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Are men from Mars, women from Venus? Investigating the determinants behind the intention to use fully automated taxis

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ABSTRACT

Acceptance by customers is key to the success of shared autonomous vehicles (SAVs). However, only a small group of early technology-savvy customers currently use such vehicles, while the general population does not. Based on the Unified Theory of Acceptance and Use of Technology, Theory of Perceived Risk, and perceived threat of unemployment combined with knowledge of automated vehicles, this research develops an integrated model to investigate the determinants behind the intention to use fully automated taxis. Furthermore, it tested the differences between gender. Through the analysis of 539 samples, the findings showed that performance expectancy, effort expectancy, social influence, and knowledge of automated vehicles positively influence acceptance intention, while perceived safety risk and the perceived threat of unemployment were negatively related to behavioral intention. Moreover, effort expectancy, social influence, and perceived safety risk showed greater influence on females, while knowledge of automated vehicles exerted stronger effects on males.

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SAV acceptance; Fully automated taxi; UTAUT; TPR; Gender differences

Introduction

Automated vehicles (AVs), commonly known as autonomous vehicles, driverless vehicles, or self-driving vehicles, are perceived as a game-changer in the automotive industry (Asgari, Gupta, and Jin 2022; Hopkins and Schwanen 2021; Nordhoff et al. 2018). With artificial intelligence and other cutting-edge technologies, AVs can partially or fully remove human drivers from the driving loop, in this way revolutionizing road transportation systems (Karuppiah and Ramayah 2022; H. Liu et al. 2019). AVs generally encompass six levels, from no automation (Level 0) to full automation (Level 5). An AV with conditional automation (Level 3), high automation (Level 4), and full automation (Level 5) can work in automated driving mode (SAE 2018).

The sharing economy becomes increasingly popular. The progress of the sharing economy is influencing a wide range of fields, including transportation. As a representative business model of shared mobility, Car-sharing offers a new way of sharing ownership or renting a vehicle without ownership (Bardhi and Eckhardt 2012). With the rising of the sharing economy, shared autonomous vehicles (SAVs) play important role in AV industry by integrating vehicle automation and shared mobility. Experts anticipate that SAVs will enhance roadway safety, decline travel expenditure, and protect environment (J. Liu, Jones, and Adanu 2020; Maeng and Cho 2022; Triantafillidi et al. 2023). Automated taxi is one of the most typical SAVs. The acceptance of automated taxi will lead to less space for parking and a more livable future. The potential market of automated taxi is big, because current taxi travelers and private car users are expected to be frequent automated taxi users.

Due to these benefits, SAVs have drawn growing attention from scholars and policymakers worldwide in recent years. The key issue that significantly affects future SAVs is user acceptance. Although SAV technology has made rapid progress so far, only a smaller group of early technology-savvy customers currently use such vehicles, while the general population does not. If the general public widely rejects SAVs, their benefits to society and environment cannot be achieved. Therefore, it is important to predict people's adoption intentions for the successful diffusion of SAV services.

The research on AV acceptance has grown tremendously in recent years (Xiao and Goulias 2022). However, only a few studies have dealt with user acceptance of SAVs. Especially, it is difficult to find an empirical research that explored consumers' adoption of automated taxis. Prior studies such as Bansal et al. (2016) and Krueger et al. (2016) employed stated preference data to explore users' SAV adoption behavior, but they ignored the key issue of SAV service attributes, such as the level of vehicle automation. Maeng and Cho (2022) used the Multiple Discrete-Continuous Extreme Value Model to investigate consumers' usage patterns of SAVs. Triantafillidi et al. (2023) employed Selection Theory to explore user acceptance of SAVs. However, these theory-based research on SAV adoption focuses only on the determinants in isolation and ignores testing the differences between demographic variables, such as gender differences.

To fill in the research gaps, this study selected automated taxis as target. We employed UTAUT, Theory of Perceived Risk (TPR), and perceived threat of unemployment combined the addition of knowledge of automated vehicles to construct an integrated model to explain and predict people's intention to adopt automated taxis. The integrated model aims to contribute to providing a more comprehensive perspective on SAV acceptance. Although the effects of the UTAUT constructs, the TPR constructs, and knowledge of automated vehicles have been examined by previous AV studies (Kaye et al. 2021; Nordhoff, Madigan, et al. 2021; Sener, Zmud, and Williams 2019; Xu et al. 2018), there is no research which integrated these theories and factors into a single model.

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Thus, there is limited knowledge on how the influences of the UTAUT constructs and the TPR constructs change. According to Nordhoff et al. (2020), even if a variable shows a significant impact on the outcome variable, its effect can disappear when it is considered together with additional variables in a model. This would then reveal that this particular variable is not needed to produce the optimal prediction of the outcome variable (Hair et al. 2014). Therefore, this research contributes to determining the power of various variables to influence the acceptance intention of AVs in a multivariable context. Moreover, the predictive role of perceived threat of unemployment in SAV acceptance has been rarely explored. According to prior studies (Eglash et al. 2020; Vu and Lim 2022), perceived threat of unemployment is an obstacle to the acceptance of AI-based products and services. Worldwide, taxis hold a prominent position in urban mobility (Karouzakis, Kopsidas, and Kepaptsoglou 2022). As an AI-based product, a fully automated taxi might also be resisted due to the perceived threat of unemployment. Thus, this research contributes to exploring more antecedents of SAV acceptance.

More importantly, this research attempts to test the moderating roles of gender differences in the integrated model. Currently, the awareness of gender in SAV acceptance is rising (Hulse, Xie, and Galea 2018). However, research exploring the moderating effects of gender differences within an integrated model is still rare (Bernhard et al. 2020). Most of the empirical studies based on theoretical models ignore the moderating roles of gender differences. Such a research gap becomes a significant barrier to personalized SAV approaches. Thus, exploring whether the effects are homogenous across gender within a model is necessary.

China has become one of the most rapidly growing markets for AVs (Luo, He, and Xing 2022). In August 2022, the government of China launched the first pilot project of fully automated (driverless) taxis in two cities (Chongqing and Wuhan). Currently, the existing literature on AV acceptance predominantly focused on automated shuttles (Bernhard et al. 2020; Madigan et al. 2017; Nordhoff, Malmsten, et al. 2021b) or automated private cars (Xu et al. 2018; T. Zhang et al. 2019), little is known about the determinants behind the intention to use fully automated taxis. Thus, this research conducted an empirical study in Chongqing to investigate the acceptance of fully automated taxis.

