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Assessing Factors Influencing Citizens' Behavioral Intention towards Smart City Living

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Abstract: The adoption and results achieved by "smart city" projects heavily rely on citizens' acceptance and behavioral intention to embrace smart city living. Understanding the factors influencing citizens' behavioral intention towards smart city living is crucial for the effective development and rollout of smart city initiatives. This research paper aims to assess the factors influencing citizens' behavioral intention towards smart city living using quantitative research methods. Through a comprehensive literature review, an ideation structure was developed, integrating theoretical perspectives from the Technology Acceptance Model (TAM). The structure encompasses key variables such as perceived utility, convenience of use, engagement, trialability, observability, interoperability, willingness, and propensity to embrace smart city lifestyles. A quantitative methodological stance was employed to gather information from a statistically significant subset of citizens residing in urban areas in developed countries. A structured questionnaire, based on the theoretical framework, was formulated and distributed to the participants. Statistical analysis techniques, including structural equation modeling, were used for investigating connections between identified factors and citizens' behavioral intention towards smart city living. Preliminary findings indicate that behavioral intention towards smart city living strongly depends on attitude and perceived usefulness. By addressing these factors, smart cities can foster greater citizen engagement, participation, and ultimately, the successful realization of smart city living.

Keywords: intention; behavior; Technology Acceptance Model (TAM); urban; techniques; engagement; smart city

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1. Introduction

Fourth-generation industrial revolution technology and shared municipal leadership are at the heart of the concept of a "smart city," which aims to improve urban living for its inhabitants. Urban issues in a variety of areas, including transportation, safety, environment, economy, welfare, power, and the effective allocation of city assets, are being solved in smart cities as global urbanization is increasing [1]. The notion of smart cities has gained significant popularity in recent years as a means to enhance the overall standard of well-being. However, this concept is still in its nascent stages of development. The effective management of population growth in urban settings requires the simultaneous consideration of environmental safety, which is a crucial aspect covered within the wider framework of sustainability. The study results revealed that the European policies focusing on sustainability and smart travel were identified as the most significant factors. The prioritization of people in the transition to a smart city is underscored by smart city managers, who place significant emphasis on the attractiveness of urban areas [2]. A global trend toward the construction of smart cities is rising. The Korea Agency for Infrastructure Technology Advancement has published a report stating that foreign nations have been actively pursuing regulatory measures for smart cities since early 2010. The "New Growth Strategy in Japan" was published in 2010 and the "Environmental, Energy-wide Strategy by Green Innovation" was promoted; both of these strategies address smart cities. In October 2013, the EU presented the Smart Cities and Communities Innovation Partnership Strategy Implementation Plan to promote smart city development across the energy, transport, and ICT sectors. China invested about USD 48.3 billion between 2011 and 2015 to boost energy efficiency by 16% and build 320 "smart cities" around the country. The RECI (Spain Smart City Network) was established in June 2011 as a central hub for all smart city data in the country [3]. Future forecasts predict that the trend toward smart cities will persist. The market share of smart cities is anticipated to expand by USD 288.7 billion between 2022 and 2027, and the CAGR for the market is predicted to reach 24.53% [4].

The idea of "smart cities" has drawn considerable attention in recent years as a promising approach to address the complex challenges posed by rapid urbanization, population growth, and the need for sustainable urban development [5,6]. Cutting-edge technology and data-driven solutions help "smart cities" in making metropolitan areas better places to reside, work, and socialize for their citizens [7,8]. By integrating cutting-edge systems like IoT (Internet of Things) technologies, computerized learning systems, and massive data analyses, smart cities seek to revolutionize fields as diverse as power, transit, medical services, administration, and public security [9,10]. However, the successful realization of the smart city vision hinges on its residents' acceptance and active participation. Therefore, understanding the variables that influence citizens' behavioral intention towards embracing smart city living becomes imperative to ensure the effectiveness and sustainability of these initiatives.

