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Factors Influencing Passengers to Use Autonomous Bus in China Cities

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ABSTRACT

Developing insight into the determinants that impact communities' willingness to accept autonomous buses has become a crucial aspect of smart city advancement. This study investigated the inclination of residents to utilize autonomous buses by employing the expanded Unified Theory of Acceptance and Use of Technology model, encompassing satisfaction, trust, and perceived risk. The UTAUT model is an influential theoretical framework used to forecast and elucidate the acceptance of new technology by people or organizations. The results show that (1) Effort expectancy, performance expectancy, social influence, and facilitating conditions have a considerable beneficial effect on both behavioral intention and satisfaction. (2) A significant positive correlation exists between behavioral intention and satisfaction and trust. (3) Perceived risk also has a detrimental moderating impact. The results offer governments and public transportation operators a valuable blueprint for the development and promotion of autonomous buses in metropolitan regions. Current findings can play as a helpful point of reference for enhancing development of autonomous public transportation in China.

1. INTRODUCTION

Significant changes have been made to the current public transport system by integrating autonomous driving technology [1]. Autonomous public transport is a crucial component in developing smart and sustainable cities [2, 3]. People's acceptance will determine whether autonomous public transport can become part of their lives. While there has been much attention given to the concerns surrounding the acceptability of self-driving automobiles, the variables influencing the acceptance of autonomous buses have been largely neglected [4, 5]. Understanding the elements affecting residents' adoption of autonomous buses is essential for improving public transportation networks [6]. It is important to successfully implementing an autonomous public transport system.

The UTAUT model helps forecasting and elucidating the process by which individuals and organizations embrace information technology. This approach has been shown to accurately predict up to 70% of individual intentions, as evidenced in several papers [7, 8]. However, the original UTAUT model should include more external factors to enhance its ability to predict the adoption of new technologies [9]. For instance, perceived risk was incorporated into the UTAUT model to forecast Chinese city dwellers' adoption of self-driving vehicles [10]. The selection of artificial intelligence and transportation services is greatly influenced by consumer satisfaction [11, 12]. Trust is a pivotal role in influencing intention of local inhabitants to embrace autonomous vehicle technology [13].

Three contributions are made in this paper. (a) This report presents empirical data collected from four prominent Chinese cities to offer insights into the feasibility of implementing autonomous buses as a public transportation system in cities. It addresses a research need in the field of urban context [14]. (b) Provides a valuable reference for developing measures that promote interaction with autonomous buses by residents, it can be effective in encouraging physical access to autonomous buses [15]. (c) Research into the moderating effects of perceived risk can help to develop more effective practice interventions.

2. LITERATURE REVIEW

2.1 Effort expectancy (EE) and performance expectancy (PE)

EE and PE have an impact on a new technology's acceptability [16]. EE describes the degree of convenience, reflecting the ease of using the technology. Moreover, PE describes people's perceptions of how much the system improves their ability to perform their jobs, indicating the possible benefits. The level of convenience directly impacts the extent to which the general public accepts autonomous bus services [17]. Autonomous buses have the potential to provide flexible services, much like autonomous taxis or shared autonomous cars [18]. And autonomous buses can thus meet passenger demand for flexibility and punctuality [19].

Moreover, PE impacts user to accept a new technologies quality [16]. Bernhard et al. [20] tested user acceptance of driver less buses in Mainz, Germany and demonstrated that PE significantly impacts behavioral intentions more than EE. Specifically, autonomous buses have lower operating costs because driver fatigue factors do not limit their service hours and can provide longer service hours [21], it can help passengers to save travel costs. And also have more efficient transport capacity and intelligent navigation capabilities, effectively reducing urban traffic congestion [22]. It reduces travel time for passengers and leads to a more positive travel experience.

