users' initial trust building process and consequently, the adoption intention of financial advisory services. Based on ELM and trust transfer theory, Chen et al. (2022) examine how livestreaming contributes to consumers' trust formation and purchase intention. In all, these studies indicate that ELM is a useful tool to explore the dual mechanism process of influence on initial trust and use intention. Therefore, in this study, ELM is integrated with trust transfer theory to identify antecedents of initial trust and acceptance towards SAVs and reveal how these factors work through central route processing or peripheral route processing.

2.2. Initial trust formation process and trust transfer theory

Previous studies show two phases of trust formation: initial trust and cumulative trust (Kim et al., 2009; McKnight et al., 1998). Initial trust is defined as a form of trust developed without prior experience but based on cognitive processes. This initial trust may evolve into the cumulative trust when users interact with the new innovative service or product and gain more experience and knowledge. In this study, since SAVs are still not available in the market, cumulative trust based on iterative interactions may not exist. Hence, it is considered appropriate to focus on the initial trust formation in SAVs.

Based on existing literature, initial trust can be established through three paths: personality-based, transfer-based, and performance-based path. Firstly, personality-based trust is associated with personality-based factors, such as trust propensity (Cao et al., 2020). According to Merritt et al. (2013), trust propensity refers to a general predisposition of a person to trust machines, rather than any specific machine, such as SAVs. Secondly, transfer-based trust is associated with transfer-based factors, such as in the SAV context, public trust may be transferred from shared mobility to SAVs. Thirdly, performance-based trust is associated with performance-based factors, such as the capability of SAVs and quality of human-SAV interaction. Both of the two factors have been found to have significant effect on initial trust (Boonlertvanich, 2019; Lee et al., 2021; Mcknight et al., 2011).

According to the trust transfer theory, users' trusting beliefs in currently available and well-known sources (such as a person or a technological device) may transfer to a new and unknown target (Stewart, 2003, 2006). To induce the transfer of trust, similarity, proximity, and common fate of the entities should be perceived. There are two potential trust sources for SAVs. One is shared mobility, and one is autonomous vehicles. However, in the present study, only trust in shared mobility would be involved in the theoretical model as a transfer-based factor. Trust in autonomous vehicles is excluded because autonomous vehicles cannot be seen as a currently accessible and well-known trusted source entity. Specifically, even in Singapore which, according to the 2020 Autonomous Vehicles Readiness Index (AVRI) compiled by KPMG, ranks first in the world in terms of its preparedness for autonomous vehicles, the public is quite unfamiliar with autonomous vehicles. The results of our pilot survey also show that most of the respondents have no prior experience with autonomous vehicles. In other words, autonomous vehicles are better considered as an unknown/unfamiliar trust target rather than a "currently available and well-known" trust source. Shared mobility can be broadly defined as the sharing of transportation resources and services among users, either simultaneously or sequentially (Machado et al., 2018). In recent years, with the emergence of apps like Uber and Lyft, shared mobility has become a common practice among modern people (QRIUS, 2018). Here, in this study, it is considered as the trusted source entity. The perceived similarity between it and SAVs is identified in two ways:

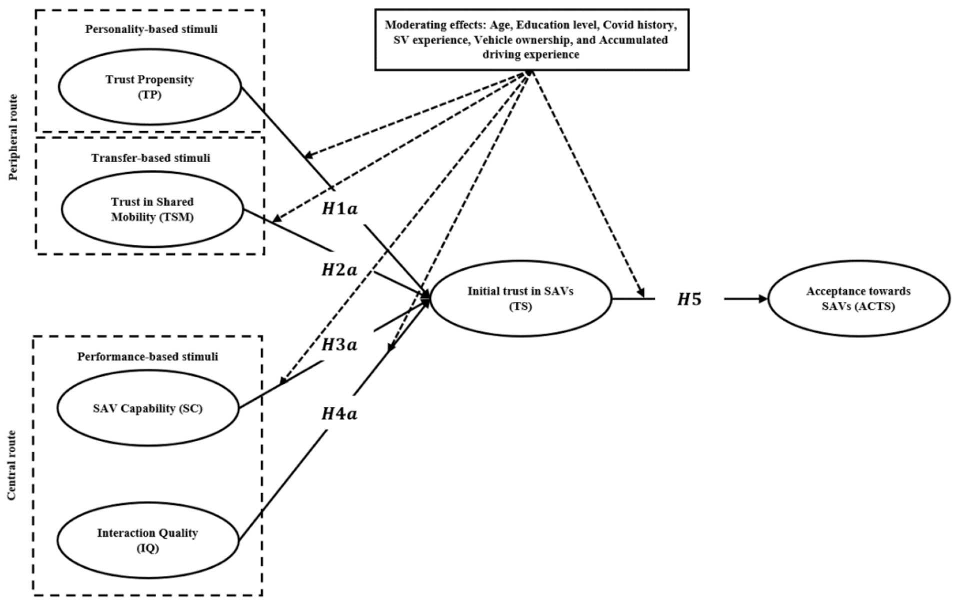

Fig. 2. The theoretical model.

literature search and pilot survey, which would be elaborated in the following hypothesis development section.

2.3. Antecedents of public initial trust and acceptance towards shared autonomous vehicles

According to the process of initial trust formation and ELM introduced above, this paper identifies two performance-based factors in the central route, and one personality-based factor and one transfer-based factor in the peripheral route to examine the positive direct effects of the four factors on initial trust and indirect effect of them on acceptance towards SAVs (See Fig. 2). Based on ELM, the major difference between the two routes is the level of cognitive effort needed: the central route requires more effort while the peripheral route requires less effort (Bhattacherjee and Sanford, 2006). As much effort and time are needed to evaluate and analyze perceived capability of SAVs and quality of human-SAV interactions, the two performance-based factors are classified into the central route. Whereas trust propensity and trust in shared mobility are classified into peripheral route because they mainly derived from subjects' association with positive or negative cues in the stimulus instead of the logical quality of the stimulus, which requires less cognitive effort.