The advent of smart city technologies has opened up a myriad of possibilities for urban dwellers. Smart transportation systems enable seamless connectivity, optimized traffic management, and enhanced mobility options, reducing congestion and improving the overall commuting experience [6,9]. Smart energy grids and intelligent buildings promote energy efficiency, conservation, and sustainability, reducing carbon footprints and promoting a greener environment. Smart healthcare solutions facilitate remote patient monitoring, personalized healthcare services, and early disease detection, improving healthcare delivery quality [2,11]. Additionally, smart governance initiatives foster citizen participation, transparency, and efficient public service delivery, promoting trust and engagement between citizens and the government [12,13]. Despite the upsides, smart city programs rely largely on public backing and commitment in order to be successful. Citizens play a crucial part in the co-creation and co-design of smart city solutions, as their needs, preferences, and behaviors directly influence the effectiveness and acceptance of these technologies. Thus, assessing the factors influencing citizens' behavioral intention towards embracing smart city living becomes crucial. Many people doubt that the increased dependency on innovation would significantly affect public involvement, as it would be economically inefficient to do without technological innovations [14]. Automated processes and services, digitalized networks, and improved communication have all contributed to a more high-tech way of life in the city. Smart urbanization, powered by the influx of ICT for software, servers, computation, and big data, intends to improve the quality of life and economic prospects for city dwellers [15]. There are monetary factors to consider when determining the residents' preferences before making any major investments, as well as the importance of determining and comprehending user acceptance attitude for technologies related to information and data communication [16]. Following these ideas, our research poses a pertinent query: What factors most significantly influence citizens' behavioral intention towards smart city living?

The perceived usefulness of smart city services and technologies is an important consideration. It is more probable that citizens will accept smart city initiatives if they recognize tangible benefits, such as improved convenience, enhanced safety, reduced costs, and increased efficiency in their daily lives [15,17]. The convenience of usage of these technologies is another vital aspect that affects behavioral intention. Citizens are more inclined to engage with smart city solutions that are intuitive, user-friendly, and require minimal effort to operate [1]. The results of this research are anticipated to add to the corpus of understanding on citizen engagement in smart cities. By identifying and understanding the factors influencing citizens' behavioral intention, policymakers and stakeholders can develop targeted interventions, communication strategies, and regulatory structures to facilitate the successful adoption and execution of smart city projects. Ultimately, this research aims to prioritize citizen-centric smart city development, ensuring that the benefits of these technological advancements are realized by the people they are intended to serve.

This study employed the Technology Acceptance Model (TAM), an established framework to comprehend and predict users' assimilation and conformity of technology [18]. The Technology Acceptance Model (TAM) was originally established for studying generic information systems. However, it has demonstrated its applicability in several domains, including the realm of smart cities. The Technology Acceptance Model (TAM) can be effectively utilized in the context of smart cities due to various factors. Firstly, the TAM is based on extensive psychological, sociological, and behavioral research, drawing from previous adoption models [19,20]. This solid foundation lends credibility to its application in understanding smart city living. Secondly, the TAM research on the uptake of e-government offerings and the general willingness to embrace information technology has already shown promising results [19,21]. Smart city technologies are intimately connected with people and expand e-government services, which further strengthens the TAM's effectiveness. The TAM framework is flexible enough to accommodate the nuanced nature of smart city services by including extra criteria beyond those revealed in interviews. As a consequence, the TAM is in an excellent position to pinpoint the most significant elements affecting the likelihood of adopting and using smart city services. City authorities and technology providers may use this information to improve implementation and assessment, leading to more services for residents and deeper community partnerships. Since the TAM is widely recognized as a theory pertinent to the adoption of electronic government offerings, it is also frequently utilized in information system research, making it an ideal framework for evaluating the acceptability of smart cities [19].

The Technology Acceptance Model (TAM) was selected for this study because of its robust theoretical underpinnings and flexibility to accommodate the nuanced dynamics of contemporary life in smart cities. TAM has been useful in a number of settings, especially when trying to comprehend how people assimilate new technologies like computerized government services. Its application to the field of smart cities is supported by the psychological and sociological foundations obtained from earlier adoption models. TAM's adaptability is a major strength, since it allows for the incorporation of aspects not often included in adoption models and the intricate nature of smart city services. In urban areas, it has been shown to be particularly useful for collecting users' positive perspectives on IT. In order to provide a more thorough explanation, this study explores the impact that initiatives and actions taken by the local government play in shaping the preferences of its citizens. This study investigates how these external elements affect inhabitants' adoption of smart city technology, acknowledging the substantial influence of local government on forming the smart city environment. With its flexibility to integrate external effects and strategic alignment with the many facets of smart city living, TAM stands out as the best model for investigating people' behavioral intentions in the context of smart city adoption.