Literature review and hypotheses development

Shared automated vehicles (SAVs) and automated taxis

Shared autonomous vehicles (SAVs) play an important role in AV industry. By integrating vehicle automation and shared mobility, SAVs offer a new business model providing on-demand mobility services (Maeng and Cho 2022). Using SAVs is believed to be an effective way to decline travel cost and mitigate air pollution (Triantafillidi et al. 2023). More importantly, the acceptance of SAVs can control the inefficient use of privately-owned AVs and affect car ownership (Maeng and Cho 2022). Lower car ownership means less space for parking and a more livable future. Automated taxi is one of the most popular SAVs in the future. It has been proposed that current taxi travelers will likely be frequent automated taxi users (J. Liu, Jones, and Adanu 2020).

The research on public acceptance of AVs has been increasing over the past decades, but the understanding on consumers' acceptance of SAVs is still limited, especially for automated taxis. Automated taxi service is not a durable possession of an owner, but a service that is used whenever necessary. Thus, it is significant to predict people's adoption intention for the successful diffusion of an automated taxi service.

Unified theory of acceptance and user of technology

Venkatesh et al. (2003) developed the Unified Theory of Acceptance and User of Technology (UTAUT) by comparing and assessing eight theoretical models. UTAUT is composed of four constructs that affect individuals' intention to use a technology (performance expectancy, effort expectancy, social influence, and facilitating conditions) (Nordhoff, Malmsten, et al. 2021b,; B. Zhang et al. 2022). According to UTAUT, performance expectancy refers to the degree to which a person believes the adoption of technology can strengthen performance (Venkatesh, Thong, and Xu 2012). Effort expectancy is defined as the degree to which a person believes that a technology is easy to use (Tak and Panwar 2017). Social influence describes the degree to which a person believes that other people think the adoption of technology is needed (Raman and Don 2013). Facilitating conditions refer to the degree to which a person perceives that the use of technology can be supported (Goh, Tang, and Lim 2016).

A growing body of literature has proved that UTAUT constructs are positively associated with people's intention to adopt AV services (Bernhard et al. 2020; K. Kaur and Rampersad 2018; Nordhoff, Madigan, et al. 2021, ; Xu et al. 2018). Specifically, Xu et al. (2018) and Farzin et al. (2022) demonstrated a positive relationship between performance expectancy and acceptance intention of AVs. Previous studies have found the positive role of effort expectancy in affecting AV acceptance (Bernhard et al. 2020; Wu et al. 2019). Moreover, Nordhoff et al. (2019) proved that social influence and facilitating conditions have a positive impact on acceptance intention of SAVs. Based on the findings above, this research expects that when people consider automated taxis useful and easy to adopt, they will be more likely to intend to use such vehicles. In addition, when important others in the social networks support the adoption of automated taxis, people will have stronger motivation. Facilitating conditions are not considered in this research. According to previous literature, facilitating conditions usually test whether individuals have the necessary facilities and resources to use a technology (Nordhoff et al. 2019; Raman and Don 2013; B. Zhang et al. 2022). As the Government of China only launched the pilot projects of fully automated taxi in Chongqing and Wuhan, no resources are needed from the individual. Thus, the respondents in this research have the same chance and similar facilitating conditions to adopt fully automated taxis. Based on the arguments above, the following hypotheses are formulated:

H1. Performance expectancy is positively related to the intention to use fully automated taxis.

H2. Effort expectancy is positively related to the intention to use fully automated taxis.

H3. Social influence is positively related to the intention to use fully automated taxis.

Theory of perceived risk

According to the Theory of Perceived Risk (TPR), perceived risk is defined as people uncertainty perception about that they may lose something when using a product (B. Zhang et al. 2022). Perceived risk is a multidimensional concept, each facet of perceived risk is formed based on particular usage conditions (Choi, Lee, and Ok 2013; Featherman and Pavlou 2003). When using private AVs and SAVs, the major concern among people should be privacy and safety (Farzin, Mamdoohi, and Ciari 2022; Xu et al. 2018; T. Zhang et al. 2019, 2021). Privacy risk originates from the feeling of uncertainty that personal information is exposed to others when using AVs (Bansal, Kockelman, and Singh 2016). People worry that their driving information and behavioral data might be transmitted to vehicle companies and insurance companies without their permission, and their data will be misused by those companies. When people perceive privacy risk, they are more likely to reduce their behavioral motivations (T. Zhang et al. 2019; Zhu et al. 2022).

Safety risk is the top concern about the use of private AVs and SAVs (Bansal, Kockelman, and Singh 2016; Menon et al. 2016; T. Zhang et al. 2019). Although AV developers assert that driverless vehicles should be much safer than human-driven cars, most users still worry about their safety due to system failure or loss of control (Alsghan et al. 2022). According to the report by Menon et al. (2016), most people were extremely (36.5%) or moderately (52.6%) worried about their safety, while only a small group of users did not care. AV is a special technology because unsafety usually means that the users' life is in danger. Thus, when people feel that the use of AVs is not safe, they are more likely to refuse such vehicles. Based on the arguments above, perceived privacy risk and perceived safety risk are taken as the two facets of risk that influence people's intention to use fully automated taxis:

H4. Perceived privacy risk is negatively related to the intention to use fully automated taxis.

H5. Perceived safety risk is negatively related to the intention to use fully automated taxis.

Perceived threat of unemployment and knowledge of automated vehicles

The perceived threat of unemployment refers to the anxiety about technologies taking over existing jobs. Job loss due to technological advances is a popular concern among individuals (Vu and Lim 2022). Historically, humans even destroyed machines because of unemployment (McClure 2018). Thus, the perceived threat of unemployment is a significant individual-level variable that may reduce the use of a technology. With the development of AI, a growing number of people might become unemployed. Eglash et al. (2020) believe that AI has the potential power to change the job market by replacing various occupations, including drivers. Through an analysis of 28-country survey data, Vu and Lim (2022) found that the perceived threat of job loss exerts negative effects on the acceptance of AI products. As an AI-based product, fully automated taxi has the potential to replace human drivers. Liu et al. (2020) believed that current taxi services with human drivers will not survive when a fleet of automated taxis are on the road. Thus, the use of fully automated taxis might be affected by the fear of unemployment.