2.3.1. Personality-based stimuli: Trust propensity

Trust propensity, as introduced above, reflects a natural inner tendency to trust (Merritt et al., 2013). It has been linked to initial trust formation in different domains over time, such as e-commerce, consumer behavior, technology adoption, and organizational relationships (Calefato et al., 2017; Chen and Barnes, 2007; Heidarian, 2019; Jessup et al., 2019; Kim et al., 2009; Koufaris and Hampton-Sosa, 2004; Li, 2005). In the context of AVs and shared mobility (which are two supersets of SAVs), trust propensity is also proved to be positively associated with public initial trust and acceptance (Asgari and Jin, 2020; Ma and Zhang, 2020, 2021). According to Baer et al. (2018) and Heyns and Rothmann (2015), people who have a higher trust propensity tend to have more initial trust in a certain machine system. Colquitt et al. (2014) and Gill et al. (2005) also suggested that people's initial trust is assumed to be significantly influenced by trust propensity when little is known about the trustee (e.g., SAVs in this study). Thus, this paper proposes the following hypothesis to test the direct effects between trust propensity and initial trust in the context of SAVs.

H1a: Trust Propensity (TP) has a direct positive influence on initial trust in SAVs (TS).

2.3.2. Transfer-based stimuli: Trust in shared mobility

When it comes to the transfer-based factor, trust in shared mobility is chosen for this study. That is because, compared to autonomous vehicles, which is another superset of SAVs, shared mobility is more common in everyday life (GVR, 2022). Industry statistics show that the value of the global ridesharing market in 2021 is US$85.8 billion and is expected to grow to US$185.1 billion by 2026 (Zippia, 2022). As in Singapore, the geographical area of the present study, revenue from the shared rides segment is anticipated to reach an annual growth rate of 4.78% between 2023 and 2027, and a projected market volume of US$2,125 million by 2027 (Statista, 2022). According to trust transfer theory, users' trusting beliefs in currently accessible and well-known sources may shift to a currently inaccessible and unknown new target. The process of transferring trust from the source (i.e., shared mobility) to the target (i.e., SAVs) relies on the perceived similarity, proximity, and common fate between the source and the target (Stewart, 2003). In this study, the perceived similarity/proximity is identified in two ways: literature search and pilot survey. First, based on the literature review, it can be noticed that many studies view SAVs as a combination of conventional ridesharing/carsharing services and autonomous vehicles (Fagnant et al., 2015; Zachariah et al., 2014; Zhang et al., 2015). In some studies, SAVs are seen as autonomous vehicles embedded with ride/car sharing service (Mounce and Nelson, 2019; Paddeu et al., 2020b). Thus, it is reasonable to assume that association (reflected by perceived similarity, proximity, and common fate) exists between SAVs and shared mobility. Second, feedback from the pilot survey which conducted before the full launch shows that respondents tend to regard SAVs as automation support enabled shared mobility and perceive similarity between the two entities. Therefore, in this study, trust in shared mobility is adopted as the transfer-based factor to test the hypothesis as follows.

H2a: Trust in Shared Mobility (TSM) has a direct positive influence on initial trust in SAVs (TS).

2.3.3. Performance-based stimuli: SAV capability

In addition to personality-based and transfer-based factors, performance-based factors may also positively associate with initial trust formation. SAV capability, in this study's context, is measured from the three dimensions, including functionality (the ability of SAVs to complete an assigned task), helpfulness (the adequate and responsive feedback from SAVs), and reliability (the expectation that SAVs can be relied on) (Mcknight et al., 2011). The reasons for selecting SAV capability as one performance-based factor can be found in existing studies. Firstly, SAVs, as an emerging mobility solution, whose primary role is to meet people's transport needs (Paddeu et al., 2020b). Therefore, whether having the ability to perform a successful riding task, would be people's first consideration when they use a SAV for the first time. Secondly, based on previous studies, adequate and responsive feedback (e.g., appropriateness of cues and effectiveness of communication) would exert a significant effect on trust development (Krueger et al., 2016; Merat et al., 2017; Mole et al., 2019; Schaefer et al., 2016; Zavala et al., 2021). Therefore, people's expectation that an SAV can provide competent guidance and the help they needed would probably boost their trust. Thirdly, to prompt people to trust SAVs, the behaviors of SAVs should also be reliable (Etminani-Ghasrodashti et al., 2021; Liu et al., 2019). Obviously, SAVs would be more readily trusted and adopted if their dependability (i.e., can be relied on to meet travel needs) is perceived by potential users. Based on the above discussion, the following hypothesis is put forward.

H3a: SAV Capability (SC) has a direct positive influence on initial trust in SAVs (TS).

2.3.4. Performance-based stimuli: Interaction quality

Another performance-based factor considered in this study is interaction quality. Interaction quality here refers to the perceived functional quality and service fit between SAVs and human beings. Measurement items of this construct are adapted from the Social Service Robot Interaction Trust (SSRIT) scale developed by Chi et al. (2021). According to Chi et al. (2021), higher perceived interaction quality would improve users' overall service evaluation, and thus their trust in service. Pelau et al. (2021) also argue that higher interaction quality leads to higher trust and acceptance towards artificial intelligence (AI) devices. Lee et al. (2021) report similar findings in the context of social robots. According to Schaefer et al. (2016), trust towards an automated device is fostered by the quality of service that the automated device provides. Since SAVs are one kind of automated, social robots equipped with a range of AI technologies, this paper proposes the following hypothesis to examine the positive effect of human-SAV interaction quality on trust development in SAVs.

H4a: Interaction Quality (IQ) has a direct positive influence on initial trust in SAVs (TS).

2.3.5. The relationship between initial trust and acceptance towards shared autonomous vehicles

Previous studies have linked trust to acceptance in the context of SAVs. For example, Merat et al. (2017) point out that trust reflects people's perceived capability or dependability of SAVs, and will ultimately decide whether the SAV would be used and adopted. Gkartzonikas and Gkritza (2019) suggest that trust, especially trust in strangers, is a key psychological factor to take into account when combing autonomous vehicles with ridesharing services. Paddeu et al. (2020a) argue that comfort and trust are two crucial factors that positively impact acceptance towards SAV shuttles. If expanded the literature review to cover autonomous vehicles and shared mobility, more papers discussing the positive relationship between trust and acceptance can be found, such as Lee and Cha (2022), Yuen et al. (2021), Dirsehan and Can (2020), Ward et al. (2017), and Shao et al. (2020). Therefore, this paper proposes the following hypotheses to test, in the SAVs context, the positive effect of initial trust on acceptance, and the indirect positive effect of four antecedents on acceptance via initial trust.

