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Sociodemographic impact on smart cities IoT adoption in China[☆]

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ABSTRACT

Digital disruption is one of the most important social megatrends that deeply impact recent and future economic activities. IoT has contributed to the development of Chinese smart cities in recent years. Building on the authors' prior study (Boustani, Xu, & Xu, 2022), which established the mediating role of blockchain adoption between IoT and continuous usage intention, this study investigates how sociodemographic variables moderate these relationships. The authors use Partial Least Squares Structural Equation Modeling (PLS-SEM) and Partial Least Squares Multi-Group Analysis (PLS-MGA) with the SmartPLS software, analyzing a dataset comprising over a thousand samples in China. The authors' findings demonstrate that age positively moderates the blockchain adoption-continuous usage intention relationship, IoT knowledge positively moderates the citizen empowerment-IoT relationship, while frequency of IoT use negatively moderates the social influence-IoT relationship. These results extend UTAUT theory by revealing boundary conditions of technology adoption in smart cities.

1. Introduction

In recent years, with rapid advancements in technology and a growing emphasis on sustainable urbanization, Chinese cities have embraced smart city solutions to improve the quality of life for their citizens. Smart cities in China are characterized by their utilization of advanced technologies, such as the Internet of Things, artificial intelligence, and big data analytics (Yang et al., 2023). These technologies are employed to optimize various aspects of city life, including transportation, energy consumption, public safety, and healthcare. Digital technologies offer wide opportunities for enhancing sustainability in the public sector (Joukhadar, Jiang, Harrington, & Thorogood, 2023). Smart cities are a rapidly emerging concept that will alter urban development in the twenty-first century. Smart cities integrate new technology and data analytics to improve inhabitants' quality of life, boost infrastructure and service efficiency, and encourage long-term economic growth (Gracias, Parnell, Specking, Pohl, & Buchanan, 2023). In the context of this study, a Smart City refers to an urban ecosystem that leverages advanced digital technologies particularly the Internet of Things (IoT), big data analytics, and artificial intelligence to

optimize infrastructure, enhance public services, and improve citizens' quality of life. This definition aligns with prevailing academic literature, where smart cities are viewed as data-driven and citizen-centered systems that integrate technology with governance and social innovation to create sustainable urban living (Albino, Berardi, & Dangelico, 2015; Chourabi et al., 2012).

This study builds upon the theoretical framework established of the authors' prior study (Boustani et al., 2022), which validated an IoT adoption model demonstrating blockchain's mediating role in enhancing continuous usage intention of IoT-based public services in Chinese smart cities. While their study confirmed the significance of five key constructs (Public Trust Value, Social Influence Value, Digital Society Affinity Value, Public Value, and Citizen Empowerment Value) in forming IoT adoption, it did not consider how individual differences might influence these relationships. Therefore, this research addresses this gap by examining the moderating effects of sociodemographic variables, contributing to a more nuanced understanding of technology adoption in diverse populations.

The "Smart City White Paper" published by the National Industrial Information Security Development Research Center (2022) highlights

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that since 2015 the new smart city concept has been elevated to a national strategy, marking a crucial milestone in China's new urbanization development. China has emerged as a global leader in smart city deployment. By 2022, the country had launched over 800 smart city pilot projects. These initiatives focus on digital governance, green energy, intelligent transportation, and public safety systems, among others. One of its critical objectives is to facilitate the integration and sharing of government information systems, thus dismantling information silos and eliminating data segmentation. The key driver of smart city development in China is the government's commitment to sustainable urbanization. Through investment in smart city solutions, the government aims to mitigate pollution, improve public health, and enhance the overall quality of urban life. Smart city technologies in China have led to measurable improvements in urban living. For instance, a 2021 study by Faraji et al. found that smart infrastructure projects in Tier-1 cities significantly reduced traffic-related pollution and improved public service efficiency. Moreover, [Chen \(2023\)](#) reports that smart energy management systems implemented in Chinese cities have reduced electricity consumption in public buildings by up to 30 %, further contributing to sustainability and citizen well-being. Furthermore, smart city development serves as a significant economic driver, creating new opportunities for innovation and entrepreneurship.

The utilization of IoTs in Chinese smart cities has experienced rapid growth over the past few years ([Boustani et al., 2022](#); [Chen, Xu, Liu, Hu, & Wang, 2014](#); [Fei, Kassim, & Mohamad, 2022](#); [Song, Cai, Chahine, & Li, 2021](#)). With the assistance of advanced technology and data analysis, these smart cities can efficiently supervise their resources and improve the quality of life for their citizens. The use of IoT in Chinese smart cities has the potential to transform urban living, creating more sustainable and efficient communities for everyone. The Internet of Things (IoT) refers to an ecosystem in which objects (things) equipped with sensors communicate with computers or mobile devices, often autonomously and without user intervention, via a variety of networking technologies, particularly wireless ones. This idea, first proposed by Kevin Ashton in 1999 ([Ashton, 2009](#)), has gained traction in the past decade, owing mostly to the use of blockchain technology. The concept of the IoT is becoming an important tool for addressing major organizational and societal challenges, such as managing megacities, environmental oversight, and supply chains ([Riggins & Wamba, 2015](#); [Wamba & Ngai, 2013](#)). Researchers' interest in the Internet of Things is still modest when evaluated from the demand side in consumer research.

The development of smart city regions demands a thorough grasp of the different service features that influence people's choices to use these services. Otherwise, they may be the source of new forms of social exclusion due to a lack of technology skills and competency ([Lytras, Visvizi, Chopdar, Sarirete, & Alhalabi, 2021](#)), infrastructure restrictions, or a lack of necessary devices ([Karvonen, Cugurullo, & Caprotti, 2018](#)). Technologies must contribute to the creation of an inclusive society marked by strong civic participation and transparency ([OECD, 2019](#)). As a result, it is necessary to examine people's behaviour, motivation, and incentives ([Mingaleva, Vukovic, Volkova, & Salimova, 2019](#)), as well as to understand the factors that influence the desire to embrace and use communication technologies in everyday activities. [Joukhadar et al. \(2023\)](#) explored digital innovation's role in promoting public sector sustainability, in this research, the authors investigate the impact of smart services in the public sector, aligning with the broader theme of digital innovation. [Song et al. \(2021\)](#) discussed the role of IoT in China's stealthy transition to smart cities while the authors emphasized IoT adoption with the broader theme of China's IoT-driven change.

While IoT has been widely discussed in various contexts ([Humayun, Alsaqer, & Jhanjhi, 2022](#); [Salimian, Ghobaei-Arani, & Shahidinejad, 2022](#)), there is a noticeable gap in research that specifically addresses the sociodemographic impact on IoT adoption in China. Our research analysis aims to explore the moderating effect of different sociodemographic impacts on the adoption of IoT technologies in Chinese smart cities. The primary goal of this study is to investigate IoT adoption in

China, namely the level of adoption and sociodemographic factors that explain this phenomenon. The authors are particularly interested in IoT users' knowledge, age, gender, and attitudes toward devices and technology operating in IoT networks, which leads to a key research question, as evidenced by the presented research: What is the moderating effect of sociodemographic differences in the adoption of IoT technologies in Chinese smart cities? The current study seeks to offer valuable insight and practical suggestions for IoT implementation strategies to governors or policymakers to support smart city advancement.

The authors conduct Partial Least Squares Multi-Group Analysis (PLS-MGA) with the SmartPLS software, analyzing a dataset comprising over a thousand samples. The analysis demonstrates that certain socio-demographic variables have a significant impact on the continuous usage intention of IoT.

In Section 2, the authors first present the theoretical background adopted and IoT adoption in smart cities, exploring the influence of various sociodemographic variables on technological adoption, and developing the research hypotheses and the conceptual model. In Section 3, the researchers present the methodology used and provide an overview of the data set describing the characteristics of the research variables. Then, in Section 4, the authors present the conceptual model and analyze the results; then, in Section 5 the authors debate and discuss the findings of the analysis, to finally conclude in Section 6, while presenting future improvement and research limitations.

2. Literature review and hypotheses development

2.1. theoretical foundation: the IoT-blockchain-CUI model

This study extends the theoretical model validated by [Boustani et al. \(2022\)](#), which integrated UTAUT theory with blockchain technology in the context of smart cities. Their model established IoT as a formative construct comprising five first-order dimensions:

- Public Trust Value (PTV): Essential for creating public value through IoT services, as diminished trust leads to reduced public perceptions of value ([Boustani et al., 2022](#))
- Social Influence Value (SIV): Reflecting how others' perceptions influence individual technology adoption decisions, consistent with UTAUT theory.
- Digital Society Affinity Value (DSAV): Based on [Rogers' \(1995\)](#) compatibility concept, representing citizens' perceived importance of e-government IoT services.
- Public Value (PV): The overall value created by government through IoT initiatives that involve citizens in the value-generation process.
- Citizen Empowerment Value (CEV): Citizens' participatory power in developing IoT services for e-government.

[Boustani et al. \(2022\)](#) demonstrated that these five dimensions significantly contribute to IoT adoption (weights ranging from 0.220 to 0.261), with blockchain adoption fully mediating the relationship between IoT and continuous usage intention. This established model provides the foundation for examining how sociodemographic factors might moderate these relationships.

2.2. Unified theory of acceptance and use of technology UTAUT

The models derived from the TAM (Technology Acceptance Model) ([Davis, 1989](#)), including the contemporary notion of UTAUT (Unified Theory of Acceptance and Use of Technology) ([Venkatesh, Morris, Davis, & Davis, 2003](#)), are the most extensively used models of ICT acceptance. Traditional TAM explains technology acceptance as a reaction to external factors such as perceived usefulness and perceived ease of use (treated as a cognitive response), both of which influence attitude toward use (affective response) and later behavioral intention to use and actual use (behavioral response). Classical TAM and its simple expansions were extensively criticized for being overly simplified

(Bagozzi, 2007; Benbasat & Barki, 2007). More antecedents of information technology adoption were required, which resulted in the described UTAUT and later UTAUT2 theory (Venkatesh, Thong, & Xu, 2012). The widely applied UTAUT2 theory is robust but complex, with its popular extensions incorporating context-specific variables that reveal limitations in current technology adoption research and provide a framework for future studies (Tamilmani, Rana, Wamba, & Dwivedi, 2021).

UTAUT theory and UTAUT2 theory are widely used by researchers to test new technology adoptions/acceptance. Chen, Khan, Shiwakoti, Stasinopoulos, and Aghabayk (2024) used the UTAUT theory to analyze how socio-demographic factors, like age, gender, educational level, etc., impact peoples' intention to use automated vehicles. Fei et al. (2022) analyzed Chinese users' intentions in IoT-based mobile health services adoption by using UTAUT theory. Ronaghi and Forouharfar (2020) utilized the UTAUT theory to investigate the IoT technology adoption in smart farming by focusing on Middle Eastern users. Shi et al. (2022) employed the UTAUT2 theory to examine the willingness of Bangladeshi farmers to use IoT in the agricultural sector. The study of Idrees and Ullah (2024) integrated UTAUT2 theory to examine the moderating effect of bank users' education level on fintech services adoption.