Behavior intention (BI) is commonly used as the dependent variable in impact assessment studies using the UTAUT paradigm [23]. BI is the degree of consciousness at which a person chooses whether or not to participate in a specific behavior in the future. Several studies [16, 24] have shown that BI is positively affected by both EE and PE. Thus,

H1: *EE play a beneficial influence on BI to embrace autonomous public' buses.*

H2: *PE play a beneficial influence on BI to accept autonomous buses.*

2.2 Social influence (SI) and facilitating conditions (FC)

SI refers to the influence of other people's perceptions, attitudes, and behaviors on the use of technology, including those of friends, family, and colleagues [25]. SI as a critical predictor of the propensity to accept self-driving technology [26, 27]. In this study, FC stands for the degree to which current infrastructure or organizations facilitate the advancement of autonomous buses and serves as a metric for evaluating the external environment [16].

SI has an impact on passengers' intention to utilize autonomous public transportation [28]. That finding agrees with the findings of the earlier investigation [20]. When examining citizens' intentions to utilize autonomous public transportation vehicles other than trains, a positive link between SI and BI was found [29]. SI and FC may influence on the desire to utilize autonomous public transport units [30]. FC influences BI to utilize autonomous public vehicles and directly effects the actual usage behavior as a measure of the external environment [20, 31].

H3: *SI play a favorable influence on individuals' BI to use autonomous buses.*

H4: *FC play a favorable influence on individuals' BI to use autonomous buses.*

2.3 Effects of satisfaction and trust

People's decision-making while deciding whether to use business intelligence is heavily influenced by factors like satisfaction and trust [9]. User's satisfaction is significantly impacted by the four UTAUT model components [32]. In the context of technological adoption, there is a substantial correlation between user satisfaction, FC, and SI [33, 34]. Furthermore, the intention to employ self-service can be positively influenced by the psychological aspect of satisfaction when applied to the UTAUT model [35]. Satisfaction influences BI when passengers use autonomous buses, it is supported in the existing literature [14, 36, 37].

Becker and Axhausen [38] released the first analysis of the literature on driver-less cars, suggesting that trust is a significant barrier to usage intentions. Trust in autonomous buses involves a trade-off between the pros and cons of the technology [31]. Besides, trust develops when advantages exceed drawbacks. Trust in driver-less buses refers to the public's inclination to accept and tolerate potential hazards. according to Xu et al. [39]. Acceptance of autonomous public buses is initially challenging to gain public trust [40, 41]. It suggests that trust in autonomous buses may require further research.

Prior research has demonstrated that attitudes toward using autonomous cars are influenced by one's degree of trust [27, 42, 43]. And also applies to autonomous buses [44-46]. Furthermore, Kaur and Rampersad [47] previously used the UTAUT model to assess the influence of trust on the usage of driverless vehicles by Australian users. However, Kabra et al. [9] suggested no obvious connection between trust and behavioral intention. An analysis of the correlation between behavioral intention and trust in autonomous buses is crucial.

H5: *Satisfaction significantly influence on the BI of residents travelling on autonomous buses.*

H6: *Trust significantly influences on BI of residents travelling on autonomous buses.*

H7: *EE significantly influence on the satisfaction of autonomous buses.*

H8: *PE significantly influence on the satisfaction of the residents travelling on autonomous buses.*

H9: *SI significantly influence on the satisfaction of autonomous buses.*

H10: *FC significantly influence on the satisfaction of autonomous buses.*

2.4 Moderating effect of perceived risk (PR)

PR is often studied in depth as an external variable in UTAUT models [48]. Passengers' concerns regarding the potential risks associated with self-driving technology hinder the choice of autonomous buses [39, 49]. One important issue affecting the commuters' adoption of autonomous technology is PR [27]. And PR is also one barrier to the advancement of intelligent technology [50]. The present research establishes the perceived windfall as the potential risks and losses passengers perceive when choosing autonomous buses [51]. Specifically, PR of using emerging self-driving technologies include accidents, breakdowns, rerouting, emergency braking, and scheduling delays [52]. When PR is reduced, autonomous public vehicles are more likely to be used. Conversely, when passengers perceive higher risk, they refuse to choose autonomous public vehicles. This finding has been reported by Hulse et al. [53] and Wang et al. [54]. This study examined how PR affects the relationship between the dependent (BI) and the independent variables (EE, PE, SI, and FC). We hypothesize that:

M1: *PR moderates the relationship between EE and BI.*

M2: *PR moderates the relationship between PE and BI.*

M3: *PR moderates the relationship between SI and BI.*

M4: *PR moderates the relationship between FC and BI.*

3. RESEARCH METHODOLOGY

3.1 Data collection

The first part of questionnaire includes thirty items assessed the eight constructs, including satisfaction, BI, trust, PE, EE, SI, and FC, and a moderator called PR. We measured each component with many items. 5-point Likert ('strongly disagree=1' and 'strongly agree=5') scale was using to measure the constructs. Age, gender, and city are among the demographic data in the second part that are displayed on a nominal scale. The questionnaire took fifteen to twenty minutes for the participants to complete.

