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The Effect of Perceived Risk on Public Participation Intention in Smart City Development: Evidence from China

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Abstract: Smart city development aims at sustainable development and high quality of urban life, which requires the participation of stakeholders. As a crucial stakeholder involved, the public's key role has been widely concerned. However, a lack of public participation in smart city development still exists due to perceived risk. In order to solve the insufficient public participation in smart city development, this study will identify the perceived risk and explore its influential impact. After defining the concept of perceived risk, this paper constructs a theoretical model concerning the effect of perceived risk on public participation intention based on the theory of reasoned action. On the basis of 193 empirical data from China, the structural equation model is applied to test the influential impact of perceived risk on the public participation intention in smart city development. The results show that the perceived risk has a significantly negative effect on public participation intention, attitude, and subjective norms, while behavioral attitude and subjective norms have positive effects on public participation intention. According to empirical research results, the risk prevention paths and methods of public participation in smart city development are proposed so as to provide useful implications for further public participation practice in smart city development.

Keywords: perceived risk; public participation; smart city development; the theory of reasoned action; empirical research

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1. Introduction

With the rapid urbanization rate and increasing population in urban areas, consequent problems hinder urban development [1] and manifest themselves in social, economic, and environmental aspects [2]. Driven by information and communication technologies (ICTs), the conception of a smart city is proposed as an innovative urban development model, aiming to achieve high-quality urban life and sustainable development. The smart city can be defined as a city where investments in human and social capital and traditional (transport) and modern (ICT) communication infrastructure fuel sustainable economic growth and high quality of life, with a wise management of natural resources, through participatory governance [3]. Particularly, participatory governance in the smart city requires the engagement of citizens, implying the notable role of public participation [4].

Smart city development is of great significance in promoting sustainable urban development [2], and facilitating cities' sustainable development is one of the positive results of smart city development [4]. Apart from promoting the quality of urbanization, smart city development can not only develop strategic emerging industries but also contribute to economic growth and environmental protection [5]. Moreover, as a crucial way to achieve urban sustainability, smart city development can also enhance cities' core competitiveness and promote urban innovation [5]. Although smart city development can bring about a dozen of positive results, potential pitfalls such as privacy leakage and the digital divide still exist [6]. In addition, factors influencing smart city development, such as civil engagement, public attitude, and social inclusion, cannot be ignored [7]. Furthermore, smart city development requires the participation of stakeholders, comprising government, enterprises, and the public, which is of great importance for its success [8].

Among these stakeholders, the public's key role in smart city development has been widely concerned. However, a lack of public participation in smart city development still exists [9]. Many research findings indicate that the public perceives plenty of risks and uncertainties, and the perceived risks are important variables affecting their participation intention in smart city development. It is noted that the public faces risks of trust, data privacy, and technical application [10]. In addition, technology issues and lack of social inclusion could also make the public less willing to involve in smart city development [11]. Moreover, insufficient public participation in smart city development and the risk from stakeholders' conflicts need to be noticed [12]. Therefore, although existing studies have analyzed different risk factors, there is still a lack of systematic research on the public's perceived risk (PR) in smart city development.

In terms of research methods, existing studies have focused more on qualitative analysis, while the research on the public's perceived risk by quantitative measurement is scarce. Theoretical research on the relationship between perceived risk and public participation intention and their influential effect on quantitative analysis is still lacking. To sum up, risks perceived by the public involve different aspects and dimensions, and further exploratory research needs to be carried out. Based on the effective identification and definition of perceived risk, a theoretical model combining the risk with the participation intention is constructed by extending the theory of reasoned action (TRA). The model not only enriches the relevant theories of smart city development but also reveals the influential mechanism of perceived risk on public participation. Practically, this model also aims to provide a theoretical basis for improving the public's intention and formulating risk prevention methods for governments and other stakeholders. The risk prevention methods are solutions and strategies to mitigate the effect of risk on public participation intention by identifying, analyzing, and ranking.

The remainder of the paper is structured as follows. Section 2 conducts the literature review. Section 3 presents the conceptual model and research hypotheses. Section 4 describes the variable measure and data collection. Section 5 reports the results of data analysis using the structural equation modeling (SEM) method. Section 6 focuses on the discussion and conclusion.

