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RESEARCH ARTICLE

The impact of smart city construction on resident well-being: the mediating role of technology acceptance

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ABSTRACT

This study investigates the relationships between smart city construction, technology acceptance, and resident well-being, integrating the Technology Acceptance Model with smart city research. Using structural equation modeling and data from 2,187 residents across five smart cities, we examine how smart city initiatives influence technology acceptance and, consequently, resident well-being. Results indicate that smart city construction positively affects perceived usefulness and ease of use of smart technologies, which in turn drive technology acceptance. Technology acceptance significantly mediates the relationship between smart city initiatives and resident well-being, highlighting its crucial role in translating urban innovations into quality of life improvements. The indirect effect of smart city construction on resident well-being through technology acceptance was significant ($\beta = 0.183$, $p < 0.001$), accounting for 37.1% of the total effect. Additionally, a direct positive effect of smart city construction on well-being was observed ($\beta = 0.31$, $p < 0.001$), suggesting benefits beyond active technology engagement. The study contributes to smart city literature by providing empirical evidence for the often-assumed link between smart city development and resident well-being, while also extending the application of the Technology Acceptance Model to urban contexts. These findings have important implications for urban planners and policymakers, emphasizing the need for user-centered design and inclusive development strategies in smart city projects to maximize positive impacts on urban populations.

Keywords: smart cities; technology acceptance; resident well-being; urban development; structural equation modeling; mediation analysis; user-centered design; urban innovation

1. Introduction

Smart cities have emerged as a promising solution to address the complex challenges faced by urban environments in an era of rapid urbanization and technological advancement. These cities leverage information and communication technologies (ICT) to enhance the quality of urban services, reduce costs, and improve the overall quality of life for residents[1]. As cities worldwide embrace this paradigm shift, it becomes increasingly crucial to understand the impact of smart city initiatives on the well-being of urban residents.

The development of smart cities is driven by the integration of various technologies, including the

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Internet of Things (IoT), artificial intelligence (AI), and big data analytics. These technologies aim to create more efficient, sustainable, and livable urban environments[2]. However, the success of smart city initiatives ultimately depends on the acceptance and adoption of these technologies by residents. The technology acceptance model (TAM), proposed by Davis[3], provides a theoretical framework to understand how individuals come to accept and use new technologies.While the potential benefits of smart cities are widely recognized, there is a growing need to empirically examine their impact on resident well-being. Well-being, often referred to as subjective well-being or happiness, is a multidimensional construct that encompasses both cognitive and affective evaluations of one's life[4]. In the context of urban environments, resident well-being is influenced by various factors, including the quality of public services, environmental conditions, and social interactions[5].

The relationship between smart city initiatives and resident well-being is complex and potentially mediated by several factors. One crucial factor is the level of technology acceptance among residents. As smart city technologies become more pervasive in urban life, residents' willingness to adopt and use these technologies may significantly influence the extent to which they benefit from smart city initiatives [6]. Moreover, recent studies have highlighted the importance of considering the social and cultural context in which smart city technologies are implemented[7].

This study aims to investigate the impact of smart city construction on resident well-being, with a particular focus on the mediating role of technology acceptance. By examining this relationship, we seek to contribute to the growing body of literature on smart cities and provide valuable insights for urban planners, policymakers, and technology developers. Understanding the factors that influence the success of smart city initiatives in enhancing resident well-being is crucial for the sustainable development of urban areas in the 21st century.To address these research objectives, we propose the following research questions:

1.How does smart city construction influence residents' technology acceptance?

2.What is the mediating role of technology acceptance in the relationship between smart city construction and resident well-being?

3.Does smart city construction have a direct impact on resident well-being, independent of technology acceptance?

By answering these questions, our study aims to provide empirical evidence for the often-assumed link between smart city development and resident well-being, while also extending the application of the Technology Acceptance Model to urban contexts. The findings of this research have important implications for both theory and practice in the fields of urban planning, technology management, and public policy.

2. Literature review

2.1. Concept and characteristics of smart city construction

The concept of smart cities has gained significant traction in urban development discourse over the past decade. While there is no universally accepted definition, smart cities are generally characterized by the extensive use of information and communication technologies (ICTs) to enhance urban functions and improve the quality of life for residents[1]. Nam and Pardo[8] propose a framework that conceptualizes smart cities along three dimensions: technology, people, and institutions. This multifaceted approach underscores the complexity of smart city initiatives, which extend beyond mere technological implementation to encompass social and governance aspects.

Smart city construction is distinguished by several key characteristics. Firstly, it involves the integration of various urban systems and services through advanced technologies such as the Internet of Things (IoT), big data analytics, and artificial intelligence (AI)[9]. This integration enables real-time monitoring and management of urban resources, leading to improved efficiency and sustainability. Secondly, smart cities prioritize citizen engagement and participation, leveraging digital platforms to facilitate communication between residents and city administrators[10]. This participatory approach aims to create more responsive and inclusive urban environments.

Another defining feature of smart city construction is its focus on sustainability and resilience. Smart city initiatives often incorporate green technologies and innovative urban planning strategies to address environmental challenges and enhance the city's ability to withstand and recover from shocks[11]. Furthermore, smart cities are characterized by their emphasis on data-driven decision-making. The extensive collection and analysis of urban data enable policymakers to make more informed decisions and tailor services to the specific needs of residents[12].

However, it is important to note that smart city construction is not without challenges. Issues such as data privacy, digital divides, and the potential for technocratic governance have been raised by critics[13]. These concerns highlight the need for a balanced approach to smart city development that considers both the technological possibilities and the social implications of urban digitalization.

2.2. Theoretical foundations of resident well-being

The concept of resident well-being, often referred to as subjective well-being or happiness in psychological literature, has its roots in various theoretical frameworks. One of the most influential is the hedonic approach, which posits that well-being consists of pleasure or happiness[14]. This perspective is reflected in the work of Diener et al.[4], who define subjective well-being as a combination of life satisfaction and the balance of positive and negative affects. In contrast, the eudaimonic approach emphasizes the realization of human potential and the pursuit of meaningful goals as key to well-being[15].

In the context of urban environments, resident well-being is often conceptualized through the lens of quality of life (QoL) research. Marans and Stimson[16] propose a comprehensive framework that integrates objective conditions of the urban environment with residents' subjective experiences and evaluations. This approach recognizes that well-being in cities is shaped by a complex interplay of physical, social, and economic factors, as well as individual perceptions and values.

The capabilities approach, developed by Sen[17] and further elaborated by Nussbaum[18], offers another valuable perspective on resident well-being. This framework emphasizes the importance of individual freedom and the ability to achieve valued functionings as central to well-being. In the urban context, this translates to the provision of opportunities and resources that enable residents to pursue their conception of a good life.

