pISSN: 1906 - 6406 The Scholar: Human Sciences
eISSN: 2586 - 9388 The Scholar: Human Sciences
https://assumptionjournal.au.edu/index.php/Scholar

Key Influencers of Intention to Use toward Internet of Things Devices for Residents in Hangzhou, China

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Received: September 08, 2024. Revised: November 19, 2024. Accepted: February 18, 2025.

Abstract

Purpose: This study investigates factors affecting Hangzhou residents' intention to use IoT devices, using a conceptual framework to explore the relationships between information quality, data risk, financial risk, self-efficacy, motivation, perceived usefulness, perceived ease of use, and intention to use. **Research Design and Methodology:** Using a multi-stage sampling method, we conducted a quantitative survey with 472 valid responses from Hangzhou residents experienced with IoT devices. Confirmatory factor analysis (CFA) and structural equation modeling (SEM) were employed to analyze the data and test hypotheses. **Results:** Information quality and motivation enhance perceived usefulness. Motivation, data risk, and financial risk affect perceived ease of use, with data and financial risks negatively impacting it. Perceived ease of use is the strongest predictor of IoT use intention, followed by perceived usefulness and self-efficacy. **Conclusions:** The study validates and extends the technology acceptance model for IoT adoption, highlighting perceived ease of use, perceived usefulness, and self-efficacy as crucial factors. Improving information quality and addressing data and financial risks can enhance IoT adoption. Recommendations include optimizing user experience, establishing trust mechanisms, and developing accurate pricing strategies to stimulate adoption in the digital age. The findings are significant for advancing IoT technology acceptance.

Keywords: Information Quality, Motivation, Data Risk, Intention to Use, Internet of Things Devices

JEL Classification Code: E44, F31, F37, G15

1. Introduction

In recent years, with the rapid development of cloud computing, intelligent manufacturing, radio frequency identification, information transmission infrared sensing, and other technologies, the development of the Internet of Things (IoT) has become more and more rapid (Mai & Khalil, 2017), which has effectively enhanced the seamless connection between things, things and people, and between people, profoundly changed the traditional industry patterns and the way of life of the general public, and bred a large number of new needs, new services, new scenarios, new modes and new business forms. Currently, information and communication systems are beginning to be invisibly embedded in all corners of people's lives (Giusto et al., 2010) and have evolved from the traditional time and place to anytime and anywhere, and will continue to gradually expand to anything (Gubbi et al., 2013; Kurakova, 2013).

IoT was first mentioned and conceptualized in the 1990s (Shao, 2017; Strnadl, 2017) and went through an embryonic period between 1995 and 2005. In 2005, the International Telecommunication Union expanded the concept of IoT (Madakam et al., 2015), and the IoT industry entered the initial development period. Until 2009, China, the European Union, and the United States all put forward national strategic-level action plans for IoT, marking the rapid development of the IoT industry.

According to the World Internet of Things Conference and the China Business Industry Research Institute, the number of global IoT device connections in 2022 was 14.3 billion, and it is expected that the number of global IoT device connections in 2030 will exceed 80 billion. China Research Network predicts that by 2025, the global output value of the IoT industry can reach about 30 trillion U.S.

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dollars, and the industry has broad prospects for development.

At the same time, China's Ministry of Industry and Information Technology was informed that the current rapid development and practical deployment of China's new generation of communication technologies, such as 5G, 6G, etc., enables the realization of the true sense of the Internet of Everything with the foundation of the communication layer of access and transmission (Yang & Wang, 2020), and the connection speed and stability of IoT devices have been significantly improved. The cost has been reduced, enabling more devices to transmit data in real-time and efficiently. By the end of 2022, China Mobile's IoT device connections will reach 1.845 billion, a net increase of 447 million compared to the end of 2021, accounting for 70% of the global total, and the industry applications are expanding to smart manufacturing, smart agriculture, smart transportation, smart logistics, and consumer IoT.

Currently, China's IoT technology has the most rapid application and development in personal/family life areas that are closely related to people's lives, with a longer development time, a more mature market, a prosperous and open platform ecological construction, and the interconnection of endpoints within the platform has begun to take shape. However, the widespread application of IoT, while increasing consumers' perception of convenience and efficiency in their daily lives, has also brought about some real-world barriers (Deursen & Mossberger, 2018). Existing IoT devices generally suffer from high product homogenization between the same domain, low product quality, insufficient user experience, lack of connectivity between heterogeneous devices, data bottlenecks, and security threat risks in device connectivity, and still have several deficiencies in computing power, communication power, decision-making power, information power, content power and security and privacy capabilities. Users are looking for IoT products that are easier to use, more useful, and substantially improve their lives to meet their diverse needs. For China's IoT device applications, which have strong development potential but many obstacles in reality, the research progress on the intention to use IoT devices has been very slow, and the existing research cannot provide sufficient and reliable conclusions. In the face of the booming turnover of IoT devices globally, it is especially necessary to research the factors influencing the intention to use IoT devices in the huge Chinese market.

Hangzhou, the capital of Zhejiang Province of China as well as the center of economy, culture, science, and education, is also the first digital city of China and ranked 14th in the global technology clusters, with continuous improvement of IoT policies, the extensive layout of the industrial application layer, the high penetration rate of IoT devices, and ahead of the curve awareness of residents' IoT applications. This study takes residents of Hangzhou, China as the research object, analyzes the key influencing factors affecting residents' intention to use IoT devices and the importance of the direct or indirect influence of each factor, and limits the IoT devices used by residents to IoT application devices of IoT technology in the field of personal/family life, including personal IoT devices (excluding computers, tablets, and cell phones), smart home devices, smart community devices, smart shopping devices, smart medical devices, wearable devices and so on. To a certain extent, this can provide suggestions for Chinese IoT enterprises to design and develop useful and easy-to-use IoT devices that can bring substantial improvement to users' lives, targeting to enhance users' use and improve users' perceptions to make it easy for consumers to feel the convenience of life and work brought by IoT devices and environments, and to alleviate the current problems of IoT industry in China, such as IoT applications floating on the surface, insufficient penetration and endogenous demand, low profitability of enterprises, and so on.