Knowledge of automated vehicles refers to preexisting knowledge or familiarity with autonomous vehicles (Kaye et al. 2021). Because SAVs have yet to be used by the general public, many people's prior knowledge of AVs is obtained from media sources rather than direct user experience (Bennett, Vijaygopal, and Kottasz 2019). These media sources include advertisements, news, movies, etc. In comparison to unfamiliar products, individuals usually tend to use familiar products because they have more confidence in the ability to control them. If people have enough prior knowledge of a product, they will be more confident that they can control and use this product (Park and Lessig 1981). Literature has increasingly identified knowledge of automated vehicles as a key determinant behind users' behavioral intention (Bennett, Vijaygopal, and Kottasz 2019; Charness et al. 2018; Rezvani, Jansson, and Bodin 2015). Thus, we hypothesize that:

H6. Perceived threat of unemployment is negatively related to the intention to use fully automated taxis.

H7. Knowledge of automated vehicles is positively related to the intention to use fully automated taxis.

The moderating roles of gender differences in AVs acceptance

The distinction between men and women provides a basic perspective to explore human behavior (Arshad et al. 2016). According to the Gender Schema Theory (GST), people develop their perceptions based on preexisting gender schemas (Bem 1981). Gender schemas result from socialization by families, institutions, and social media (Vilela and Nelson 2016). Such schemas polarize individuals into traditional gender roles, emphasizing relationship maintenance, interdependence and risk avoidance among women, and focusing on aggression, independence, and self-orientation among men (Bem 1981). People's attitudes and behavioral intentions build on their gender schemas and gender roles (Arshad et al. 2016). Because men are self-orientated, they tend to emphasize the performance of a new technology (B. Zhang et al. 2022). Previous studies have proved that performance expectancy and perceived usefulness show more influence on males (Kwateng, Atiemo, and Appiah 2019). In addition, because men are more aggressive, easy to use is not a key factor when they evaluate a new technology. Prior studies found that females rate effort expectancy higher compared to males (Bennett, Vijaygopal, and Kottasz 2019; Venkatesh, Morris, and Ackerman 2000). Because women highlight interdependence and relationship maintenance, they tend to care more about others. Thus, females will feel more upset if other people lose their jobs. Accordingly, the perceived threat of unemployment may have a stronger influence on women. According to GST, men depend more on their own beliefs when making a decision because they are more independent, while women are communal and rely more on other people's suggestions (Arshad et al. 2016). Thus, social influence is expected to strongly impact females when deciding to use a new technology (Kimbrough et al. 2013).

Gender Motivation Theory (GMT) suggests that women are risk-reduction types (Winstok, Weinberg, and Smadar-Dror 2017). When females feel that the use of a product contains risks and uncertainty, risk reduction drives them to display more sensitivity, caution, and restraint (Winstok and Straus 2011). Thus, compared to males, females are more influenced by privacy and safety risks when deciding to use a technology (Zhu et al. 2022). In addition, Selectivity Hypothesis Theory (SHT) proposes that women tend to collect more information and process messages comprehensively when deciding to use a technology, while men tend to concentrate on important information and process messages selectively (Meyers-Levy 1988; B. Zhang et al. 2022; Zhu et al. 2022). Thus, females need more knowledge and information about automated vehicles when making decisions, and they are more likely to be influenced by their knowledge of automated vehicles. Based on the arguments above, we hypothesize that:

H8a. The relationship between performance expectancy and intention to use fully automated taxis among males is stronger.

H8b. The relationship between effort expectancy and intention to use fully automated taxis among females is stronger.

H8c. The relationship between social influence and intention to use fully automated taxis among females is stronger.

H8d. The relationship between perceived privacy risk and intention to use fully automated taxis among females is stronger.

H8e. The relationship between perceived safety risk and intention to use fully automated taxis among females is stronger.

H8f. The relationship between the perceived threat of unemployment and the intention to use fully automated taxis among females is stronger.

H8g. The relationship between knowledge of automated vehicles and intention to use fully automated taxis among females is stronger.

Figure 1 illustrates the research model and hypotheses.

Methodology

Data

The Chinese market was surveyed in this research. According Luo et al. (2022), China is the most rapidly growing market for AVs after Europe and the United States. In August 2022, the government of China launched the pilot project of fully automated (driverless) taxis in two cities (Chongqing and Wuhan). We conducted our empirical study in Chongqing. In total, 5 full automated taxis were used within 30 square kilometers in Yongchuan District, Chongqing. A taxi could carry up to 3 passengers per trip and run at an average speed of 40 km/h. No steward was inside the taxi to intervene when driving. The residents in Chongqing could use apps to reserve a taxi. Each automated taxi cost around 5 yuan per kilometer. Because this is the first pilot project of fully automated taxis in Chongqing, the majority of respondents have not use such vehicles before.

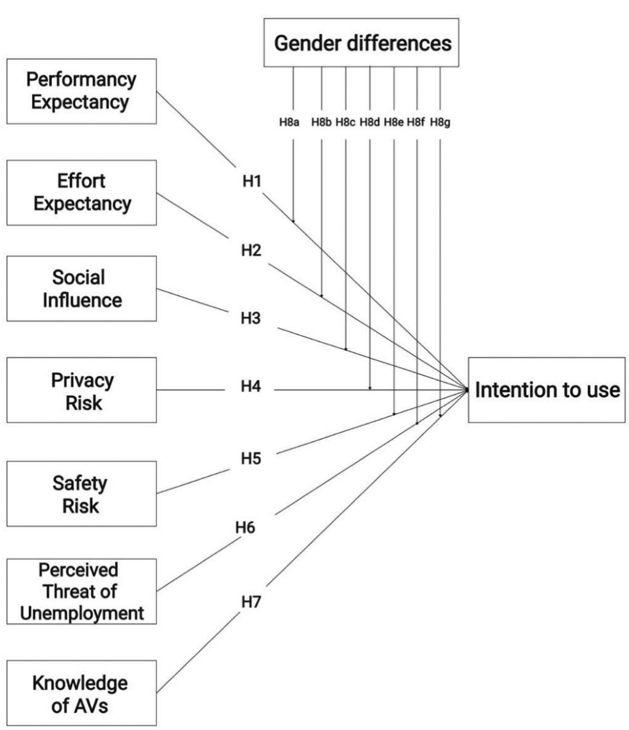

Figure 1. The integrated research model.