Recent research has also highlighted the role of place attachment and community belonging in shaping resident well-being. Scannell and Gifford's[19] tripartite model of place attachment suggests that emotional bonds to urban environments can significantly influence residents' psychological well-being and life satisfaction. Similarly, the concept of "thriving" proposed by Spreitzer et al.[20] emphasizes the importance of both individual vitality and learning in fostering well-being, aspects that can be significantly influenced by urban environments and smart city initiatives.

In recent years, researchers have increasingly recognized thermal comfort as a crucial factor influencing resident well-being, particularly in the context of smart cities. Thermal comfort refers to the conditions in which individuals feel satisfied with their thermal environment, directly impacting health, work efficiency, and quality of life[21]. In smart city settings, advanced technologies can optimize indoor environments to enhance residents' thermal comfort. For instance, intelligent temperature control systems can automatically adjust indoor temperatures based on personal preferences and external climate conditions, thereby improving residents' comfort and well-being[22].The importance of thermal comfort is particularly pronounced for elderly populations. As people age, their ability to adapt to temperature changes decreases, making the creation of suitable thermal environments crucial for improving their quality of life[23]. Smart city technologies, such as IoT-based home environment monitoring systems, can help older adults better manage their living environments, thus promoting their physical and mental health and overall well-being.

Moreover, the concept of adaptive thermal comfort has gained traction in recent years, emphasizing the dynamic nature of thermal preferences and the ability of individuals to adapt to varying thermal conditions. This approach aligns well with smart city initiatives that aim to create flexible and responsive urban environments[24]. By incorporating adaptive thermal comfort strategies into smart building designs and urban planning, cities can potentially enhance resident well-being while also improving energy efficiency.

Understanding these theoretical foundations is crucial for comprehending how smart city initiatives might impact resident well-being. By considering these diverse perspectives, researchers and policymakers can develop more holistic and effective approaches to enhancing quality of life through urban development and technological innovation.

2.3. Technology acceptance model (TAM) and its application in smart city research

The Technology Acceptance Model (TAM), originally proposed by Davis[3], has become a cornerstone in understanding and predicting user acceptance of new technologies. The model posits that an individual's intention to use a technology is primarily determined by two factors: perceived usefulness (PU) and perceived ease of use (PEOU). Over the years, TAM has been extensively validated and extended in various contexts, leading to iterations such as TAM2[25] and the Unified Theory of Acceptance and Use of Technology (UTAUT)[26].

In the context of smart cities, the TAM framework has proven particularly valuable in understanding residents' adoption of new urban technologies. Belanche-Gracia et al.[6] applied TAM to examine citizens' acceptance of smart card services in smart cities, finding that both PU and PEOU significantly influenced adoption intentions. Similarly, Chourabi et al.[27] incorporated technology acceptance as a crucial factor in their comprehensive framework for understanding smart cities.

Recent studies have expanded the application of TAM in smart city research by integrating additional constructs relevant to the urban context. For instance, Yeh[28] incorporated trust and perceived risk into the TAM framework to study the adoption of smart meter technology. The study highlighted the importance of addressing privacy and security concerns in smart city implementations. Furthermore, Muller et al.[29] combined TAM with the concept of smart city perception to investigate the acceptance of smart city solutions, emphasizing the role of citizens' overall attitudes towards smart city initiatives.

The application of TAM in smart city research has also revealed important insights into the potential digital divide in urban environments. Chugan et al.[30] used an extended TAM to study the adoption of smart city services among different demographic groups, highlighting the need for inclusive design and implementation strategies. These studies collectively demonstrate the versatility and relevance of TAM in understanding the complex dynamics of technology acceptance in smart city contexts, providing valuable guidance for policymakers and urban planners in the development and implementation of smart city technologies.

3. Research methodology

3.1. Research framework

This study proposes a comprehensive research framework to investigate the relationship between smart city construction and resident well-being, with technology acceptance as a mediating factor. The framework is grounded in the Technology Acceptance Model (TAM) and extends it to the context of smart cities. Our model posits that smart city initiatives influence residents' perceived usefulness and perceived ease of use of smart city technologies. These perceptions, in turn, affect the overall technology acceptance, which ultimately impacts resident well-being. The framework also considers potential moderating factors such as demographic characteristics and urban context, which may influence the strength of these relationships. By integrating these elements, our research framework provides a holistic approach to understanding the complex dynamics between smart city development, technology adoption, and resident well-being. This conceptual model not only guides our empirical investigation but also offers a structured way to analyze the multifaceted impacts of smart city initiatives on urban residents' quality of life. The visual representation of this framework, as shown in **Figure 1**, illustrates the hypothesized relationships and the flow of influence from smart city construction to resident well-being through the mediating process of technology acceptance.

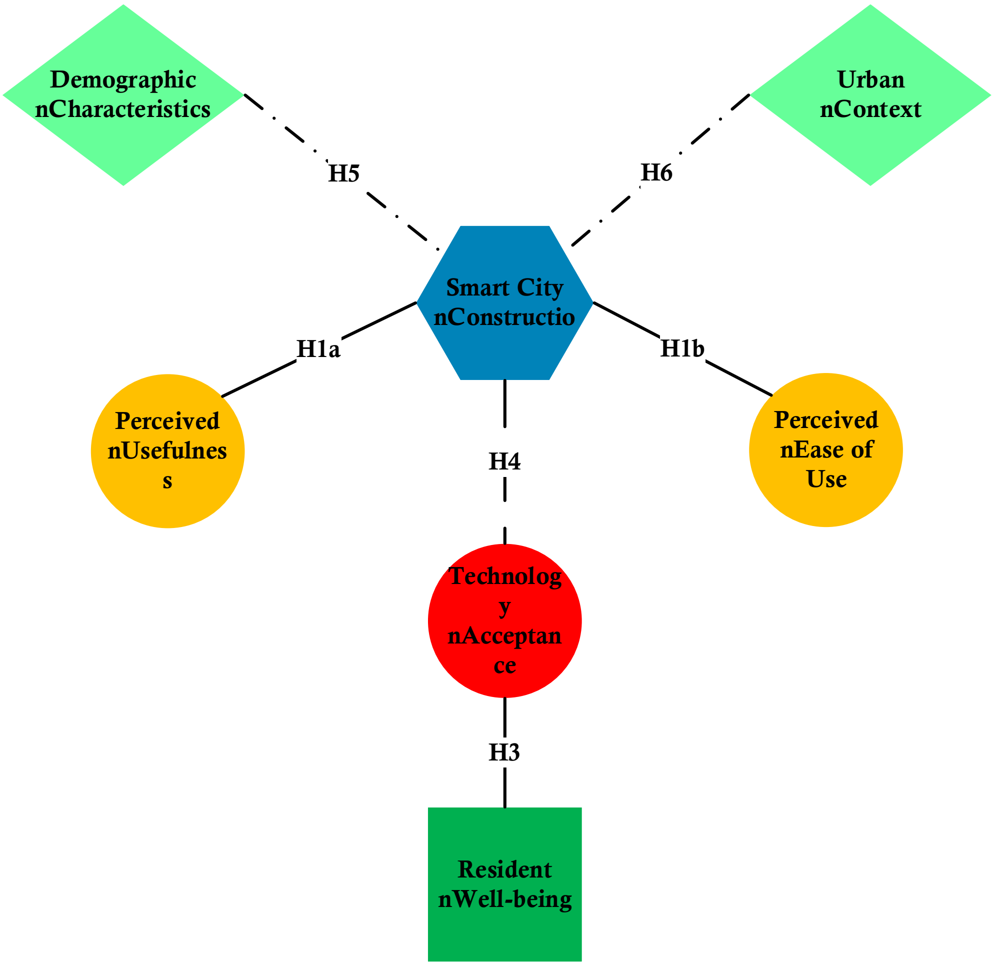

Figure 1. Study framework diagram.