H1b: Trust Propensity (TP) has a positive indirect effect on acceptance towards SAVs (ACTS) via initial trust in SAVs (TS).
H2b: Trust in Shared Mobility (TSM) has a positive indirect effect on acceptance towards SAVs (ACTS) via initial trust in SAVs (TS).
H3b: SAV Capability (SC) has a positive indirect effect on acceptance towards SAVs (ACTS) via initial trust in SAVs (TS).
H4b: Interaction Quality (IQ) has a positive indirect effect on acceptance towards SAVs (ACTS) via initial trust in SAVs (TS).
H5: Initial trust in SAVs (TS) has a direct positive influence on acceptance towards SAVs (ACTS).

3. Method

3.1. Measures

To test the hypotheses, pre-validated measurement items are adapted from existing literature (see Table 1). As shown in Table 1, all constructs are measured using 3–5 questions. Besides, to capture the best sentiment of the respondents and reach better accuracy on the results, a 7-point Likert Scale is used in this study (Sullivan and Artino, 2013).

3.2. Survey design and administration

The survey used in this study consists of three parts. The first part includes greetings, brief survey introductions, and questionnaire completion instructions. The second part collects demographic information, travel characteristics, and prior experience of respondents. The third part is the most important part, which contains measurement items designed for each construct.

Two rounds of questionnaire surveys were conducted between 18th February 2022 and 2nd April 2022 in Singapore through Qualtrics. The first round was a pilot survey (between 18th February and 25th February) and collected 50 responses. The pilot test resulted in minor revisions to the questionnaire. Then, the second round, which is the full launch (between 9th March and 2nd April), was conducted and finally collected 451 valid responses. For the full launch, a series of demographic quotas were set according to the Singapore Census of Population 2020, to guarantee the representativeness of the participants and reduce self-selection bias. Data quality and validation were also carried out throughout the data collection phase. First, an attention check question was used to screen out careless respondents who might not have given the survey questions enough attention and thus be trapped by the check question. Additionally, a fee was paid to the survey company for the "survey fraud & poor quality detection" service, which assisted in avoiding undesirable survey behaviors like speeding, random responding, inconsistent or illogical responding, overusing the "Don't Know" or "I Don't Know" responses, and inconsistent or illogical responses (too rapid survey completion). Finally, in exchange for the financial incentives, the survey respondents were obligated to follow the rules of the member agreement, which prohibits at any moment intentionally submitting any false data or other information.

Table 1
Scale development.

Construct	Item	Source
Trust Propensity (TP)	TP1: I have a strong tendency to trust intelligent machines. TP2: It is easy for me to put my faith in intelligent machines to do tasks. TP3: Even if I have limited knowledge about an intelligent machine, I am likely to trust it.	(Merritt et al., 2013)
Trust in Shared Mobility (TSM)	TSM1: I trust that Shared vehicles can be relied on to complete journeys efficiently. TSM2: If the shared vehicles manufacturer's reputation is safe and dependable, I would be more likely to trust them. TSM3: If the shared vehicles operator's reputation is safe and dependable, I would be more likely to trust them. TSM4: My trust in shared vehicles will be based on the dependability of the underlying technologies, such as big data, 5G, and Internet of Things (IoT). TSM5: I feel that in shared vehicles drivers and co-passengers can be trusted.	(Goel and Haldar, 2020; Yuen et al., 2021)
SAV Capability (SC)	SC1: I believe that Shared Autonomous Vehicles will have the functionalities to serve me. SC2: I believe that, during driving, Shared Autonomous Vehicles can give me competent instruction. SC3: I believe that Shared Autonomous Vehicles will have the necessary characteristics to serve me. SC4: I believe that Shared Autonomous Vehicles will have the overall capabilities to serve me. SC5: I believe that Shared Autonomous Vehicles can meet my requirement for a ride through various characteristics and technologies.	(Chi et al., 2021; Lankton et al., 2014; Mcknight et al., 2011)
Interaction Quality (IQ)	IQ1: I believe that what Shared Autonomous Vehicles can give me and what I'm seeking for in my ride provided by these vehicles could be a good match. IQ2: I believe that the service provided by Shared Autonomous Vehicles can meet all of my expectations for a ride. IQ3: I believe that the services provided by Shared Autonomous Vehicles presently can offer me almost all I want from these services.	(Cable and DeRue, 2002; Chi et al., 2021)
Initial trust in SAVs (TS)	TS1: I trust that Shared Autonomous Vehicles can drive without my help. TS2: In extreme weather, I trust Shared Autonomous Vehicles to be safe and dependable. TS3: I trust that Shared Autonomous Vehicles' driving skills are better than mine. TS4: I trust that Shared Autonomous Vehicles can be relied on to complete journeys efficiently.	(Yuen et al., 2021)
Acceptance towards SAV (ACTS)	ACTS1: When Shared Autonomous Vehicles become accessible on the market, I will consider using them. ACTS2: I would encourage others to use Shared Autonomous Vehicles. ACTS3: I have positive things to say about Shared Autonomous Vehicles.	(Yuen et al., 2021)

Notes: A 7-point Likert Scale (i.e., 1 represents "strongly disagree", 4 represents "neither agree nor disagree", 7 represents "strongly agree") is used in this measurement scale.

As for statistical power, to detect an effect size of 0.5 and statistical power level of 0.8 while maintaining a significance level of 5% and power (β) of 95%, a minimum sample size of 110 is recommended for a study that uses a structural equation model. When the population size of Singapore (lower than 6,000,000[1]) is considered, a 95% confidence interval with a 5 percent margin of error required a minimal sample size of 385. Consequently, a sample size of 451 citizens is sufficient for the following empirical studies.

3.3. Sample characteristics

Table 2 shows the demographic features of the 451 respondents. Among the survey respondents, 48.1% are males and 51.9% are females, which is consistent with Singapore's sex ratio (i.e., 957male(s)/1000female(s)) shown in the Singapore Census of Population 2020. Age distribution of the sample generally reflects the 2020 Census demographics. Regarding household income, the sample is fairly diversified. When it comes to the education background, the average education level of this sample is somewhat higher than the national education level reported in the Singapore Census of Population 2020, with almost half of respondents (47.2%) having earned a bachelor's degree. Therefore, the study sample can be considered representative of the eligible study population.