We conducted our survey in Yongchuan District through both paper and online questionnaires. We distributed paper questionnaires in commercial centers, subway stations, and taxi stations. In addition, snowballing techniques were employed, and respondents were invited to share online questionnaires with familiar people. The SoJump survey platform (http://www.sojump.com) was selected to send online questionnaires.

The survey was conducted from August to September 2022. Before the formal survey, we conducted the pilot examination with 23 individuals, including undergraduate students and graduate students. Meanwhile, two AV practitioners and a professor were invited to give their suggestions. We modified the measurements according to the pilot test to ensure the survey's appropriateness and representativeness. The formal questionnaire consisted of a cover page, demographic information questions, and measurement items.

A total of 571 respondents were surveyed. After deleting those questionnaires with incomplete data, wrong answers, and other errors, 539 valid samples were found. The final data included 295 males (54.7%) and 244 females (45.3%). The majority of the respondents held their driver license for less than 4 years (72.4%). In addition, 81.7% of the respondents were between 18 and 40, and only 4.2% respondents were over 50. Table 1 shows the demographic information.

Measures

In this research, measurement items included performance expectancy (PE), effort expectancy (EE), social influence (SI), perceived privacy risk (PR), perceived safety risk (SR), perceived threat of unemployment (PTU), knowledge of automated vehicles (KAV), and intention to use (IU). Following the previous studies on acceptance of AVs (H. Liu et al. 2019; Nordhoff, Malmsten, et al. 2021b; Xu et al. 2018), 5 point Likert-type scales were employed to measure the items, from 1 (very disagree) to 5 (very agree). Specifically, measures for performance expectancy were modified according to the research by Nordhoff et al., 2021b, 2021). Items measuring effort expectancy were modified based on Venkatesh et al. (2003) and Bernhard et al. (2020). The measurement items for social influence were adapted from Madigan et al. (2017). Perceived privacy risk was measured using the items proposed by Zhu et al. (2022a) and Zhang et al. (2022). Moreover, measures for perceived safety risk were adapted from Zhang et al. (2019) and Nordhoff et al. (2020). Items for perceived threat of unemployment originating from Vu and Lim (2022) were modified, and items for knowledge of automated vehicles were adapted from Bennett et al. (2019). Finally, we modified the items in the research by Liu et al. (2019) to measure the intention to use. Table 2 shows the measurement items and their sources.

Research results

Measurement model test

Following a two-step approach as suggested by many previous studies (Anderson and Gerbing 1988; Seo and Bernsen 2016; B. Zhang and Zhu 2021; B. Zhang et al. 2022; Zhu et al. 2022),

Table 1. Demographic information.

	Number	Percentage
Gender		
Male	295	54.7%
Female	244	45.3%
Age		
18–30	295	54.7%
31–40	145	27.0%
41–50	76	14.1%
Above 50	23	4.2%
Education		
Under high school	53	9.8%
High school	119	22.1%
Polytechnic college	133	24.7%
Bachelor degree	184	34.1%
Postgraduate degree	50	9.3%
Annual income		
Below 50,000 CNY	204	37.8%
50,000–100,000 CNY	190	35.3%
100,001–300,000 CNY	90	16.7%
300,001–500,000 CNY	37	6.9%
Above 500,000 CNY	18	3.3%
Driving experience		
Have no drive license	63	11.7%
Below 1 year	166	30.8%
1–3 years	161	29.9%
4–10 years	72	13.4%
Above 10 years	77	14.3%

Note. 1 CNY ≈ 0.139 USD.

this research conducted the analysis using AMOS 22.0 and SPSS 23.0. First, we ran the measurement model to test the reliability, validity, and goodness of fit. Then, we ran the structural model to examine the research hypotheses.

Table 3 shows the results of the confirmatory factor analysis (CFA). Cronbach's alpha and Composite reliability (CR) were both over the recommended value of 0.7 (Nordhoff, Madigan, et al. 2021). Thus, internal reliability was confirmed. The average variance

Table 2. Measurement items and sources.

Constructs and measurement items	References
Performance Expectancy (PE)	Zhang et al. (2020); Nordhoff et al. (2021b)
PE1: Using a fully automated taxis can help me achieve things effectively.	
PE2: I think our transport systems benefit from fully automated taxis.	
PE3: Using fully automated taxis will be useful in meeting my demands.	
PE4: Fully automated taxis will be useful when I am impaired, such as drunk and drowsy.	
Effort Expectancy (EE)	Venkatesh et al. (2003); Bernhard et al. (2020)
EE1: I believe fully automated taxis is easy to use (e.g. booking, entering, getting seated, leaving, etc.).	
EE2: Interaction with fully automated taxis is clear and easy.	
EE3: Learning how to use fully automated taxis is easy.	
Social Influence (SI)	Madigan et al. (2017)
SI1: My families think I should use fully automated taxis.	
SI2: My friends think I should use fully automated taxis.	
SI3: My colleagues/classmates think I should use fully automated taxis.	
Perceived Privacy Risk (PR)	Zhu et al. (2022); Zhang et al. (2022)
PR1: Fully automated taxis will misuse my personal information for other purposes without my authorization.	
PR2: Fully automated taxis will share my personal information without my authorization.	
PR3: When using fully automated taxis, my personal information may be stolen.	
Perceived Safety Risk (SR)	Zhang et al. (2019); Nordhoff et al. (2020)
SR1: Fully automated taxis may lose control when driving.	
SR2: Fully automated taxis are dangerous.	
SR3: The general safety of fully automated taxis is not ensured.	
Perceived Threat of Unemployment (PTU)	Vu and Lim (2022)
PTU1: The development of fully automated taxis will cause unemployment among taxi drivers.	
PTU2: Fully automated taxis will take over existing jobs.	
PTU3: The development of fully automated taxis cannot create more jobs for humans.	
Knowledge of Automated Vehicles (KAV)	Bennett et al. (2019)
KAV1: I have enough knowledge about fully automated taxis.	
KAV2: I know well about fully automated taxis.	
KAV3: I have read enough information about fully automated taxis.	
KAV4: I am familiar with the idea of fully automated taxis.	
Intention to use (IU)	Liu et al. (2019)
IU1: I intend to use fully automated taxis.	
IU2: I think I will often use fully automated taxis in the future.	
IU3: I will recommend others to use fully automated taxis.	

extracted (AVE) values ranged from 0.514 to 0.773, exceeding the recommended value of 0.5 (B. Zhang and Zhu 2021). Factor loadings of all measurement items were higher than the recommended value of 0.6 (Choe, Kim, and Hwang 2021), ranging from 0.661 to 0.920. Figure 2 shows the bar chart of factor loading and mean of each item.