Methodologically, the study consists of the following steps. The relevance of "smart cities" and widespread use of technology is explored in the paper's second half. The study concludes with a discussion of the theoretical underpinnings and model construction involved in investigating residents' behavioral intentions in relation to life in a smart city. The gathering and analysis of data is covered in depth in the fourth part. An evaluation of the study's results is included here as well. The report's findings and interpretation of those findings are presented in Section 5. The last section of the paper evaluates the work's own contributions, implications, limits, and potential future research directions.

2. Literature Review and Hypothesis Development

2.1. Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a theoretical framework that has been developed to analyze and foresee how various technologies will be received by their intended audiences. The Technology Acceptance Model (TAM) is an approach to understanding why people choose to use and embrace certain technologies. It was developed by Fred Davis in the late 1980s. An individual's perception of a technology's ease of use indicates the degree to which they feel utilizing the technology will be effortless, while an individual's perception of the technology's usefulness indicates the degree to which they believe using the technology will increase their performance or productivity. TAM is based on the premise that these two aspects interact to determine how people will utilize a technology and how they will feel about it. Due to its solid psychological and sociological base, TAM has been extensively utilized in different situations, including smart cities, making it an adaptable and useful model for studying the adoption of technology in a variety of settings.

The Technology Acceptance Model (TAM) has previously been used to examine the acceptability of technologies in smart cities due to the importance of location-specific elements in the adoption of technology and its application to varied populations [15]. Davis's [18] Technology Acceptance Model (TAM), which expands upon Fishbein and Ajzen's [22] theory of reasoned behavior, is widely used by researchers seeking to comprehend individuals' responses and acceptance of novel technologies. The study of "smart cities" and other technological fields has found widespread use for this approach. The Technology Acceptance Model (TAM) provides a helpful framework for analyzing the ways in which residents of smart cities respond to and incorporate new technologies into their daily lives [8,23]. Transit, energy conservation, public facilities, and citizen involvement are just some of the areas that can be improved by implementing the kinds of cutting-edge technology used in smart cities. However, the successful implementation and adoption of these technologies rely on citizens' acceptance and willingness to utilize them [24].

The TAM can be used by urban designers, politicians, and tech developers to gain insight into what variables affect people's openness to adopting smart city technologies. Perceived usefulness is a critical factor in this context. To increase the possibility of widespread adoption of smart city technologies, it is important to demonstrate to residents how they will benefit from their use [3]. The ease with which people perceive that smart city technology can be utilized also plays a significant influence in their widespread adoption. User-friendly, intuitive, and low-effort technologies are more likely to be adopted by the general public [25]. Complex and difficult-to-use technologies may deter individuals from embracing them, regardless of their potential benefits [26].

Perceived usefulness refers to an individual's subjective assessment of the extent to which utilizing a specific system would enhance their effectiveness in performing their current job tasks [18]. Perceived ease of use, on the other hand, describes how little a person thinks they will have to work to make use of technology. According to TAM, people's motives for adopting or making use of new technologies are crucial factors. The individual's behavioral intention is influenced by their perception of the value and convenience of use, as well as their own perspective. Perceived utility and perceived ease of use have been identified by several TAM-based studies as critical criteria affecting the public adoption of smart city technologies. Prasetyo and Santiago [27] found that the enabling circumstance plays a significant role in shaping the behavioral intention of individuals employed in smart cities globally. Their study indicates that the extent to which the work and living environment accommodate individuals greatly influences their BI to persist in their work, regularly attend their jobs, and perform effectively and efficiently.

Han and Kim [15] present a critical study of the smart city concept in the context of citizen acceptability of sustainable smart living. The study highlights the multifaceted factors that influence citizen adoption and emphasizes the need for a comprehensive and sustainable approach to smart city projects. The results provide insight into the challenges of promoting public participation and fostering environmentally responsible urban growth in the larger context of smart cities. Hamamurad et al. [17] shed light on the factors influencing stakeholder approval of a smart city in Malaysia. The findings highlight the importance of perceived benefits, stakeholder involvement, awareness, and supportive regulations in shaping stakeholder attitudes towards smart city adoption. The study offers useful information for legislators, urban designers, and technology suppliers in Malaysia's efforts to increase stakeholder acceptability and participation in the creation and execution of smart city programs. Still, this study is only confined to the cities of Malaysia and does not indicate the extent to which the results can be transferred to other countries and regions. Myeong et al. [1] provide a comprehensive overview of research strategies and techniques employed in smart city studies. The findings highlight the diversity of approaches used in this field and underscore the need for interdisciplinary research to address the multifaceted nature of smart cities. Findings from this study can assist researchers in better comprehending the landscape of smart city research methodology and direct future investigations in this area. The elements that influence inhabitants' adoption of smart city technology are explored in depth by Habib et al. [8]. The results emphasize the relevance of inhabitants' perceptions of utility, ease of use, trust, social impact, compatibility, risk, and personal innovation in determining their attitudes and intentions towards smart city technology. Through its findings, the study helps to better understand how to create and execute smart city programs that are well-received and actively participated in by locals.