Figs. 3 and 4 shows the prior experience and travel characteristics of the 451 respondents, respectively. To be specific, as presented in Fig. 3, among the 451 respondents, 25.7% answer yes when asked if they have infected COVID-19 before. 52.8% of them answer yes when asked if they have used shared mobility before, indicating easy public access to this mobility solution. Regarding travel

[1] Singapore Population (LIVE): https://www.worldometers.info/world-population/singapore-population/.

Table 2
Demographic characteristics of respondents (N = 451).

Demographic characteristics		Frequency	Percent (%)
Age	19 and below	17	3.8
	20–24	62	13.8
	25–29	51	11.3
	30–34	71	15.7
	35–39	71	15.7
	40–44	54	12.0
	45–49	52	11.5
	50 and above	73	16.2
Gender	Male	217	48.1
	Female	234	51.9
Monthly household income	Below 3000 SGD	88	19.5
	3000 to <10,000 SGD	197	43.7
	10,000 to <15,000 SGD	106	23.5
	15,000 SGD and above	60	13.3
Educational background	Primary and below	3	0.7
	Secondary	59	13.1
	Post secondary (Junior Colleges/ITEs)	59	13.1
	Diploma and professional qualifications	117	25.9
	University	213	47.2
Total		451	100.0

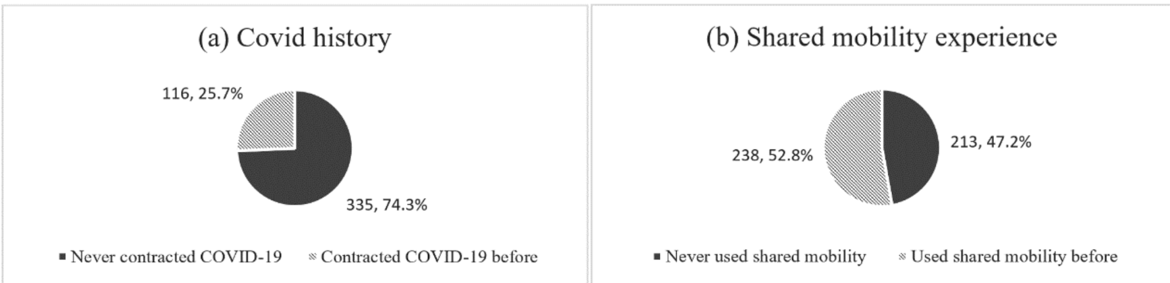

Fig. 3. Prior experience of respondents (N = 451).

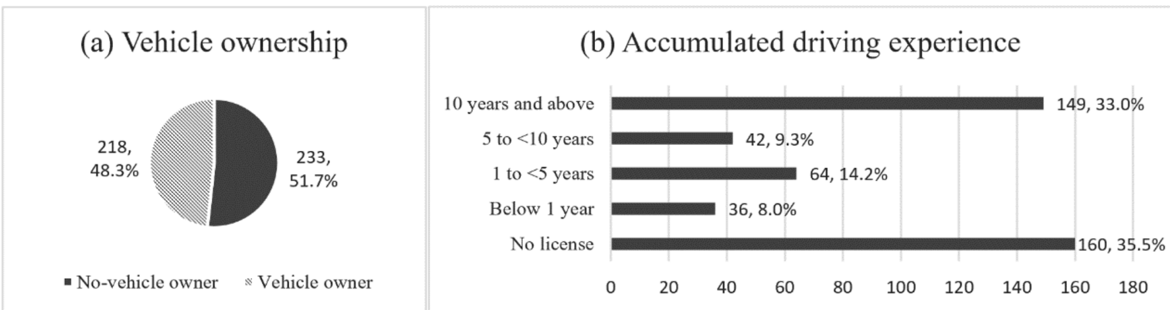

Fig. 4. Travel characteristics of respondents (N = 451).

characteristics, it can be seen in Fig. 4 that about half (48.3%) of the sample members are vehicle owners. In addition, a majority (35.5%) of the respondents report that they have no driving license. The remaining respondents with driving license report their accumulated driving experience as follows: 8.0% are below 1 year, 14.2% are between 1 and 5 years, 9.3% are between 5 and 10 years, and 33.0% are above 10 years. Based on the above details of participants' experience and ownership, the size of the subgroup provided sufficient statistical power of the following moderation analysis.

3.4. Measurement analysis

Before the formal hypotheses testing, a confirmatory factor analysis (CFA) is conducted to assess the reliability and validity of the measurement items (Hair, 2009). Results are presented in Tables 3 and 4.

Table 3 shows the standardized factor loadings (λ), Cronbach's α, composite reliability (CR), and average variance extracted (AVE) of each construct. It can be noted that factor loadings, Cronbach's α, and CR values are all above 0.7, and AVE values are all above 0.5, all of which are acceptable (Bland and Altman, 1997; Fornell and Larcker, 1981). The model fit indices, presented at the bottom of Table 3, also reach the recommended value requirements (Hu and Bentler, 1999; Iacobucci, 2010).

Table 4 presents the discriminant validity of the model. Since the square root of AVE of each construct is higher than its inter-construct Pearson correlations, it can be concluded that the discriminant validity is confirmed (Fornell and Larcker, 1981).

4. Results and discussion

4.1. Theoretical model estimation and path analysis

In this study, structural equation modelling is conducted to evaluate the theoretical model. Results are standardized and depicted in Fig. 5. The model fit statistics are shown at the bottom of Fig. 5, all of which are within acceptable range (Bentler, 1990; Hu and Bentler, 1999; Iacobucci, 2010). In addition, the squared multiple correlations (SMC), which indicates the variance level reflected by predictors (Byrne, 2013), of the two dependent variables – initial trust in SAVs and acceptance towards SAVs – are 0.824 and 0.753 respectively. Since all SMC values are higher than 0.5, sufficient explanatory power of the model has been achieved.