2. Literature Review

2.1 Information Quality

Information quality is the ability of a system to convey the intended meaning, reflecting success at the semantic level (Wang & Lin, 2012), and plays an important role in the validity or otherwise of a technology (Cao et al., 2005; Negash et al., 2003). For the IoT domain, information quality refers to the extent to which the information, data, or content provided by the IoT is highly rated in terms of quality. The information should be able to effectively communicate relevant information, such as the source of the technology and intention to use it and to ensure that the information communicated is accurate and timely (Kim & Wang, 2021). Nelson et al. (2005) suggest that information quality is measured in terms of accuracy (reflecting intrinsic quality), completeness and timeliness (reflecting situational quality), and format (reflecting representational quality). Lee et al. (2002) categorized information quality dimensions into four dimensions. They developed the AIMQ methodology to effectively prioritize efforts to improve information quality and rationally allocate resources, providing a rigorous and pragmatic foundation for information quality assessment and benchmarking.

By integrating the D&M IS and TAM models, Wixom and Todd (2005) found that information quality has a positive effect on perceived ease of use and perceived usefulness and that the quality of information presented by a technology shapes an individual's satisfaction and motivation for the technology, which in turn affects the perceived usefulness and perceived ease of use of the technology, and ultimately influences the technology's intention to use it. Lin and Lu (2000) argue that information quality is an important predictor of perceived usefulness and ease of use. According to Kim and Wang (2021), information quality has a positive impact on users' motivation to use IoT and the perceived usefulness of IoT, and an in-depth understanding of users' characteristics, providing them with accurate, complete, easy-to-understand, and meaningful up-to-date information, and guaranteeing the informational quality of the information provided should be the top priority for service providers (Kim & Wang, 2021; Wang & Lin, 2012). Therefore, this study proposes the following hypotheses.

H1: Information quality has a significant effect on motivation.

H2: Information quality has a significant effect on perceived usefulness.

2.2 Motivation

Motivation is an intrinsic psychological need or drive that stimulates, regulates, maintains, and directs people to engage in certain activities (Fletcher et al., 2001; Harackiewicz et al., 2012), a general tendency to influence people's behaviors to satisfy their needs or desires, and is largely influenced by individual backgrounds and characteristics that drive consumers to make conscious choices and actively apply them when adopting new technologies (Park, 2010; Rubin, 2009). According to existing research on the role of motivation in the use of new technologies, it has been found that motivation is driven by perceived needs and individual differences (Rosengren, 1974) and plays a key role in increasing people's intention and actual use of new technologies (Lin, 1998; Park et al., 2008; Stafford & Stern, 2002).

Numerous studies based on TAM and U&G have shown that motivation has a positive effect on perceived ease of use and perceived usefulness and that the stronger a consumer's motivation, the more likely they are to perceive the ease of use and usefulness of new technology (Davis et al., 1989, 1992; Lin, 1998; Stafford & Stern, 2002). Motivation plays an important role in influencing perceived ease of use, perceived usefulness, system functionality ratings, and intention to continue using the system, and strong motivation of the user leads to higher perceived ease of use and perceived usefulness, which contributes to the eventual intention to use to continue using the system (Joo & Sang, 2013; Park et al., 2008). The high information quality, system quality, and effective knowledge dissemination of IoT will stimulate greater motivation to use and increase perceived usefulness and ease of use. It can effectively promote the adoption and use of IoT technology (Kim & Wang, 2021). Therefore, this study proposes the following hypotheses.

H3: Motivation has a significant effect on perceived usefulness.

H4: Motivation has a significant effect on perceived ease of use.

2.3 Data Risk

Data risk is associated with the leakage of users' personal information, an inherent risk and a major bottleneck in the current adoption of new technologies (Saheb et al., 2021, 2022). In the IoT environment, data risk refers to the risk of data bottlenecks and security threats resulting from the large amount of data generated by the myriad of connected IoT devices that are being sent and need to be protected by appropriate authentication and authorization mechanisms (Davim, 2018; Saheb & Izadi, 2019).

Users' concerns about data risks are directly or indirectly related to their behavior of adopting new technologies (Saheb, 2020). For IoT applications in digital agriculture, the perceived risk of data misuse can discourage prudent farmers from adopting IoT technologies. It is the responsibility of IoT technology providers to ensure that privacy safeguards are in place to prevent leakage of confidential farm data and to restore farmers' trust in IoT technology providers based on processes, systems, and features, which reduces the risk of data, increases the perceived value, and facilitates IoT adoption (Jayashankar et al., 2018). For IoT, the greater the data risk perceived by users, the lower the perceived ease of use of IoT devices, potentially posing a significant challenge to technology adoption (Saheb et al., 2022). Therefore, this study proposes the following hypothesis.

H5: Data risk has a significant effect on perceived ease of use.

2.4 Financial Risk

The concept of financial risk, a key element in understanding consumer behavior since the 1960s (Featherman & Pavlou, 2003; Jacoby & Kaplan, 1972), is particularly relevant in the context of IoT adoption. Financial risk, the potential monetary loss associated with a purchase (Laroche et al., 2004), includes the initial purchase price of a product and the subsequent cost of maintaining and repairing the product. The price of the product is an intrinsic component of financial risk (Grewal et al., 1994; Hutton & Wilkie, 1980). Lee (2009) defines financial risk as the possibility of financial loss and subsequent product maintenance costs from a single purchase. In the context of IoT adoption, financial risk refers to the financial constraints imposed by the adoption of an IoT device, often related to the cost of adopting that device (Saheb et al., 2022). However, despite these risks, the potential of IoT adoption is vast and promising.