2.2. Behavioral Intention to Adopt Smart City Living

An individual's degree of commitment to doing a certain activity is measured by their behavioral intentions. According to Venkatesh et al. [28], it is a crucial indicator of technological adoption and has been utilized extensively in prior studies on individual acceptance. The influence of digital technology on residents' mental health in smart cities during the COVID-19 epidemic is a topic of study for [29]. One can predict whether or not a user will adopt a technology based on their behavior of purpose. To provide one concrete example, consider a city resident who, while looking for a parking place, announces that they plan to use a smart city parking app.

2.3. Perceived Usefulness

Perceived usefulness is a crucial factor in the acceptance and usage of smart city technologies [30]. When individuals comprehend that smart city solutions can bring tangible benefits and improve their lives, they are more likely to embrace and engage with these technologies. The concept of perceived usefulness suggests that individuals assess the potential usefulness of smart city applications based on their own requirements, expectations, and past experiences. Based on the concept of perceived utility, individuals are inclined to embrace smart city technologies if they perceive them as a means to simplify their lives [10]. In certain instances, government and large organizational bureaucracies can be complex, time-consuming, and inefficient, particularly in emerging nations [31]. Perceived usefulness refers to individuals' subjective evaluation of the extent to which smart city technologies can enhance their lives and fulfill their needs. If individuals believe that smart city initiatives and technologies can provide advantages such as convenience, efficiency, improved quality of services, and enhanced sustainability, they are more inclined to have a positive opinion of smart cities and consider moving there [4,32]. As a result of the overall review and underlying literature, the study put forth the following hypotheses.

H1. *Perceived usefulness influences attitude to adopt smart city living.*

H2. *Perceived usefulness influences behavioral intention to adopt smart city living.*

2.4. Perceived Ease of Use

The concept of perceived ease of use pertains to an individual's subjective view of required effort to effectively utilize smart technology. It relates to individuals' subjective assessment of how easy it is to understand and use smart city technologies. When individuals comprehend smart city technologies as user-friendly, intuitive, and accessible, it enhances their perception of ease of use [4]. When people see smart city technologies as being simpler to implement, they are more likely to embrace them and the concept of smart cities as a whole. Studies have shown that users' impressions of how simple and straightforward a technology is to use have a significant role in the product's overall success [33,34]. In view of that, this study proposed the following hypotheses.

H3. *Perceived ease of use influences perceived usefulness.*

H4. *Perceived ease of use influences attitude to adopt smart city living.*

2.5. Resident Engagement

Human nature and behavior are greatly influenced by the social atmosphere of a particular place, as well as interactions with neighbors, leading to flexible and malleable citizen behavior and judgment [35]. The extent to which citizens engage with their city's affairs depends on their place of residence and their experiences interacting with other residents [36]. The level of engagement is significantly influenced by interactions among citizens and their perception of the environment, including the activities of fellow citizens and neighbors [37]. Environmental perception plays a crucial role in citizens' engagement and commitment to utilizing IT-based services provided to them [38]. In proposed smart cities, deep citizen engagement and commitment to utilizing IT services provided by local authorities can contribute to the city's modernization and overall improvement [39,40]. The creation and execution of smart city programs are greatly aided by resident participation. When residents are actively engaged, they contribute valuable insights, ideas, and feedback, leading to more citizen-centric and effective solutions. Engaged residents are more inclined to embrace and utilize smart city technologies, as they feel a sense of ownership and are invested in the success of their city's transformation. The effectiveness and acceptability of smart city programs are intertwined with the level of resident participation and attitude towards smart city life [27]. In view of that, this study proposed the following hypotheses.

H5. *Resident engagement influences attitude to adopt smart city living.*

2.6. Trialability

Trialability refers to individuals' ability to trial and experiment with smart city technologies and initiatives before fully committing to them [32]. It involves providing opportunities for hands-on experiences, demonstrations, or pilot projects that allow residents to interact with and explore the functionalities, benefits, and usability of smart city solutions. Trialability plays a crucial role in reducing uncertainty, building familiarity, and generating a positive attitude towards adopting smart city technologies. By enabling residents to experience the practicality and value of these technologies firsthand, trialability encourages their engagement and acceptance [41]. In view of that, this study proposed the following hypothesis.