Path analysis results are shown in Table 5. It can be seen that trust propensity (β = .183, p <.001), trust in shared mobility (β = .302, p <.001), SAV capability (β = .142, p <.001), and interaction quality (β = .392, p <.001) all significantly contribute to initial trust formation in SAVs. Therefore, H1a, H2a, H3a, H4a, and H5 get supported.

By comparing the path coefficients, it can be noticed that interaction quality is the most important contributor among the four factors. This result is expected: higher interaction quality means higher perceived degree of fit between the consumers and the SAV service, which is expected to lead to higher customers' overall service evaluation and thus their initial trust in SAVs (Chi et al., 2021). The other investigated performance-based factor, which is SAV capability, also has a significant positive effect on initial trust formation. It is not surprising to see SAV capability as a significant factor increasing initial trust in SAVs because, in this study, SAV

Table 3
Confirmatory factor analysis and scale reliability.

Construct	Item	λ	t-value	α	CR	AVE
Trust Propensity (TP)	TP1	0.856	–	0.880	0.883	0.717
	TP2	0.908	24.289			
	TP3	0.771	19.259			
Trust in Shared Mobility (TSM)	TSM1	0.826	–	0.914	0.915	0.685
	TSM2	0.859	21.759			
	TSM3	0.876	22.286			
	TSM4	0.789	19.250			
	TSM5	0.783	19.353			
SAV Capability (SC)	SC1	0.822	–	0.942	0.942	0.764
	SC2	0.891	23.845			
	SC3	0.880	23.255			
	SC4	0.900	23.968			
	SC5	0.875	22.987			
Interaction Quality (IQ)	IQ1	0.850	–	0.896	0.899	0.748
	IQ2	0.902	25.103			
	IQ3	0.841	21.986			
Initial Trust in SAVs (TS)	TS1	0.844	–	0.903	0.904	0.702
	TS2	0.847	22.539			
	TS3	0.792	19.889			
	TS4	0.868	22.948			
Acceptance towards SAV (ACTS)	ACTS1	0.830	–	0.888	0.890	0.730
	ACTS2	0.867	22.154			
	ACTS3	0.865	21.824			

Note: Model fit statistics: χ^2 = 560.116, df = 215, χ2/df = 2.605, p =.000;
CFI = 0.963, TLI = 0.956, SRMR = 0.035, RMSEA = 0.060, 0.054 < RMSEA < 0.066 at 90% confidence interval.

Table 4
Discriminant validity.

	AVE	IQ	SC	TP	TSM	ACTS	TS
IQ	0.748	**0.865**					
SC	0.764	0.711	**0.874**				
TP	0.717	0.739	0.632	**0.847**			
TSM	0.685	0.746	0.681	0.670	**0.828**		
ACTS	0.730	0.850	0.726	0.746	0.750	**0.854**	
TS	0.702	0.810	0.707	0.730	0.787	0.810	**0.838**

Notes: Square root of AVE in bold on diagonals.
Off diagonals are Pearson correlation of constructs.

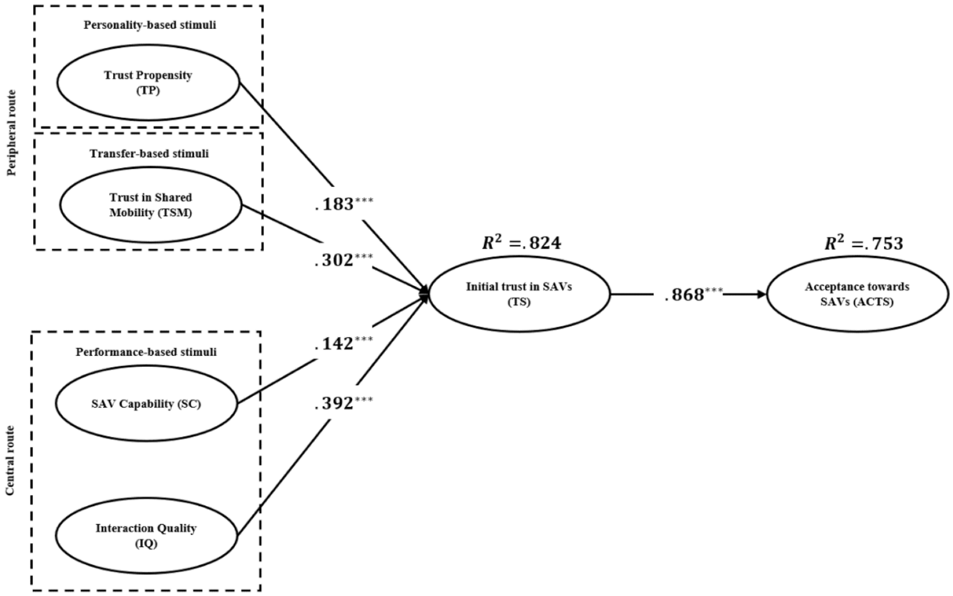

Fig. 5. Structural estimation of the theoretical model, Notes: * p <.05, ** p <.01, *** p <.001, Model fit statistics: χ^2 = 653.567, df = 219, χ^2/df = 2.984, p =.000; CFI = 0.953, TLI = 0.945, SRMR = 0.045, RMSEA = 0.066, 0.061 < RMSEA < 0.072 at 90% confidence interval.

Table 5
Significance test of the path coefficients.

Path	β	t-value	Hypothesis
TP → TS	0.183	3.881***	H1a accepted
TSM → TS	0.302	6.084***	H2a accepted
SC → TS	0.142	3.266***	H3a accepted
IQ → TS	0.392	6.686***	H4a accepted
TS → ACTS	0.868	17.287***	H5a accepted

Notes: * p <.05, ** p <.01, *** p <.001.
TP refers to trust propensity, TSM refers to trust in shared mobility, SC refers to SAV capability, IQ refers to interaction quality, TS refers to initial trust in SAVs, and ACTS refers to acceptance towards SAVs.

capability is designed to measure the functionality, helpfulness, and reliability of SAVs. Naturally, people would be more inclined to trust this new mode of transport, when they perceive SAVs to have the ability to (a) complete an assigned task, (b) offer adequate and responsive feedback, and (c) exhibit competitive reliability and stability.