2. Literature Review

2.1. Public Participation in Smart City Development

With the continuous promotion of smart city development, the content of public participation presents new changes. Public participation in smart city development refers to the decision-making process at the beginning, subsequently lays emphasis on data collection and urban management, finds solutions to urban problems, and then underlines urban operation [13]. To be specific, public participation was an important aspect of smart city development, which was highlighted in the decision-making of urban development. Especially, democratic decision-making and transparency could be improved through public participation [10]. Furthermore, as an important part of smart city development governance, no or minimal public participation was unsatisfactory [14]. Moreover, the public not only generated data by using ICTs and applications but actively utilized sensors or other mobile devices to gather information and data [13].

The specific forms of urban management also became more dependent on citizen involvement and ICTs used by the public. Moreover, citizen participation has become common in smart city operations, especially in European cities [13]. The smart city operation requires not only the integration of ICTs but also related data from citizen participation. Furthermore, the need for public participation in seeking solutions to cities' problems has been recognized [7], and the role of public participation in dealing with urban problems has been enhanced. Moreover, smart city development is regarded as an efficient and novel solution using ICTs to solve urban problems, and the public's role in finding solutions to urban problems is increasingly important [15]. It was also mentioned that public participation had potential value in effectively solving urban problems [16].

Despite the fact that the public is a key stakeholder in smart city development, the research on the public's intention to participate is still lacking [9]. Previous studies focus much on the importance of public participation but lack systematic analysis on how to enhance the public participation intention. Particularly, the public involved in smart city development perceives a variety of risks, which will have an impact on their participation intention.

2.2. Smart City Development in China

Recently, there has been a growing trend of smart city development in developing countries, such as China [2]. The concept of a smart city was introduced to China in 2010 and has officially been defined as an urban development model [17]. The Chinese government started to carry out smart city pilot policies in 2012 [18]. The Chinese Ministry of Housing and Urban-Rural Development (MOHURD) issued a notice on carrying out national smart city pilot work in December 2012, officially pointing out that smart city development was an important measure to promote urbanization and could improve urban management and service level. Moreover, the smart city development in China can be divided into three stages: the pilot stage (November 2012–March 2014), the standardization stage (March 2014–December 2015), and the new-type smart city stage (December 2015–present) [19]. By 2018, more than 500 smart cities had been located in China, which ranked first all over the world [18]. Currently, the State Council issued a notice of the "14th Five-year Plan for Digital Economy Development" in December 2021, which regarded the new-type smart city development as an effective measure to accelerate the urban data fusion and industrial ecology cultivation and improve the urban data operation, development, and utilization level.

Smart city development in China is generally led by the government [18], which lays emphasis on people-centric characteristics [20] and increasingly focuses on public participation [21]. Recently, multiple stakeholders' involvement and public participation in the smart city development of China have been increasingly emphasized [22]. Therefore, it is necessary to formulate risk prevention methods for governments and other stakeholders in order to improve the public's intention to participate in smart city development.

2.3. Perceived Risk

Perceived risk was defined as the expectation of losses related to the consumer's purchasing behavior [23]. Whereafter, the concept of perceived risk has been drawn to measure the effect on other different behavior [24]. The perceived risk has been defined as the degree of potential for loss before or during the use of social assistive technologies [25]. Based on the literature, perceived risk concerns the public's subjective evolution of the uncertainty and loss during participation in smart city development.

In smart city development, perceived risk can be defined as the public's subjective assessment of potential danger and loss caused by privacy, technology, safety, and conflict. The application of ICTs not only helps to improve urban operation but also increases the public's perception degree of privacy risk [26]. In terms of technical risk, the public may lack intention and competence due to technical issues [11]. Citizens need to use applications, information platforms, and social media to participate in smart city development. However, the public's lack of intention and competence always leads to a digital divide [12], further bringing the risk of social inclusion [6]. The safety risk refers to negative emotions generated by information leakage and application insecurity. Particularly, if the public does not perceive that the security of personal information is protected, they will undermine trust and create negative feelings such as distrust, especially using incorrect or inaccurate information and unsafe applications [27]. The last risk concerns potential conflicts between participants and other stakeholders. Smart city development emphasizes the role of government leadership and the support of stakeholders involving enterprises, academies, and the public [8]. However, the public's potential conflicts with other stakeholders become complex because of different interest demands [12].

To sum up, public participation can perceive a variety of risks, which need to be further defined and measured. Moreover, studies on the relationship between perceived risk and public participation intention still lack, and a comprehensive framework needs to be constructed and empirically tested. Moreover, research from the perspective of perceived risk can contribute to exploring internal logic concerning the effect of perceived risk on public participation intention.