Using a cross-sectional survey to gather empirical data for the study, which was done between the time frame of October 1 to October 31, 2023. Participants from four cities (Beijing, Guangzhou, Shanghai, and Zhengzhou) were invited to completed the survey. 881 questionnaires were gathered for the survey. These four cities are pilot cities for autonomous buses (Ministry of Transport of the People's Republic of China, 2022), and most of the residents have experience with autonomous bus services. For data collection, respondents were given the survey near autonomous bus stops, directly offline or online later. Additionally, these four cities are among the top ten cities in China in terms of population size (National Bureau of Statistics, 2023), making the sample data representative and generalizable. The demographic data from the different cities do not significantly differ in characteristics. Therefore, this paper does not intend to do a sub-group analysis based on demographic data.

Control methods for common method bias are categorized as procedural and statistical [55]. To procedural control and protect the participants' privacy, research assistants in each city distributed and gathered the online questionnaires. The brand of the car and any commercial information were not disclosed in the surveys. Every participant provided their informed consent after learning about the study. Anonymity and confidentiality were guaranteed to all volunteers who participated in the survey. The statistical approach for statistical controls used in this study was Harman's single-factor test, which is a generally employed technique in business research. The proportion of variation accounted for was 32.111%, which is lower than the essential threshold of 50% [56]. Therefore, this research does not have common method bias.

3.2 Research measurement

There are three items in the EE measure [16], three items in the PE measure [16, 57], four items in the SI measure [58, 59], three items in the FC measure [58], and three things in the BI measure [57]. There are four components to satisfaction [60, 61] and four components to trust [62-64]. Finally, PR consists of six elements [25, 27]. This study uses average variance extraction (AVE) and composite reliability to assess convergent validity. The subsequent section provides an in-depth analysis of the results.

To verify each measurement item's precision and accuracy and assess the questionnaire's dependability, a pilot study was carried out [65]. Cronbach's alpha was used to assess the reliability of each construct. The threshold was set at 0.7 [65]. For the pilot test, 89 complete replies were submitted by citizens of Beijing and Zhengzhou. The reliability was assessed using Cronbach's alpha, which ranged from 0.759 for FC to 0.898 for PR. Every Cronbach's alpha score was more than 0.7, demonstrating the final questionnaire's practicality and dependability.

4. RESULTS

4.1 Data analysis

The conceptual model was tested using partial least squares structural equation modeling (PLS-SEM) and Smart PLS 3.3.9 software [66]. The analytical technique consisted of two steps: first, testing the proposed hypotheses using the structural model assessment, and second, assessing the measurement model for validity and reliability [67]. The structural model describes the relationships between the components, while the measurement model describes how each construct is specifically measured for this study. PLS-SEM considers both the measurement and the structural models, it produces estimates that are more accurate [68].

4.2 Respondents' profile and characteristics

According to Table 1, the statistics, 203 respondents (50.7%) were women and 197 (49.3%) were males. The participants' ages were distributed as follows: 26% of the participants were between 18 and 25 years old, 40% were between 30 and 40 years old, 5% were between 40 and 50 years old, 1% were between 50 and 60 years old, and 5% were over 60 years old. In addition, 6% of the participants were under 18 years old. Regarding the educational background of the respondents, only 27.2% had completed high school, 36% had attended college, 32.3% had a bachelor's degree, and 25.8% had a master's degree or higher. With regards to their frequency of bus usage, participants reported using the bus less than once a week (25.7%), one to two times a week (24.5%), three to five times a week (26%), and more than six times a week (23.8%).