H6. *Trialability influences attitude to adopt smart city living.*

2.7. Observability

Observability relates to the visibility of the benefits and outcomes of using smart city technologies. It encompasses the ability of individuals to observe and perceive the positive impacts and tangible results that smart city initiatives bring to their daily lives [32]. Visible benefits can include improved efficiency in transportation systems, enhanced sustainability practices, increased safety and security, and better access to services. When individuals can witness the positive changes and experiences resulting from smart city solutions, it strengthens their confidence, trust, and acceptance. Observability contributes to shaping positive attitudes and fostering continued engagement with smart city living. In view of that, this study proposed the following hypothesis.

H7. *Observability influences attitude to adopt smart city living.*

2.8. Compatibility

Compatibility refers to the alignment and fit between individuals' existing lifestyles, values, and needs with smart city technologies and initiatives. It encompasses the degree to which these technologies integrate seamlessly into residents' routines, preferences, and cultural norms [32]. Compatibility is essential for overcoming resistance to change and promoting the adoption of smart city solutions. Factors such as user-friendliness, accessibility, affordability, and integration with existing infrastructures and services influence compatibility. Smart city technologies that align with residents' expectations and requirements are more likely to be adopted and embraced. Considering compatibility throughout smart city initiatives' design, implementation, and deployment enhances their relevance, effectiveness, and user satisfaction. The extent to which two systems are compatible significantly impacts how quickly an invention is adopted. The possibility of an invention being adopted increases the more it is seen as fitting in with the status quo [41]. Given that, this study proposed the following hypothesis.

H8. *Compatibility influences attitude to adopt smart city living.*

2.9. Attitude to Adopt Smart City Living

The perception and attitude towards living in smart cities are pivotal factors in the effective implementation and widespread adoption of smart city initiatives [29]. The examination of the relevant research reveals that several significant factors influence individuals' perspectives on smart cities. One of the most important factors in whether or not people will adopt smart city technologies is their acceptance of technological innovations. [3,25]. Additionally, sustainability and environmental concerns are crucial, as positive attitudes towards environmental preservation and sustainable practices foster acceptance and engagement with smart city living. Hence, this study proposed the following hypotheses.

H9. *Attitude influences behavioral intention to adopt smart city living.*

H10 to H18. *Attitude to adopt smart city living mediates the relationship between perceived usefulness, perceived ease of use, resident engagement, trialability, observability, compatibility, and behavioral intention to adopt smart city living.*

Figure 1 shows our research model. We have 6 independent variables (left side), 1 mediating variable (center), and 1 dependent variable (right side). Arrows show the relationship and influence of independent variables on mediating variable (attitude) and dependent variable (intention).

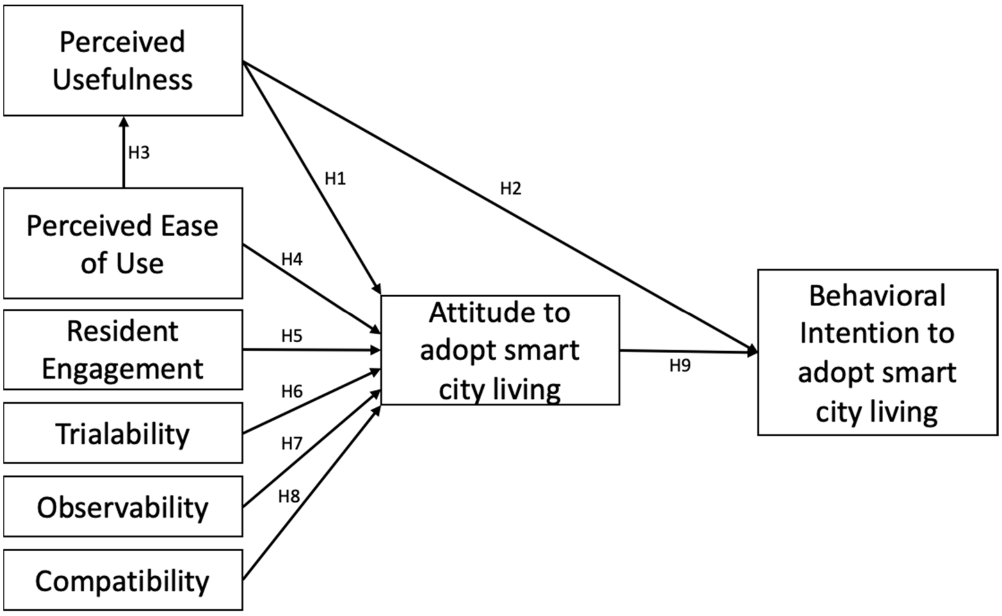

Figure 1. Smart city citizens' behavioral intention model.