Gender, age, experience, and willingness to use moderate described relationships, and the research model based on UTAUT2 includes new variables that explain behavioral intention and use behaviour, as well as new direct links and interactions, resulting in a complicated structural model that reflects determinants of individual information technology adoption. The author's strategy was to see if any UTAUT2 components (and maybe the entire model) combined with Blockchain, and chosen demographic characteristics could help explain IoT uptake among Chinese consumers.

Moreover, most demographic factors significantly moderate user attitudes, except for educational background, which did not exhibit a moderating effect (Chawla & Joshi, 2018). By extending the Technology Acceptance Model (TAM) and Diffusion of Innovations theory, they studied the factors shaping consumer behaviour in mobile banking adoption. On the other hand, (Strzelecki & ELArabawy, 2024) studied the moderating effects of gender and study level on technology adoption and results indicate that performance expectancy, effort expectancy, and

social influence significantly shape students' behavioral intentions, while facilitating conditions further impact actual use behaviour. There is a dearth of such studies on the Internet of Things case.

Using current technology is now well-perceived socially, and as time passes, IoT solutions become less expensive, which encourages their adoption. On the other hand, various objections remain, notably due to privacy concerns, which may make IoT adoption slower and more complex, and this inconvenience may be mitigated with Blockchain incorporation into the research model.

The moderating influence of each continuous variable (age, e-government experience, knowledge of IoT, frequency of IoT use, and daily use of IoT) on the relationships within the authors' conceptual model (see Fig. 1 for the overall model structure, which extends the authors' prior work in Boustani et al., 2022) was verified using SmartPLS 4.1.0.9's two-stage method. This analytical approach involves utilizing latent variable scores obtained from the main effects model (i.e., the base model without interaction terms, as established in Boustani et al., 2022). These scores, for both the latent predictor and latent moderator variables, are then used to compute product indicators for the second stage of the analysis, which includes the interaction term alongside the original predictor and moderator variables.

2.3. Hypothesis statements

2.3.1. Age and generation in IoT adoption

Millennials/young generation are keen on new and innovative technology. High-tech devices are essential for their daily life. Many researchers questioned the generation differences in adopting new advanced technologies and proved that the Millennials / young generation have a high acceptance of digital gadgets and new technologies (Kim & Huh, 2007; Kumar & Lim, 2008; Manfreda, Ljubi, & Groznik, 2021; Yang, Lee, & Lee, 2018).

As a modern technology, IoT has been seamlessly interwoven into people's daily life. Albert, Rodan, Aggarwal, and Hill (2019) used an online survey with 436 samples and found no age variations in IoT familiarity. At the same time, Albert et al. (2019) discovered that younger generations are more sensitive to IoT security issues, which will influence their IoT usage intentions. Arfi, Nasr, Khvatova, and Zaied (2021)

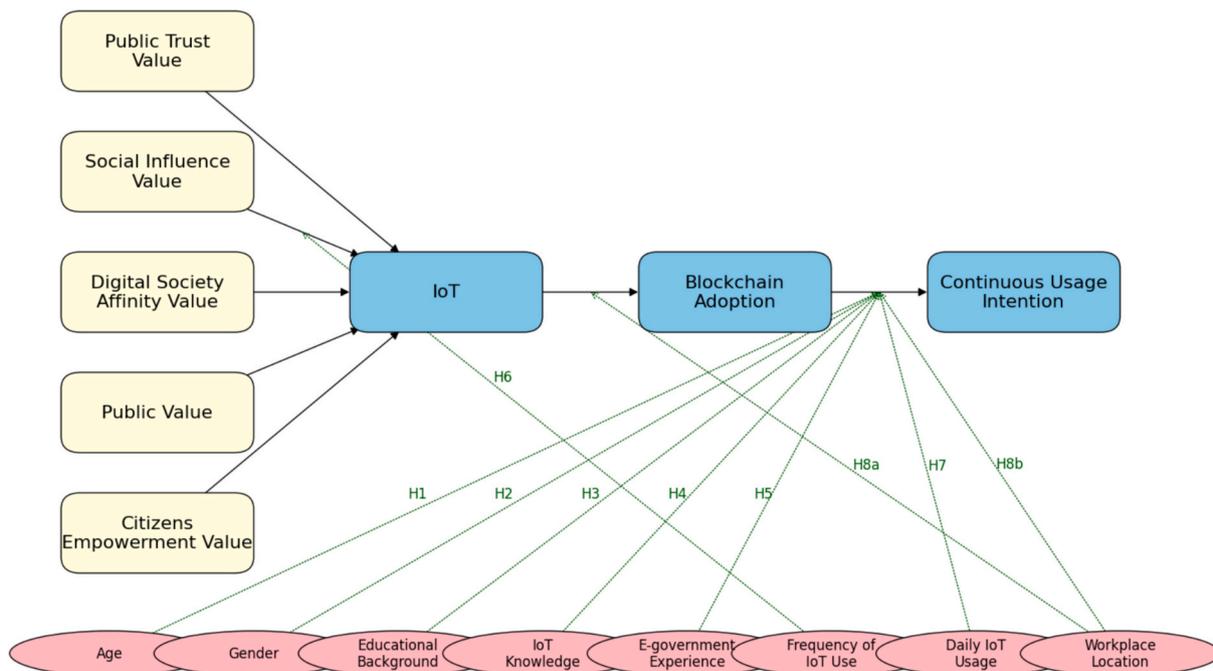


Fig. 1. The conceptual model. Source: Authors.

used the UTAUT theory to study IoT adoption in the eHealth industry and discovered that age is an important mediator of people's intentions to use IoT in eHealthcare. Alhwaiti (2023) used UTAUT to assess the acceptance of artificial intelligence applications in the post-COVID era, as well as the impact on faculty members' occupational well-being and teaching self-efficacy. Boustani (2022) also examined the impact of artificial intelligence on the banking sector in a developing country.

H1. *Age moderates the relationship between blockchain adoption and CUI (Continuous Usage Intention).*

2.3.2. Gender differences in IoT adoption

Regarding technology utilization, the authors cannot ignore the gender gap. While males are often seen as early adopters of new technology and have a high familiarity and acceptance or use of new technology, females tend to be more cautious and hesitant when trying new devices and software (Alraja, 2022; Goswami & Dutta, 2015; Li & Kirkup, 2007; Nysveen, Pedersen, & Thorbjørnsen, 2005). Albert et al. (2019) discovered that compared with males, females are less familiar with IoT utilization and more concerned about IoT security risks. However, it is important to note that this gap is slowly closing as more and more technologies are integrated into our daily lives.

A study on the acceptance and adoption of smartphone uses among Chinese college students (Pan, Chen, & Rau, 2013) discovered that social influence, entertainment utility, and smartphone compatibility influence Chinese college students' PU and attitude to use. Kim (2014) found that in Korea, the unified theory of acceptance and use of technology (UTAUT) is a useful tool for anticipating technology usage intentions. Moon and Chang (2014) discovered that user attitude and social influence were both statistically significant concerning intention of use in their study on technology acceptance and adoption of innovative smartphone uses in specific industries, such as the medical sector and among hospital employees, with user attitude being greater than social influence. Understanding gender differences in individual technology adoption and usage is a crucial issue to recognize given the lack of research into gender differences in IoT adoption (Tashakkori & Thompson, 1990); however, little, if any, previous research has examined gender differences in the salience of different determinants.

H2. *Gender moderates the relationship between blockchain adoption and CUI.*

2.3.3. Education differences in IoT adoption

Education plays a crucial role in improving our understanding of technology. By learning about the underlying principles and applications of different technologies, the authors can better understand how they work, how they impact our lives, and how the authors can use them to solve problems. Studies by Acheampong and Cugurullo (2019) and Said, Najdawi, and Chabani (2021) support that education level influences technology adoption. The high-skilled and highly-trained people are more likely to adopt new digital technologies (Cirillo, Fanti, Mina, & Ricci, 2023; Eker, Fountas, Anastasopoulos, & Still, 2020; Zhang & Kamargianni, 2022).

H3. *Educational background influences the moderating effect of blockchain adoption on CUI.*

2.3.4. Knowledge of IoT & E-government using experience

A deeper understanding of technology or related technological experience can enhance the adoption of new technological advancements (Eker et al., 2020; Zhang & Kamargianni, 2022). Those who are knowledgeable about the latest trends and advancements are much more likely to embrace them and incorporate them into their daily lives. Al-Momani, Mahmoud, and Ahmad (2018) discusses different factors that influence IoT acceptance and finds IT knowledge as one of the most important factors. Alkawsu and Baashar (2020) find that knowledge influences the IoT-based smart meter acceptance in Malaysia. Therefore,

the authors hypothesize:

H4. *IoT knowledge moderates the effect of blockchain adoption on CUI.*

Prior technology experience shapes users' mental models and expectations for new technologies (Venkatesh et al., 2003). E-government experience specifically develops users' trust in digital government services and their understanding of security mechanisms (Mahmood, Osmani, & Sivarajah, 2014). Users with extensive e-government experience may better appreciate blockchain's security benefits, potentially strengthening its impact on continuous usage intention. Conversely, those with limited experience may not fully understand blockchain's value proposition, weakening this relationship. Therefore, the authors hypothesize:

H5. *Experience with e-government services moderates the effect of blockchain adoption on CUI.*

2.3.5. Frequency of IoT use & daily use of IoT

Usage frequency reflects the degree of technology integration into daily routines (Limayem, Hirt, & Cheung, 2007). High-frequency users develop habitual usage patterns that may reduce their susceptibility to social influence (Venkatesh et al., 2012). When IoT use becomes routine, decisions are driven more by personal experience than others' opinions. Conversely, infrequent users may rely more heavily on social cues to guide their adoption decisions. Building on Pahlila, Siponen, and Zheng (2011) and Singh and Matsui (2017), the authors propose:

H6. *Frequency of IoT use moderates the relationship between SIV (System Influence Value) and IoT adoption.*

Daily use represents deep integration of technology into essential life activities, distinct from mere frequency (Thatcher & Perrewew, 2002). Users who incorporate IoT into daily routines develop stronger dependencies and higher switching costs (Kim & Son, 2009). For these users, blockchain's security assurances become more critical as they have more at stake, potentially amplifying blockchain's impact on continuous usage intention. Therefore, the authors hypothesize:

H7. *Daily IoT usage moderates the effect of blockchain adoption on CUI.*

2.3.6. Location of work impact on IoT adoption

Concerning the location of work, rural or urban, while technology is becoming more commonplace in both settings, each has unique challenges and opportunities. In rural areas, access to technology can be limited due to factors such as distance, cost, and infrastructure. However, there are also benefits to technology adoption in these areas, such as increased access to healthcare and education resources. While, in urban areas, technology is more readily available, there can be concerns about privacy and security. Therefore, the authors hypothesize:

H8. *Workplace location (urban vs. rural) moderates the relationship between IoT adoption and blockchain adoption.*

3. Methodology and data collection

3.1. Methodology

The authors extend the base model (Boustani et al., 2022) by incorporating sociodemographic variables as moderators to examine their influence on the established relationships. The study employs a comprehensive two-tier methodological approach combining PLS-SEM for continuous variables and PLS-MGA for categorical variables, using SmartPLS 4.1.0.9. This dual approach was selected due to its ability to handle complex path models with latent variables while accommodating both continuous and categorical moderating effects (Hair Jr, Sarstedt, Ringle, & Gudergan, 2017; Sarstedt, Henseler, & Ringle, 2011). For continuous variables (Age, Knowledge of IoT, Frequency of IoT use, Daily use of IoT, E-government using experience), the authors utilized

PLS-SEM to examine their moderating effects on the structural model relationships. PLS-SEM (Partial Least Squares Structural Equation Modeling) enables the simultaneous examination of multiple relationships between latent variables while handling measurement errors (Hair Jr et al., 2017). PLS-MGA (Multi-Group Analysis) extends this by allowing comparison of path coefficients across different groups within categorical variables (Henseler, Ringle, & Sinkovics, 2009). For categorical variables (Education, Gender, Location of work) in this study, PLS-MGA was employed to assess group differences in path coefficients.

Model estimation followed rigorous configuration settings. The bootstrapping procedure was performed with 5000 subsamples to ensure stable results. Sample size requirements were met following the “10 times rule” for PLS-SEM, with the authors’ sample of 1008 responses exceeding the minimum threshold. Significance levels were set at $p < 0.01$ and $p < 0.05$ for hypothesis testing. The PLS-SEM algorithm was configured with a path weighting scheme, maximum iterations set to 300, and a stop criterion of 10^{-7} .

To address potential nonlinear relationships in the model, the authors conducted quadratic nonlinear effects analysis using SmartPLS’s two-stage approach. Quadratic effects analysis helps identify relationships between constructs that may not follow a simple linear pattern, providing a more nuanced understanding of the relationships (Hair Jr et al., 2017). This study involved examining nonlinear effects between latent predictor variables and their outcomes, with particular attention to relationships between key constructs (PTV, SIV, DSAV, PV, CEV, Blockchain Adoption, and CUI). The quadratic terms were generated using standardized latent variable scores from the main effects model.

For endogeneity concerns, the authors implemented the Gaussian copula approach for the main constructs (PTV, SIV, DSAV, PV, CEV, Blockchain Adoption, and CUI). The Gaussian copula approach serves as an instrumental variable-free method to detect and correct for endogeneity in structural model relationships, addressing potential bias from omitted variables or measurement errors (Hair Jr et al., 2017). The Gaussian copula terms were added to the model following the control function approach, allowing for multiple endogenous regressors simultaneously.

3.2. Data collection

The data used in this study is the same to the authors’ prior work (Boustani et al., 2022). Its collection occurred from June to September 2022. The authors designed a questionnaire and used the Chinese Credamo platform from where participants were randomly selected. The Credamo platform is a leading Chinese questionnaire platform, especially for data research and analysis. Its registered participants are more than three million. The authors’ research strived to analyze Chinese citizens’ IoT continuous usage intention via blockchain adoption. Invitations to the authors’ questionnaire were extended to more than 1500 individuals through email and phone communication. Finally, the authors collected 1008 samples after eliminating incomplete entries and disengaged responses.

The authors’ questionnaire was administered in both Chinese and English to ensure respondent comprehension. It collected the following information: Sociodemographic information (12 items), Public Trust Value (PTV) (4 items), Social Influence Value (SIV) (4 items), Digital Society Affinity Value (DSAV) (4 items), Public Value (PV) (4 items), Continuous Usage Intention (CUI) (4 items), Citizens Empowerment Value (CEV) (4 items), Blockchain implementation impact (5 items). Sociodemographic information includes age, gender, educational level, knowledge of IoT, frequency of IoT use, daily use of IoT, living environment, cities, working sector, and e-government experience.

3.3. Sample characteristics

The authors collected data using an online questionnaire via the Chinese Credamo platform and gained 1008 reliable responses. The

survey is anonymous. The characteristics of the sample provide essential demographic information about the respondents, which is crucial for understanding the generalizability and applicability of the study’s findings. Here’s an analysis of the characteristics of the sample:

- 1) Gender Distribution: The sample consists of 38.1 % male and 61.9 % female respondents. The distribution indicates a slightly higher representation of females in the survey. Researchers should be cautious about potential gender-related differences in responses and consider this factor when interpreting the results.
- 2) Age Distribution: The participants’ age distribution shows that 39.88 % fall between 18 and 29 years, 44.84 % between 30 and 39 years, and 15.18 % between 40 and 60 years. The majority of respondents belong to the younger age groups, indicating that the study may have a stronger representation of the younger population’s perspectives on IoT usage.
- 3) Geographic Location: More than 95 % of the participants reside in Chinese metropolitan areas. This strong representation of urban respondents suggests that the study primarily captures the viewpoints and experiences of individuals living in urban settings. The results may not fully represent the perspectives of individuals from rural areas. In China, the majority of platform users may reside in urban areas, which could explain the high percentage of urban respondents in this study. Moreover, according to the [National Bureau of Statistics \(The People’s Republic of China\) \(2024\)](#), over 66 % of the population lives in urban areas.
- 4) Education Level: The educational attainment of the participants is diverse, with 78.17 % having a Bachelor’s degree, 14.09 % having a Master’s degree, and 1.88 % holding a Doctorate (PhD) degree. The sample’s high proportion of individuals with Bachelor’s degrees indicates that the study is well-represented among relatively educated individuals. A report from the [Ministry of Education \(The People’s Republic of China\) \(2023\)](#) mentioned that in 2022, gross enrolment in higher education (postgraduate and undergraduate students) reached 59.6 %.

The sample appears to be predominantly composed of urban residents, with a significant representation of well-educated young adults. The findings from this sample may be more relevant and generalizable to a similar population within China’s metropolitan areas. However, caution should be exercised when applying these results to rural areas or other regions with different demographic characteristics.

4. Results

The base model contains formatively and reflectively measured latent variables. PTV, SIV, DSAV, PV, CEV, BA and CUI are the reflective variables, while IoT is the formative variable; PTV, SIV, DSAV, PV and CEV, which are the dimensions of the IoT, form the variable of IoT (Boustani et al., 2022). Before examining moderating effects, the authors first summarise the measurement of the base model established by the authors’ prior work (Boustani et al., 2022). The results confirm adequate measurement properties.

Also, the authors implemented the analysis of quadratic nonlinear effects and Gaussian copula. Then, all continuous control variables were tested and simultaneously applied to the model. Finally, each control variable was tested separately.

4.1. Reliability and validity of reflective constructs

For reflective constructs, the authors assessed internal consistency (Composite Reliability >0.7), convergent validity (AVE > 0.5), and discriminant validity (HTMT <0.9) (Tables 1 and 2). All the results meet the criteria: composite reliability more than 0.7, AVE scores more than 0.5 and HTMT less than 0.9 (Hair, Risher, Sarstedt, & Ringle, 2019).

Table 1
Reliability and convergent validity of reflective constructs.

Construct Items	Loading	t Values	p Values	Composite Reliability(CR)	AVE
PTV				0.817	0.598
Q2.2	0.778	50.639	0.000		
Q2.3	0.755	36.834	0.000		
Q2.4	0.787	40.415	0.000		
SIV				0.798	0.552
Q3.2	0.746	35.880	0.000		
Q3.3	0.750	44.982	0.000		
Q3.4	0.764	38.424	0.000		
DSAV				0.843	0.642
Q4.1	0.815	55.496	0.000		
Q4.3	0.799	53.129	0.000		
Q4.4	0.789	47.180	0.000		
PV				0.802	0.574
Q5.1	0.723	28.845	0.000		
Q5.2	0.744	35.103	0.000		
Q5.4	0.804	50.538	0.000		
CEV				0.820	0.603
Q8.1	0.786	46.817	0.000		
Q8.3	0.779	58.124	0.000		
Q8.4	0.764	41.725	0.000		
BA				0.833	0.625
Q7.1	0.784	44.043	0.000		
Q7.3	0.828	65.156	0.000		
Q7.5	0.759	35.769	0.000		
CUI				0.786	0.551
Q6.1	0.755	33.837	0.000		
Q6.2	0.735	30.375	0.000		
Q6.4	0.736	31.184	0.000		

4.2. Formative convergent validity and collinearity

In the model, the authors established: (1) a formative part (IoT-form) composed of the five first-order dimensions (PTV, SIV, PV, DSAV, and CEV) with their respective weights, and (2) a reflective part (IoT-refl) using the relative complete indicator set to capture the overall IoT concept reflectively (Boustani et al., 2022). In Fig. 2, the path coefficient between the formative IoT construct and the reflective measure is 0.991 ($p < 0.001$), substantially exceeding the recommended threshold of 0.70 (Hair et al., 2019). Furthermore, the R^2 value of 0.983 surpasses the suggested minimum of 0.50, indicating that the formative measurement explains 98.3 % of the variance in the reflective measure (Hair et al., 2019). These results provide robust evidence for the convergent validity of the formative IoT construct. The high correlation between the two measurement approaches confirms that the five dimensions appropriately and comprehensively capture the underlying IoT concept as theorized. This validation is further supported by the significance of all formative weights (Table 3: weights of PTV = 0.230, SIV = 0.230, DSAV = 0.263, PV = 0.227, CEV = 0.240; all $p < 0.001$) and the absence of multicollinearity issues (Table 4: all VIFs <5) (Hair et al., 2019).

4.3. Common method bias assessment

Following Kock (2015), the authors examined Variance Inflation Factor (VIF) values in the full collinearity test. All VIF values are below

Table 2
Discriminant validity of reflective constructs.

	BA	CEV	CUI	DSAV	IoT	PTV	PV	SIV
BA								
CEV	0.857							
CUI	0.209	0.382						
DSAV	0.899	0.463	0.866					
IoT	0.729	0.768	0.056	0.441				
PTV	0.850	0.633	0.670	0.815	0.343			
PV	0.651	0.560	0.150	0.884	0.791	0.578		
SIV	0.852	0.485	0.872	0.309	0.076	0.891	0.418	

3.3 (Tables 4 and 5), suggesting CMB is not a significant concern in this study.