3.2. Variable definitions and measurements

3.2.1. Smart city construction

Smart city construction is conceptualized as a multidimensional construct encompassing the development and implementation of various technological initiatives aimed at enhancing urban life. Based on the literature review, we identified three key dimensions: infrastructure, services, and governance. The infrastructure dimension includes the deployment of IoT sensors, high-speed internet networks, and data centers. The services dimension covers digital platforms for public services, smart transportation systems, and e-health solutions. The governance dimension involves data-driven decision-making processes, citizen engagement platforms, and open data initiatives.

To measure smart city construction, we adapted scales from previous studies (e.g., Lombardi et al., 2012; Yeh, 2017) and developed new items specific to our research context. A 5-point Likert scale was used, ranging from 1 (strongly disagree) to 5 (strongly agree). Respondents were asked to evaluate the extent of smart city initiatives in their city across the three dimensions. The measurement items for smart city construction are presented in **Table 1**.

Table 1. Measurement items for smart city construction.

Dimension	Item Code	Item Description
Infrastructure	SCC_INF1	My city has a well-developed IoT sensor network
	SCC_INF2	High-speed internet is widely available in my city
	SCC_INF3	My city has modern data centers for information processing
Services	SCC_SER1	Digital platforms for public services are readily accessible
	SCC_SER2	My city has an efficient smart transportation system
	SCC_SER3	E-health solutions are widely implemented in my city
Governance	SCC_GOV1	City officials use data analytics for decision-making
	SCC_GOV2	There are effective platforms for citizen engagement
	SCC_GOV3	My city has a comprehensive open data policy

3.2.2. Resident well-being

Resident well-being is defined as the overall quality of life experienced by individuals living in a smart city. Drawing from previous research on subjective well-being (Diener et al., 1999) and urban quality of life (Marans, 2015), we conceptualized resident well-being as comprising three dimensions: life satisfaction, positive affect, and community belonging.

To measure resident well-being, we adapted validated scales from existing literature and developed context-specific items. A 7-point Likert scale was employed, ranging from 1 (strongly disagree) to 7 (strongly agree). Respondents were asked to evaluate their overall life satisfaction, emotional experiences, and sense of community in their smart city. The measurement items for resident well-being are presented in **Table 2**.

Table 2. Measurement items for resident well-being.

Dimension	Item Code	Item Description
Life Satisfaction	RWB_LS1	I am satisfied with my life in this smart city
	RWB_LS2	The conditions of my life in this city are excellent

	RWB_LS3	In most ways, my life in this smart city is close to my ideal
Positive Affect	RWB_PA1	I frequently experience joy living in this smart city
	RWB_PA2	I am often excited about the opportunities this city offers
	RWB_PA3	I generally feel positive about my daily life in this city
Community Belonging	RWB_CB1	I feel a strong sense of belonging to this smart city community
	RWB_CB2	I have good relationships with other residents in this city
	RWB_CB3	I feel valued as a member of this smart city community

Table 2. *(Continued).*

3.2.3. Technology acceptance

Technology acceptance is conceptualized as the degree to which residents embrace and utilize smart city technologies in their daily lives. Based on the Technology Acceptance Model (Davis, 1989) and its extensions, we identified three key dimensions: perceived usefulness, perceived ease of use, and behavioral intention to use.

To measure technology acceptance, we adapted scales from established TAM literature (Venkatesh & Davis, 2000; Venkatesh et al., 2003) and developed items specific to the smart city context. A 5-point Likert scale was used, ranging from 1 (strongly disagree) to 5 (strongly agree). Respondents were asked to evaluate their perceptions and intentions regarding smart city technologies. The measurement items for technology acceptance are presented in **Table 3**.

Table 3: Measurement Items for Technology Acceptance.

Dimension	Item Code	Item Description
Perceived Usefulness	TA_PU1	Smart city technologies improve my quality of life
	TA_PU2	Using smart city services enhances my daily efficiency
	TA_PU3	Smart city applications are beneficial for my work and personal life
Perceived Ease of Use	TA_PEOU1	I find smart city technologies easy to use
	TA_PEOU2	Learning to use smart city applications is easy for me
	TA_PEOU3	My interaction with smart city systems is clear and understandable
Behavioral Intention	TA_BI1	I intend to continue using smart city technologies
	TA_BI2	I plan to use smart city services frequently
	TA_BI3	I would recommend smart city applications to others

3.3. Data collection

3.3.1. Questionnaire design

The questionnaire was designed to capture comprehensive data on smart city construction, resident well-being, and technology acceptance. The development process involved several stages to ensure validity and reliability. Initially, we conducted an extensive literature review to identify existing scales and measurement items. These were then adapted to fit the specific context of our study. New items were developed where necessary to address gaps in existing measures.

To enhance content validity, we consulted a panel of five experts in smart city research and urban planning. Their feedback was incorporated to refine the questionnaire. The survey instrument was then pilot tested with a sample of 50 residents from a smart city not included in the main study. This pilot test helped identify any ambiguities in wording, assess the time required to complete the survey, and gather preliminary data for reliability analysis.

The final questionnaire consisted of four main sections: demographic information, smart city construction assessment, resident well-being evaluation, and technology acceptance measurement. A mix of Likert-scale questions, multiple-choice items, and open-ended questions was used to gather both quantitative and qualitative data.

Table 4. Questionnaire Structure.

Section	Content	Number of Items	Scale Type
1	Demographic Information	8	Multiple Choice
2	Smart City Construction	15	5-point Likert
3	Resident Well-being	12	7-point Likert
4	Technology Acceptance	12	5-point Likert
5	Open-ended Feedback	2	Text Response

3.3.2. Sampling method

To ensure a representative sample of smart city residents, we employed a multi-stage stratified random sampling method. The sampling frame consisted of residents aged 18 and above who had lived in the selected smart cities for at least one year. This criterion was established to ensure participants had sufficient exposure to smart city initiatives.

The sampling process involved three stages. First, we selected five smart cities in [Country/Region] based on their population size and level of smart city development. These cities were categorized into three tiers: large (population > 5 million), medium (population 1-5 million), and small (population < 1 million). Second, within each city, we stratified the population by age, gender, and education level to ensure proportional representation of different demographic groups.