Table 4 reports that the square root of AVE for every construct was above the correlation value between any two constructs (Zhu et al. 2022). Moreover, none of the independent variables in the correlation exceeded the 0.9 criterion (P. Kaur et al. 2018). Thus, discriminant validity was acceptable. The goodness of fit is shown in Table 5, all fit indices satisfied the following requirements: x^2 statistics/degree of freedom (df) is 2.107 (≤3), comparative fit index (CFI) was 0.964 (≥0.90), goodness-of-fit index (GFI) was 0.926 (≥0.90), incremental fit index (IFI) was 0.921 (≥0.90), normed fit index (NFI) was 0.934 (≥0.90), root mean squared residual (RMR) was 0.042 (≤0.05), standardized root mean squared residual (SRMR) was 0.044 (≤0.05), and root mean square error of approximation (RMSEA) was 0.045 (≤0.08) (Anderson and Gerbing 1988;

Table 3. The results of the CFA.

Construct and items	Factor loading	Mean	Alpha	CR	AVE
Performance expectancy			0.713	0.776	0.514
PE1	0.796	4.14			
PE2	0.784	3.92			
PE3	0.811	3.90			
PE4	0.661	3.24			
Effort expectancy			0.879	0.880	0.709
EE1	0.814	4.40			
EE2	0.827	4.21			
EE3	0.884	4.29			
Social influence			0.841	0.842	0.641
SI1	0.729	4.56			
SI2	0.803	3.60			
SI3	0.864	3.53			
Perceived privacy risk			0.908	0.910	0.771
PR1	0.890	2.99			
PR2	0.822	2.81			
PR3	0.920	3.06			
Perceived safety risk			0.899	0.901	0.753
SR1	0.877	3.21			
SR2	0.882	2.97			
SR3	0.844	2.90			
Perceived threat of unemployment			0.848	0.853	0.662
PTU1	0.675	3.86			
PTU2	0.877	3.75			
PTU3	0.873	3.71			
Knowledge of AVs			0.869	0.871	0.629
KAV1	0.749	2.75			
KAV2	0.841	2.77			
KAV3	0.802	2.78			
KAV4	0.778	2.79			
Intention to use			0.889	0.891	0.773
IU1	0.820	3.90			
IU2	0.845	3.88			
IU3	0.902	3.81			

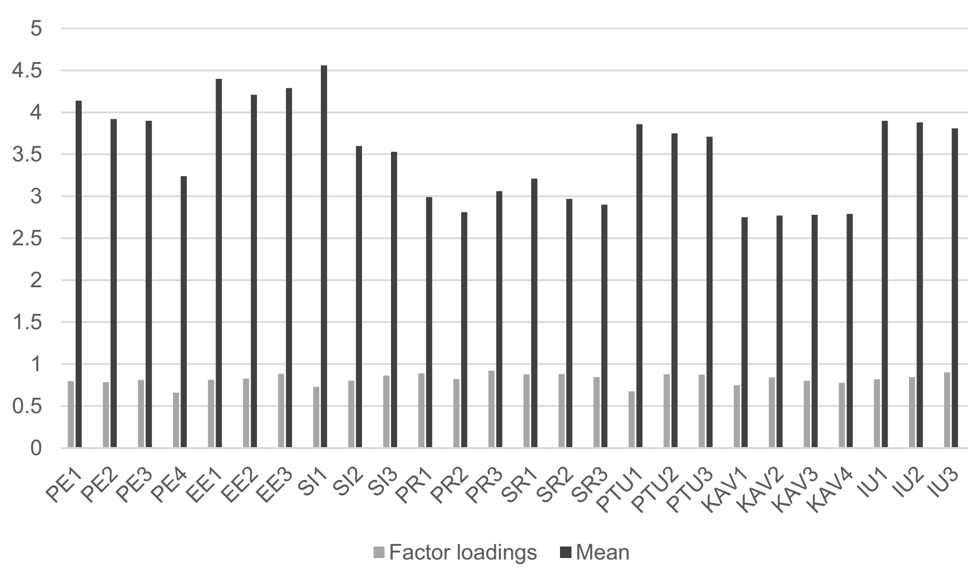

Figure 2. The bar chart of factor loading and mean.

Table 4. Discriminant validity.

	PE	EE	SI	PR	SR	PTU	KAV	IU
PE	0.703							
EE	0.183	0.842						
SI	0.215	0.361	0.801					
PR	0.127	0.294	0.204	0.878				
SR	−0.106	−0.357	−0.261	−0.284	0.868			
PTU	−0.106	−0.245	−0.129	−0.199	0.512	0.814		
KAV	0.240	0.369	0.329	0.389	−0.315	−0.271	0.793	
IU	0.455	0.442	0.438	0.347	−0.449	−0.386	0.526	0.856

Table 5. Measures of the model fit.

Goodness-of-fit	CMIN/df	GFI	CFI	RMR	SRMR	IFI	NFI	RMSEA
Recommended value	≤3	≥0.90	≥0.90	≤0.05	≤0.05	≥0.90	≥0.90	≤0.08
This model	2.107	0.926	0.964	0.042	0.044	0.921	0.934	0.045

Browne and Cudeck 1992; Hair et al. 2014; B. Zhang et al. 2022). Thus, a good model fit was found in the measurement model.

Common method bias

A principal component analysis method with 'Harman's one-factor test' was used to evaluate Common method bias (CMB). When the value of a single construct is less than 50% of the variance, there is no CMB in the research data (Chang, Hsu, and Lan 2019; Harman 1976; Zhu et al. 2023). In this research, the percent of the variance of a single construct was 30.83%, indicating that the research data was without CMB.