Table 1. Profile of respondents (N = 400)

Characteristics	Values	Frequency	Percentage (%)
Gender	Male	197	49.3
	Female	203	50.7
Age	Below 18	27	6.8
	18~25	107	26.8
	26~30	172	43
	31~40	59	14.8
	41~50	22	5.5
	51~60	7	1.8
	Above 60	6	1.5
Education level	High school and below	24	27.2
	College degree	144	36
	Bachelor's degree	129	32.3
	Master's degree and above	103	25.8
Frequency	＜1 time	103	25.8
	1–2 times	98	24.5
	3–5 times	104	26
	＞6 times	95	23.8

4.3 Assessment of measurement model

Table 2, where it is clear that all constructs had indicator loadings ranging from 0.797 to 0.914, above the typical range of 0.7 that is advised [69, 70]. The correlation coefficient (CR) and Cronbach's alpha are used to assess a construct's reliability, which show how effectively items assess a particular construct. The Cronbach's alpha values showed high internal consistency and exceeded the 0.7 threshold, ranging from 0.794 to 0.901 [71]. The CR values for FC and EE, which ranged from 0.830 to 0.936, were more than the critical limit of 0.7. Consequently, Cronbach's alpha and CR were verified [72].

Convergent validity was evaluated by using AVE analysis and factor loadings [71]. Table 2 displays the AVE values, 0.755 (BI), 0.829 (EE), 0.780 (PE), 0.662 (SI), 0.746 (FC), 0.670 (PR), 0.701 (satisfaction), and 0.647 (trust). Of these, trust is the lowest and EE is the highest. These values exceed the recommended limit of 0.5 given by Fornell and Larcker [73]. The report offers a CV regarding the measurement of several conceptually linked things. To provide excellent discriminant validity (DV), a construct's square root of its AVE has to be larger than its association with other constructs [67, 73]. It also recommends that the values on the corresponding columns' and rows' diagonals be more significant than those on the non-diagonal [70]. A respectable degree of DV was shown in Table 3 by the square roots of the AVE (highlighted on the diagonal), which were shown to be more significant than the interstructural correlation for each construct.

In response to inquiries from particular academics on earlier techniques for evaluating discriminant validity (DV), our investigation presented a novel standard, the "heterotrait-monotrait ratio (HTMT)" as put forth by et al. [74]. As demonstrated in Table 4, where all values are below the suggested criterion of 0.85 [75], the HTMT ratio performs better than earlier criteria. Thus, based on both evaluation criteria, we conclude that discriminant validity is established and the HTMT condition is met.

Table 2. Results of measurement model

Constructs	Items	Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Behavioral Intention	BI1	0.876	0.837	0.902	0.755
	BI2	0.868			
	BI3	0.862			
Effort Expectancy	EE1	0.910	0.897	0.936	0.829
	EE2	0.908			
	EE3	0.914			
Performance Expectancy	PE1	0.869	0.859	0.914	0.780
	PE2	0.899			
	PE3	0.881			
Social Influence	SI1	0.797	0.855	0.902	0.662
	SI2	0.852			
	SI3	0.854			
	SI4	0.836			
Facilitating Conditions	FC1	0.880	0.830	0.898	0.746
	FC2	0.875			
	FC3	0.836			
Perceived Risk	PR1	0.819	0.901	0.924	0.670
	PR2	0.834			
	PR3	0.809			
	PR4	0.800			
	PR5	0.814			
	PR6	0.833			
Satisfaction	Sat1	0.839	0.858	0.903	0.701
	Sat2	0.830			
	Sat3	0.851			
	Sat4	0.828			
Trust	Tru1	0.839	0.864	0.902	0.647
	Tru2	0.847			
	Tru3	0.832			
	Tru4	0.828			

Table 3. Correlation matrix and square root of the AVE

	BI	EE	FC	PR	PE	Sat	SI	Tru
BI	**0.869**							
EE	0.376	**0.911**						
FC	0.411	0.266	**0.864**					
PR	-0.408	-0.275	-0.260	**0.818**				
PE	0.414	0.285	0.350	-0.304	**0.883**			
Satisfaction	0.529	0.487	0.459	-0.348	0.484	**0.837**		
SI	0.354	0.218	0.228	-0.226	0.223	0.462	**0.835**	
Trust	0.346	0.117	0.214	-0.263	0.204	0.233	0.202	**0.837**