3. Research Methodology

3.1. Participants and Procedure

The study employed a sample size of 327 people residing in urban areas of developed countries for the analysis. Their residence in urban areas served as the basis for the inclusion criterion for respondents, guaranteeing that they were either directly impacted by or exposed to smart city efforts. The choice to zero in on urban areas was motivated by the fact that smart city projects are often executed in these kinds of places and that people living in these kinds of places are more likely to come into contact with and make use of smart city technology.

The criteria for inclusion were further narrowed by focusing on those who were actively involved in urban life, as opposed to those who were passively exposed to city life. The target audience for this method was composed of those who would most benefit from the smart city's technical improvements and infrastructure. To guarantee a more nuanced depiction of the target demographic, factors including the length of urban residence, frequency of contact with smart city technology, and familiarity with digital urban services were taken into account. The inclusion criteria were developed with the goal of increasing the study's applicability to those who are shaping the future of smart city life and who are directly engaged in shaping it. This method helps ensure that the study findings are generalizable to the setting of urban areas in industrialized nations. The minimum sample size was determined based on the statistical power requirement, utilizing G*Power 3.1 software as described by Kang [42]. The research model comprised seven predictors, with an effect size of 0.15 and a power of 0.95. Based on this specific criterion, it was determined that a minimum sample size of 74 was necessary. Therefore, the sample size chosen for this investigation surpassed the minimum threshold. The deliberate evaluation of sample size following the specified criteria has proven beneficial in the literature, as it allows for efficient use of time and effectively manages budgetary constraints. The convenience sampling technique was employed to gather the data, a method commonly used in various smart city research studies [43,44]. Data were collected through electronic form questionnaires distributed among participants who volunteered to fill them out. The participants were primarily from LinkedIn and other social networks. Detailed descriptive statistics are mentioned in Table 1.

Table 1. Demographic characteristics (n = 327).

	Frequency	Percent
Gender		
Male	171	52%
Female	156	48%
Marital Status		
Married	217	66%
Single	110	34%
Age		
18–24 years old	23	7%
25–34 years old	56	17%
35–44 years old	112	34%
45–54 years old	89	27%
55–64 years old	32	10%
65–74 years old	15	5%
Current state of living		
Homeowner	74	23%
Renter	211	65%
Lessee	31	9%
Other	11	3%
Employment status		
Full-time	191	58%
Part-time	51	16%
Freelance	38	12%
Retired	47	14%
Education		
High school diploma	19	6%
Associate degree	37	11%
Bachelor's degree	179	55%
Trade school certification	27	8%
Master's degree	57	17%
Other	8	2%
Annual income		
Less than USD 10,000	47	14%
USD 10,000–50,000	195	60%
USD 50,000–100,000	68	21%
USD 100,000–150,000	12	4%
USD 150,000+	5	2%

3.2. Study Measures

The survey commenced with an introduction outlining the study's objectives and guidance on how to complete the questionnaires. Participants were asked to furnish personal information, including demographic details, in the following section. The third component of the survey was a Likert scale with five points, from 1 to 5, to evaluate the agreement level among respondents about the main research questions. A rating of 1 denoted a response of "strongly disagree," while a rating of 5 denoted a response of "strongly agree." A total of 36 items were employed to assess all the structures. The components utilized in the creation of the Behavioral Intention to Adopt the Smart City Living construct were derived from previous studies conducted by Venkatesh et al. [28], Habib et al. [8], Chua and Hu [45], and Venkatesh and Davis [46]. The measures employed to evaluate the perceived usefulness, perceived simplicity of use, and attitude toward adopting smart city living were derived from the works of Davis et al. [47] and Park and Chen [32]. The items used for the trialability construct were derived from the works of Moore and Benbasat [48] and Park and Chen [32]. The elements utilized for observability and compatibility building are derived from the works of Moore and Benbasat [48], Wu and Wu [49], and Park and Chen [32]. For the resident engagement construct, items were adapted from Chatterjee and Kar [23].