The type of perceived risk that has a greater impact on a consumer's decision to adopt new technologies and products is financial risk, with a positive correlation between price and financial risk and a warranty reducing the consumer's perception of financial risk, the presence of which can discourage consumers from adopting new technologies or products (Featherman & Pavlou, 2003; Kaplan et al., 1974; Shimp & Bearden, 1982). Saheb et al. (2022) found that financial risk hurts the perceived ease of use of IoT wearables and that perceived ease of use has a positive impact on intention to use. Managers can design risk reduction strategies based on consumers' concerns about financial risk and build trust mechanisms to encourage the adoption of emerging technologies and products such as IoT (Ko et al., 2009). Therefore, this study proposes the following hypothesis.

H6: Financial risk has a significant effect on perceived ease of use.

2.5 Perceived Ease of Use

Perceived ease of use is the extent to which a person perceives using a particular system as effortless. Other things being equal, a technological system that is perceived to be easy to use is more likely to be accepted by the user, and greater perceived usefulness will result from the user's perceived ease of use and positive attitude (Bandura, 1982; Davis, 1989; Davis et al., 1989). Ndubisi et al. (2003) define perceived ease of use as the clarity and comprehensibility of a system or technology. Perceived ease of use is similar to workload expectations in UTAUT and complexity in IDT (Venkatesh et al., 2003).

According to the TAM, the intention to use a new information technology is determined by the perceived usefulness and perceived ease of use of the new information technology (Gefen et al., 2003). From multiple disciplinary perspectives, perceived usefulness and perceived ease of use are fundamental and distinct factors influencing technology decisions. While they are not the only variables that explain user behavior, they do play a central role, with perceived ease of use positively influencing perceived usefulness (Davis et al., 1989; Kuo & Yen, 2009; Lee et al., 2012; Venkatesh et al., 2012) and has a facilitating effect on users' intention to continue using new technologies (Kim & Wang, 2021). Many prior studies have confirmed the significant effect of perceived ease of use on intention to use, including both direct and indirect effects on intention to use through acting on perceived usefulness (Hu & Bentler, 1999; Jackson et al., 1997; Venkatesh, 1999). In the context of IoT adoption, Saheb et al. (2022) concluded that perceived ease of use positively impacts users' intention to use IoT wearable devices such as smartwatches. Therefore, this study proposes the following hypothesis.

H7: Perceived ease of use has a significant effect on perceived usefulness.

H9: Perceived ease of use has a significant effect on intention to use.

2.6. Perceived Usefulness

Perceived usefulness is the subjective likelihood that a potential user believes using a particular application will improve his or her job performance in an organizational setting (Bandura, 1982; Davis, 1989; Davis et al., 1989). Gefen et al. (2003) view perceived usefulness as an individual's subjective assessment of the utility provided by new technology in a particular task context. Perceived usefulness is similar to performance expectations in UTAUT and relative merits in IDT (Venkatesh et al., 2003, 2012) and refers to the user's perception of performance improvement when using new technology (Gao & Bai, 2014). Previous studies have explored the factors affecting perceived usefulness from three main perspectives: one based on TAM, which argues that perceived ease of use is the main factor affecting perceived usefulness (Porter & Donthu, 2006); one based on the idea that PCI, compatibility, result verifiability, and trialability are the main factors affecting perceived usefulness (Gumussoy & Calisir, 2009; Hong & Tam, 2006) and one that explores how specific perceptual variables affect perceived usefulness based on consumer acceptance of new information systems (Chang & Yang, 2013; Kim et al., 2009; Park et al., 2009; Thiesse, 2007).

According to TAM, intention to use depends on the user's perceived usefulness and perceived ease of use of the technology, while usage behavior depends on the user's intention to use (Davis, 1989; Davis et al., 1989). In areas such as online shopping, online banking, and online education, a large number of previous studies have confirmed that perceived usefulness has a significant positive effect on users' intention to (continue to) use the technology (Al-Maghrabi & Dennis, 2010; Chang & Yang, 2013; Igbaria, 1993; Kim, 2012; Koufaris, 2002; Mohamed et al., 2014; Wu & Wang, 2005). Concerning IoT applications, perceived usefulness is the most important driver of intention to use IoT (Dong et al., 2017), positively impacting users' intention to use IoT wearable devices such as smartwatches (Saheb et al., 2022). Therefore, this study proposes the following hypotheses.

H8: Perceived usefulness has a significant effect on intention to use.

2.7 Self-efficacy

Self-efficacy, a key component of social cognitive learning theory developed by American psychologist Bandura (1997) is an individual's estimate of the extent to which he or she can perform the actions required to cope with future situations (Bandura, 1982). According to Bandura's theory, self-efficacy beliefs are proximal determinants of behavior. Self-efficacy is a self-assessment, and people's beliefs about self-efficacy affect their choices, aspirations, and the amount of effort they put into a given endeavor (Bandura, 1997). According to Eastin and LaRose (2000), self-efficacy refers to the belief that individuals believe that the self can accomplish a task using the skills the individual possesses. Bandura believes that individuals can assess self-efficacy by obtaining information primarily from four sources: experience, alternative experience, verbal persuasion, and physiological indicators (Bandura, 1986).