4.4. Structural model measurement

The analysis confirmed no multicollinearity issues among predictor latent variables, as all VIF scores (Table 5) are below the threshold of 5, a standard suggested by Hair et al. (2019). All hypothesized paths (Table 6) in the model exhibit statistically significant weights ($p < 0.001$), indicating meaningful relationships as per Hair et al. (2019). The R^2 values (Table 7) demonstrate substantial predictive power for IoT ($R^2 = 0.990$) and Blockchain Adoption ($R^2 = 0.549$), and a near-moderate level for CUI ($R^2 = 0.423$), when assessed against benchmarks for substantial (0.75), moderate (0.50), and weak (0.25) predictive accuracy (Hair et al., 2019). Finally, the f^2 effect sizes (Table 8: e.g., IoT → Blockchain Adoption = 0.217; Blockchain Adoption → CUI = 0.734) indicate medium to large impacts of exogenous constructs on the R^2 of endogenous constructs, based on thresholds for small (0.02), medium (0.15), and large (0.35) effects (Cohen, 2013; Hair et al., 2019).

4.5. Quadratic nonlinear effects

The analysis of quadratic nonlinear effects above (Table 9) reveals that most relationships in the model exhibit linear patterns, with only three relationships showing significant nonlinear effects: CEV - > IoT ($O = -0.010, T = 3.228, p < 0.001$), IoT - > Blockchain Adoption ($O = -0.011, T = 2.781, p < 0.005$), and Blockchain Adoption - > CUI ($O = -0.018, T = 2.633, p < 0.000$). Although these nonlinear relationships are statistically significant, their effect sizes are relatively small (all

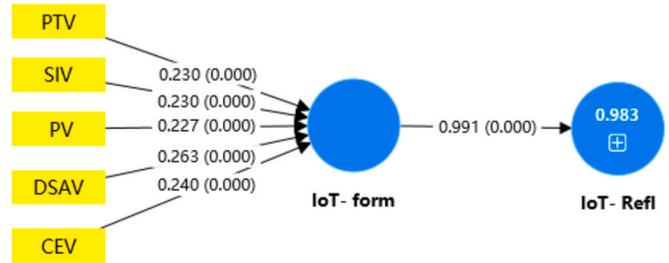


Fig. 2. IoT convergent validity.

Table 3
Formative variable weights and significance.

	Weights	Standard Deviation (STDEV)	T Statistic	P Values
CEV - > IoT- form	0.240	0.011	22.753	0.000
DSAV - > IoT- form	0.263	0.011	23.392	0.000
PTV - > IoT- form	0.230	0.009	25.386	0.000
PV - > IoT- form	0.227	0.009	24.693	0.000
SIV - > IoT- form	0.230	0.010	23.352	0.000

Table 4
Formative-reflective VIF scores.

	VIF
CEV	2.679
DSAV	2.805
PTV	2.112
PV	2.042
SIV	2.136
Q2.1	1.307
Q2.2	1.551
Q2.3	1.488
Q2.4	1.635
Q3.1	1.323
Q3.2	1.498
Q3.3	1.736
Q3.4	1.495
Q4.1	1.873
Q4.2	1.207
Q4.3	1.864
Q4.4	1.774
Q5.1	1.536
Q5.2	1.516
Q5.3	1.501
Q5.4	1.627
Q8.1	1.617
Q8.2	1.544
Q8.3	1.812
Q8.4	1.852

Table 5
VIF Scores for the model.

	VIF
Blockchain Adoption - > CUI	1.000
IoT - > Blockchain Adoption	1.000
CEV - > IoT	2.679
DSAV - > IoT	2.800
PTV - > IoT	2.113
PV - > IoT	2.046
SIV - > IoT	2.129

Table 6
Structural model weights.

	Weights	Standard Deviation (STDEV)	T Statistics	P Values
Blockchain Adoption - > CUI	0.651	0.029	22.590	0.000
IoT - > Blockchain Adoption	0.741	0.023	32.015	0.000
CEV - > IoT	0.231	0.010	22.408	0.000
DSAV - > IoT	0.261	0.012	21.536	0.000
PTV - > IoT	0.222	0.009	26.059	0.000
PV - > IoT	0.249	0.011	23.022	0.000
SIV - > IoT	0.220	0.009	25.860	0.000

Table 7
R² in the model.

	R ²	R ² Adjusted
Blockchain Adoption	0.549	0.549
CUI	0.423	0.423
IoT	0.990	0.990

coefficients < |0.03|). The remaining relationships (PTV - > IoT, SIV - > IoT, DSAV - > IoT, and PV - > IoT) show no significant nonlinear patterns ($p > 0.05$). Subsequent analysis including moderating variables produced consistent results, with no meaningful changes in the significance patterns or effect sizes of these nonlinear relationships. Following Hair Jr et al. (2017), when nonlinear effects are statistically significant

Table 8
Structural model effect size f^2 values.

	f^2
IoT - > Blockchain Adoption	0.217
Blockchain Adoption - > CUI	0.734
CEV - > IoT	1.994
DSAV - > IoT	2.422
PTV - > IoT	2.335
PV - > IoT	3.036
SIV - > IoT	2.271

Table 9
Quadratic nonlinear effects.

	Original sample (O)	Sample mean (M)	STDEV	T statistics (O/STDEV)	P values
QE (PTV) - > IoT	-0.003	-0.003	0.002	1.335	0.182
QE (SIV) - > IoT	0.003	0.003	0.002	1.522	0.128
QE (DSAV) - > IoT	0.001	0.001	0.003	0.231	0.817
QE (PV) - > IoT	-0.004	-0.005	0.003	1.763	0.078
QE (CEV) - > IoT	-0.010	-0.010	0.003	3.228	0.001
QE (IoT) - > Block-chain Adoption	-0.011	-0.011	0.007	2.781	0.005
QE (Block-chain Adoption) - > CUI	-0.018	-0.019	0.003	2.633	0.000

QE: Quadratic nonlinear effects; STDEV: Standard Deviation. Source: Authors.

but have very small effect sizes (typically < |0.05|), researchers can proceed with the linear model specification for parsimony without meaningful loss of explanatory power. Therefore, the authors maintain the linear model specification for subsequent analyses.

4.6. Gaussian copula analysis

The Gaussian copula analysis above (Table 10) reveals no significant endogeneity concerns in the model's key relationships (all $p > 0.05$). The highest effect is observed in the Block-chain Adoption - > CUI relationship ($O = -0.028, T = 3.555, p = 0.080$), but it still fails to reach statistical significance at conventional levels. Other relationships show even lower effects, with T-statistics ranging from 0.174 to 2.299.

Table 10
Gaussian copula.

	Original sample (O)	Sample mean (M)	STDEV	T statistics (O/STDEV)	P values
GC (PTV - > IoT) - > IoT	-0.015	-0.014	0.006	2.299	0.072
GC (SIV - > IoT) - > IoT	-0.001	-0.002	0.007	0.174	0.862
GC (DSAV - > IoT) - > IoT	-0.005	-0.004	0.007	0.702	0.483
GC (PV - > IoT) - > IoT	-0.009	-0.010	0.006	1.495	0.135
GC (CEV - > IoT) - > IoT	-0.011	-0.012	0.007	1.460	0.144
GC (IoT - > Block-chain Adoption) - > Block-chain Adoption	0.005	0.005	0.005	0.910	0.363
GC (Block-chain Adoption - > CUI) - > CUI	-0.028	-0.023	0.039	3.555	0.080

GC: Gaussian copula; STDEV: Standard Deviation. Source: Authors.

Following Hair Jr et al. (2017), when Gaussian copula terms are not statistically significant, researchers can proceed with the assumption that endogeneity does not pose a substantial threat to the model's validity. Subsequent analysis including moderating variables still produced consistent results, with no significant changes in the endogeneity patterns. Therefore, following Hair Jr et al. (2017), the authors maintain the original model specification without endogeneity corrections for subsequent analyses, as the results suggest that omitted variables and measurement errors do not significantly bias the model parameter estimates.

4.7. Moderating effect of combined continuous moderators

To identify the most salient simultaneous moderating effects of continuous control variables, a systematic model refinement approach was adopted. Initially, all continuous control variables investigated in this study (namely Age, E-government Experience, Knowledge of IoT, Frequency of IoT Use, and Daily Use of IoT) were concurrently tested for their moderating influences on the structural model paths. Non-significant interaction terms were subsequently removed to achieve a more parsimonious model. The resulting model, which highlights the significant simultaneous moderating effects of Age, Knowledge of IoT, and Frequency of IoT Use, is presented in Fig. 3 and Table 11.

When examining multiple moderators simultaneously, three significant effects emerge. IoT knowledge positively moderates the CEV-IoT relationship ($\beta = 0.014, t = 3.892, p < 0.01$), reinforcing that empowerment effects are amplified among knowledgeable users. Frequency of use negatively moderates the SIV-IoT relationship ($\beta = -0.008, t = 2.002, p < 0.05$), confirming that habitual users rely less on social influence. Age positively moderates the blockchain-CUI relationship ($\beta = 0.122, t = 5.240, p < 0.01$), with older users showing stronger responses to blockchain adoption. These simultaneous effects demonstrate that sociodemographic factors operate independently, each creating unique boundary conditions for technology adoption.

Table 11
The moderating effect of combined continuous moderators.

Moderating Effect Path	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics (O/STDEV)	P Values
Moderating Effect of Age on BA - > CUI	0.122	0.120	0.023	5.240	0.000
Moderating Effect of Knowledge of IoT on CEV - > IoT	0.014	0.014	0.004	3.892	0.000
Moderating Effect of Frequency of IoT Use on SIV - > IoT	-0.008	-0.007	0.004	2.002	0.045

STDEV: Standard Deviation
Source: Authors.

4.8. Moderating the effect of control variables separately

4.8.1. The moderating effect of age

Fig. 4 and Table 12 show the significant moderating effect of Age on the model. The results show that age positively moderates the relationship between blockchain adoption and CUI ($\beta = 0.122, t = 5.240, p < 0.001$). This positive moderation indicates that the effect of blockchain adoption on continuous usage intention is stronger for older users than younger users. Specifically, while blockchain adoption enhances CUI for all age groups, this effect is amplified among older participants who may place greater value on the security assurances blockchain provides. This finding aligns with the outcome of the studies conducted by Hur, Kim, and Kim (2014) and Rahim, Chibuike, Uche, Okikiola, and Olatoye (2024) who report that age could influence new technology adoption.