2.4. Theoretical Basis

The TRA was proposed to predict individual behavior [28], which has become a classical and widely used theory. The TRA assumes that persons are rational and will think about the meaning, consequences, and implications of their behavior before they decide to perform a given action [29]. Behavioral intention is the most proximal determinant of behavior, and the intention is determined by two constructs: attitude (AT) and subjective norm (SM). Moreover, the TRA had proposed and tested additional variables, which were included in or expanded the theory.

The TRA has been widely applied and extended in different academic fields. For example, an extended TRA model was proposed to predict citizens' behavior intention of using eco-label products, which added two constructs, namely perceived authority support and perceived environmental concern [30]. In addition, previous studies have added the relationship between perceived risk and behavioral intention by extending the TRA. Pavlou [31] added and empirically tested the research hypothesis of perceived risk on acceptance intention of e-commerce. Featherman et al. [32] also added a theoretical hypothesis of perceived risk on the public's purchase intention.

According to the TRA, attitude and subjective norms are the key determinants of behavioral intention, which are also affected by antecedents such as perceived risk. Klobas et al. [33] empirically tested that perceived security risk negatively affected the attitude to use smart devices. Xu et al. [34] extended a predicting model of public participation behavior in air pollution control, which added and empirically confirmed theoretical hypotheses of perceived risk on attitude and social norms.

The TRA has been widely applied to explain and predict behavioral intention, but its application in smart city development is lacking. In smart city development, the risk perceived by the public has increasingly become a key variable affecting public participation intention. Nevertheless, literature involving a comprehensive understanding of determinants affecting public participation intention is still scarce. Additionally, little is known about how perceived risk influences public participation intention. Therefore, the theoretical framework concerning the effect of perceived risk on public participation intention needs to be performed. In this article, the TRA is contextualized to extend a model of public participation intention for smart city development.

3. Conceptual Model and Research Hypothesis

3.1. Effect of Perceived Risk on Participation Intention

According to the TRA, the individual's behavioral intention refers to the subjective evaluation of carrying out a given behavior and also the direct antecedent that determines whether to perform the behavior or not [35]. The negative effect of perceived risk on behavioral intention has been confirmed by many previous studies of different contexts. Rahmafitria et al. [36] also confirmed that the tourist's perceived risk was negatively associated with the intention to travel during the COVID-19 pandemic. Zhang and Luo [37] empirically tested the negative influence of perceived risk on consumers' intentions to purchase remanufactured products. Therefore, it could be assumed that the public's intention to participate in smart city development is negatively affected by perceived risk.

In smart city development, public participation intention can be defined as the subjective evaluation of participating behavior. When the public comes into contact with the smart city unfamiliar, they tend to resist due to the doubts, uncertainties, and risks. Moreover, the public may not obtain direct benefits from participating as smart city development is a long-term project. Moreover, when the public perceives the existence of risks, their intention will be inhibited due to the risk aversion tendency [38]. In other words, if the public perceives a higher risk, they are less likely to have participating intention (PI). Therefore, the following hypothesis is developed:

H1. *Perceived risk negatively affects the public participation intention.*

3.2. Effects of Perceived Risk on Attitude and Subjective Norm

Based on the TRA, an attitude refers to the degree to which an individual has a positive or negative evaluation of the behaviors [35]. Previous research has proved that perceived risk exerts a negative effect on behavioral attitude. Klobas et al. [33] examined the negative relationship between perceived safety risk and householders' intentions to use smart home devices. As such, Li et al. [39] also confirmed that perceived risk negatively influenced attitude toward risky driving. According to Zhang and Liu [40], perceived risk also had a negative impact on consumers' attitudes toward using eco-friendly smart home services. Consequently, it could be assumed that the higher risk perceived by the public, the more negative their attitudes toward participating in smart city development.

Subjective norm refers to the perceived social pressure before an individual decides to perform a given behavior or not [28], where important people to the individual will expect him or her to perform the act. Previous studies have proved that perceived risk exerted a negative effect on subjective norms. Luo and Zhu [41] explored the determinants of customers' intention to apply Yu'e bao, which is a third-party mobile and online payment platform, and identified the perceived social risk had a negative influence on subjective norms. Jing et al. [42] also tested that perceived risk was also negatively associated with travelers' subjective norm of autonomous vehicles. In smart city development, when the public realizes the potential risk of participating, they may doubt whether the important people for them will support their participation or not. Based on the above viewpoints, this study developed the hypotheses as follows:

H2. *Perceived risk negatively affects attitude to participate in smart city development.*

H3. *Perceived risk negatively affects the subjective norm of participating in smart city development.*

3.3. Effects of Attitude and Subjective Norm on Participation Intention

According to the TRA, individuals' attitudes and subjective norms have positive effects on their behavioral intention. Nadlifatin et al. [30] proved the positive effect of attitude on the citizens' behavioral intention regarding eco-label product usage. Liu and Tsaur [43] verified the positive impact of attitude on purchase intention through the SEM method. In smart city development, the more positive the public's attitude to participation, the greater their participation intention. Hence, the public with a positive attitude toward participating behavior has a high intention to perform such behavior.