As can be seen from Table 5, trust in shared mobility, is the second most important contributor among four factors, just next to interaction quality. This result aligns with the trust transfer theory (Stewart, 2003, 2006). Initial trust could be transferred from shared mobility (which is now common in everyday life) to SAVs (which is an emerging mobility solution unavailable in the market) as similarity and proximity are perceived between the two entities. Thus, it is reasonable to expect that SAV manufacturers and operators, in the future, could target people with more favorable evaluations of ridesharing/carsharing services as their potential customers.

In addition to performance-based and transfer-based factors, the personality-based factor: trust propensity has also shown to be significant, which is in line with previous studies in other contexts (Asgari and Jin, 2020; Ma and Zhang, 2020, 2021). The underlying reason could be that when there is little information available about the trustee (i.e., SAVs), people's initial trust would be primarily driven by a natural inner tendency (Gill et al., 2005; Merritt et al., 2013).

Moreover, the direct effect of initial trust on acceptance towards SAVs is also positive and significant ($\beta = .868$, $p < .001$). The result indicates that initial trust plays a crucial role in people's adoption of SAVs, which has been verified in prior studies (Gkartzonikas and Gkritza, 2019; Merat et al., 2017; Paddeu et al., 2020a).

4.2. Mediation analysis

In this study, the indirect effects of the four antecedents on acceptance towards SAVs via initial trust in SAVs are tested with the widely used bootstrap method. It is a computer-intensive resampling technique first proposed by Efron (1979) and first applied to mediation analysis by Bollen and Stine (1990). As bootstrapping is a non-parametric technique based on repeated sampling with replacement (usually between 1000 and 10,000 iterations), it is superior to classical methods to reflect asymmetric distributions and produce bias-corrected intervals for indirect effects (Bollen and Stine, 1990). Judgment is made based on the interval estimate instead of the point estimate because the interval estimate (a) employs stricter criteria for the examination of indirect effects (point estimate is included in the interval estimate since Interval estimate = Point estimate ± Margin of error), and (b) takes the most advantage of the bootstrap resampling method. If 0 is not included in the intervals, it can be concluded that indirect effects exist. In this study, the bias-corrected confidence level is set at 95% and the number of iterations is set to 5000.

Table 6 shows the results of the mediation effect tests. As shown in the table, the bias-corrected confidence intervals for the indirect effect of trust propensity, trust in shared mobility, SAV capability, and interaction quality on acceptance towards SAVs via initial trust are [0.054, 0.268], [0.158, 0.417], [0.033, 0.261], and [0.201, 0.570] respectively, all without 0 included, and all values in the confidence intervals are positive. Therefore, it can be concluded that the four factors have positive indirect effects on public acceptance via the mediating effect of initial trust. In other words, H1b, H2b, H3b, and H4b get supported.

The logic behind is straightforward. As discussed above (See Section 4.1), trust propensity, trust in shared mobility, SAV capability, and interaction quality are four significant contributors to initial trust in SAVs. Initial trust, meanwhile, has been proven to have a significant positive effect on people's acceptance towards SAVs. Therefore, it is logical that a higher perceived level of trust propensity, SAV capability, interaction quality, and trust in shared mobility may lead to a higher level of initial trust, which successively leads to a higher level of acceptance towards SAVs.

4.3. Moderation analysis

In this study, multigroup analysis (MGA) is conducted to investigate the significant difference across subgroups with different characteristics, such as age, education level, covid history, shared mobility experience, vehicle ownership, and accumulated driving experience (See Table 7). According to previous studies (Etminani-Ghasrodashti et al., 2022; Golbabaei et al., 2020; Merfeld et al., 2019; Polydoropoulou et al., 2021; Shamshiripour et al., 2020; Yuen et al., 2020), these 'background characteristics' are important

Table 6
Direct, indirect, and total effects.

	Estimate	Standard Error	Bias-Corrected 95% Confidence Interval		Hypothesis
			Lower	Upper	
Total effect					
TP → TS	0.179	0.063	0.062	0.308	
TSM → TS	0.314	0.079	0.173	0.474	
SC → TS	0.162	0.065	0.039	0.292	
IQ → TS	0.430	0.098	0.236	0.627	
TP → ACTS	0.159	0.055	0.054	0.268	
TSM → ACTS	0.279	0.068	0.158	0.417	
SC → ACTS	0.144	0.059	0.033	0.261	
IQ → ACTS	0.382	0.092	0.201	0.570	
TS → ACTS	0.888	0.059	0.766	1.004	
Direct effect					
TP → TS	0.179	0.063	0.062	0.308	
TSM → TS	0.314	0.079	0.173	0.474	
SC → TS	0.162	0.065	0.039	0.292	
IQ → TS	0.430	0.098	0.236	0.627	
TS → ACTS	0.888	0.059	0.766	1.004	
Indirect effect					
TP → ACTS	0.159	0.055	0.054	0.268	H1b accepted
TSM → ACTS	0.279	0.068	0.158	0.417	H2b accepted
SC → ACTS	0.144	0.059	0.033	0.261	H3b accepted
IQ → ACTS	0.382	0.092	0.201	0.570	H4b accepted

Table 7
Subgroups with different backgrounds.

Group	Subgroup	Group size
Age	Young (age < 35)	201
	Old (age ≥ 35)	250
Gender	Male	217
	Female	234
Income	Low (monthly household income < 10,000)	285
	High (monthly household income ≥ 10,000)	166
Housing size	Small (number of rooms < 5)	254
	Large (number of rooms ≥ 5)	197
Covid history	No	335
	Yes	116
Shard mobility experience	No	213
	Yes	238
Vehicle ownership	No	233
	Yes	218
Driving experience	Short (accumulated driving experience < 5 years)	260
	Long (accumulated driving experience ≥ 5 years)	191

moderators in human-vehicle interaction. Before performing the multigroup analysis, this paper conducts a multigroup confirmatory factor analysis to confirm that measurement invariance for moderating effect testing has been established. A multigroup confirmatory factor analysis, as an extension of CFA, can examine the cross-group invariance of the estimated parameters of two nested models (Cheung and Rensvold, 2002). Results of the multigroup confirmatory factor analysis are shown in Table 8. According to previous studies, at least metric invariance (i.e., identical factor loadings and factor structure across groups) is necessary for reliable inferences to be drawn from moderation analysis (Henseler et al., 2016; Milfont and Fischer, 2010). As recommended by Cheung and Rensvold (2002), $\Delta CFI \leq 0.01$ and $\Delta TLI \leq 0.05$ indicate practical model invariance. Little (1997) points out that non-significant difference in χ^2 is an indicator of equality restrictions. Therefore, based on the model comparison results shown in Table 8, metric invariance has been established for all six moderators. Thus, a multigroup analysis can be conducted.