Prior research has found self-efficacy to be a key predictor of users' intention to use (Downey, 2006; Hernandez et al., 2009; Padumadasa, 2012). In the e-learning context, there is a positive effect between self-efficacy and e-learning intention to (continue to) use (Tarhini et al., 2017). In terms of IoT applications, IoT studies in different fields have identified self-efficacy as a factor in adapting to IoT technologies, and self-efficacy significantly influences users' decision to use IoT technologies (Gao et al., 2015; Wu et al., 2011) Ibrahim et al. (2020) demonstrated that self-efficacy significantly affects physicians' intention to use IoT medical devices' intention to use them. Therefore, this study proposes the following hypothesis.

H10: Self- efficacy has a significant effect on intention to use.

2.8 Intention to Use

Intention to use measures the strength of a person's intention to perform a specific behavior (Fishbein & Ajzen, 1977). According to the Theory of Planned Behavior (TPB), intention to use is a type of motivation that directly influences an individual's decision whether to perform a particular behavior, indicating how much effort people are willing to invest and plan to invest in performing the behavior. Intention to use can only be expressed in behavior if the behavior is under volitional control (Ajzen, 1991). According to TRA, user intention to use is an important determinant of behavior, and attitudes toward the behavior and subjective norms determine how well a person performs the behavior (Ajzen & Fishbein, 1980). The technology acceptance model (TAM) further suggests that user intention to use is a leading indicator of framework utilization (Davis et al., 1989). Intention to use is an individual's willingness to expend a certain amount of spontaneity and effort to perform a specific behavior (Ko & Kim, 2018), an individual's propensity to perform a specific behavior (Belanche et al., 2012), and a proxy for consumer acceptance (Venkatesh & Davis, 2000).

Numerous studies have confirmed the influence of perceived usefulness and perceived ease of use on intention to use (Kim, 2012; Miltgen et al., 2013; Wu & Wang, 2005). For the adoption of emerging technologies such as IoT, factors such as compatibility, image, cost, privacy, and computer self-efficacy of healthcare IoT devices significantly impact physicians' intention to use healthcare IoT devices (Ibrahim et al., 2020). Opasvitayarux et al. (2022) argued that the ability to adapt, innovate, and share information directly affects the intention to use IoT for quality management.

3. Research Methods and Materials

3.1 Research Framework

The conceptual framework is developed based on studying related theories and theoretical frameworks. This study utilizes the Technology Acceptance Model, Uses and Gratifications Theory, DeLone and McLean Information Systems Success Model, and Stimulus-Organism-Behavior-Consequence Model, and three theoretical frameworks from previous studies to support and develop the conceptual framework. The four core theoretical models support the development of this study in terms of the four dimensions of demand motivation for the generation of user behavior, factors influencing user acceptance of technology, the relationship between external stimuli and users' internal mental processes, and factors measuring system success, emphasizing the mediating effect of the relationship between perceived usefulness and perceived ease of use on the relationship between external variables and intention to use. The first of the three theoretical frameworks was proposed by Kim and Wang (2021), which verified that information quality provided by new IoT products or technologies has a significant effect on motivation and perceived usefulness, motivation has a significant effect on perceived ease of use and perceived usefulness, perceived ease of use significantly influences perceived usefulness, and perceived ease of use and perceived usefulness have a significant effect on intention to use. The second theoretical framework was proposed by Saheb et al. (2022), which verified that data risk and financial risk have a significant negative effect on the perceived ease of use of IoT devices such as smartwatches, and perceived ease of use has a significant positive effect on the intention to use. The third theoretical framework, proposed by Ibrahim et al. (2020), examined physicians' intention to use IoT medical devices during the COVID-19 pandemic and found that physicians' self-efficacy significantly influenced the intention to use IoT medical devices. The conceptual framework of this study, shown in Figure 1, aims to explore the key influences and the significance of direct or indirect influences on the intention to use IoT devices among residents of Hangzhou, China, including information quality, motivation, data risk, financial risk, self-efficacy, perceived usefulness, and perceived ease of use.

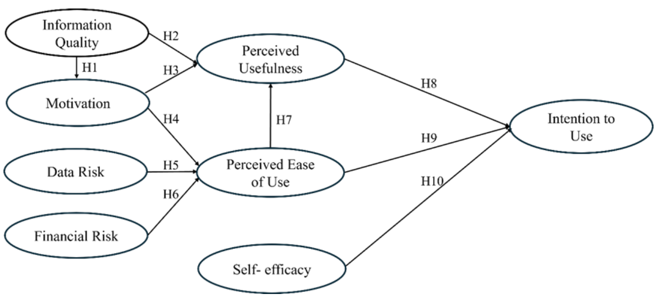

Figure 1: Research Conceptual Framework

H1: Information quality has a significant effect on motivation.
H2: Information quality has a significant effect on perceived usefulness.
H3: Motivation has a significant effect on perceived usefulness.
H4: Motivation has a significant effect on perceived ease of use.
H5: Data risk has a significant effect on perceived ease of use.
H6: Financial risk has a significant effect on perceived ease of use.
H7: Perceived ease of use has a significant effect on perceived usefulness.
H8: Perceived usefulness has a significant effect on intention to use.
H9: Perceived ease of use has a significant effect on intention to use.
H10: Self- efficacy has a significant effect on intention to use.

3.2 Research Methodology

This study adopted a quantitative research methodology using a questionnaire as the survey instrument for data collection. The developed questionnaire was distributed online to residents with experience using IoT devices in thirteen districts (counties and cities) under the jurisdiction of Hangzhou, China, and the collected data were analyzed to explore the key influencing factors that affect Hangzhou residents' intention to use IoT devices. The questionnaire consisted of three parts. The first part consisted of screening questions to narrow down and select appropriate target respondents. The second part used a five-point Likert scale (1=strongly disagree, 2=disagree, 3=neutral, 4=agree, 5=strongly agree) to measure the variables. The last part collected information on the demographic characteristics of the target respondents.