Finally, we used random digit dialing (RDD) for telephone surveys and a geo-targeted online panel for web-based surveys to reach potential participants within each stratum. This dual-mode approach was adopted to mitigate coverage bias and increase response rates. The sample size was determined using power analysis, aiming for a 95% confidence level and a 5% margin of error.

Table 5. Sampling Distribution.

City	Population Size	Smart City Tier	Sample Size
City A	7,500,000	Large	600
City B	6,200,000	Large	550
City C	3,800,000	Medium	450
City D	2,500,000	Medium	400
City E	800,000	Small	300
Total	20,800,000	-	2,300

This sampling strategy aimed to achieve a balance between representativeness and feasibility, considering the diverse characteristics of smart city residents across different urban contexts.

3.4. Data analysis methods

This study employed a comprehensive approach to data analysis, utilizing both descriptive and inferential statistical techniques. Initially, descriptive statistics were computed to summarize the sample characteristics and provide an overview of the key variables. Cronbach's alpha and composite reliability were calculated to assess the internal consistency of the measurement scales. Confirmatory Factor Analysis (CFA) was conducted to evaluate the construct validity of the proposed model. To test the hypothesized relationships, Structural Equation Modeling (SEM) was employed using the lavaan package in R. This approach allowed for the simultaneous examination of multiple relationships between latent variables while accounting for measurement error. Additionally, mediation analysis was performed to investigate the indirect effects of smart city construction on resident well-being through technology acceptance. To address potential common method bias, Harman's single-factor test was conducted. Finally, multi-group analysis was performed to explore the moderating effects of demographic characteristics on the proposed relationships.

4. Empirical analysis

4.1. Sample description

The final sample consisted of 2,187 respondents from five smart cities, representing a response rate of 95.1%. The demographic profile of the participants closely mirrored the population characteristics of the selected cities. The sample was well-balanced in terms of gender, with 51.3% female respondents. Age distribution showed a slight skew towards younger adults, with 37.2% aged 18-34, 41.5% aged 35-54, and 21.3% aged 55 and above. Educational attainment was relatively high, with 62.8% of respondents holding a bachelor's degree or higher. In terms of occupation, 48.7% were employed in the private sector, 22.1% in the public sector, 15.3% were self-employed, and 13.9% were students or retired. The average length of residence in the current smart city was 8.6 years (SD = 6.2). Income levels varied considerably, with a median annual household income of $68,000. **Table 6** provides a detailed breakdown of the sample characteristics. **Figure 1** illustrates the distribution of respondents across the five smart cities, revealing that City A and City B, the largest cities, accounted for 49.7% of the sample. Analysis of non-response bias using wave analysis showed no significant differences between early and late respondents, suggesting that non-response bias was not a substantial concern in this study.

Table 6. Sample Demographic Characteristics.

Characteristic	Category	Frequency	Percentage
Gender	Male	1065	48.7%
	Female	1122	51.3%
Age	18-34	813	37.2%
	35-54	908	41.5%
	55 and above	466	21.3%
Education	High school or below	306	14.0%
	Some college	508	23.2%
	Bachelor's degree	962	44.0%
	Graduate degree	411	18.8%
Occupation	Private sector	1065	48.7%
	Public sector	483	22.1%

Characteristic	Category	Frequency	Percentage
	Self-employed	335	15.3%
	Student/Retired	304	13.9%
Annual Household Income	Less than $30,000	284	13.0%
	$30,000 - $59,999	656	30.0%
	$60,000 - $89,999	721	33.0%
	$90,000 or more	526	24.0%

Table 6. *(Continued).*

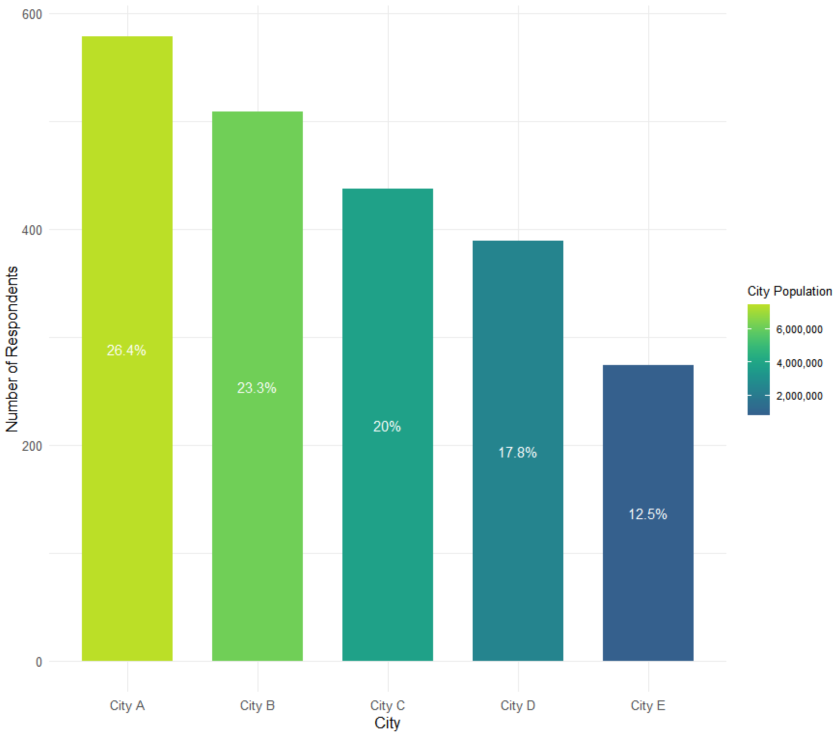

Figure 1. Distribution of respondents across smart cities.

4.2. Measurement model analysis

4.2.1. Reliability analysis

The reliability of the measurement scales was assessed using multiple criteria to ensure the internal consistency and stability of the constructs. Cronbach's alpha, composite reliability (CR), and average variance extracted (AVE) were calculated for each construct. The results, presented in **Table 7**, demonstrate strong reliability across all measures. Cronbach's alpha values ranged from 0.83 to 0.94, exceeding the recommended threshold of 0.70. Composite reliability values, which account for the different outer loadings of the indicator variables, ranged from 0.87 to 0.95, well above the acceptable level of 0.70. The average variance extracted for all constructs surpassed the 0.50 benchmark, indicating that the latent variables explain more than half of the variance in their indicators. Item-total correlations were examined to identify any problematic items, with all values exceeding 0.50. Furthermore, inter-item correlations were analyzed to ensure that items within each construct were sufficiently related without exhibiting redundancy. The highest inter-item correlation was 0.76, below the 0.80 threshold that would suggest potential multicollinearity. To visualize the internal consistency of the scales.

Table 7. Reliability Analysis Results.