Hypothesis testing

The results of hypothesis testing are shown in Figure 3. Prior studies prescribed the R^2 values of 0.15, 0.35, and 0.67 as weak, moderate, and substantial, respectively (Chin 1998; Seo and Bernsen 2016). The research model predicted 65% of the variance (R^2) for the intention to use fully automated taxis. Performance expectancy ($\beta = 0.334$, $p < 0.001$), effort expectancy ($\beta = 0.130$, $p < 0.01$), and social influence ($\beta = 0.192$, $p < 0.001$) had significant and positive influences on people's intention to adopt fully automated taxi. Therefore, H1, H2, and H3 are supported. In addition, perceived safety risk (β=-0.134, $p < 0.01$) exerted a negative impact on behavioral intention, while perceived privacy risk ($\beta = 0.069$, $p > 0.05$) was insignificantly related to acceptance intention. Thus, H5 is supported and H4 is rejected. The perceived threat of unemployment (β=-0.174, $p < 0.001$) also negatively affected the intention to use fully automated taxis, offering support to H6. Moreover, knowledge of automated vehicles ($\beta = 0.256$, $p < 0.001$) was positively correlated with acceptance intention, supporting H7.

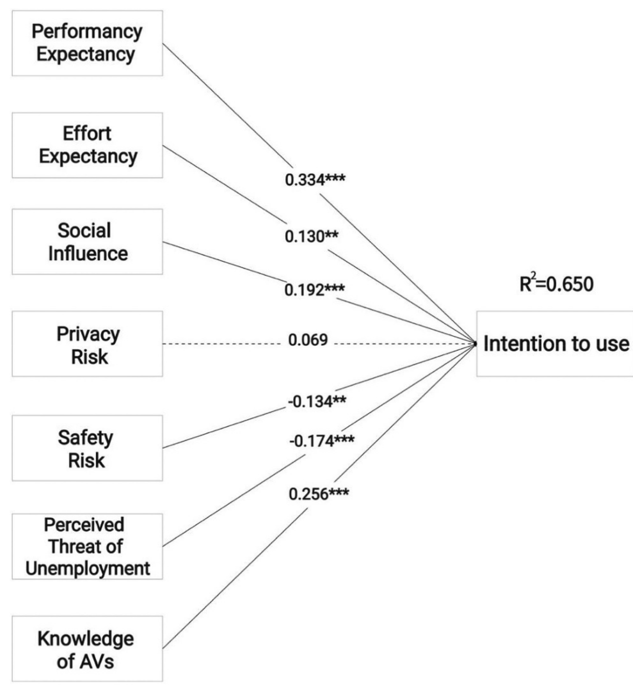

Figure 3. The results of path analysis. **p<0.01, ***p<0.001.

The moderating role of gender differences

Following previous studies, this research employed three hierarchical regressions to examine the moderating effects of gender differences (Lee et al. 2015; Yin, Yan, and Guo 2022; Zhu et al. 2023). First, age, education, income, and driving experience were entered at Step 1 as a control variable to reduce the endogeneity issues (Yin, Yan, and Guo 2022). Thus, we configured the baseline Model 1 through:

$$IU = \beta_0 + \beta_1 Age + \beta_2 Edu + \beta_3 Income + \beta_4 Driving + \beta_5 PE + \beta_6 EE + \beta_7 SI + \beta_8 PR + \beta_9 SR + \beta_{10} PTU + \beta_{11} KAV + e$$

Second, the effects of gender, performance expectancy, effort expectancy, social influence, perceived privacy risk, perceived safety risk, perceived threat of unemployment, and knowledge of automated vehicles was entered in Step 2. Thus, The Model 2 was configured through:

$$IU = \beta_0 + \beta_1 Age + \beta_2 Edu + \beta_3 Income + \beta_4 Driving + \beta_5 PE + \beta_6 EE + \beta_7 SI + \beta_8 PR + \beta_9 SR + \beta_{10} PTU + \beta_{11} KAV + \beta_{12} Gender + e$$

Third, all conceptually relevant two-way interaction terms were included in Step 3: performance expectancy × gender, effort expectancy × gender, social influence × gender, perceived privacy risk × gender, perceived safety risk × gender, perceived threat of

Table 6. The results of three hierarchical regressions.

Variables	Step 1 (Model 1)	Step 2 (Model 2)	Step 3 (Model 3)
Age	0.039 (*t*=1.565)	0.036 (*t*=1.452)	0.035 (*t*=1.416)
Education	−0.018 (*t*=−0.714)	−0.019 (*t*=−0.745)	0.097 (*t*=1.858)
Income	0.153***(*t*=4.227)	0.145***(*t*=4.027)	0.133***(*t*=3.674)
Driving experience	0.043 (*t*=1.482)	0.046 (*t*=1.480)	0.048 (*t*=1.532)
PE	0.263***(*t*=8.783)	0.228***(*t*=7.323)	0.211***(*t*=6.669)
EE	0.081*(*t*=2.318)	0.103**(*t*=3.036)	0.130***(*t*=3.662)
SI	0.140***(*t*=4.330)	0.164***(*t*=5.016)	0.179***(*t*=4.881)
PR	0.060 (*t*=1.879)	0.063(*t*=1.921)	0.058 (*t*=1.732)
SR	−0.152***(*t*=−4.315)	−0.173***(*t*=−4.901)	−0.160***(*t*=−4.522)
PTU	−0.137***(*t*=−4.089)	−0.132**(*t*=3.978)	−0.134***(*t*=−4.035)
KAV	0.238***(*t*=7.084)	0.272***(*t*=7.900)	0.266***(*t*=7.654)
Gender		−0.129***(*t*=−3.668)	−0.148***(*t*=−4.206)
PE × Gender			−0.054 (*t*=−1.644)
EE × Gender			0.111**(*t*=2.751)
SI × Gender			0.090*(*t*=2.357)
PR × Gender			0.018 (*t*=0.607)
SR × Gender			0.105**(*t*=2.927)
PTU × Gender			−0.033 (*t*=−0.995)
KAV × Gender			−0.084*(*t*=−2.340)
R^2	0.574	0.583	0.595
ΔR^2	0.582	0.010	0.017
Sample size	539	539	539

unemployment × gender, and knowledge of automated vehicles × gender. Thereby, the Model was formulated through:

$$\begin{aligned} IU = {} & \beta_0 + \beta_1 Age + \beta_2 Edu + \beta_3 Income + \beta_4 Driving + \beta_5 PE \\ & + \beta_6 EE + \beta_7 SI + \beta_8 PR + \beta_9 SR + \beta_1 0PTU + \beta_{11} KAV \\ & + \beta_{12} Gender + \beta_{13} PE * Gender + \beta_{14} EE * Gender + \beta_{15} SI \\ & * Gender + \beta_{16} PR * Gender + \beta_{17} SR * Gender + \beta_{18} PTU \\ & * Gender + \beta_{19} KAV * Gender + e \end{aligned}$$