Table 4. Heterotrait-monotrait (HTMT) ratio

	BI	EE	FC	PR	PE	Sat	SI	Tru
BI								
EE	0.430							
FC	0.492	0.307						
PR	0.466	0.306	0.295					
PE	0.485	0.322	0.414	0.344				
Satisfaction	0.622	0.555	0.539	0.395	0.563			
SI	0.418	0.251	0.270	0.258	0.261	0.538		
Trust	0.407	0.131	0.254	0.301	0.235	0.270	0.233	

4.4 Assessment of structural model

The coefficient of determination (R^2) is typically calculated to evaluate the effectiveness of structural models. Table 5 demonstrates that the combined EE, PE, SI, and FC theories may explain 50.4% of enjoyment. Moreover, the interplay of EE, PE, SI, FC, satisfaction, trust, and PR accounts for 42.2% of BI. These results provide significant explanatory power, exceeding the modest criterion of 33% proposed by Chin [69].

The study's analysis of effect sizes (f^2) yielded the following results: 0.02 for small effects, 0.15 for medium effects and 0.35 for large effects [67, 76, 77]. The effect sizes indicated that the exogenous variables had little effect on the endogenous variables, suggesting that the exogenous factors may only be marginal predictors of the endogenous variables. However, if the medium and large effect sizes are present, it may be inferred that the exogenous factors have medium to large influence on the endogenous variables [78]. The study's findings indicate that EE (f^2=0.018), PE (f^2=0.020), SI (f^2=0.015), FC (f^2=0.026), Trust (f^2=0.015) and PR (f^2=0.037) on BI. For satisfaction, significant effects were found for EE (f^2=0.147), PE (f^2=0.111), SI (f^2=0.154), and FC (f^2=0.085). The results show that while the other dimensions have minor effects on both BI and satisfaction, SI has a medium effect on satisfaction. The model's effect sizes (f^2) are shown in Table 5.

Using blindfolding as the predictive relevance criteria and an omission distance of 7, the predictive relevance (Q^2) was computed by the methodology outlined by Hair et al. [67] and Chin [76]. As seen in Table 5, a Q^2 value larger than 0 is typically regarded as a sign of predictive importance. Studies by Chin [76] and Hair et al. [79] show that satisfaction (Q^2=0.349) and BI (Q^2=0.295) are predictive indicators. These findings imply that the UTAUT indicator is predictive of contentment and that UTAUT indicators, in conjunction with PR, satisfaction, and trust, are predictive of BI.

Since no formative models were available for this investigation, only reflective models were employed. Therefore, assessing the goodness of fit (GoF) was deemed appropriate. For this purpose, the formula utilized by Alolah et al. [80] was adopted: GoF= $\sqrt{(AVE*R^2)}$. For both mean covariance and R^2 values, the geometric mean is between 0 and 1 (0<GoF<1). In our investigation, a GoF value of 0.578 was found. This figure is higher than the figure of Tenenhaus et al. [81] benchmark value of 0.36. Consequently, the proposed model shows superiority over the given benchmark value and fits the data quite well overall. This measure has been widely used in empirical PLS path modeling applications [82, 83]. The benchmark value proposed by Tenenhaus et al. [81] is more suitable for SmartPLS than CBSEM [84]. This metric has also been used in research on traffic behavior [85, 86], and autonomous buses [39, 87], and shows to be useful in evaluating the model's capacity for prediction.

Using bootstrapping (5000 sub-samples) regression and predicted weights, we examined the importance of the path [88, 89]. Ten significant route relationships are revealed in Table 6, which displays the predicted path relationships for each pair of research constructs using PLS regression. For the UTAUT model's constructs, it was discovered that EE (β=0.117, $p<0.05$), PE (β=0.127, $p<0.01$), SI (β=0.105, $p<0.05$), and FC (β=0.141, $p<0.01$) significantly improved public acceptability of BI for driver-less buses. As a result, hypotheses 1-4 were confirmed. Moreover, it was discovered that trust and pleasure significantly improved BI (β=0.202 and 0.165, $p<0.01$), confirming hypotheses 5 and 6. Hypotheses 7, 8, 9, and 10 were supported by the identification of EE (β=0.290, $p<0.01$), PE (β=0.258, $p<0.01$), SI (β=0.290, $p<0.01$), and FC (β=0.225, $p<0.01$) as significant antecedents of contentment.