4.8.2. Moderating effect of gender

Table 13 above shows the moderating effect of Gender on the model. The results show that after incorporating Gender into the research model, the Path Coefficients have no significant difference between

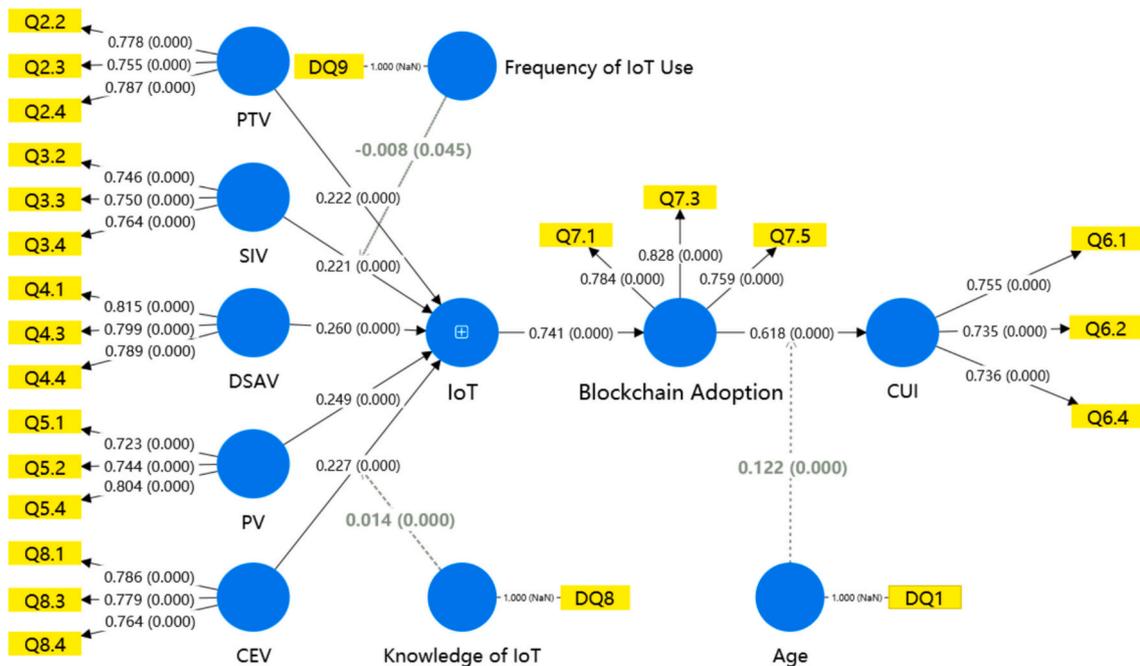


Fig. 3. The moderating effect of combined continuous moderators.
Source: Authors.

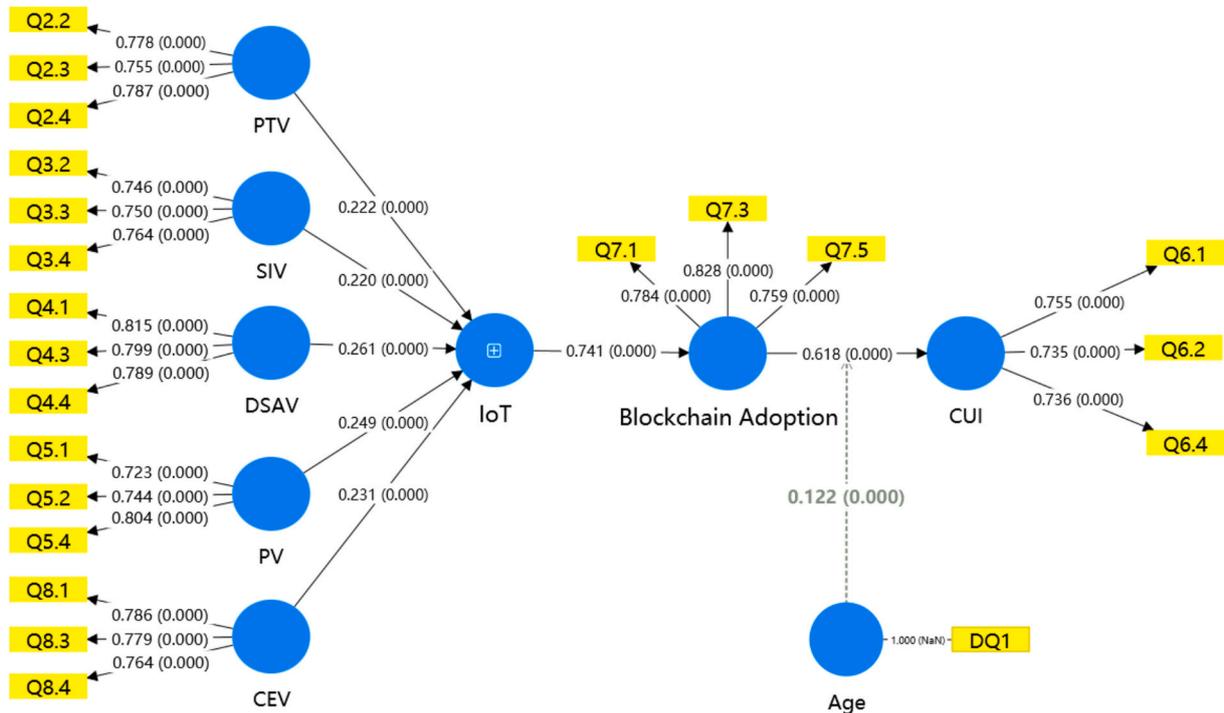


Fig. 4. The moderating effect of age.
Source: Authors.

Table 12
The moderating effect of age.

Moderating Effect Path	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics (O/STDEV)	P Values
Blockchain Adoption -> CUI	0.122	0.120	0.023	5.240	0.000

STDEV: Standard Deviation.
Source: Authors.

Table 13
Moderating effect of gender.

Moderating Effect Path	Path Coefficients-diff (Female - Male)	p-Value original 1-tailed (Female vs Male)	p-Value (Female vs Male)
Blockchain Adoption -> CUI	0.002	0.499	0.998
CEV -> IoT	-0.011	0.700	0.600
DSAV -> IoT	-0.001	0.512	0.975
IoT -> Blockchain Adoption	-0.056	0.888	0.224
PTV -> IoT	-0.011	0.722	0.555
PV -> IoT	0.032	0.068	0.136
SIV -> IoT	0.006	0.384	0.767

Source: Authors.

Females and Males, indicating that Gender cannot moderate the model. This finding is consistent with the research result of Faqih and Jaradat (2015), which indicates that the gender factor does not have a moderating effect on the adoption of mobile commerce.

4.8.3. The moderating effect of education

The blue numbers in Table 14 above show the significant moderating effect of education on the model.

Table 14
The moderating effect of education (high school).

Moderating Effect Path	Path Coefficients-diff (Female - Male)	p-Value original 1-tailed (Female vs Male)	p-Value (Female vs Male)
Blockchain Adoption -> CUI	0.186	0.001	0.003
CEV -> IoT	-0.032	0.798	0.403
DSAV -> IoT	-0.080	0.961	0.077
IoT -> Blockchain Adoption	0.156	0.001	0.002
PTV -> IoT	0.004	0.468	0.937
PV -> IoT	0.079	0.017	0.034
SIV -> IoT	-0.047	0.931	0.139

Source: Authors.

Education level (high school) shows significant moderating effects on three relationships. First, it positively moderates the blockchain adoption-CUI relationship (diff = 0.186, $p < 0.01$), indicating that blockchain's impact on continuous usage is stronger among high school-educated users compared to those with other education levels. This suggests that users with basic education may place greater value on blockchain's trust-building features. Second, high school education positively moderates the IoT-blockchain adoption relationship (diff = 0.156, $p < 0.01$), meaning IoT's influence on blockchain adoption is stronger for this group. Third, it positively moderates the PV-IoT relationship (diff = 0.079, $p < 0.05$), suggesting public value perceptions more strongly drive IoT adoption among high school-educated users.

The blue numbers in Table 15 above show the significant moderating effect of education on the model.

Bachelor's degree education shows contrasting moderation patterns. It negatively moderates the blockchain adoption-CUI relationship (diff = -0.154, $p < 0.01$), indicating blockchain's impact on continuous usage is weaker among bachelor's degree holders. These users may have alternative trust mechanisms or greater confidence in digital systems,

Table 15
The moderating effect of education (bachelor's degree).

Moderating Effect Path	Path Coefficients-diff (Female - Male)	p-Value original 1-tailed (Female vs Male)	p-Value (Female vs Male)
Blockchain Adoption - > CUI	-0.154	0.996	0.007
CEV - > IoT	0.032	0.105	0.211
DSAV - > IoT	0.054	0.024	0.048
IoT - > Blockchain Adoption	-0.123	0.996	0.008
PTV - > IoT	0.028	0.072	0.144
PV - > IoT	-0.061	0.994	0.012
SIV - > IoT	0.039	0.033	0.065

Source: Authors.

reducing blockchain's relative importance. Bachelor's education positively moderates the DSAV-IoT relationship (diff = 0.054, $p < 0.05$), suggesting digital society affinity more strongly influences IoT adoption among university-educated users. However, it negatively moderates both the IoT-blockchain adoption relationship (diff = -0.123, $p < 0.01$) and the PV-IoT relationship (diff = -0.061, $p < 0.05$), indicating these relationships are weaker among bachelor's degree holders who may have more complex decision criteria.

The numbers highlight in Table 16 above show the moderating effect of education on the model. The results show that after putting a Master's Degree in education into the model, the Path Coefficients have no significant difference between a Master's Degree and Non-Master's Degree, indicating that a Master's Degree cannot moderate the model.

For the PhD Degree of Education, as only 19 people chose a PhD, the cases are less than 21, and the sample size is too small to do PLS-MGA. The sample size for estimating the PLS path model must be larger than the maximum number of indicators in a measurement model or the maximum number of predictors (exogenous) variables in a structural regression. Therefore, the authors do not know if a PhD Degree in Education can moderate the model.

4.8.4. Moderating effect of knowledge of IoT

Fig. 5 and Table 17 above show the significant moderating effect of Knowledge of IoT on the model.

The results reveal that IoT knowledge positively moderates the relationship between CEV and IoT adoption ($\beta = 0.011, t = 3.262, p < 0.01$). This positive moderation indicates that citizen empowerment has a stronger influence on IoT adoption among users with higher IoT knowledge. Knowledgeable users better understand how IoT enables their participation in smart city governance, thus amplifying the empowerment effect. Furthermore, IoT knowledge positively moderates the blockchain adoption-CUI relationship ($\beta = 0.085, t = 2.873, p <$

Table 16
The moderating effect of education (master's degree).

Moderating Effect Path	Path Coefficients-diff (Female - Male)	p-Value original 1-tailed (Female vs Male)	p-Value (Female vs Male)
Blockchain Adoption - > CUI	-0.011	0.535	0.929
CEV - > IoT	-0.013	0.655	0.690
DSAV - > IoT	-0.007	0.589	0.823
IoT - > Blockchain Adoption	0.006	0.435	0.869
PTV - > IoT	-0.033	0.921	0.157
PV - > IoT	0.019	0.289	0.578
SIV - > IoT	-0.004	0.577	0.846

Source: Authors.