Before distributing the questionnaire, an Item-Objective Congruence (IOC) test was conducted with three experts, and results passed at over 0.6. In additional, a pilot test was administered to 35 target respondents to ensure the reliability and validity of the questionnaire, with all constructs were approved by Cronbach's alpha value at over 0.7. The questionnaire was distributed to the target respondents, and 472 valid questionnaire data were obtained. The data collected were analyzed using SPSS and AMOS 23.0 statistical packages. The analyses included Confirmatory factor analysis (CFA) and Structural Equation Modeling (SEM) to determine convergent validity and discriminant validity and test the significance of the effects among the variables.

3.3 Population and Sample Size

The target population of this study was residents of the thirteen districts (counties and cities) under the jurisdiction of Hangzhou, China, who have experience using IoT devices to ensure that they can provide meaningful responses regarding the perceptual, psychological, and behavioral aspects of using IoT devices. According to Kerkhoff (2017), the statistical technique used for the research project determines the minimum sample size. The minimum sample size for this study was calculated using the Structural Equation Modeling A Priori Sample Size Calculator, available on Daniel Soper's website. Based on the fact that there are eight latent variables and 28 observed variables to set the parameter values for this study, with the probability level set at 0.05, the minimum sample size suggested by the structural equation modeling was calculated to be 444. Considering the results of previous studies and the statistical technique of structural equation modeling, the sample size of this study was 500, and 500 questionnaires were distributed to the target respondents.

3.4 Sampling Technique

This study utilizes a multi-stage sampling method for quantitative research. In the first stage, the judgmental sampling technique is used to select 13 districts (counties and cities) under the jurisdiction of Hangzhou, China, based on the regional division of Hangzhou and the current development of IoT. In the second stage, quota sampling was used to determine the sample size for each of the 13 districts (counties and cities) under the jurisdiction of Hangzhou, China, based on the proportion of residents in each district, as shown in Table 1, to select an appropriate number of representative sample sizes from a large population (Fottrell & Byass, 2008). In the third stage, a convenience sampling technique was used to filter participants through screening questions in the questionnaire to ensure that the target respondents were residents of the 13 districts (counties and cities) under the jurisdiction of Hangzhou who had experience in using IoT devices.

Table 1: Sample Units and Sample Size

Thirteen Main Subjects	Population Size	Proportional sample size
Residents of Xiaoshan District	2,110,000	85
Residents of Shangcheng District	1,371,000	56
Residents of Yuhang District	1,364,000	55
Residents of Linping District	1,108,000	45
Residents of Gongshu District	1,177,000	48
Residents of Xihu District	1,191,000	48
Residents of Fuyang District	851,000	34
Residents of Qiantang District	797,000	32
Residents of Lin'an District	648,000	26
Residents of Binjiang District	530,000	21
Residents of Tonglu County	458,000	19
Residents of Chun'an County	325,000	13
Residents of Jiande City	446,000	18
Total	**12,376,000**	**500**

Source: Constructed by author

4. Results and Discussion

4.1 Demographic Information

Of the 472 respondents, 53.6% (253) were male and 46.4% (219) were female. In terms of age groups, respondents aged 31-40 years old accounted for the largest share of 30.7% (145), followed by 25.0% (118) aged 18-25 years old, 21.6% (102) aged 26-30 years old, 18% (85) aged 41 years old or older, and 4.7% (22) under the age of 18 years old. In terms of the Hangzhou sub-districts (counties and cities) where the respondents live, 17.2% (81) of the respondents are in Xiaoshan District, 11.7% (55) are in Yuhang District, 11.0% (52) are in Shangcheng District. The proportions of the respondents from Xihu District, Gongshu District, Liping District, Fuyang District, Qiantang District, Lin'an District, Binjiang District, Tonglu County, Jiande City, and Chun'an County are respectively 9.7%, 9.5%, 8.1%, 6.6%, 6.6%, 5.1%, 4.4%, 3.8%, 3.8%, 2.5%. In terms of income, respondents with a monthly income of 10,001-20,000 yuan accounted for the largest share of 29.7% (140), followed by those with a monthly income of 6,001-10,000 yuan at 27.1% (128), those with a monthly income of 3,001-6,000 yuan at 15.5% (73), and those with a monthly income of 20001-50000 yuan at 14.4% (68), and those with a monthly income of less than 3,000 yuan at 12.1% (57), and 1.2% (6) of the respondents with a monthly income higher than 50000 yuan. In terms of the educational level of the respondents, 39.2% (185) had a bachelor's degree, 17.4% (82) had a master's degree or above, 25.4% (120) had a junior college degree, and 18% (85) had a senior high school degree or lower.

Table 2: Demographic Profile

Demographic and General Data (N=472)		Frequency	Percentage
Gender	Male	253	53.60%
	Female	219	46.40%
Age	Under 18 years old	22	4.7%
	18-25 years old	118	25.0%
	26-30 years old	102	21.6%
	31-40 years old	145	30.7%
	41-50 years old	51	10.8%
	51-60 years old	22	4.7%
	Over 60 years old	12	2.5%
Education Hangzhou sub-district (county, city) where the residence is located	Xiaoshan District	81	17.2%
	Shangcheng District	52	11.0%
	Yuhang District	55	11.7%
	Linping District	38	8.1%
	Gongshu District	45	9.5%
	Xihu District	46	9.7%
	Fuyang District	31	6.6%
	Qiantang District	31	6.6%
	Lin'an District	24	5.1%
	Binjiang District	21	4.4%
	Tonglu County	18	3.8%
	Chun'an County	12	2.5%
	Jiande City	18	3.8%
Income	Less than 3000 yuan	57	12.1%
	3001-6000 yuan	73	15.5%
	6001-10000 yuan	128	27.1%
	10001-20000 yuan	140	29.7%
	20001-50000 yuan	68	14.4%
	More than 50000 yuan	6	1.2%
Education	Elementary School or lower	2	0.4%
	Junior High School	32	6.8%
	Senior High School	51	10.8%