To examine the moderating effects, we used a process macro model [90] with the three steps shown in Table 7. The data results show that PR moderates behavioral intention in all of Models 1-4, all of which are significant ($p<0.001$). In addition, PR had a significant and negative moderating effect on BI when the independent variables were EE (β=-0.2714, $P<0.001$), PE (β=-0.2697, $P<0.001$), SI (β=-0.2426, $P < 0.001$), and FC (β=-0.2764, $P<0.001$). Therefore, hypotheses M1, M2, M3, and M4 were supported.

Table 5. Predictive accuracy (R^2), predictive relevance (Q^2) and effect sizes (f^2)

	R Square	Q Square	Behavioral Intention (f^2)	Satisfaction (f^2)
Effort Expectancy			0.018 (Small)	0.147 (Small)
Performance Expectancy			0.020 (Small)	0.111 (Small)
Social Influence			0.015 (Small)	0.154 (Medium)
Facilitating Conditions			0.026 (Small)	0.085 (Small)
Trust			0.015 (Small)	
Perceived Risk			0.037 (Small)	
Behavioral Intention	0.422	0.295		
Satisfaction	0.504	0.349		

Table 6. Hypotheses testing results

Hypothesis	Structural Path	Path Coefficient (β)	t-value (Bootstrap)	p-value	Results
H1	EE -> BI	0.117	2.575	0.010	**Supported**
H2	PE -> BI	0.127	2.821	0.005	**Supported**
H3	SI -> BI	0.105	2.246	0.025	**Supported**
H4	FC -> BI	0.141	2.886	0.004	**Supported**
H5	Satisfaction -> BI	0.202	3.855	0.000	**Supported**
H6	Trust -> BI	0.165	3.624	0.000	**Supported**
H7	EE -> Satisfaction	0.290	7.942	0.000	**Supported**
H8	PE -> Satisfaction	0.258	6.410	0.000	**Supported**
H9	SI -> Satisfaction	0.290	8.024	0.000	**Supported**
H10	FC -> Satisfaction	0.225	5.519	0.000	**Supported**

Table 7. Moderating effects of perceived risk on behavioral intention

Model 1: Moderating Effect Testing Between EE and BI				**Model 2: Moderating Effect Testing Between PE and BI**			
Variables	**β**	**S.E**	**P**	**Variables**	**β**	**S.E**	**P**
EE	1.1153	0.1692	.0000	PE	1.1298	0.1552	.0000
PR	0.6368	0.2089	.0025	PR	0.6057	0.1815	.0009
EE*PR	-0.2714	0.0535	.0000	PE*PR	-0.2697	0.0483	.0000
R^2 (EE*PR)	0.0469		.0000	R^2 (PE*PR)	0.0545		.0000
F	25.7457 (P=.0000)			F	31.1336 (P=.0000)		
Model 3: Moderating Effect Testing Between SI and BI				**Model 4: Moderating Effect Testing Between FC and BI**			
Variables	**β**	**S.E**	**P**	**Variables**	**β**	**S.E**	**P**
SI	1.0253	0.1742	.0000	FC	1.1681	0.1621	.0000
PR	0.4795	0.2117	.0240	PR	0.6529	0.1992	.0011
SI*PR	-0.2426	0.0563	.0000	FC*PR	-0.2764	0.0516	.0000
R^2 (SI*PR)	0.0342		.0000	R^2 (FC*PR)	0.0499		.0000
F	18.5400 (P=.0000)			F	28.6915 (P=.0000)		