The TRA posits that the individual's subjective norms are positively related to his or her intention to perform a given behavior [35]. A person is more likely to perform a specific behavior when most of the people who are important to him or her believe the given behavior should be performed. Previous studies have validated that the individual's subjective norm positively affects his or her behavioral intention. Raman [44] also examined the positive relationship between subjective norms and consumers' intentions to shop online by using an SEM approach. Dalvi-Esfahani et al. [45] validated the influence of subjective norms on students' adoption intentions of green information technology. In the context of smart city development, the more positive subjective norm perceived by the public, the stronger their intentions to participate. Therefore, we propose the following hypotheses:

H4. *Attitude positively affects public participating intention in smart city development.*

H5. *Subjective norm positively affects public participating intention in smart city development.*

Accordingly, based on the above research hypotheses, a conceptual model is constructed and shown in Figure 1. The model aims to indicate the effect of perceived risk on the public's intention to participate in smart city development.

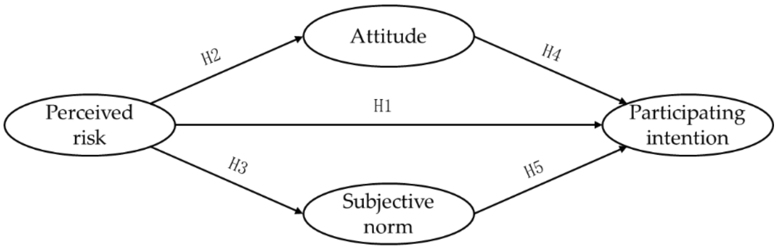

Figure 1. Research model.

4. Methodology

4.1. Survey Design

A questionnaire survey concerning the public from the above cities in Mainland China was conducted from October 2021 to February 2022. The questionnaire mainly consists of four parts, involving the evaluation of perceived risk, attitude, subjective norm, and participating intention. The initial items used to measure the variables in this paper are drawn from previous research and adapted to the context of smart city development. Subsequently, four experts with more than 10 years experience in smart cities are invited to evaluate the items, which are modified and improved according to the experts' evaluations. Accordingly, the specific items and references of each variable are shown in Table 1.

Table 1. The variable, items, and references.

Variable		Items	References
Perceived risk	PR1	Participating in smart city development may bring about a potential threat to my personal privacy.	[46,47]
	PR2	Participating in smart city development may expose me to the risk of technology use, and potentially result in a growing digital divide.	
	PR3	Participating in smart city development may cause the risk of information disclosure and insecurity for me, leading to negative feelings such as distrust.	
	PR4	Participating in smart city development may bring about a potential threat to my personal privacy.	
Attitude	AT1	I like to participate in smart city development.	[48,49]
	AT2	It is wise for me to participate in smart city development.	
	AT3	It is beneficial for me to participate in smart city development.	
Subjective norm	SN1	Most people who are important for me expect me to participate in smart city development.	[50,51]
	SN2	Most people who are important for me encourage me to participate in smart city development.	
	SN3	Most people who are important for me are willing to participate in smart city development.	
	SN4	Most people who are important for me support me to participate in smart city development.	
Participating intention	PI2	I am probably willing to participate in smart city development in the future.	[49,51]
	PI3	I will try to participate in smart city development in the future.	
	PI4	I will insist on participating in smart city development in the future.	
	PI2	I am probably willing to participate in smart city development in the future.	

All items of each variable above are measured by five-point Likert scale (1 means “strongly disagreed”, 2 means “disagreed”, 3 means “no opinion”, 4 means “agreed”, and 5 means “strongly agreed”). The higher the score evaluated by the responders, the higher the level of conformity. Take a score of 1 for example, it means “strong disagreement” on the item. Conversely, a score of 5 indicates “strong agreement” about the item.