0.01). This indicates that the positive impact of blockchain adoption on continuous usage intention is stronger for users with higher IoT knowledge. Knowledgeable users may better appreciate blockchain's benefits (e.g., security, transparency), thus amplifying its importance for their continued engagement with IoT services.

The results align with the research of Pahnla et al. (2011) and Singh and Matsui (2017).

4.8.5. Moderating effect of E-government using experience

Fig. 6 and Table 18 above show the moderating effect of Experience of using e-Government on the model. The results show that after putting the Experience of using e-Government into the model, the product term of Experience of using e-Government and each variable has no significant effects on the model, indicating that Experience of using e-Government cannot moderate the model. This result is in line with the research by Faqih and Jaradat (2015), which mentioned that experience could not play a moderating role in the adoption of new technology.

4.8.6. Moderating effect of frequency of IoT use

The Fig. 7 and the Table 19 above show shows the significant moderating effect of Frequency of IoT Use on the model. Frequency of IoT use demonstrates dual moderating effects. First, it positively moderates the CEV-IoT relationship ($\beta = 0.013, t = 3.008, p < 0.01$), indicating that citizen empowerment more strongly influences IoT adoption among frequent users. Regular engagement with IoT services enhances users' appreciation of participatory opportunities, strengthening the empowerment-adoption link. Second, frequency negatively moderates the SIV-IoT relationship ($\beta = -0.01, t = 2.037, p < 0.05$). This negative moderation reveals that social influence has a weaker effect on IoT adoption among frequent users. As usage becomes habitual, personal experience supersedes social opinions in driving adoption decisions, reducing susceptibility to peer influence. The results align with the research of Pahnla et al. (2011) and Singh and Matsui (2017).

4.8.7. The moderating effect of daily IoT use

Fig. 8 and Table 20 above show the significant moderating effect of IoT on Daily life in the model. Daily IoT use positively moderates the blockchain adoption-CUI relationship ($\beta = 0.076, t = 2.486, p < 0.05$). This positive moderation indicates that blockchain's influence on continuous usage intention is stronger among users who integrate IoT into their daily routines. For these deeply engaged users, blockchain's security and trust features become more valuable as they have greater personal investment in the system, thus amplifying blockchain's role in sustaining their usage. The results align with the research of Pahnla et al. (2011) and Singh and Matsui (2017).

4.8.8. Moderating effect of location of work

Table 21 above shows the significant moderating effect of the Location of work on the model.

Work location demonstrates significant moderating effects, with rural location strengthening key relationships. The blockchain adoption-CUI relationship is significantly stronger in rural areas (diff = 0.189, $p < 0.05$), suggesting rural users derive greater value from blockchain's trust and security features. This may reflect limited alternative trust mechanisms in rural contexts, making blockchain more critical for sustained usage.

Similarly, the IoT-blockchain adoption relationship is stronger among rural workers (diff = 0.164, $p < 0.05$). Rural users who adopt IoT show greater propensity to embrace blockchain, potentially viewing it as essential infrastructure for reliable smart city services. These findings highlight the heightened importance of trust-building technologies in less developed areas where traditional institutional trust may be weaker.

5. Discussion and findings

This study extends Boustani et al.'s (2022) IoT adoption model by

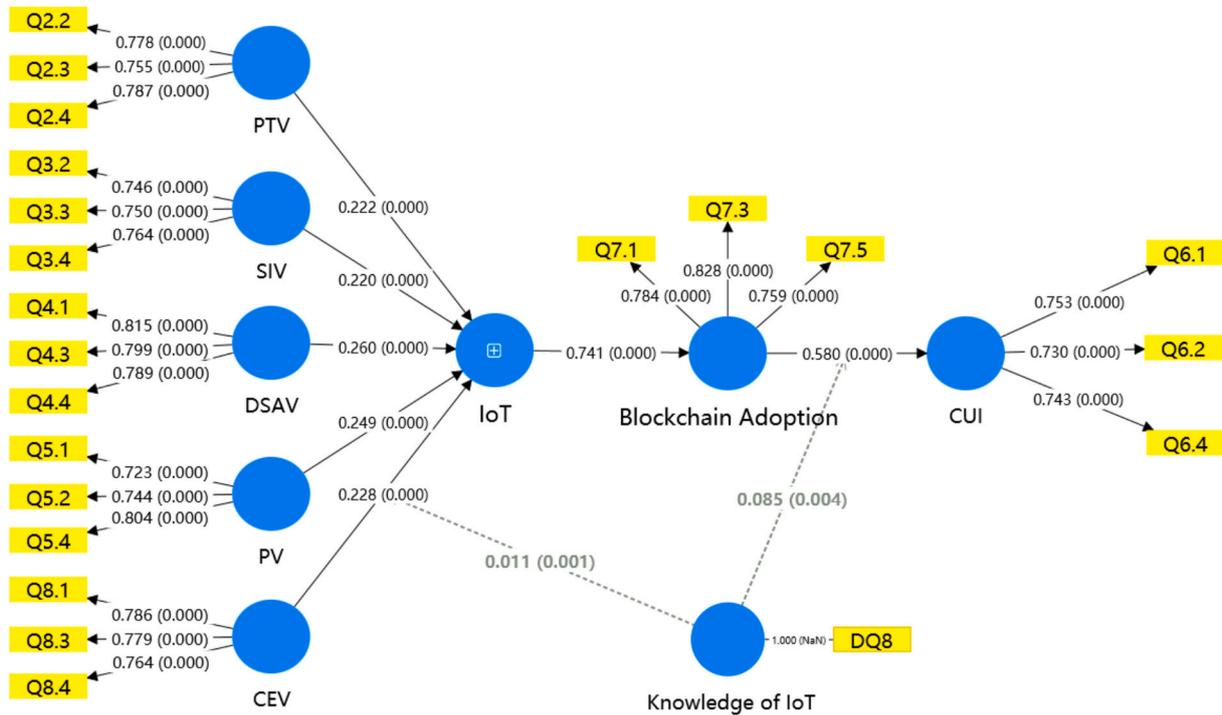


Fig. 5. Moderating effect of knowledge of IoT. Source: Authors.

Table 17 Moderating effect of knowledge of IoT.

Knowledge of IoT Moderating Effect Path	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics (O/STDEV)	P Values
Block-chain Adoption- > CUI	0.085	0.084	0.030	2.873	0.004
CEV- > IoT	0.011	0.011	0.003	3.262	0.001

STDEV: Standard Deviation. Source: Authors.

revealing how sociodemographic factors create boundary conditions for technology adoption in smart cities. The authors’ findings demonstrate that individual characteristics significantly influence the established relationships between IoT adoption, blockchain, and continuous usage intention, providing a more nuanced understanding of technology adoption in diverse populations.

5.1. Analysis of the moderating effect of frequency of iot use

The results presented in Fig. 7 and Table 19 show the significant moderating effect of the Frequency of IoT Use on the model.

Regulation of CEV on IoT: The effect of CEV (Citizens Empowerment Value) on IoT is found to be significant (O = 0.227, T = 23.414, p < 0.01) when the Frequency of IoT Use is considered. This means that the more frequently individuals use IoT devices, the stronger the influence of Citizens Empowerment Value on their intention to use IoT. In other words, people who frequently use IoT devices are more likely to be influenced by the perceived value of empowerment in their decision to continue using IoT technology.

Regulation of SIV on IoT: Similarly, the effect of SIV (Social Influence Value) on IoT is significant (O = 0.221, T = 27.770, p < 0.01) when the Frequency of IoT Use is considered. This suggests that the frequency of using IoT devices can regulate the impact of social influence on an individual’s intention to use IoT. Those who use IoT devices more

frequently are less affected by social influence in their decision to use IoT technology compared to those who use IoT devices less frequently.

Frequency of IoT Use on SIV: The product term of SIV and Frequency of IoT Use has a significant effect on IoT (O = -0.010, T = 2.037, p < 0.05). This indicates that the frequency of using IoT devices has a moderating effect on the relationship between social influence and IoT usage. The more frequently individuals use IoT devices, the weaker the influence of social influence on their intention to use IoT. In other words, frequent IoT users are less likely to be influenced by others’ opinions or recommendations when deciding to use IoT technology.

Overall, these findings suggest that the frequency of using IoT devices plays a crucial role in moderating the effects of Citizens Empowerment Value and Social Influence Value on individuals’ intention to use IoT technology. As individuals use IoT devices more frequently, their decision-making process regarding IoT adoption becomes less influenced by external factors (such as social influence) and more driven by their own perceived value of empowerment.

5.2. Analysis of the moderating effect of daily IoT use

The results presented in Fig. 8 and Table 20 show the significant moderating effect of IoT on Daily Life in the model. When analyzing the implications of this moderating effect on the specific model variables, the research findings are as follows:

Moderation of Blockchain Adoption on CUI: The product term of Blockchain Adoption and Knowledge of IoT has a significant effect on CUI (O = 0.076, T = 2.486, p < 0.05) when IoT of Daily Life is considered. This indicates that the adoption of blockchain technology in IoT is influenced by an individual’s daily life usage of IoT devices. It suggests that individuals who frequently incorporate IoT devices into their daily activities are more likely to be influenced by the adoption of blockchain technology in their intention to continue using IoT.