Demographic and General Data (N=472)		Frequency	Percentage
	Junior College	120	25.4%
	Bachelor's degree	185	39.2%
	Master's degree or a bove	82	17.4%

4.2 Confirmatory Factor Analysis (CFA)

Originally proposed by Jöreskog (1969), Confirmatory Factor Analysis (CFA) replaced the older construct validity analysis method proposed by Campbell and Fiske (1959) and allows for verification of the interrelationships between observed and latent variables, examination of the fit of the measurement model to the data, and testing of multiple hypotheses of the measurement model at the same time to determine the research model's internal consistency, discriminant and convergent validity (Arbuckle, 2008; Brown, 2006; Jöreskog, 1969). Factors Loading can assess convergent validity, Average Variance Extracted (AVE), and Composite Reliability (CR), and it is generally accepted that factors loading greater than 0.50, CR above the threshold of 0.7, and AVE above the threshold of 0.4 ensure convergent validity of the model (Fornell & Larcker, 1981; Hair et al., 2006). Based on the results in Table 3, it is verified that the research model has good convergent validity.

Table 3: Confirmatory Factor Analysis Result, Composite Reliability (CR) and Average Variance Extracted (AVE)

Variables	Source of Questionnaire (Measurement Indicator)	No. of Item	Cronbach's Alpha	Factors Loading	CR	AVE
Information Quality (IQ)	Nelson et al. (2005)	5	0.866	0.735-0.760	0.866	0.564
Motivation (MO)	Joo and Sang (2013)	3	0.772	0.714-0.740	0.773	0.531
Data Risk (DR)	Saheb et al. (2022)	3	0.790	0.679-0.816	0.794	0.564
Financial Risk (FR)	Saheb et al. (2022)	3	0.779	0.730-0.746	0.780	0.542
Perceived Usefulness (PU)	Davis (1989)	4	0.810	0.682-0.771	0.811	0.518
Perceived Ease of Use (PEOU)	Davis (1989)	3	0.772	0.686-0.761	0.774	0.534
Self- efficacy (SE)	Mouakket and Bettayeb (2015)	4	0.820	0.707-0.743	0.820	0.533
Intention to Use (IU)	Wixom and Todd (2005)	3	0.799	0.732-0.780	0.800	0.572

Commonly used goodness-of-fit metrics in CFA include CMIN/DF, GFI, AGFI, NFI, CFI, TLI, and RMSEA fit metrics. There have been many scholars who have clearly defined the criteria for the definition of the fit indicators, as shown in Table 4, the values of the fit indicators of the measurement model in this study all meet the acceptable critical value, and the overall fit of the measurement model is good.

Table 4: Goodness of Fit for Measurement Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	1.260
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.942
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.927
NFI	≥ 0.80 (Wu & Wang, 2006)	0.927
CFI	≥ 0.80 (Bentler, 1990)	0.984
TLI	≥ 0.80 (Sharma et al., 2005)	0.981
RMSEA	< 0.08 (Pedroso et al., 2016)	0.024
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

Before conducting research hypothesis testing, it is important to ensure discriminant validity (Hamid et al., 2017). The test of discriminant validity is assessed by calculating the square root of each AVE (Fornell & Larcker, 1981). As shown in Table 5, the square root of AVE for each construct in this study is greater than the correlation coefficient between the constructs. Thus, the discriminant validity of the research model is affirmed.

Table 5: Discriminant Validity

	IQ	MO	DR	FR	PU	PEOU	SE	IU
IQ	**0.751**							
MO	0.060	**0.729**						
DR	-0.262	-0.386	**0.751**					
FR	-0.242	-0.409	0.427	**0.736**				
PU	0.312	0.313	-0.406	-0.344	**0.720**			
PEOU	0.236	0.451	-0.321	-0.379	0.355	**0.731**		
SE	0.310	0.380	-0.357	-0.341	0.526	0.374	**0.730**	
IU	0.200	0.358	-0.376	-0.339	0.379	0.367	0.358	**0.756**

Note: The diagonally listed value is the AVE square roots of the variables
Source: Created by the author.

4.3 Structural Equation Model (SEM)

Structural equation modeling (SEM) is used as a multivariate statistical technique to measure the degree of fit of structural research models and their paths to a comprehensive framework of covariance structural analysis

(Dragan & Topolšek, 2014). The goodness of fit (GoF) explains how well the research model fits the observations of the structural equation model (Schermelleh-Engel et al., 2003). As shown in Table 6, the fit index values of the structural model of this study are CMIN/DF = 2.769, GFI = 0.865, AGFI = 0.839, NFI = 0.831, CFI = 0.884, TLI = 0.871, and RMSEA = 0.061, and all the values of fit indexes satisfy the acceptable critical values. The goodness of fit of the structural model is affirmed.