4.2. Data Collection and Descriptive Statistical Analysis

A total of 248 questionnaires were received in two ways, including online platform [52] and paper-printed survey. The received questionnaires were reviewed, and the invalid ones were eliminated, such as selecting the same scores, incomplete responses, or non-responses. Finally, 193 valid samples were obtained and used for further analysis. Hence, the response rate of the survey was 77.82% (193 of 248).

The demographics of qualified respondents are shown in Table 2. Of the 193 respondents, 104 (53.89%) are males, and 89 (46.11%) are females. Moreover, the respondents are mainly concentrated in the age ranges of “18–28” and “29–38”, which numbers are 84 (43.52%) and 68 (35.23%), respectively. In terms of the familiar degree, the numbers of respondents who are “generally familiar” and “quite familiar” with smart cities are 70 (36.27%) and 49 (25.39%), respectively. The numbers of the respondents located in East China, Northeast China, and Southwest China are 51, 37, and 30, respectively, which are totally accounting for 61.14%. Moreover, the number of respondents who have a bachelor’s degree is 96 (49.74%), followed by a master’s and above degree (55, 28.50%) and a high school diploma (42, 21.76%).

Table 2. The respondents’ demographics.

Characteristics	Category	Frequency	%	Characteristics	Category	Frequency	%
Gender	Male	104	53.89	Location	East China	51	26.42
	Female	89	46.11		Middle China	16	8.29
Age	18–28	84	43.52		South China	17	8.81
	29–38	68	35.23		North China	24	12.44
	39–48	32	16.58		Northeast China	37	19.17
	≥49	41	21.24		Northwest China	18	9.33
Familiar degree	Unfamiliar	45	23.32		Southwest China	30	15.54
	Generally	70	36.27	Education	High school	42	21.76
	Quite	49	25.39		Bachelor	96	49.74
	Very	32	16.58		Master and above	55	28.50

4.3. Research Method

The structural equation modeling (SEM) method is a typical empirical analysis method used in different research topics. On the basis of the SEM method, the SPSS and AMOS software was employed to test reliability, validity, and hypothesis. An overview of the methodology is shown in Figure 2.

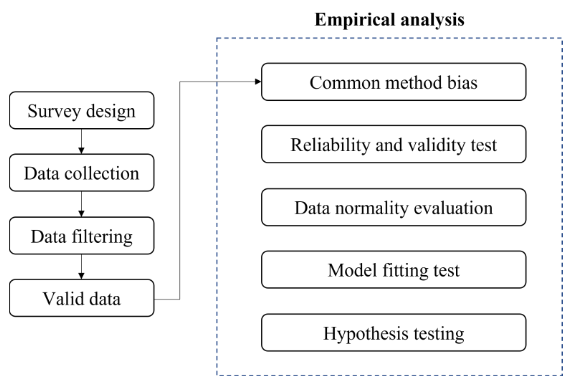

Figure 2. The overview of the methodology.

5. Empirical Results

5.1. Common Method Bias

As the questionnaire employed in this paper was from a single respondent, the risk of common method bias (CMB) might exist. Several measures were taken to control the CMB, including easily understanding and objective expression in questionnaire design and filling in the questionnaire anonymously. After the valid questionnaires were sorted out, the statistical method was also used to test the CMB. Harman's one-factor test was applied to estimate the CMB. The results indicated that the first single factor before rotating explained 30.54% of the variance, and Kaiser–Meyer–Olkin (KMO) was 0.779 (the significance level of Bartlett's test of sphericity was less than 0.000). This suggested that there was no single factor to explain most of the variance, and the CMB did not have a significant threat [46].

5.2. Reliability and Validity Test

Before assessing the research hypothesis, the reliability and validity of the measurement model should be tested. Reliability is often tested by Cronbach's α coefficient (CA) and composite reliability (CR), and the recommended values of them are both greater than 0.70 [40]. According to the results in Table 3, the CA values of the variables were between 0.811 and 0.895, and the CR values ranged from 0.815 to 0.895, which were all greater than the recommended value of 0.70. Therefore, the results indicated high reliability of data.

Table 3. Reliability analysis results.

Variable	CA	CR	Number of the Items
Perceived risk	0.812	0.815	4
Attitude	0.811	0.824	3
Subjective norm	0.895	0.895	4
Participating intention	0.838	0.844	4

Before the validity test, the SEM method was used to fit the conceptual model and sample data. The results showed that χ^2/df = 138.487/84 = 1.661, comparative fit index (CFI) = 0.958, goodness of fit index (GFI) = 0.917, Tucker–Lewis index (TLI) = 0.948, incremental fit index (IFI) = 0. 959, and root mean square error of approximation (RMSEA) = 0.059. All of these above values of fit indices meet the recommended thresholds [40], showing a satisfactory fit of the model and the data.