Overall, this finding implies that the integration of IoT devices into individuals’ daily routines can play a moderating role in the relationship between blockchain adoption and their intention to use IoT technology. Daily IoT users may be more receptive to the adoption of blockchain

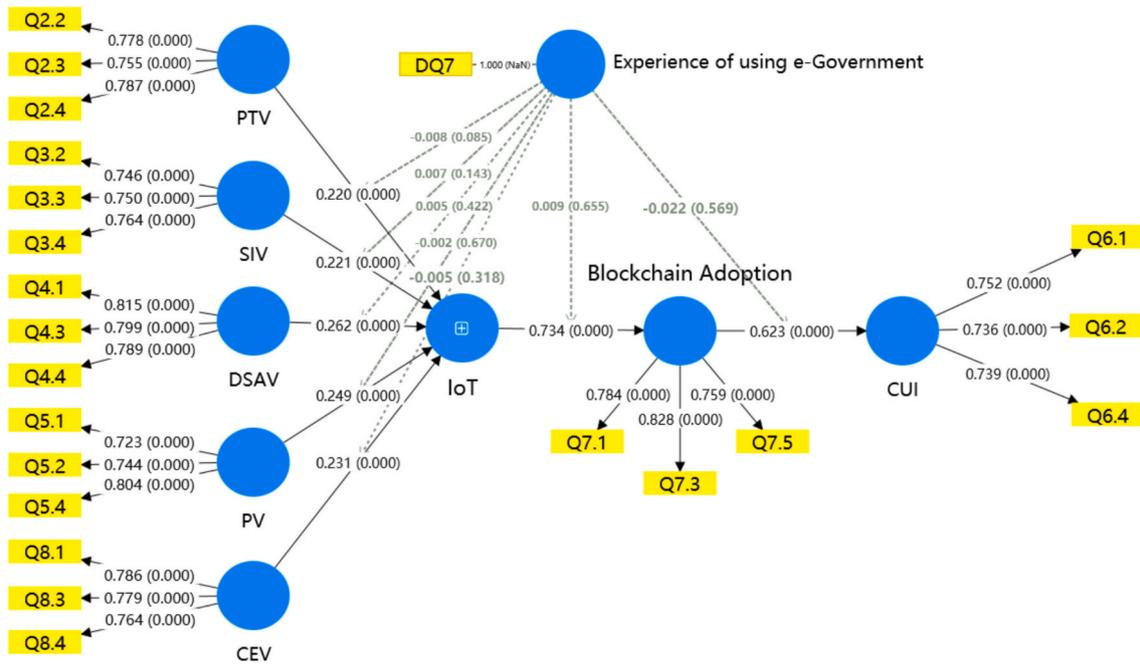


Fig. 6. Moderating effect of E-government using experience. Source: Authors.

Table 18 Moderating effect of E-government using experience.

E-government using experience Moderating Effect Path	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics	P Values
CEV → IoT	-0.005	-0.005	0.005	0.999	0.318
IoT → Blockchain Adoption	0.009	0.008	0.019	0.447	0.655
PTV → IoT	-0.008	-0.008	0.004	1.725	0.085
Blockchain Adoption → CUI	-0.022	-0.023	0.039	0.569	0.569
PV → IoT	-0.002	-0.002	0.005	0.426	0.670
SIV → IoT	0.007	0.006	0.005	1.464	0.143
DSAV → IoT	0.005	0.005	0.006	0.803	0.422

STDEV: Standard Deviation. Source: Authors.

technology in IoT applications compared to those who do not use IoT devices as frequently in their daily lives.

The results presented in Table 21 show the significant moderating effect of the Location of Work on the model.

5.3. Moderation of blockchain adoption on CUI

The Path Coefficients of Blockchain Adoption -> CUI has a significant difference between Rural and Urban (Diff = 0.189, p < 0.05) when the Location of Work is considered. This indicates that the location of an individual's workplace can moderate the relationship between blockchain adoption and their intention to use IoT technology. People working in rural areas may have different perceptions and attitudes toward blockchain adoption in IoT compared to those working in urban areas.

5.4. Moderation of IoT on blockchain adoption

Similarly, the Path Coefficients of IoT -> Blockchain Adoption have a significant difference between Rural and Urban (Diff = 0.164, p < 0.05) when the Location of Work is considered. This suggests that the

location of work can also moderate the effect of IoT usage on individuals' adoption of blockchain technology. IoT users working in rural areas may have different levels of interest or need for blockchain technology compared to their urban counterparts.

Overall, these findings imply that the location of work can influence individuals' perceptions and decisions regarding both blockchain adoption in IoT and their intention to use IoT technology. Differences in rural and urban environments may lead to varying levels of interest, understanding, and acceptance of these technologies, thereby influencing their adoption in smart cities. The study by Boustani et al. (2022), which investigated the combination of blockchain and IoT in China's smart public services, is consistent with the authors' findings, underlining the importance of location in technological adoption.

In conclusion, the analysis of the moderating effects of Frequency of IoT Use, Daily IoT Use, and Location of Work provides valuable insights into how these factors can influence the adoption and usage of IoT technology in smart cities. Understanding these moderating effects can assist policymakers and urban planners in tailoring smart city initiatives to the specific needs and preferences of different user groups based on their IoT usage habits and location of work. Additionally, these findings can also guide companies and technology developers in designing IoT solutions that align with the varying characteristics and demands of different user segments in smart cities.

5.5. Analysis of the moderating effect of age, knowledge of IoT, and frequency of IoT use together

Knowledge of IoT moderates the effect of CEV (Citizens Empowerment Value) on IoT (p < 0.01), indicating that individuals' knowledge of IoT can influence how much they are empowered by IoT technology.

Frequency of IoT Use moderates the effect of SIV (Social Influence Value) on IoT (p < 0.01), suggesting that the frequency of using IoT devices can impact how much social influence affects individuals' IoT usage decisions.

Age moderates the effect of Blockchain Adoption on CUI (Continuous Usage Intention of IoT) (p < 0.05), implying that age plays a role in how individuals' intention to continue using IoT is influenced by blockchain adoption.

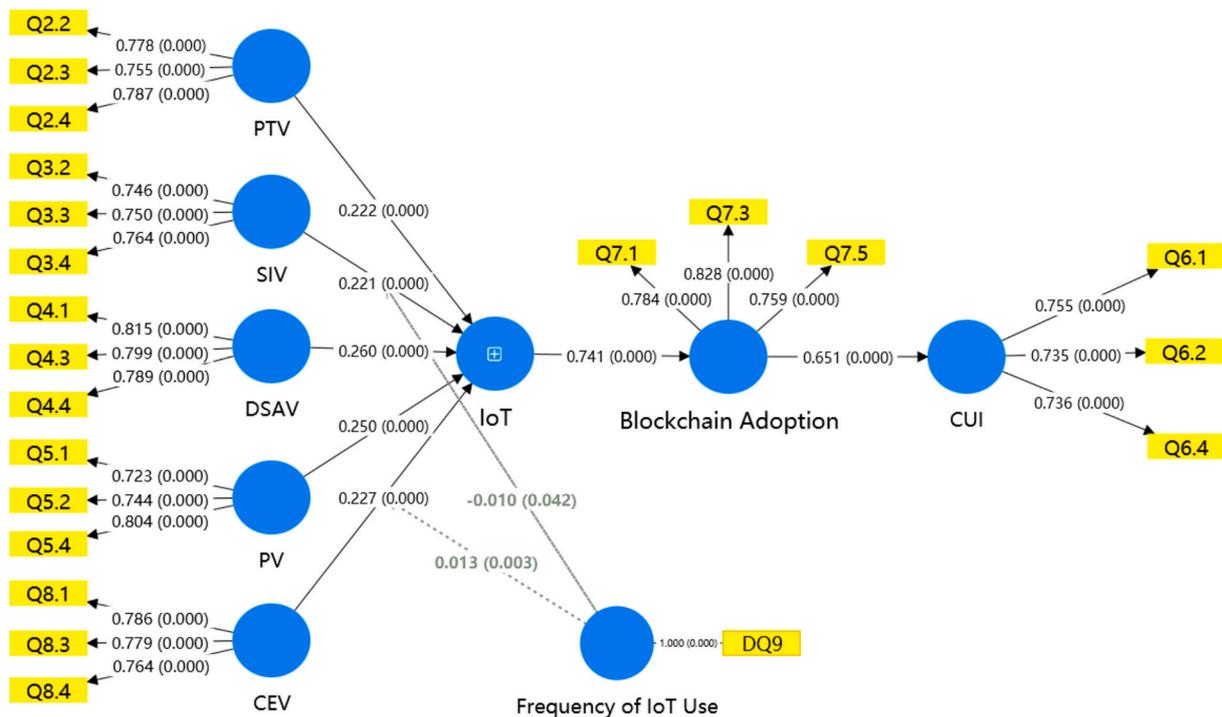


Fig. 7. Moderating effect of frequency of IoT use. Source: Authors.

Table 19 Moderating effect of frequency of IoT use.

Frequency of IoT Use Moderating Effect Path	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics (O/STDEV)	P Values
CEV -> IoT	0.013	0.013	0.004	3.008	0.003
SIV -> IoT	-0.010	-0.010	0.005	2.037	0.042

STDEV: Standard Deviation. Source: Authors.

5.6. Analysis of the moderating effect of control variables separately

Moderating Effect of Age: Age moderates the effect of Blockchain Adoption on CUI ($p < 0.01$), suggesting that the age of respondents influences how blockchain adoption affects their continuous intention to use IoT.

Moderating Effect of Gender: Gender does not have a significant moderating effect on the model, indicating that gender differences do not substantially impact the relationships among the variables.

Moderating Effect of Education: Education level shows significant moderating effects on the model. Both High School and Bachelor's Degrees can moderate the effect of Blockchain Adoption on CUI, and Bachelor's degrees can moderate the effect of DSAV (Daily IoT Use) on IoT.

5.7. Analysis of the moderating effect of knowledge of IoT

Knowledge of IoT moderates the effect of CEV on IoT ($p < 0.01$) and the effect of Blockchain Adoption on CUI ($p < 0.01$), suggesting that individuals' understanding of IoT technology can influence the impact of value perception and blockchain adoption on their intention to use IoT.

5.8. Analysis of the moderating effect of E-government using experience

Experience of using e-Government does not have a significant moderating effect on the model, indicating that this variable does not substantially influence the relationships among the studied factors.

These research findings related to sociodemographic factors can be split into compliant or different from previous studies in this field.

To begin with, gender has no significant influence on the model. This finding is consistent with the findings of Albert et al. (2019), who explored gender and generational differences in views of IoT devices and found that gender had no significant moderating effect on the model. Furthermore, the study by Goswami and Dutta (2015), which examined gender variations in technology usage, is consistent with the authors' findings that gender may not have a substantial influence on attitudes toward IoT adoption in some settings. Li and Kirkup (2007) explored gender and cultural disparities in Internet usage in China and the United Kingdom. While the context differs, the current study's conclusion of gender not significantly modifying the model is consistent with the premise that gender effects on technology adoption may vary between cultures. Nysveen et al. (2005) investigated mobile chat service intention and the moderating effect of gender. This conclusion that gender did not significantly influence the model is consistent with the idea that gender impacts on technology adoption may differ depending on the technology and circumstance. Boudreau and Kaushik (2023) conducted a field experiment on gender differences in responses to competitive organizations using IoT platforms, whereas Goswami and Dutta (2015) evaluated gender variations in technology utilization. Despite differences in context, both papers emphasize the need for gender issues in IoT research. Our findings that gender had no substantial moderating effect on the model are consistent with earlier research, implying that gender may not have a significant influence on attitudes regarding IoT adoption.