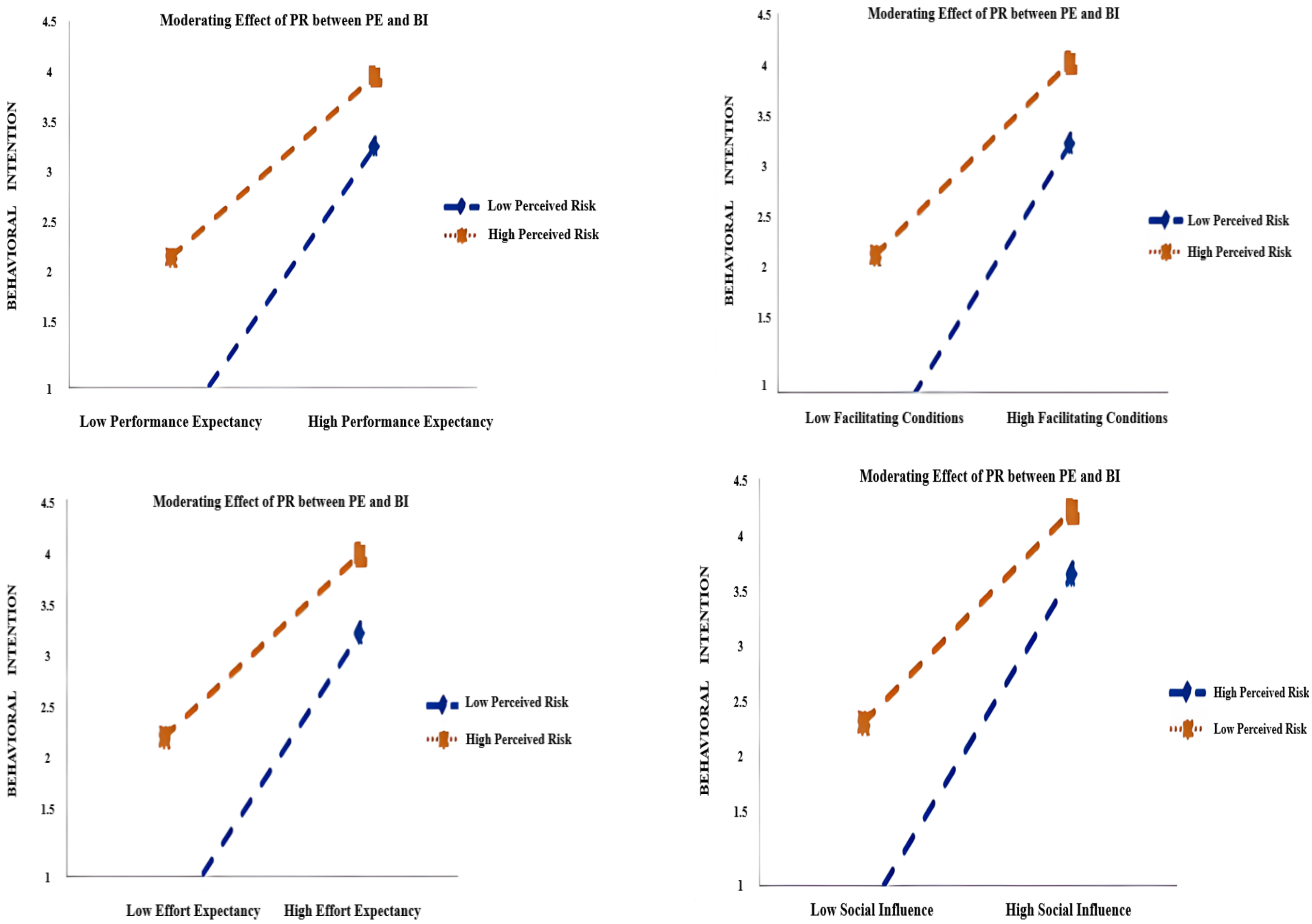

Figure 1. Moderating effect of PR

To demonstrate the influence of various factors, the study compared predicted BI with different levels of PE, EE, SI, and FC. This comparison was illustrated in Figure 1, where a higher level was defined as one standard deviation below the mean. A value that is one standard deviation below the mean is regarded as a lower level, whereas a value that is one standard deviation above the mean is deemed greater. Figure 1 demonstrates that passengers with low PR exhibit a negative relationship between greater levels of EE (β=0.5463, p<0.001), PE (β=0.5644, p<0.001), SI (β=0.5167, p<0.001), FC (β=0.5167, p<0.001), and BI. The role of PE, EE, SI, and FC on BI remained negative in relation to PR. Nevertheless, the impact of reduced PR on the influence of EE (β=0.0776, P>0.05), PE (β=0.0986, P>0.05), SI (β=0.0977, P>0.05), and FC (β=0.1114, P>0.05) on BI was not significant.