Table 6: Goodness of Fit for Structural Model

Fit Index	Acceptable Criteria	Statistical Values
CMIN/DF	< 5.00 (Al-Mamary & Shamsuddin, 2015; Awang, 2012)	2.769
GFI	≥ 0.85 (Sica & Ghisi, 2007)	0.865
AGFI	≥ 0.80 (Sica & Ghisi, 2007)	0.839
NFI	≥ 0.80 (Wu & Wang, 2006)	0.831
CFI	≥ 0.80 (Bentler, 1990)	0.884
TLI	≥ 0.80 (Sharma et al., 2005)	0.871
RMSEA	< 0.08 (Pedroso et al., 2016)	0.061
Model Summary		**Acceptable Model Fit**

Remark: CMIN/DF = The ratio of the chi-square value to degree of freedom, GFI = goodness-of-fit index, AGFI = adjusted goodness-of-fit index, NFI = normalized fit index, CFI = comparative fit index, TLI = Tucker Lewis index, and RMSEA = root mean square error of approximation

4.4 Research Hypothesis Testing Result

As shown in Table 7, the SEM results validate the relationship between the proposed constructs and support all hypotheses except H1. Information quality and motivation have a significant positive effect on perceived usefulness; motivation, data risk, and financial risk significantly affect perceived ease of use, with data risk and financial risk significantly negatively correlating with perceived ease of use. Perceived ease of use is the strongest predictor of the users' intention to use an IoT device. of IoT devices, followed by perceived usefulness and self-efficacy. IoT devices perceived as easy to use trigger higher usefulness and intention to use, and increased usefulness leads to higher intention to use.

Table 7: Hypothesis Results of the Structural Equation Modeling

Hypothesis	(β)	t-value	Result
H1: IQ → MO	0.095	1.693	Not Supported
H2: IQ → PU	0.288	5.388*	Supported
H3: MO → PU	0.196	3.037*	Supported
H4: MO → PEOU	0.454	7.249*	Supported
H5: DR → PEOU	-0.168	-3.101*	Supported
H6: FR → PEOU	-0.304	-5.244*	Supported
H7: PEOU → PU	0.286	4.298*	Supported
H8: PU → IU	0.239	3.849*	Supported
H9: PEOU → IU	0.326	4.933*	Supported
H10: SE →IU	0.171	3.182*	Supported

Note: * $p<0.05$
Source: Created by the author

From the results of hypothesis testing in Table 7, 9 out of 10 hypotheses were supported. H1 was not supported. The relationship between information quality accessed through IoT devices and the motivation to use IoT devices showed a positive but not significant relationship, which is inconsistent with the findings of Kim and Wang (2021). One possible explanation is that the modeling setup in this study did not consider currency, accuracy, and other effects on information quality, making it difficult to capture the true relationship in the data accurately; another possible explanation is that the IoT market in China is highly competitive, with incompatible devices, brand competition, and model differences all leading to potential differences in information quality of devices.

In H2, there is a significant positive effect between information quality and the user's perceived usefulness of the IoT device. This finding is consistent with the findings of Lin and Lu (2000) and Wixom and Todd (2005), where the higher the completeness, accuracy, and currency of the information obtained through the IoT device implies that the higher information quality, the higher the user's perception will also be higher. For H3 and H4, motivation has a significant positive effect on perceived ease of use and usefulness, and motivation's impact on perceived ease of use is more significant. This finding supports the U&G theory and is consistent with the findings of Park et al. (2008), Joo and Sang (2013), Kim and Wang (2021) that users who are strongly motivated to use the IoT users are more likely to find the technology easy to use and useful. From the results of H5, there is a significant negative correlation between data risk and perceived ease of use, which is consistent with the studies of Jayashankar et al. (2018), Saheb (2020), and Saheb et al. (2022) that the higher the perceived risk of data misuse, the lower the perceived ease of use of the IoT device by the users, and that there is a need to establish a trust based on the processes, systems, and features of trust mechanisms to reduce the perceived risk, enhance the perceived value, and promote the adoption of IoT devices. The results of H6 indicate that financial risk has a significant negative impact on the perceived ease of use of IoT devices, consistent with Featherman and Pavlou (2003) and Saheb et al. (2022). There is a strong need to reduce the risk of IoT devices based on the user's concerns about financial risk, designing strategies to reduce financial risk, and establishing trust mechanisms to encourage the adoption of IoT devices. From the results of H7, H8, and H9, the finding that IoT devices perceived to be easy to use had higher usefulness and intention to use, which in turn led to higher intention to use, supports TAM and is consistent with the findings of Davis et al. (1989), Gefen et al. (2003), Kim and Wang (2021). In H10, there is a positive and significant correlation between self-efficacy and intention to use IoT devices, which is consistent with the studies of Hernandez et al. (2009), Gao et al. (2015), Tarhini et al. (2017), and Ibrahim et al. (2020), where self-efficacy beliefs, as behavioral proximal determinants that affect their choice of IoT devices, the decision to adopt IoT devices, level of effort and persistence in the face of obstacles, and ultimately mastery of the adoption behavior.

5. Conclusion and Recommendation

5.1 Conclusion

This study aims to investigate the key influencing factors that affect the intention to use IoT devices among Hangzhou residents in China, as well as the importance of direct or indirect influences. The research factors include information quality, data risk, financial risk, self-efficacy, motivation, perceived usefulness, perceived ease of use, and intention to use. Based on the theoretical frameworks of TAM, U&G theory, D&M IS success model, SOBC model, and previous empirical studies, the conceptual framework of this study was constructed, and a quantitative research method was used to carry out the study, using a questionnaire as a survey tool for data collection, which was distributed to 500 residents with experience of IoT device use in 13 districts (counties and cities) under the jurisdiction of Hangzhou, China, and 472 pieces of successfully recovered valid questionnaire data were collected. The collected data were analyzed using Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) to validate the model's reliability and validity and ensure the model's overall fit to study the direct and indirect relationships between the constructs and to test the research hypotheses proposed.

This study utilizes the D&M IS model, U&G theory, and SOBC theory to identify factors related to user, content, and system characteristics of IoT devices, integrating them with the TAM model as exogenous variables of perceived ease of use and perceived usefulness. The findings demonstrate the applicability of TAM to IoT adoption and extend the original TAM by validating a set of key antecedents of perceived usefulness and perceived ease of use, establishing a comprehensive theory of IoT device acceptance.