3.3. Data Analysis Techniques

The research employed structural equation modeling (SEM) using Smart PLS (v4), a highly regarded software package for conducting SEM-based analysis [50]. SEM offers a comprehensive approach to analyzing both direct and indirect impacts of latent variables, making it suitable for studying complex models [51]. In the field of management science studies, SEM has been the preferred method for assessing model fit and consistency with data [52]. In the field of structural equation modelling (SEM), two primary methodologies are commonly employed: covariance-based SEM (CB-SEM) and partial least squares SEM (PLS-SEM). This study chose PLS-SEM due to its ability to handle complex relationships between constructs, establish theoretical levels, and provide relative path coefficient values [53]. Since the study model incorporates mediating variables, the use of PLS-SEM ensures accurate terms for theory validation and prediction of relationships among variables [54]. PLS-SEM is a highly regarded methodology that is commonly employed to investigate complex interactions. One of its notable strengths is its ability to establish discriminant validity, without being constrained by constraints in sample size. The partial least squares (PLS) technique employs a two-step procedure, encompassing a measurement model (inner model) and a structural model (outer model), in order to establish connections among latent variables.

4. Results

Table 1 presents a comprehensive snapshot of the demographic characteristics of the study's 327 participants. Regarding gender distribution, 52% of the participants identify as male, while 48% identify as female. Marital status reveals that 66% of the participants are married, and 34% are single. Age diversity is evident, with participants falling into various age groups: 7% are aged 18–24, 17% are aged 25–34, 34% are aged 35–44, 27% are aged 45–54, 10% are aged 55–64, and 5% are aged 65–74. Participants' current living situations comprise 23% homeowners, 65% renters, 9% lessees, and 3% classified as "Other." Employment status reflects a range of roles; 58% are full-time employees, 16% are part-time, 12% are freelancers, and 14% are retired. Educational backgrounds span diverse qualifications; 6% hold a high school diploma, 11% an associate degree, 55% a bachelor's degree, 8% a trade school certification, 17% a master's degree, and 2% fall under "Other." The distribution of annual income reveals that 14% earn less than USD 10,000, 60% earn between USD 10,000 and USD 50,000, 21% earn between USD 50,000 and USD 100,000, 4% earn between USD 100,000 and USD 150,000, and 2% earn above USD 150,000.

4.1. Measurement Model

In order to better comprehend the dynamics involved in implementing smart city living, Table 2 provides a complete analysis of numerous constructions and their constituent elements. Each concept stands for a different factor that influences people's propensity to use smart city services. The study evaluates the constructs' reliability and validity using many essential metrics, such as loadings, Cronbach's alpha, composite reliability, and average variance extracted (AVE). Cronbach's alpha and composite reliability both have respectable values, demonstrating the consistency and dependability of the study's metrics. The average variance extracted (AVE) also shows that the construct under study has a large amount of explanatory power. Individuals' intentions to maintain using smart city services are downplayed by the behavioral desire to embrace the smart city living construct. The combined value of its parts (BI1, BI2, and BI3) indicates a solid connection to the stated goal. The idea has satisfactory internal consistency and reliability, as measured by a Cronbach's alpha and composite reliability both above 0.7. The large AVE score indicates that there is a great deal of common variation among the items. The perceived usefulness metric gauges how people feel smart city services benefit them. All elements (PU1 to PU6) have high loadings, which indicates that they all contribute significantly to the build. With inadequate loading ratings from perceived utility, however, "Using the smart city services would make it easier to do my routine work" was eliminated. How people feel about using smart city services is explored in the category of "perceived ease of use." The items (PEU1 to PEU6) with the highest loadings have a strong relationship to the build. Composite reliability and Cronbach's alpha indicate that this construct accurately captures internal consistency. A high AVE suggests that a lot of variation is captured by the structure itself. Individuals' propensity to accept smart city living indicates their level of enthusiasm for the concept. All four components (ATT1-ATT4) have significant loadings, indicating their relevance to the construct. This construct has strong internal reliability, since both Cronbach's alpha and composite reliability are within acceptable ranges. The strong AVE indicates that the construct successfully explains inter-item variation. The relevance of trial experiences in implementing smart city services is emphasized by factors such as trialability, observability, compatibility, and resident involvement. High loadings across the board for all elements for each build indicate that they all play an important role. Internal consistency is captured by this concept, as shown by high values of Cronbach's alpha and composite dependability. The high AVE score suggests that a significant amount of variability may be attributed to the construct.