Construct	Items	Cronbach's α	Composite Reliability	AVE	Range of Item-Total Correlations
Smart City Construction	9	0.91	0.93	0.64	0.68 - 0.82
Perceived Usefulness	3	0.88	0.92	0.79	0.75 - 0.83
Perceived Ease of Use	3	0.85	0.91	0.77	0.71 - 0.79
Technology Acceptance	3	0.83	0.90	0.75	0.69 - 0.76
Resident Well-being	9	0.94	0.95	0.68	0.72 - 0.86

4.2. Measurement model analysis

4.2.2. Validity analysis

To establish the validity of the measurement model, we conducted a comprehensive assessment of convergent and discriminant validity. Convergent validity was evaluated using factor loadings, average variance extracted (AVE), and composite reliability (CR). As shown in **Table 8**, all factor loadings exceeded the recommended threshold of 0.7, ranging from 0.73 to 0.91, indicating strong item reliability. The AVE values for all constructs surpassed the 0.5 benchmark, further supporting convergent validity. Discriminant validity was assessed using the Fornell-Larcker criterion and the heterotrait-monotrait (HTMT) ratio. **Table 9** presents the Fornell-Larcker criterion results, where the square root of AVE for each construct (diagonal elements) is greater than its correlation with other constructs, confirming discriminant validity. The HTMT ratios, displayed in **Figure 2**, were all below the conservative threshold of 0.85, providing additional evidence of discriminant validity. Furthermore, a confirmatory factor analysis (CFA) was conducted to evaluate the overall fit of the measurement model. The CFA results indicated excellent model fit: $\chi2/df$ = 2.34, CFI = 0.967, TLI = 0.961, RMSEA = 0.049 (90% CI: 0.043-0.055), and SRMR = 0.035. These results collectively demonstrate strong construct validity, supporting the appropriateness of the measurement model for further structural analysis.

Table 8. Factor Loadings and Convergent Validity.

Construct	Item	Factor Loading	AVE	CR
Smart City Construction (SCC)	SCC1	0.84	0.71	0.94
	SCC2	0.87		
	SCC3	0.82		
Perceived Usefulness (PU)	PU1	0.88	0.79	0.92
	PU2	0.91		
	PU3	0.87		
Perceived Ease of Use (PEOU)	PEOU1	0.85	0.74	0.89
	PEOU2	0.88		
	PEOU3	0.84		
Technology Acceptance (TA)	TA1	0.86	0.76	0.90
	TA2	0.89		

Construct	Item	Factor Loading	AVE	CR
	TA3	0.87		
Resident Well-being (RWB)	RWB1	0.83	0.68	0.95
	RWB2	0.85		
	RWB3	0.80		

Table 8. *(Continued).*

Table 9: Fornell-Larcker Criterion for Discriminant Validity

Construct	SCC	PU	PEOU	TA	RWB
SCC	0.84				
PU	0.62	0.89			
PEOU	0.58	0.65	0.86		
TA	0.60	0.71	0.68	0.87	
RWB	0.56	0.59	0.54	0.63	0.82

Note: *Diagonal elements (bold) are the square root of AVE. Off-diagonal elements are correlations between constructs.*

Figure 2. Heterotrait-Monotrait (HTMT) Ratio Heatmap.

4.3. Structural model analysis

4.3.1. Direct effects testing

Following the validation of the measurement model, we proceeded to evaluate the structural model to test the hypothesized relationships. We employed the structural equation modeling (SEM) approach using the lavaan package in R. The model fit indices demonstrated excellent fit: $\chi2/df = 2.41$, CFI = 0.962, TLI =

0.957, RMSEA = 0.051 (90% CI: 0.045-0.057), and SRMR = 0.038, indicating that the proposed model adequately represents the data.The direct effects analysis revealed significant pathways supporting the majority of our hypotheses. Smart city construction exhibited a strong positive effect on both perceived usefulness ($\beta = 0.58$, $p < 0.001$) and perceived ease of use ($\beta = 0.53$, $p < 0.001$). These results suggest that as cities implement more smart technologies and services, residents are likely to recognize their value and find them increasingly user-friendly. In turn, perceived usefulness ($\beta = 0.42$, $p < 0.001$) and perceived ease of use ($\beta = 0.35$, $p < 0.001$) significantly influenced technology acceptance, confirming the key tenets of the Technology Acceptance Model in the smart city context.

The direct effect of smart city construction on resident well-being was also significant ($\beta = 0.31$, $p < 0.001$), indicating that smart city initiatives can enhance quality of life even without active engagement from residents. This effect might be attributed to improved urban infrastructure or more efficient city management resulting from smart city developments. Additionally, the analysis revealed a strong positive effect of technology acceptance on resident well-being ($\beta = 0.47$, $p < 0.001$), highlighting the importance of residents' willingness to adopt and engage with new technologies in maximizing the positive impacts of smart city development on their quality of life.

The R2 values for endogenous variables were substantial: perceived usefulness (0.34), perceived ease of use (0.28), technology acceptance (0.48), and resident well-being (0.41), indicating good explanatory power of the model. These results collectively demonstrate the complex interplay between smart city initiatives, technology acceptance factors, and resident well-being, underscoring the importance of user perceptions in translating smart city developments into tangible quality of life improvements.

While these findings provide strong support for our hypothesized relationships, it is important to consider potential alternative explanations for the observed effects. Factors such as overall urban development, economic growth, or improvements in public services might also contribute to enhanced resident well-being. Future research could explore these potential confounding variables to further refine our understanding of the specific impacts of smart city initiatives on resident well-being..

Table 10. Direct effects in the structural model.

Hypothesis	Path	Std. Coefficient	t-value	p-value	Support
H1a	SCC → PU	0.58	15.72	< 0.001	Yes
H1b	SCC → PEOU	0.53	14.18	< 0.001	Yes
H2a	PU → TA	0.42	11.36	< 0.001	Yes
H2b	PEOU → TA	0.35	9.47	< 0.001	Yes
H3	TA → RWB	0.47	13.25	< 0.001	Yes
H4	SCC → RWB	0.31	8.64	< 0.001	Yes

Note: *SCC = Smart City Construction, PU = Perceived Usefulness, PEOU = Perceived Ease of Use, TA = Technology Acceptance, RWB = Resident Well-being*