Each of individual variable used in this model was the average of the item scores. The results of hierarchical multiple regressions were shown in Table 6. The coefficients for effort expectancy × gender ($\beta = 0.111$, $p < 0.01$) and social influence × gender ($\beta = 0.090$, $p < 0.05$) were significant, indicating that the positive effects on females were stronger than on males. Hence, H8b and H8c should be supported. In addition, the relationship between perceived safety risk and acceptance intention was significantly moderated by gender differences ($\beta = 0.105$, $p < 0.01$), and the negative influences on women were stronger than on men, supporting H8e. Although gender differences significantly moderated the relationship between knowledge of automated vehicles and acceptance intention (β=-0.084, $p < 0.05$), the influences were stronger among males. Thus, H8g is rejected. Meanwhile, gender differences failed to significantly moderate other relationships (performance expectancy × gender, perceived privacy risk × gender, and perceived threat of unemployment × gender). Thus, H8a, H8d, and H8f are not supported.

Discussion and implications

Through the integrated research model, this study strengthened our understanding of the determinants behind people's intention to use fully automated taxis. In line with many previous studies (Bernhard et al. 2020; Madigan et al. 2017; Nordhoff, Madigan, et al. 2021; Nordhoff, Malmsten, et al. 2021b), the findings of this research revealed that the UTAUT constructs (performance expectancy, effort expectancy, and social influence) are key predictors of acceptance intention. UTAUT has been used to predict people's intention to adopt various types of AVs, such as automated shuttles (Nordhoff, Madigan, et al. 2021) and automated private cars (Farzin, Mamdoohi, and Ciari 2022). Our findings shows that the UTAUT constructs are also important to the acceptance intention of automated taxis when other factors originating from other models are considered.

As expected, perceived safety risk was empirically evidenced to be an important factor influencing the intention to use fully automated taxis. This finding is in line with the research by Zhang et al. (2019) and Xu et al. (2018). Because safety is the basic requirement when driving, one of the most indispensable factors for a fully automated taxi should be safety. Moreover, the perceived threat of unemployment was negatively related to acceptance intention. As prior studies have suggested, the fear of job loss causes resistance to AI-based products (Eglash et al. 2020; Vu and Lim 2022). In addition, knowledge of automated vehicles had a positive impact on acceptance intention, which corresponds with Bennett et al. (2019). If people know a product well, they will tend to adopt it because they have the confidence to control it (Park and Lessig 1981). Thus, this implies that it is important to enhance people's knowledge about fully automated taxis.

However, the effects of perceived privacy risk were insignificant. This finding contradicts the studies by Menon et al. (2016). Privacy protection is one of the top concerns among US users. Previous literature has reported that around one-third of the US-drivers extremely care about privacy risks when using AVs (Menon et al. 2016; Schoettle and Sivak 2014). However, the findings in this research might indicate that Chinese users do not care much about privacy information when using AVs. A possible explanation is that Chinese users are characterized by collectivistic culture (T. Zhang et al. 2020). Thus, they do not think that someone sharing private data with others is a huge problem (Zhu et al. 2023).

The findings of this research also revealed how gender differences moderated the relationships between determinant factors and acceptance intention. Effort expectancy, social influence, and perceived safety risk strongly influenced females. These findings are in line with previous studies on information systems (Kimbrough et al. 2013; Venkatesh, Morris, and Ackerman 2000). In addition, knowledge of automated vehicles showed more effects on men. SHT proposes that females tend to collect more information and process messages comprehensively when making a decision to use a technology. However, our findings are contradictory to SHT. A potential explanation for this is lower driving license ownership.

Currently, females are more regular users of classic taxis, while the adoption of private cars in males is relatively high. The reason for this is that smaller percentages of females have driving license, as compared to males. If a woman does not use a private vehicle daily, she will be more open to alternative options, such as taxi services. Thus, those females without driving license might do not collect much information when they decide to take an automated taxi. In addition, this research's findings indicated insufficient evidence to demonstrate the existence of gender differences in the use of fully automated taxi among other three relationships (performance expectancy × gender, perceived privacy risk × gender, and perceived threat of unemployment × gender).

Theoretical implications

This research added salient contributions to the existing SAV acceptance literature in the following ways. First, this study is the first to develop an integrated model in the context of automated taxi acceptance through UTAUT, TPR, perceived threat of unemployment, and knowledge of automated vehicles. Currently, most of the existing studies on AV acceptance explore determinants in isolation, and thus there is a lack of perspectives from different influential disciplines (Nordhoff, Madigan, et al. 2021). This research constructed an integrated theoretical model that can provide a more comprehensive perspective to predict the acceptance of automated taxis. Furthermore, as an important type of AVs, automated taxi is expected to play an essential role in future transport systems. However, the determinants behind people's intention to use fully automated taxis are still unexplored. Through the integrated model analysis, this study proved that performance expectancy, effort expectancy, social influence, and knowledge of automated vehicles positively influence behavioral intention, while perceived safety risk and threat of unemployment exerted negative effects on acceptance intention. Thus, this research extended the literature on the acceptance of AVs. The integrated model in this research can be considered by the future studies on acceptance of automated taxis.

Second, this study extended the use of UTAUT in the context of SAV acceptance. As one of the most significant theoretical models in the field of technology acceptance, UTAUT has been widely employed to explain the intention to use AVs. However, previous studies have predominantly concentrated on automated private cars (Xu et al. 2018; T. Zhang et al. 2019, 2020). This research is an early attempt to demonstrate that UTAUT can predict people's behavioral intention in the context of fully automated taxis. In their research, Nordhoff et al. (2021b) recommended future studies to retest the UTAUT construct 'effort expectancy' in a wider field of AV acceptance. Our study responds to this call by revealing a positive relationship between effort expectancy and intention to use fully automated taxis.

Third, the findings of this research strengthened our understanding of determinants influencing SAV acceptance. Humans destroyed machines due to unemployment in the 19th century (McClure 2018). Previous studies have found that the perceived threat of job loss exerts negative effects on the acceptance of AI technologies (Vu and Lim 2022). As an AI-based technology, automated taxi also has the potential to eliminate millions of jobs (Eglash et al. 2020). This study is the first to empirically investigate how the perceived threat of unemployment influences people's intention to use fully automated taxis. The findings proved that the effects of the perceived threat on unemployment is significant and negative. Thus, the perceived threat of unemployment can be regarded as a key determinant, and should be included in future studies.