Intention to use is directly and significantly positively influenced by self-efficacy, perceived usefulness, and perceived ease of use; indirectly and significantly positively influenced by perceived ease of use, information quality, and motivation; and indirectly and significantly negatively influenced by data risk and financial risk; perceived ease of use has the greatest influence on intention to use and is one of the antecedents of perceived usefulness. This means that perceived ease of use of IoT devices is the most important factor to focus on when IoT enterprises enhance users' intention to use, which can start from the dimensions of IoT devices' user-friendly interface, ease of operation, user manuals, etc., and from the perspectives of users' learning curves, personalization, etc., to give users a deep sense of how easy it is to use the IoT devices and to achieve a wider range of users' use (Davis et al., 1989; Gefen et al., 2003; Hu & Bentler, 1999; Kim & Wang, 2021; Lee et al., 2012; Venkatesh et al., 2012).

Perceived usefulness is directly and significantly influenced by information quality, motivation, and perceived ease of use. Information quality is measured by accuracy, completeness, currency, and format (Nelson et al., 2005). Motivation is driven by perceived needs and individual differences (Rosengren, 1974). Optimizing IoT products and services to provide users with accurate, complete, easy-to-understand, and up-to-date information that enhances the user's perceived experience and perceived ease of use can motivate users to perceive IoT devices as useful (Ibrahim et al., 2020; Joo & Sang, 2013; Park, 2010; Wixom & Todd, 2005).

Perceived ease of use is directly and significantly positively affected by motivation and directly and significantly negatively affected by data risk and financial risk. In the era of digital transformation, users are more aware of data privacy protection than ever before, and the establishment of incentives, risk assessment, and coping mechanisms, as well as trust mechanisms based on processes, systems, and features, and the development of more accurate pricing and promotional strategies to reduce data risk and financial risk awaken users' motivation to use, which will in turn enhance the perceived ease of use of IoT devices (Featherman & Pavlou, 2003; Kim & Wang, 2021; Park et al., 2008; Saheb, 2020; Saheb et al., 2022). Differences in personal motivation play an integral role in determining the adoption of IoT devices, and users who are strongly motivated to use an IoT device are more likely to find it easy to use and useful.

5.2 Recommendation

This study finds that the key influencing factors affecting residents' intention to use IoT devices are information quality, motivation, data risk, financial risk, self-efficacy, perceived ease of use, and perceived usefulness. Based on this, IoT enterprises should actively optimize the influence of these factors during the development process to target the enhancement of user use and improvement of user perception and to alleviate the problems of IoT applications landing on the surface, insufficient penetration depth, and endogenous demand, and low profitability of enterprises that exist in China's IoT industry at present:

(1) IoT enterprises should continue optimizing the IoT software and hardware to collect and analyze through the connection of intelligent objects. They should exchange information in a useful and user-friendly way, ensure the generation and delivery of accurate, complete, reliable, and timely information to users, and truly build an Internet of Things ecosystem where everything is interconnected to stimulate users' higher perceived usefulness.

(2) IoT companies urgently need to establish trust mechanisms based on processes, systems, and features, strengthen data encryption and data access control, and implement privacy protection measures to realize users' control over their own data, reduce data risks, enhance user confidence, improve users' perceived ease of use of IoT devices, and promote the adoption of IoT devices (Jayashankar et al., 2018).

(3) There is an urgent need for IoT companies to approach product or service design from the user's perspective, develop genuinely useful product features and content, and utilize big data analytics and artificial intelligence technologies to analyze consumer behavior and listen to consumer feedback, develop more accurate pricing and promotional strategies, reduce the user's perception of financial risk, and enhance the user's perceived usefulness (Eriksson et al., 2005).

(4) IoT enterprises should develop strategic marketing and coaching plans to promote users' understanding and awareness of the benefits of IoT technology, leverage the strong social and marketing attributes of the Internet of Everything ecosystem structured by IoT devices, establish incentive mechanisms, optimize the user experience, strengthen the emotional connection, and implement milestone establishment and feedback, to awaken a strong motivation to use IoT, and to enhance the perceived usefulness, perceived ease of use, and self-efficacy of users , and achieve wider adoption.

(5) IoT involves various technologies and industrial fields, and user experience designers need to collaborate and innovate with experts from other disciplines, focusing on the user's immersive experience and interactive experience and jointly promoting user experience design innovation for IoT devices. Optimizing the user experience of IoT devices in terms of operation simplicity, interface friendliness, device compatibility, functional utility, and demand fulfillment will directly and effectively enhance the users' perception of IoT devices as easy to use and useful and promote IoT devices to be applied and promoted in a wider range of fields and scenarios.

5.3 Limitation and Further Study

This study has certain limitations that can be expanded and extended in subsequent research:(1) In exploring the key influences on residents' intention to use IoT devices, this study only focused on seven influences, namely, information quality, motivation, data risk, financial risk, self-efficacy, perceived ease of use, and perceived usefulness, and did not assess the users' perceived needs and individual differences, users' security and trust perceptions, system quality and quality of service, performance risk, and other drivers, and more in-depth and comprehensive studies can be conducted in the future to better understand the ethical impacts, technological determinants, quality needs, and individual impacts of IoT devices; (2) This study is the first time that the SOBC model has been applied to the adoption of IoT devices, and subsequent studies can incorporate this model more into IoT technology adoption research, which is not limited to the focus on intention to use, but is used to analyze the actual use and behavior of users, the persistence of user use, and the factors that discourage or encourage users to continue using IoT devices.

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