Age, on the other hand, has the potential to greatly mitigate the influence of Blockchain Adoption on the Continuous Usage Intention of IoT (CUI). This finding is consistent with the findings of Acheampong and Cugurullo (2019), who discovered that age was a key moderator in

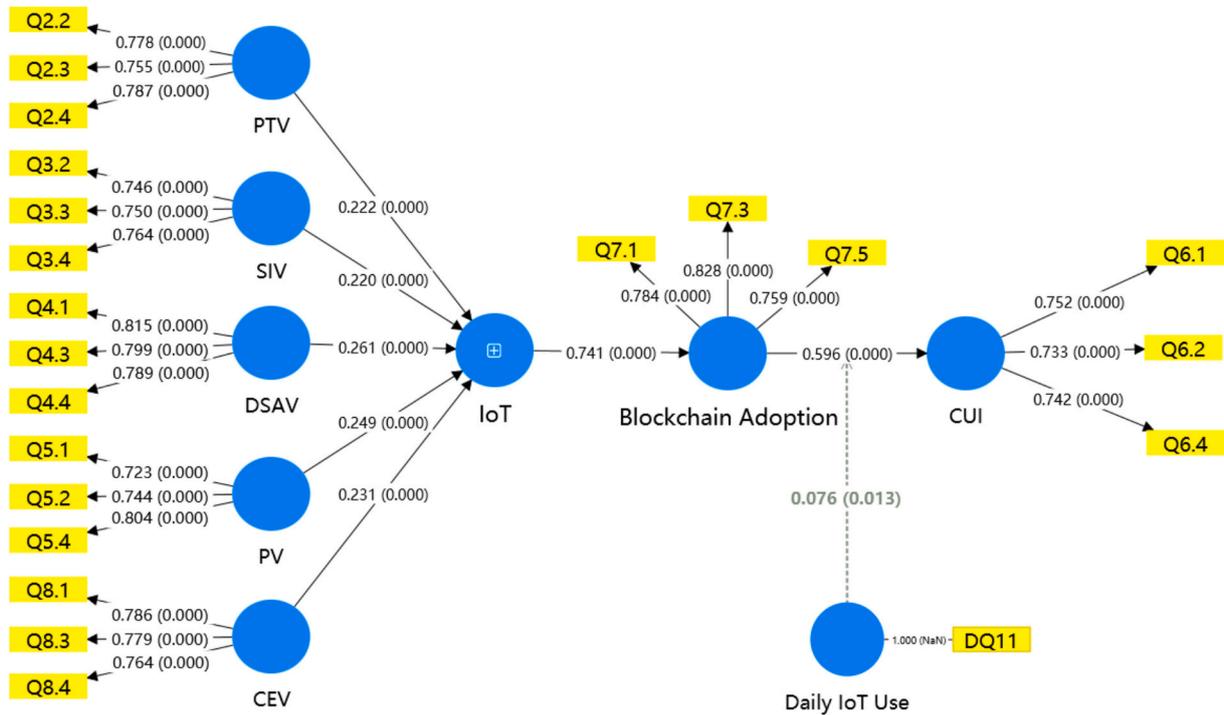


Fig. 8. The moderating effect of daily IoT use. Source: Authors.

Table 20 The moderating effect of daily IoT use.

Daily IoT Use Moderating Effect Path	Original Sample (O)	Sample Mean (M)	STDEV	T Statistics (O/STDEV)	P Values
Block-chain Adoption -> CUI	0.076	0.076	0.031	2.486	0.013

STDEV: Standard Deviation. Source: Authors.

Table 21 Moderating effect of location of work.

Moderating Effect Path	Path Coefficients-diff (Female - Male)	p-Value original 1-tailed (Female vs Male)	p-Value new (Female vs Male)
Blockchain Adoption -> CUI	0.189	0.021	0.042
IoT -> Blockchain Adoption	0.164	0.005	0.01

Source: Authors.

the association between blockchain adoption and IoT continuous usage intention. Similarly, a study conducted by Eker et al. (2020) on public perceptions of flying cars underscores the importance of demographic characteristics such as age in affecting attitudes toward technological breakthroughs. Kim and Huh (2007) studied the consumption ideals and lifestyles of several generations, including Generation Y. The current study's emphasis on age disparities in technology usage highlights the importance of taking generational views into account while implementing IoT. Kumar and Lim (2008) investigated generational disparities in mobile service perceptions among Generation Y and baby boomers. Our findings on the moderating effect of age on blockchain

adoption and continuous usage intention are consistent with earlier research highlighting age-based disparities in technology views. The findings of the authors' study on age moderation are consistent with the importance of demographic considerations in affecting attitudes toward technological developments. Alraja (2022) researched the behavioral intentions of frontline healthcare providers toward IoT-enabled healthcare applications. Despite differences in context, earlier research and the current study both emphasize the importance of gender and generational disparities in technology adoption decisions. Acheampong and Cugurullo (2019) discovered that numerous behavioral variables influenced autonomous vehicle adoption.

However, regarding the Usage findings, the authors can say that for the level of Knowledge of IoT, the authors' research discovered that Knowledge of IoT can moderate the influence of Consumer Experience Value (CEV) on IoT and the effect of Blockchain Adoption on CUI. This finding is consistent with the findings of Arfi et al. (2021), who explored the acceptability of eHealthcare by IoT natives and immigrants and underlined the role of knowledge and awareness as major determinants influencing technology acceptance. Furthermore, for the Frequency of IoT Use, the authors' research discovered that Frequency of IoT Use can regulate the influence of CEV on IoT as well as the effect of Social Influence Value (SIV) on IoT. Additionally, the study by Al-Momani et al. (2018), which investigated factors influencing the acceptability of IoT services, confirms the significance of usage frequency in defining the impact of specific aspects on IoT adoption.

Alkaws and Baashar (2020) investigated Malaysians' acceptance of IoT-based smart meters. While the current study was conducted in a different setting (China), both studies underline the importance of knowledge and awareness in mitigating the influence of certain factors on IoT adoption. Arfi et al. (2021) evaluated IoT natives' and immigrants' acceptability of eHealthcare. The findings concerning education's moderating effect are consistent with the emphasis on knowledge and awareness as important elements influencing technology acceptance. Yang et al. (2018) investigated IoT smart home adoption and the significance of automation, with the findings emphasizing the moderating effect of Frequency of IoT Use on IoT adoption as well as the value

of continuous usage in IoT adoption decisions. Zhang and Kamargianni (2022) examined the factors influencing the adoption of new mobility technologies such as driverless vehicles and the Internet of Things. While the exact topic of each study differs, both emphasize the significance of examining factors influencing technology adoption.

The finding that age positively moderates the blockchain adoption–continuous usage intention relationship aligns with studies emphasizing older users' preference for secure systems (Miltgen & Peyrat-Guillard, 2014), though it contrasts with Western literature where age often inhibits adoption (Charness & Boot, 2009). This points to the distinct digital transformation environment in China. Similarly, IoT knowledge as a positive moderator of the citizen empowerment–IoT relationship supports empowerment theory (Zimmerman, 2000) and reinforces the role of digital literacy in driving engagement. Interestingly, frequent IoT users were less influenced by social norms, suggesting that as users become more experienced, they rely less on peer opinions—diverging from earlier-stage adoption models (Taylor & Todd, 1995).

Overall, the authors' findings are consistent with prior studies, notably in the gender and age groups, as well as usage results relating to IoT expertise, frequency of IoT use, and work location.

5.9. Limitations and future studies

To maintain the survey's basic focus, the study encountered various challenges and did not address the factors that could influence the target respondents' use of technologies and IoT, as well as their opinion of blockchain. The study attempted to identify the influence of UTAUT2 characteristics on sociodemographic variables on IoT use and validated its findings using hypothesis testing. The authors were successful in integrating blockchain concepts into the UTAUT2 paradigm. Further research could concentrate on incorporating more sociodemographic variables to obtain innovative outcomes.

It is worth noting that the authors' research contributes to the growing body of literature on smart cities, IoT, and technology adoption, particularly in China. The findings can help to improve policy planning, targeted interventions, and informed decision-making when creating and implementing smart city programs specially for young generation and tackling rural regions as well. As the study investigates how age, gender, education, IoT expertise, frequency of IoT use, daily IoT use, and work location influence IoT technology adoption in Chinese smart cities, the authors may consider the implications of the research findings and their potential applications in real-world smart city initiatives in future studies.

Furthermore, future research could delve into the reasons for the observed moderating effects, investigate more constructs when current moderating variables are considered direct predictors rather than moderators (including potential endogeneity), and incorporate broader demographic controls such as income levels and detailed urban-rural distinctions to improve model generalizability. Also, look into how user education and awareness efforts might help increase adoption of IoT technology in various demographics.

From a managerial and policy standpoint, the findings of this study have significant implications for the design and implementation of smart city initiatives. The positive influence of age on the blockchain adoption–continuous usage intention link suggests that different age groups respond differently to technological integration, calling for age-sensitive engagement strategies and training programs. As IoT knowledge enhances the effect of citizen empowerment on IoT adoption, it becomes essential for urban managers and decision-makers to prioritize public education and digital literacy initiatives. Enhancing citizens' understanding of IoT technologies will likely foster more active and empowered participation in smart city environments.

The observation that frequency of IoT use negatively moderates the relationship between social influence and IoT adoption indicates that habitual users rely less on social cues, suggesting the need for

personalization in service design. Smart city solutions should therefore cater to user-specific needs rather than depend solely on peer influence or social trends to drive adoption. These insights advocate for a more inclusive approach to policy-making, where technological solutions are aligned with the diverse capabilities and preferences of the population.

Moreover, the confirmed mediating role of blockchain technology highlights its strategic value in fostering trust, transparency, and accountability in smart city operations. Governments and urban planners should leverage blockchain-enabled systems to enhance citizen confidence, particularly in managing personal data and delivering public services. By acknowledging and acting upon the differentiated needs of citizens, policy frameworks can better support the inclusive and sustainable growth of smart cities.

6. Conclusion

This study extends Boustani et al.'s (2022) IoT-blockchain adoption model by revealing the moderating influence of sociodemographic factors. It sheds light on the adoption of IoT technologies in Chinese smart cities and how various sociodemographic characteristics influence people's desire to use these technologies. Understanding these moderating effects is essential for policymakers and technology developers seeking to customize their strategies and solutions to certain demographic groups and increase general adoption of smart city technologies.

In conclusion, the results of the moderating effects indicate that age, knowledge of IoT, and frequency of IoT use significantly influence the relationships among the variables in the model. These findings can provide valuable insights for policymakers, researchers, and businesses in understanding how demographic and usage-related factors can impact individuals' attitudes and intentions toward IoT adoption and usage. Additionally, the results highlight the importance of considering education levels and knowledge of IoT when designing and implementing IoT initiatives in smart city contexts.

CRedit authorship contribution statement

Nada Mallah Boustani: Validation, Project administration, Formal analysis, Writing – original draft, Supervision, Methodology, Writing – review & editing, Conceptualization. **Qing Xu:** Investigation, Conceptualization, Visualization, Data curation. **Yan Xu:** Software, Validation, Resources.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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