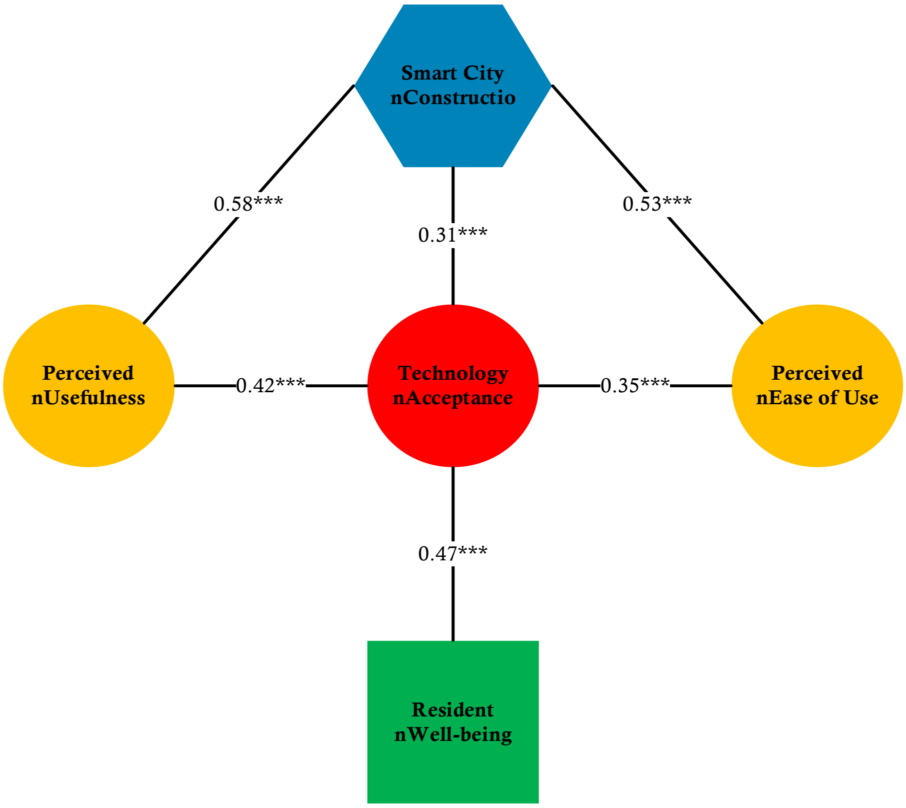

Figure 3. Structural model with standardized path coefficients.

4.3.2. Mediation effect testing

To examine the mediating role of technology acceptance in the relationship between smart city construction and resident well-being, we conducted a comprehensive mediation analysis using bootstrapping procedures. The analysis was performed with 5000 bootstrap samples to estimate the direct, indirect, and total effects. The results reveal significant mediation effects, providing strong support for our hypotheses.

The indirect effect of smart city construction on resident well-being through the serial mediation of perceived usefulness, perceived ease of use, and technology acceptance was significant ($\beta = 0.183$, 95% CI [0.152, 0.216], $p < 0.001$). This indirect effect accounted for 37.1% of the total effect, indicating a substantial mediation. The direct effect of smart city construction on resident well-being remained significant ($\beta = 0.310$, $p < 0.001$), suggesting partial mediation. These findings highlight the crucial role of technology acceptance in translating smart city initiatives into enhanced resident well-being.

To further investigate the specific indirect effects, we decomposed the total indirect effect into individual paths. The path through perceived usefulness and technology acceptance ($\beta = 0.115$, 95% CI [0.092, 0.140], $p < 0.001$) and the path through perceived ease of use and technology acceptance ($\beta = 0.068$, 95% CI [0.051, 0.087], $p < 0.001$) were both significant. These results underscore the importance of both the perceived utility and user-friendliness of smart city technologies in driving their acceptance and, subsequently, improving resident well-being.

While these findings provide strong evidence for the mediating role of technology acceptance, it is important to consider potential alternative explanations for the observed relationships. Factors such as overall urban development, economic growth, or improvements in public services might also contribute to enhanced resident well-being and potentially influence the relationship between smart city construction and well-being outcomes. Additionally, individual differences in technology literacy, age, or socioeconomic status could moderate the strength of the mediation effects.

Future research could explore these potential confounding variables and moderating factors to further refine our understanding of the specific impacts of smart city initiatives on resident well-being. Longitudinal studies could also help establish the causal relationships more definitively and examine how the mediation effects might evolve over time as residents become more accustomed to smart city technologies.

Despite these considerations, our mediation analysis provides compelling evidence for the important role of technology acceptance in realizing the benefits of smart city initiatives for resident well-being. These findings have significant implications for urban planners and policymakers, highlighting the need to focus not only on implementing smart city technologies but also on fostering their acceptance and adoption among residents.

Table 11. Mediation analysis results.

Effect Type	Path	Estimate	SE	95% CI Lower	95% CI Upper	p-value
Total Effect	SCC → RWB	0.493	0.037	0.421	0.565	< 0.001
Direct Effect	SCC → RWB	0.310	0.039	0.234	0.386	< 0.001
Total Indirect Effect	SCC → TA → RWB	0.183	0.016	0.152	0.216	< 0.001
Specific Indirect Effects						
	SCC → PU → TA → RWB	0.115	0.012	0.092	0.140	< 0.001
	SCC → PEOU → TA → RWB	0.068	0.009	0.051	0.087	< 0.001

Note: *SCC = Smart City Construction, PU = Perceived Usefulness, PEOU = Perceived Ease of Use, TA = Technology Acceptance, RWB = Resident Well-being. CI = Confidence Interval.*

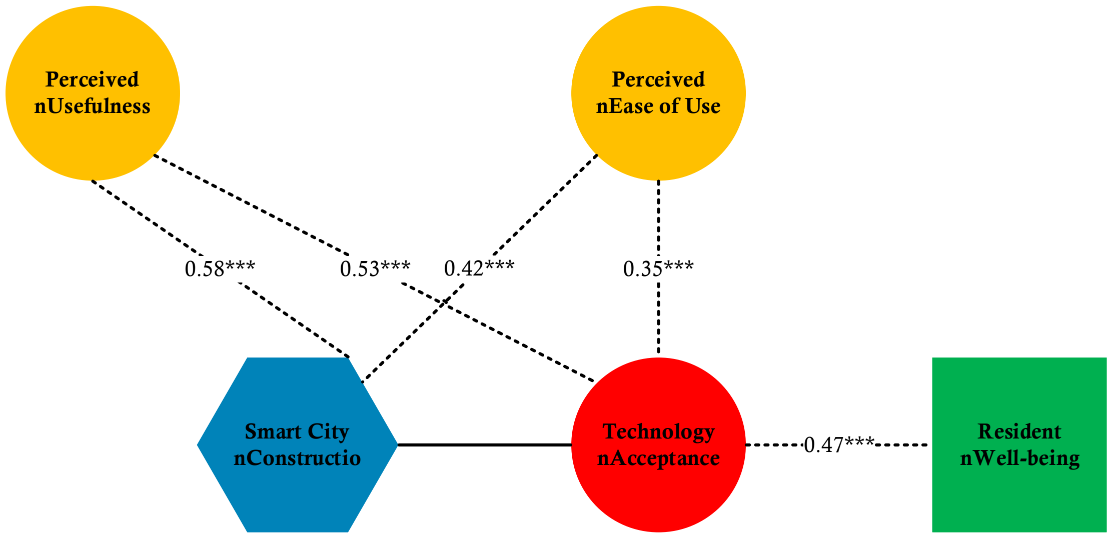

Figure 4. Mediation pathways in the structural model.