Finally, this research also clarified the moderating roles of gender differences in the integrated model. According to GST, GMT, and SHT, men and women are motivated differently when making a decision. However, recent studies have pointed out that these traditional gender theories may lose power in the context of cutting-edge technology acceptance (B. Zhang et al. 2022; Zhu et al. 2023). This study demonstrated that there were significant differences between males and females in effort expectancy, social influence, perceived safety risk, and knowledge of automated vehicles, while the differences among performance expectancy, perceived privacy risk, and unemployment was insignificant. These findings revealed that the differences between men and women when deciding to take a fully automated taxis can be partially explained by the roles of GST, GMT, and SHT. Thus, this research enhanced our understanding of the roles of GST, GMT, and SHT in the context of SAV acceptance.

Practical implications

The research yielded significant implications for policymakers, AV developers, and designers. First, improving system performance to help users achieve their transport objectives in an effective and efficient manner becomes a key task for AV developers. Specifically, it is necessary to ensure that a fully automated taxi can arrive in time after passengers book it. Then, AV developers should ensure that the automated taxi navigation system can follow the most effective way and avoid traffic jams. Meanwhile, AV developers also need to enhance the connection between automated taxis and other transport services to make sure that transport systems can benefit from the use of automated taxis. Second, the findings of this research emphasized the importance of improving operation and interaction. Unlike previous studies asserting that the adoption of AVs does not contain continuous input/effort and new skills (Madigan et al. 2017), the use of fully automated taxis is a systematical process that includes booking, paying, entering, checking, and many other steps. Thus, AV developers should make the operation process as easy as possible to improve human-computer interaction. Also, they need to consider simple but effective ways to teach passengers the necessary skills when taking fully automated taxis.

The perceived safety risk is a key obstacle to the adoption of automated taxis. Prior studies have found that people are most concerned about riding in a car without driver controls (Brell, Philipsen, and Ziefle 2019; Woldeamanuel and Nguyen 2018). The fear of a driverless vehicle is not far-fetched, because most people have been educated that they should never take their hands off the steering wheel since they were children. Thus, it is impossible today the general public can suddenly allay their concerns about driverless vehicles. To improve perceived safety, AV developers should allow passengers to control automated taxi. For instance, emergency stop buttons should be obviously shown inside a taxi. Passengers can stop vehicles whenever they want. In addition, vehicle systems should allow passengers to input and control the maximum speed, which cannot exceed 50 km/h. The second way is to apply layers of anthropomorphic cues to a fully automated taxi. People feel strong uncertainty because automated taxis are driven by 'cold' computer systems. Anthropomorphism induced by human-like appearance, giving an automated taxi name, age, gender, personality, and voice, can evoke the feeling of social presence, which positively influences perceived safety and trust in automated taxis (Hegner, Beldad, and Brunswick 2019). These strategies should focus more on female users because they worry more about safety when deciding to use automated taxis.

Moreover, advertisements and governmental education campaigns can be used to educate the general public about the benefits and risks of automated taxis. Knowledgeable individuals have a better understanding of automated taxi, promoting such vehicles' adoption. Our findings indicated that these educational strategies should focus more on male users because they are more likely to be motivated by prior knowledge of AVs. In addition, consider to use social networks of individuals, especially in China. According to Zhang et al. (2020), China is characterized by collectivistic culture. In such an environment, a person's decision is more likely to be influenced by others' suggestions due to face-saving and group conformity (Zhou and Li 2014). Thus, government and and AV developers should launch some projects among citizens' networks, such as communities and civil society organizations. For instance, a course of lectures on AVs can be arranged to stimulate people's adoption intention within a community. If a person decides to use automated taxi, others in the same community will be influenced by this person. Importantly, these projects should concentrate more on female users because they are more likely to be influenced by social networks. Furthermore, the anxiety about automated taxis taking over existing jobs is real. Therefore, policy-makers should make a clear plan to ensure that the development of AV industry can create sufficient jobs. Then, they should share this plan with the general public and conduct it step by step to reduce the perceived threat of unemployment.

Conclusion and limitations

Although AV industry has made great achievements in recent years, the use of automated taxi has been rarely investigated. This research developed an integrated model based on UTAUT, TPR, the perceived threat of unemployment, and knowledge of automated vehicles to explore the determinants behind people's intention to use fully automated taxis. The findings showed that performance expectancy, effort expectancy, social influence, and knowledge of automated vehicles are positively associated with behavioral intention, while perceived safety risk and unemployment threat are negatively related to acceptance intention. In addition, perceived privacy risk did not significantly impact the intention to use fully automated taxis. Moreover, this research investigated the role of gender differences in the research model. The findings revealed that effort expectancy, social influence, and perceived safety risk had greater influences on women, while knowledge of automated vehicles exerted stronger effects on men. However, the relationships between performance expectancy, perceived privacy risk, perceived threat of unemployment, and gender differences did not significantly moderate behavioral intention. The findings of this research enhance the existing literature on SAV acceptance by revealing new determinants and the moderating roles of gender differences. We also expect that the findings of this study can help policy-makers, AV developers, engineers, and designers to promote the adoption of automated taxis.

However, several limitations of this research should be pointed out. First, because the empirical study relied on the pilot project of fully automated taxi in Chongqing, we only collected data in Chongqing, China. We recommend to validate our findings in larger samples and areas. Culture might play a role and influence the outcomes. Second, this research only investigated acceptance intention, which means the respondents in this study might not have actual experience of fully automated taxis. Thus, the determinants in this research might not motivate the actual usage behavior. Future studies should investigate people's actual use behavior and continuance use behavior because these outcome variables are key to the success of SAVs. Third, this study is not without the limitations of cross-sectional study. The relationships identified in this research might change over time. Thus, longitudinal studies are recommended to further explore the relationships between influencing factors and SAV acceptance. Fourth, snowballing techniques ask respondents to share online questionnaires with familiar people. Thus, this study has selection bias risk. Finally, there is a selection bias of age (mostly young people) in this study. Thus, the findings represent a convenience sample that consists of younger individuals. It is recommended that future studies keep a balance between young users and old users.

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