5. DISCUSSION

The acceptance of autonomous buses by the public is a crucial issue in transportation research [1, 2, 29]. This study analyzes passengers' BI about autonomous buses. The investigation was carried out in four pilot towns in China where autonomous buses were undergoing testing. This study looks into how BI is affected by PE, EE, SI, FC, satisfaction, and trust. It also looks at PR's moderating effect on the interactions between PE, EE, SI, FC, and BI. Current research has not thoroughly investigated these matters.

The subsequent discoveries are pertinent: The variables of PE, EE, SI, and FC have a notable and positive impact on the BI to embrace autonomous buses. It implies that travelers will take into account not just convenience and efficiency, but also social group attitudes and transportation amenities. If individuals find these elements satisfactory, their inclination to select autonomous buses is likely to be higher. This discovery is consistent with prior investigations [24, 91].

Furthermore, we observed a direct relationship between the variables of PE, EE, SI, and FC with satisfaction. The factors that have the greatest influence on satisfaction are PE and SI. Both of these variables have path coefficients of 0.290. Furthermore, BI is strengthened by an increase in satisfaction (β=0.202). In conclusion, passengers are highly concerned about the convenience and ease of use of autonomous buses, as well as the perception of autonomous buses by social groups, which influences passengers' satisfaction. The government can improve the public's perception of satisfaction with autonomous buses by improving the service quality and optimizing the operation scheme. Furthermore, this study supports previous research [33, 34] that shows that an increase in passenger satisfaction positively influences the choice of public transport. This study extends this finding to autonomous buses, providing support for the development of the theory.

Thirdly, trust has a more significant impact on BI (β=0.165) than EE (β=0.117), PE (β=0.127), SI (β=0.105), and FC (β=0.141). This finding is consistent with recent research by Pak et al. [92]. However, the effect of trust on BI was smaller than the effect of satisfaction (β=0.202), which is in line with findings by Chao [93]. Therefore, the decision to choose autonomous buses is influenced by trust but depends more on satisfaction.

Fourth, this study demonstrates that PR can counteract the beneficial effects on BI that come from PE, EE, SI, and FC. It suggests that PR acts as a negative moderator on BI. We observed that low risk had a significant negative moderating effect, while high risk did not have a significant negative moderating effect. Passengers may have concerns about the risks associated with autonomous buses, but these concerns are not severe given the increasing sophistication and popularity of the technology. Chao [93] found that when passengers perceive autonomous buses as being riskier, their utilization rate decreases. This study explored the moderating effect of PR based on the validation of previous research.

6. LIMITATIONS AND FUTURE RESEARCH

This study has some limitations. Firstly, the data sample was limited to daily commuters. In future studies, this limitation could be removed to include leisure and long-distance travel to give rise to a more thorough comprehension of user approval. Secondly, the study did not consider demographic characteristics. Subsequent studies could be conducted by subgroups based on demographic characteristics. In addition, the observation period for the data in this cross-sectional study was short. Studies could use a longitudinal strategy to track changes in passenger perceptions in the future.

7. CONCLUSIONS

It investigates the determinants that impact passengers' inclination to embrace autonomous buses in four Chinese cities by this study. The emphasis is placed on those who have already encountered autonomous buses. The study revealed a favourable correlation between PE, EE, SI, FC, satisfaction, and BI. Simultaneously, both satisfaction and trust exerted an impact on BI, with satisfaction exhibiting a more significant influence compared to trust. Furthermore, the influence of PR on BI was shown to be negative, especially when PR was low, resulting in a considerable moderating impact.

In conclusion, service providers and the government should work together to enhance the convenience and user-friendliness of autonomous buses. They should also promote and establish the positive impact of autonomous public transport. Additionally, improving service quality and increasing passenger satisfaction and trust can help to boost acceptance. The safety and reliability of autonomous buses should be continuously optimized to reduce the PR to the public. It will contribute to the development and application of autonomous public buses in cities.

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