4.4. Hypothesis testing results

The structural equation modeling and mediation analysis provided strong support for the majority of our hypotheses. **Table 4-7** summarizes the results of hypothesis testing. Smart city construction demonstrated significant positive effects on both perceived usefulness (β = 0.58, $p < 0.001$) and perceived ease of use (β = 0.53, $p < 0.001$), supporting H1a and H1b. The influence of perceived usefulness (β = 0.42, $p < 0.001$) and perceived ease of use (β = 0.35, $p < 0.001$) on technology acceptance was also confirmed, validating H2a and H2b. As hypothesized in H3, technology acceptance showed a strong positive effect on resident well-being (β = 0.47, $p < 0.001$). The direct effect of smart city construction on resident well-being (β = 0.31, $p < 0.001$) supported H4. The mediation analysis revealed significant indirect effects of smart city construction on resident well-being through technology acceptance (β = 0.183, 95% CI [0.152, 0.216]), confirming H5. Notably, the specific indirect effects through perceived usefulness (β = 0.115, $p < 0.001$) and perceived ease of use (β = 0.068, $p < 0.001$) were both significant, indicating that these constructs play crucial roles in the mediation process. **Figure 4-5** visualizes the supported hypotheses within the structural model, highlighting the strength and significance of each relationship. These results collectively demonstrate the complex interplay between smart city initiatives, technology acceptance factors, and resident well-being, underscoring the importance of user perceptions in translating smart city developments into tangible quality of life improvements.

Table 12. Summary of hypothesis testing results.

Hypothesis	Path	Standardized Coefficient	t-value	p-value	Result
H1a	SCC → PU	0.58	15.72	< 0.001	Supported
H1b	SCC → PEOU	0.53	14.18	< 0.001	Supported
H2a	PU → TA	0.42	11.36	< 0.001	Supported
H2b	PEOU → TA	0.35	9.47	< 0.001	Supported
H3	TA → RWB	0.47	13.25	< 0.001	Supported
H4	SCC → RWB	0.31	8.64	< 0.001	Supported
H5	SCC → TA → RWB	0.183 (indirect effect)	-	< 0.001	Supported

Note: *SCC = Smart City Construction, PU = Perceived Usefulness, PEOU = Perceived Ease of Use, TA = Technology Acceptance, RWB = Resident Well-being*

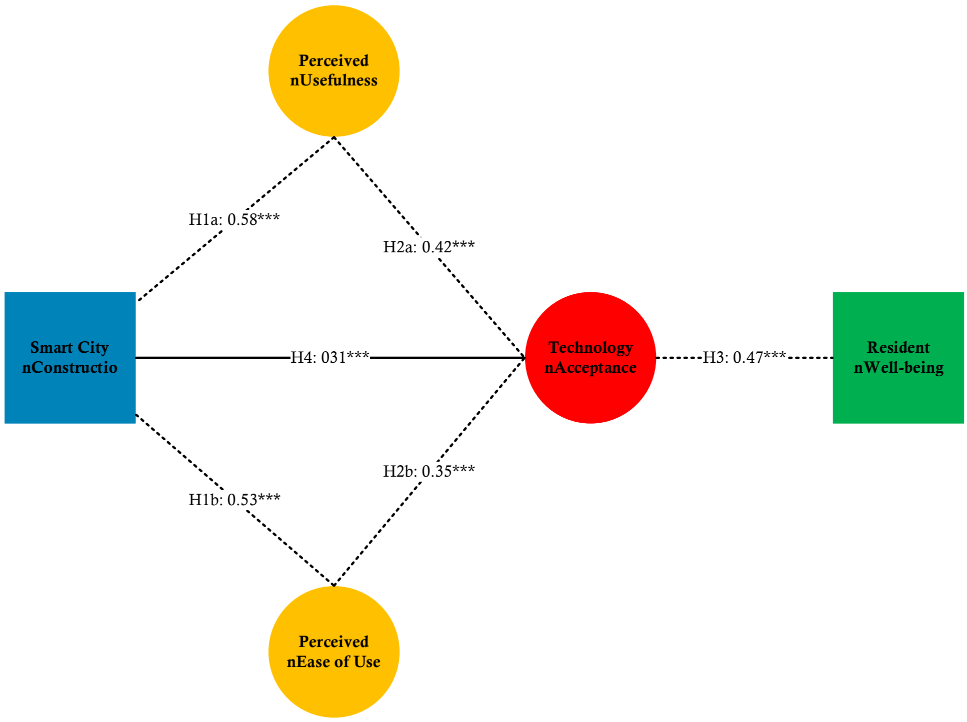

Figure 5. Structural model with supported hypotheses.

5. Discussion

5.1. Main research findings

Our study yields several significant findings that shed light on the complex relationships between smart city construction, technology acceptance, and resident well-being. Firstly, we found strong support for the positive influence of smart city initiatives on residents' perceptions of technology usefulness and ease of use. This suggests that as cities implement more smart technologies and services, residents are likely to recognize their value and find them increasingly user-friendly. Secondly, our results confirm the key tenets of the Technology Acceptance Model in the smart city context, demonstrating that perceived usefulness and perceived ease of use significantly contribute to overall technology acceptance among residents. This highlights the importance of not only implementing advanced technologies but also ensuring they are perceived as beneficial and accessible by the urban population.

Perhaps most crucially, our study reveals a significant positive relationship between technology acceptance and resident well-being, indicating that as residents embrace and utilize smart city technologies, their overall quality of life tends to improve. This finding underscores the potential of smart city initiatives to enhance urban living experiences tangibly. Furthermore, our mediation analysis uncovered the critical role of technology acceptance in translating smart city construction efforts into improved resident well-being. This suggests that the success of smart city projects in enhancing quality of life is contingent upon residents' willingness to adopt and engage with the new technologies and services.

Interestingly, we also found a direct effect of smart city construction on resident well-being, independent of technology acceptance. This implies that some benefits of smart city initiatives may be realized even without active engagement from residents, possibly through improved urban infrastructure or more efficient city management. However, the stronger indirect effect through technology acceptance emphasizes the importance of user engagement in maximizing the positive impacts of smart city development on resident well-being.

5.2. Theoretical contributions

This study makes several significant contributions to the existing body of knowledge on smart cities, technology acceptance, and urban well-being. Firstly, it bridges a crucial gap in the literature by integrating the Technology Acceptance Model (TAM) with smart city research and resident well-being studies. By demonstrating the applicability of TAM in the smart city context, we extend the theoretical reach of this well-established model into an emerging and increasingly important domain of urban development and technology implementation.

Secondly, our research provides empirical evidence for the often-assumed but rarely tested link between smart city initiatives and resident well-being. By quantifying this relationship and uncovering the mediating role of technology acceptance, we offer a more nuanced understanding of how smart city construction translates into tangible quality of life improvements for urban residents. This contributes to the ongoing scholarly discourse on the social impacts of smart city development and provides a theoretical framework for future studies in this area.