The confirmatory factor analysis (CFA) was used for the validity test, including convergent validity and discriminant validity. The convergent validity was evaluated by the average variance extracted (AVE) and factor loading, which benchmark values were both greater than 0.50 [49]. As shown in Table 4, the minimum AVE value of each variable is 0.526, which was more than the threshold of 0.50. In addition, the factor loading of each item, ranging from 0.608 to 0.900, exceeded the recommended threshold of 0.50. All the above measures suggested a good convergent validity. Moreover, when the square root of each variable's AVE is greater than the correlation coefficients between the variable and all other variables, the discriminant validity is satisfactorily tested.

Table 5 shows the results of discriminant validity, in which the diagonal values are the square roots of the AVE, and other values are the correlation coefficients. The AVE square root of each variable exceeds its correlation coefficients with other variables, indicating that the discriminant validity is acceptable.

Table 4. The CFA results.

Variable	Item	Mean	Factor Loading	*t*-Value	AVE
Perceived risk	PR1	4.15	0.900 ***	12.337	0.526
	PR2	4.02	0.695 ***	9.591	
	PR3	3.85	0.706 ***	9.381	
	PR4	4.08	0.763 ***	10.620	
Attitude	AT1	3.83	0.600 ***	8.705	0.615
	AT2	3.92	0.844 ***	13.600	
	AT3	3.94	0.796 ***	12.555	
Subjective norm	SN1	3.74	0.763 ***	13.124	0.682
	SN2	3.66	0.770 ***	13.931	
	SN3	3.77	0.770 ***	13.338	
	SN4	3.86	0.719 ***	13.434	
Participating intention	PI2	4.02	0.608 ***	9.295	0.578
	PI3	3.92	0.741 ***	11.868	
	PI4	3.94	0.795 ***	14.250	
	PI2	3.99	0.652 ***	11.284	

Note: *** $p < 0.001$.

Table 5. The results of discriminant validity.

	Perceived Risk	Attitude	Subjective Norm	Participating Intention
Perceived risk	0.725			
Attitude	−0.173 *	0.784		
Subjective norm	−0.244 **	0.207 **	0.826	
Participating intention	−0.312 ***	0.343 ***	0.385 ***	0.760

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

5.3. Hypothesis Testing

According to the method of evaluating data normality in previous studies [53], the results calculated by the method showed that the data satisfied normal distribution. Subsequently, the AMOS software was used for model testing, and the results are shown in Figure 3. The test of the model fit resulted in an χ^2 value of 143.841 with 85 degrees of freedom. Moreover, the normed χ^2 value was 1.692, which was below the threshold of 3.0 and met the requirement [40]. Other fit indices also satisfied the recommended thresholds as the values of CFI = 0.956, GFI = 0.913, TLI = 0.945, IFI = 0.956 and RMSEA = 0.060 were all within the suggested range [40].

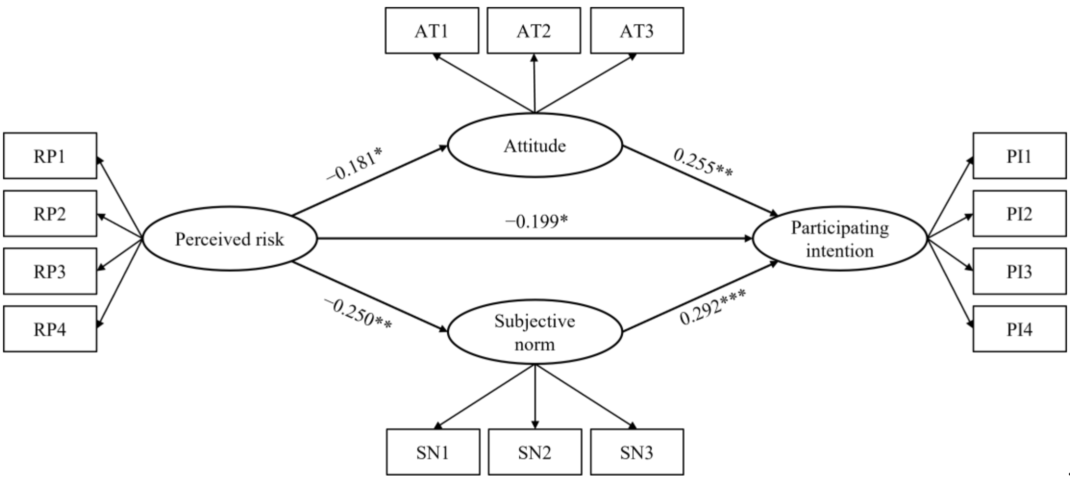

Figure 3. The SEM results. Note: * $p < 0.05$; ** $p < 0.01$; and *** $p < 0.001$.