Table 9 shows the results of the multigroup analysis. As can be seen from the table, age has a moderating influence on the relationship between trust in shared mobility and initial trust in SAVs, with path coefficients of 0.434 (for the young group) and 0.211 (for the old group) respectively. It implies that trust is relatively more easily transferred from shared mobility to SAVs for young people. This difference may be due to the fact that, according to Herrando et al. (2019), younger people develop trust based more on user-generated information (i.e., the information generated by consumers themselves) while older people develop trust based more on

Table 8
Measurement invariance.

Model	χ^2	*df*	*CFI*	*TLI*	*SRMR*	*RMSEA*	Model Comparison			
							$\triangle CFI$	$\triangle TLI$	$\triangle\chi^2$ *p-value*	Decision
Age										
Configural	856.222	430	0.955	0.947	0.043	0.047	–	–	–	–
Metric	874.131	447	0.955	0.949	0.046	0.046	0	0.002	0.395	Accept
Education level										
Configural	946.516	430	0.945	0.935	0.051	0.041	–	–	–	–
Metric	971.942	447	0.944	0.936	0.049	0.040	-0.001	0.001	0.086	Accept
Covid history										
Configural	941.988	430	0.945	0.936	0.038	0.051	–	–	–	–
Metric	963.23	447	0.945	0.938	0.037	0.051	0	0.002	0.216	Accept
Shared mobility experience										
Configural	897.773	430	0.948	0.939	0.045	0.049	–	–	–	–
Metric	922.634	447	0.947	0.940	0.041	0.049	-0.001	0.001	0.098	Accept
Vehicle ownership										
Configural	935.515	430	0.945	0.936	0.043	0.051	–	–	–	–
Metric	962.316	447	0.944	0.937	0.043	0.051	-0.001	0.001	0.061	Accept
Driving experience										
Configural	884.679	430	0.951	0.943	0.047	0.049	–	–	–	–
Metric	910.516	447	0.950	0.944	0.044	0.048	-0.001	0.001	0.077	Accept

Table 9
Multigroup analysis results.

Group	Relationship	β_0	β_1	Coefficient Difference
Young (0) vs Old (1)	TP → TS	0.145*	0.234***	0.089
	TSM → TS	0.434***	0.211***	-0.223*
	SC → TS	0.025	0.223***	0.198
	IQ → TS	0.374***	0.378***	0.004
	TS → ACTS	0.885***	0.861***	-0.024
Low education (0) vs High education (1)	TP → TS	0.102	0.290***	0.188
	TSM → TS	0.297***	0.340***	0.043
	SC → TS	0.086	0.189**	0.103
	IQ → TS	0.489***	0.243**	-0.246**
	TS → ACTS	0.815***	0.920***	0.105
No covid history (0) vs Covid history (1)	TP → TS	0.248***	0.106	-0.142
	TSM → TS	0.334***	0.225*	-0.109
	SC → TS	0.133**	0.113	-0.020
	IQ → TS	0.301***	. 577***	0.276*
	TS → ACTS	0.870***	0.871***	0.001
No shared mobility experience (0) vs Shared mobility experience (1)	TP → TS	0.073	0.263***	0.190
	TSM → TS	0.249***	0.344***	0.095
	SC → TS	0.166***	0.135	-0.031
	IQ → TS	0.542***	0.253**	-0.289**
	TS → ACTS	0.875***	0.833***	-0.042
No vehicle ownership (0) vs Vehicle ownership (1)	TP → TS	0.097	0.300***	0.203
	TSM → TS	0.350***	0.229***	-0.121
	SC → TS	0.054	0.238***	0.184
	IQ → TS	0.481***	0.269***	-0.212*
	TS → ACTS	0.848***	0.891***	0.043
Short driving experience (0) vs Long driving experience (1)	TP → TS	0.158**	0.214*	0.056
	TSM → TS	0.367***	0.203**	-0.164
	SC → TS	0.034	0.319***	0.285**
	IQ → TS	0.439***	0.299***	-0.140
	TS → ACTS	0.846***	0.900***	0.054

Notes: * p <.05, ** p <.01, *** p <.001.

company-generated information (i.e., the information provided by service/product producers). Therefore, prior user experience in a trusted source entity (i.e., shared mobility) is relatively easier to convert into initial trust in SAVs for younger ones. Education background has also been shown to be a significant moderating variable. Specifically, the effect of interaction quality on initial trust in SAVs among low-education group members ($\beta_0 = .489$) is higher than that among high-education group members ($\beta_1 = .243$). This result can be explained as follows. In most cases, compared to higher-educated people, lower-educated people are thought to be (a) less competent, and (b) more in need of help (Dubois, 2016; Raaphorst, 2017). Therefore, it is reasonable that interaction quality (which assesses the fit between the help needed by consumers and the services offered by SAVs) would exert a stronger effect on people with lower education levels.

In addition to demographic information, travel characteristics and prior experience of respondents are also found to be significant moderating variables. First, covid history, shared mobility experience, and vehicle ownership moderate the path between interaction quality and initial trust in SAVs. To be specific, for the moderating effect of covid history, the path coefficient of respondents who have never been infected with COVID-19 before is 0.301 while of those who have been infected with COVID-19 before is 0.577. One possible explanation for this discrepancy comes from the psychological stress caused by previous infection history. According to Singh et al. (2020), this psychological stress may prevent people from using public transport to maintain the physical-distancing. These people will prefer to go alone or with their family and friends (which is one of the most important benefits of SAVs), rather than use public transport. Therefore, when perceiving the interaction quality to be high, those people who have been infected with COVID-19 before are more likely to trust and adopt SAVs as an alternative. As for the moderating effect of shared mobility experience, the path coefficient of respondents who have never used shared mobility before ($\beta_0 = .542$) is higher than that of those who have used it before ($\beta_1 = .253$). The finding is not unexpected because, for respondents without shared mobility experience (compared to those with such experience), initial trust that can be established through the transfer-based path (i.e., trust in shared mobility) is limited (see Table 9). Hence, their initial trust in SAVs tends to rely more on the performance-based path (i.e., interaction quality). Regarding the moderating effect of vehicle ownership, it can be found that the positive effect of interaction quality on initial trust in SAVs is stronger for non-vehicle owners ($\beta_0 = .481$) than for vehicle owners ($\beta_1 = .269$). The result is consistent with Qian et al. (2017). When faced with a new vehicle, vehicle owners could access their knowledge about the vehicle through their ownership experience while non-vehicle owners couldn't. Therefore, vehicle owners' subjective knowledge and behavioral intention would be affected more by extrinsic attributes (e.g., price and country-of-origin) while those of non-vehicle owners would be affected more by intrinsic attributes (e.g., function and interaction quality).