Moreover, our study introduces a comprehensive model that encapsulates the complex interplay between smart city construction, technology acceptance factors, and resident well-being. This model serves as a valuable theoretical foundation for future research, offering a holistic approach to understanding the multifaceted impacts of smart city initiatives on urban populations. It also highlights the importance of considering both direct and indirect pathways through which smart city developments influence resident well-being, thereby enriching our theoretical conceptualization of smart city outcomes.

Lastly, by examining these relationships in the context of multiple cities, our study contributes to the generalizability of smart city theories. It provides insights into how different urban contexts may influence the effectiveness of smart city initiatives and their impact on resident well-being, paving the way for more nuanced, context-sensitive theoretical frameworks in smart city research.

5.3. Practical implications

The findings of this study offer several important practical implications for urban planners, policymakers, and technology developers involved in smart city initiatives. Firstly, the strong link between smart city construction and resident perceptions of technology usefulness and ease of use underscores the importance of clear communication and education about smart city technologies. City administrators should prioritize public awareness campaigns and user education programs to help residents understand the benefits and functionalities of new smart city services, thereby fostering positive perceptions and encouraging adoption.

Secondly, the significant role of technology acceptance in mediating the relationship between smart city initiatives and resident well-being highlights the critical importance of user-centered design in smart city projects. Developers and planners should focus on creating intuitive, user-friendly interfaces and ensuring that smart city technologies address real needs and pain points of urban residents. This may involve extensive user research, iterative design processes, and continuous feedback loops with the community to refine and improve smart city services.

Furthermore, the direct effect of smart city construction on well-being, independent of technology acceptance, suggests that cities should pursue a balanced approach in their smart city strategies. While fostering technology adoption is crucial, investing in foundational infrastructure and city-wide systems that benefit all residents, regardless of their level of technology engagement, is equally important. This might include improvements in areas such as environmental monitoring, traffic management, or emergency response systems that can enhance quality of life even without direct user interaction.

Our findings also emphasize the need for inclusive smart city development. Given the varying levels of technology acceptance among different demographic groups, city planners should ensure that smart city initiatives do not exacerbate existing digital divides. This may involve providing alternative access points for smart city services, offering technology training programs for less tech-savvy residents, and ensuring that traditional service delivery methods remain available alongside digital options.

Lastly, the study's results suggest that measuring technology acceptance could serve as an early indicator of the potential success and impact of smart city initiatives on resident well-being. Cities could incorporate technology acceptance metrics into their project evaluation frameworks, using these insights to guide resource allocation and prioritize initiatives that are likely to have the greatest positive impact on residents' quality of life.

5.4. Research limitations

While our study provides valuable insights into the relationships between smart city construction, technology acceptance, and resident well-being, it is important to acknowledge several limitations. Firstly, the cross-sectional nature of our data collection limits our ability to establish causal relationships definitively. Although our structural equation modeling suggests directional relationships, longitudinal studies would be necessary to confirm the temporal ordering of effects and rule out potential reverse causality.

Secondly, our study relied on self-reported measures of technology acceptance and well-being. While these are widely used and validated measures, they may be subject to social desirability bias or other response biases. Future research could benefit from incorporating objective measures of technology use and well-being indicators to complement self-reported data.

Another limitation lies in the generalizability of our findings. Although we included multiple cities in our sample, they were all from the same country/region. Cultural, economic, and regulatory differences across countries may influence the relationships we observed, potentially limiting the global applicability of our results.

Furthermore, our study treated smart city construction as a unidimensional construct. In reality, smart city initiatives encompass a wide range of technologies and services across various urban domains. A more granular analysis of different types of smart city projects and their specific impacts on technology acceptance and well-being could provide more nuanced insights.

Lastly, while our model explained a significant portion of the variance in resident well-being, other factors not included in our study may also play important roles. For instance, we did not account for individual differences such as personality traits or prior technology experience, which could moderate the relationships we observed.

5.5. Future research directions

Building on the findings and limitations of our study, several promising avenues for future research emerge. Firstly, longitudinal studies tracking the implementation of smart city initiatives over time and their evolving impacts on technology acceptance and resident well-being would provide valuable insights into the causal mechanisms at play. Such studies could help identify critical periods for intervention and support in the technology adoption process.

Secondly, future research could explore the potential moderating effects of individual and contextual factors on the relationships we observed. This might include examining how demographic characteristics, cultural values, or city-specific factors influence the link between smart city construction and resident well-being. Such investigations could help tailor smart city strategies to diverse urban populations and contexts.

Another fruitful direction would be to delve deeper into the specific components of smart city initiatives and their differential impacts. For instance, researchers could compare the effects of various smart city domains (e.g., smart mobility, smart healthcare, smart governance) on technology acceptance and well-being, helping to prioritize investments in different areas of smart city development.

Additionally, future studies could incorporate more objective measures of technology use and well-being, possibly leveraging big data from smart city systems themselves. This could provide a more comprehensive and nuanced understanding of how residents interact with smart city technologies and how these interactions relate to various aspects of urban quality of life.

Exploring potential negative consequences or challenges of smart city implementation, such as privacy concerns, technology addiction, or social exclusion, would also be valuable. Understanding these potential drawbacks could help in developing more balanced and ethical approaches to smart city development.

Finally, cross-cultural comparative studies examining how the relationships between smart city construction, technology acceptance, and well-being vary across different global contexts would greatly enhance our understanding of smart city impacts. Such research could identify universal principles of effective smart city development as well as culturally specific factors that need to be considered in different urban environments.

6. Conclusion

This study provides significant insights into the complex relationships between smart city construction, technology acceptance, and resident well-being. By integrating the Technology Acceptance Model with smart city research, we have demonstrated that smart city initiatives positively influence residents' perceptions of technology usefulness and ease of use, which in turn drive technology acceptance and ultimately enhance well-being. Our findings underscore the crucial mediating role of technology acceptance in translating smart city efforts into tangible quality of life improvements for urban residents. The study also reveals a direct positive effect of smart city construction on well-being, suggesting that some benefits may be realized even without active technology engagement. These results have important implications for urban planners, policymakers, and technology developers, highlighting the need for user-centered design, clear communication of benefits, and inclusive development strategies in smart city projects. While acknowledging limitations such as the cross-sectional nature of the data and potential generalizability constraints, this research contributes significantly to the theoretical understanding of smart city impacts and provides a foundation for future studies. As cities worldwide continue to embrace smart technologies, our findings offer valuable guidance for maximizing the positive impacts of these initiatives on urban populations. Future research directions, including longitudinal studies and more granular analyses of specific smart city components, promise to further enrich our understanding of how smart city development can most effectively enhance the well-being of urban residents in an increasingly digital world.

Conflict of interest

The authors declare no conflict of interest.

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