It can be concluded from Figure 2 that perceived risk has a negative impact on attitude (β = −0.199, * $p < 0.05$). Additionally, perceived risk also has a significantly negative influence on attitude (β = −0.181, * $p < 0.05$) and subjective norm (β = −0.250, ** $p < 0.01$), respectively. Moreover, attitude (β = 0.255, *** $p < 0.001$) and subjective norm (β = 0.292, *** $p < 0.001$) are significantly and positively associated with participating intention. These specific results of hypothesis testing are shown in Table 6.

Table 6. The results of hypothesis testing.

Hypothesis	Path	Path Coefficient	*t*-Value	*p*-Value	Testing Result
H1	PR→PI	−0.199 *	−2.380	0.017	Supported
H2	PR→AT	−0.181 *	−2.092	0.036	Supported
H3	PR→SN	−0.250 **	−2.994	0.003	Supported
H4	AT→PI	0.255 **	2.967	0.003	Supported
H5	SN→PI	0.292 ***	3.473	0.000	Supported

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

According to the results in Table 6, perceived risk is negatively associated with participating intention (*t*-value = −2.380); hence, H1 was supported by sample data. Additionally, perceived risk is negatively correlated with attitude (*t*-value = −2.092), which indicates that H2 is supported. Moreover, perceived risk exerts a significant and negative influence on subjective norms (*t*-value = −2.380), therefore supporting H3. By contrast, attitude (*t*-value = 2.967) and subjective norm (*t*-value = 3.473) positively influence the public's participation intention in smart city development, hence supporting H4 and H5, respectively.

6. Discussion and Conclusions

Based on the TRA, this study constructed a theoretical model concerning the public's perceived risk, attitude, subjective norm, and participating intention for smart city development. The model aimed to reveal the influence mechanism of perceived risk on the public-participating intention. To the best of our knowledge, the research is the first study to investigate the influential effect of the publics' perceived risk on their participation intention in smart city development literature.

This research empirically tested the proposed hypotheses by using AMOS software and obtained the following findings. First, perceived risk has a negative impact on the public intention to participate in smart city development. The negative relationship between perceived risk and participation intention was verified by the questionnaire data, namely, the higher the publics' perceived risk, the lower their intention to participate in smart city development. Second, perceived risk is directly and negatively associated with attitude and subjective norms. Perceived risk has a stronger impact on subjective norms. Third, perceived risk exerts an indirect influence on the public's participating intention through attitude and subjective norms. Finally, attitude and subjective norms are both significantly and positively related to the public participation intention in smart city development. The results indicate that attitude and subjective norms are important determinants of public participation intention. The more positive the public's attitude is, the stronger their intention to participate in smart city development will be. Similarly, the more positive the subjective norm is perceived by the public, the stronger their intention is to participate in smart city development.

6.1. Theoretical Contribution

This study has contributed to the smart city development literature in several aspects. Firstly, this research explored the relationship of perceived risk with participating intention, which further expanded the research boundary and application of the TRA in the context of smart city development. Based on the TRA, this study constructed an expanded model concerning the effect of perceived risk on public participation intention. Moreover, it integrated perceived risk into the TRA model, which could expand the traditional TRA and further enrich research in other regions.

Secondly, this research defined the risk perceived by the public, including the aspects of potential threat to personal privacy, risk of technology use, negative emotion, and potential conflicts, which further enriched the theory of risk perception in the context of smart city development. Furthermore, this study explored the effect of perceived risk on public participation intention, and the finding provided a perceptive understanding of their relationship. Accordingly, with the characteristic of smart city development, perceived risk played a negative role in public participation intention.

Lastly, the findings on public participation intention in smart city development vary from previous studies, indicating discrepancies in different backgrounds. Among the factors directly influencing the public's intention to participate in smart city development, the findings showed that the path coefficient of the subjective norm was the largest. In addition, this study was a pioneer in the field of smart city development from the perspective of the public in China, which can further enrich regional research.