Then, accumulated driving experience is shown to have a moderating effect on the relationship between SAV capability and initial trust in SAVs. For respondents with long driving experience ($\beta_1 = .319$), initial trust in SAVs shall be more positively affected by perceived capability of SAVs than those with short driving experience ($\beta_0 = .034$). This discrepancy may be due to the differences in interventional skills among these two groups (i.e., driving-experienced group vs. driving-inexperienced group). According to Schaefer et al. (2016), for sophisticated automated device, high perceived capability is often associated with more independent intelligence and decision-making authority, and consequently more risk of vehicles spinning "out of control". Since driving-experienced respondents (compared to driving-inexperienced respondents) are more confident in their ability to intervene if vehicles get out of control (He et al., 2022), they are more likely to increase their initial trust in SAVs due to high perceived capability.

5. Conclusion

5.1. Summary

The main purpose of this study is to examine (a) the roles of personality-based, transfer-based, and performance-based factors in forming initial trust in SAVs, and (b) their indirect effect on the acceptance of SAVs via initial trust. In order to answer these questions, a structural equation modelling is conducted in this study based on a valid survey sample of 451 participants in Singapore. The key findings are as follows.

Firstly, personality-based (i.e., trust propensity), transfer-based (i.e., trust in shared mobility), and performance-based (i.e., SAV capability and interaction quality) factors all have positive (a) direct effects on initial trust in SAVs, and (b) indirect effect on acceptance towards SAVs via initial trust.

Secondly, among three trust-building paths, the performance-based one which includes SAV capability and interaction quality has shown to be the most important. Then, the second most important path is the transfer-based one (i.e., trust in shared mobility). The personality-based one (i.e., trust propensity) turns out to be the least influential among the three.

Thirdly, the moderating effects of age, education level, covid history, shared mobility experience, vehicle ownership, and accumulated driving experience have also been confirmed. First, relationship between trust in shared mobility and initial trust in SAVs is negatively moderated by age, which implies that trust is relatively more easily transferred from shared mobility to SAVs for young people. Then, the positive effect of interaction quality on initial trust in SAVs is moderated by education level, covid history, shared mobility experience, and vehicle ownership. Specifically, the positive effect is stronger for people with the following characteristics: (1) low-education, (2) infected Covid-19 before, (3) never used shared mobility before, and (4) non-vehicle owner. Finally, the path between SAV capability and initial trust in SAVs is moderated by accumulated driving experience. The positive effect of SAV capability on initial trust formation is higher among driving-experienced people (compared to driving-inexperienced people).

5.2. Implications, limitations, and recommendations

This paper contributes to both theories and applications. From the theoretical perspective, this paper has confirmed three paths (i.e., personality-based, transfer-based, and performance-based) that led to the development of initial trust in SAVs. This paper also distinguishes initial trust from cumulative trust, to provide a more fine-grained analysis of the initial trust-building process. Previous studies rarely differentiate between the two kinds of trust, which is unrealistic. This is because cumulative trust resulting from iterative interactions cannot be established at the present stage (i.e., the stage when SAVs are still not available in the market).

From the managerial perspective, our findings have the following implications. Policy makers, SAV operators, and manufacturers could increase public initial trust and adopt intention towards SAVs through the three trust-building paths. To be specific, they could educate the public about the shared mobility-SAV relations by holding online seminars, distributing leaflets, or developing role-playing games to promote trust transmission. Moreover, SAV operators and manufacturers could send targeted advertising campaigns to clients of ridesharing/carsharing services because these people are much more likely to use the services. They should also fully understand the clients' needs to improve the fit between these needs and services offered, and the functions and designs of SAVs. Feedback from potential customers could also help them improve the functions and designs of their products/services, which is also an important contributor to the initial trust and adoption intention of SAVs.

In spite of the contributions of this study, there are still some limitations. Firstly, respondents in the present study reflect a somewhat higher education background. Even though, this is not a major issue in the current study because Singapore's education system has been consistently ranked as one of the highest in the world by the OECD. However, not all regions or countries are top performers in education such as Singapore. Therefore, in future studies, samples with an even distribution of educational levels should be used to achieve more general results. Secondly, in future studies, more factors belonging to personality-based, performance-based, and transfer-based stimuli could be integrated into the model to provide stronger explanations for the formation of initial trust and adoption intentions toward SAVs. These factors can include extraversion, neuroticism, openness to experience, agreeableness, and conscientiousness under the personality category (McCrae and John, 1992); the autonomy level and communication mode under the performance category; and trust in autonomous driving technology (when it becomes available and mature technologies to the public) under the transfer category. By highlighting the importance of different trust-building factors, SAV-related entities (such as policy makers, operators, and manufacturers) can better graph the manpower and resource requirements during the development of SAVs. Finally, as argued elsewhere, research findings may be sensitive to the socio-cultural contexts. For example, Kajonius and Mac Giolla (2017) point out that country differences in personality traits are significant and should be considered in large-scale studies. It is also reasonable to expect that in leading shared mobility countries, such as Russia, Germany, and China, the transfer-based factors instead of performance-based factors might be more important. Therefore, future studies may be done in other countries with various socio-cultural contexts, to further validate the findings of the study.

CRediT authorship contribution statement

Min Wu: Conceptualization, Methodology, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Kum Fai Yuen:** Supervision, Project administration.

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.

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