6.2. Practical Implications

Perceived risk negatively influenced the public participation intention in smart city development. Hence, measures should be taken to reduce the risk. This study offers practical implications that are beneficial to policymakers, related enterprises, and other stakeholders.

First, smart city development and subsequent operation are typically data-driven. The public is not only a vital participant in smart city development but also an important provider of data sources and feedback. However, the public is expected to improve their awareness of privacy protection and proactive prevention so as to avoid potential security risks and loss of personal information disclosure. In order to further enhance their ability to protect privacy, learning personal privacy protection policies and related procedures should be strengthened by the public. Moreover, the city government should improve the privacy protection mechanism and policies and reduce the possibility and loss of risk by increasing appropriate punishment. Some cities have already begun to formulate relevant policies, such as "Shanghai data regulations", released in November 2021. For the sake of increasing the public's ability to identify and screen risk, the government also needs to extend various channels of publicity and reinforce the guidance of public opinion. Accordingly, a solid institutional guarantee for public privacy protection should be provided and improved by the government.

Second, smart city development requires the application of ICTs, but the public's discrepancies in accessing, applying, and affording new technologies might lead to a digital divide. The divide will further affect their participation intention and degree. Therefore, the city government and relevant associations could set up corresponding training courses, which can equip the public with appropriate skills and qualities to use technologies and avoid being gradually marginalized. For example, the training activity on information technology application for special education was held in Qingdao. In addition, for the disabled, aged, and other vulnerable groups, alternative technologies, products, or services should be developed and supplied by related enterprises. These alternative ones can not only increase the channels and pervasiveness of public participation but also enhance the social inclusion of smart city development.

Third, the potential risks of information security and use have been encountered by the public during their participation in smart city development. The risks may result in negative emotions, such as distrust, which can further inhibit their participating intentions. Combining the actual characteristics of digital and network space in smart city development, the government should increasingly improve special policy systems of information usage and security. For example, an action plan for data security and personal information protection was implemented in Tianjin. Moreover, the behaviors of information insecurity and usage infringement should be explicitly defined, and corresponding punishments also need to be provided. Accordingly, the government should strengthen the penalty for infringement behavior and actively promote the credit system of digital space and network environment through the development of smart cities. In addition to emphasizing institution construction and government supervision, the industry self-discipline with relevant enterprises and practitioners should be further strengthened.

Forth, potential conflicts between the public and other stakeholders involved in smart city development should be considered, which can negatively affect the public's participation intention. In order to reduce the conflicts, it is necessary to build a cooperation mechanism involving multiple stakeholders. By enhancing different stakeholders' communication and cooperation and optimizing and adjusting the allocation of urban resources, the different stakeholders' uneven interests should be further balanced. Accordingly, a flat urban governance structure, including the government, enterprises, and the public as main participants, should be constructed. Taking Jinan as an example, a co-contribution and coordinating model by the main participants is emphasized. This is not only conducive to the effective supply of public services but also creates conditions for conflict resolution and collaborative governance of all participants.

Lastly, attitudes and subjective norms are found to be both positively associated with public participation intention. To increase the public's positive attitude toward participating in smart city development, the government can establish partnerships with the public, relevant enterprises, and other stakeholders. Moreover, the publicity for smart city development should be strengthened by the government and companies to attract more public participation. In addition, participating channels for public participation can also be expanded by the government and enterprises, such as offline activity and online platforms. In terms of subjective norms, the public feels social pressure when they are making decisions to participate in smart city development. The citizens of Shanghai can fill in the online questionnaire about their needs for a smart city by Apps. Therefore, except for the policy guidance and extended publicity by the government, urban culture and atmosphere that encourage public participation need to be considered.

6.3. Limitations

The limitations should also be highlighted for future research. First, the data applied in this research were all collected in Mainland China, which may reduce the generalizability of the results due to the differences in culture and development context. In addition, the cross-sectional data might also limit the generalizability as public participation in smart city development tends to vary with time. Future research will expand the regions of data collection, and increase the number of valid data, so as to further improve the universality of the research conclusions. Second, few studies on the perceived risk of public participation in smart city development have been conducted, and the definition of the perceived risk might be different from diverse perspectives. In future research, the connotation, extension, and system framework of risk perceived by the public need to be further improved. Third, this study mainly explored the effect of perceived risk on the public participation intention in smart city development. However, there might be other crucial determinants that are significantly related to the intention. Since public participation plays a notable role in smart city development and operation, future studies need to investigate other antecedent factors (e.g., participation cost) influencing public participation intention and behavior from different viewpoints.

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