Table 2. Measurement model.

Constructs and Items	Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Behavioral intention to adopt smart city living (BI)		0.702	0.834	0.626
BI1. I look forward to future use of smart city services.	0.785			
BI2. I want to make frequent use of Mart City's offerings.	0.786			
BI3. I anticipate maintaining a high frequency of usage for smart city services.	0.803			
Perceived usefulness (PU)		0.750	0.833	0.50
PU1: With the help of smart city services, I could get more done in less time.	0.70			
PU2: My productivity would increase significantly if I made use of the smart city's offerings.	0.736			
PU3: The incorporation of smart city services into my daily routine would allow me to do more.	0.70			
PU4: The smart city services would help me be more productive in my daily life.	0.729			
PU6: The smart city services will improve my quality of life.	0.709			
Perceived ease of use (PEU)		0.815	0.866	0.520
PEU1: I think I could quickly pick up the skills necessary to use the smart city's amenities.	0.734			
PEU2: I could easily use the smart city services to achieve my goals.	0.734			
PEU3: I could have an easy-to-understand experience with the smart city services.	0.741			
PEU4: The smart city services I anticipate using are adaptable and easy to use.	0.70			
PEU5: I could learn to use the smart city services in no time.	0.722			
PEU6: The convenience of the smart city services would appeal to me.	0.70			

Table 2. *Cont.*

Constructs and Items	Loadings	Cronbach's Alpha	Composite Reliability	Average Variance Extracted (AVE)
Attitude to adopt smart city living (ATT)		0.823	0.883	0.655
ATT1: Taking advantage of life in a smart city is a promising prospect.	0.822			
ATT2: It is not fun to use smart city services in daily life.	0.837			
ATT3: My life has improved since I started using smart city services.	0.846			
ATT4: I like (would enjoy) making use of life-enriching smart city services.	0.728			
Trialability (TR)		0.813	0.877	0.642
TR1: I need to give the smart city services a try before determining whether or not to embrace them.	0.782			
TR2: In order to make an informed decision on whether or not to use the smart city services, I need to give them a thorough tryout first.	0.746			
TR3: I would be given a trial period of smart city services during which I may put them to use.	0.825			
TR4: I am aware of where I may go to get a good feel for the smart city services available to me.	0.848			
Observability (OB)		0.777	0.900	0.818
OB1: It is simple for me to see how other people benefit from the smart city services.	0.914			
OB2: I have got several chances to see the practical use of smart city services.	0.894			
Compatibility (CM)		0.710	0.838	0.633
CM1: The services provided by the smart city work well with the rest of my life.	0.767			
CM2: The convenience of the smart city's services complements my way of life.	0.798			
CM3: Using the smart city services seems like it will complement my lifestyle well.	0.821			
Resident Engagement (RE)		0.829	0.875	0.538
RE1: Through various smart city services, residents are in close contact with the municipal government.	0.70			
RE2: E-governance is the government's preferred method of providing services to citizens.	0.706			
RE3: Residents use IT-enabled services to take part in a variety of community activities.	0.784			
RE4: Residents of a smart city interact with one another using a variety of services made possible by information technology.	0.767			
RE5: The government uses several forms of digital media to provide information to the residents.	0.764			
RE6: Residents' use of a variety of online services to participate in the community is well-established.	0.706			
RE7: The increased quality of life is a direct result of the widespread use of IT-enabled services by residents.	0.70			
RE8: Participation in government through the use of a variety of IT-enabled services is well-established.	0.706			

Table 3 offers a comprehensive overview of the results derived from a discriminant validity analysis, a crucial assessment to ascertain the uniqueness and differentiation among various constructs within the study. The elements that line up with the major diagonal of the matrix reflect the square roots of the average variance extracted (AVE) for each construct. The diagonal elements in this context function as an indicator for evaluating the extent to which the components within a construct correlate with one another. However, these higher correlations might still be considered acceptable, especially if the context of the study suggests that these constructs could be related. The analysis offers valuable insights into the interconnections and unique characteristics of the examined variables, contributing to the establishment of the distinct reliability of the measurement model.

Table 3. Discriminant validity.

	ATT	BI	CM	OB	PEU	PU	RE	TR
ATT	0.875							
BI	0.541	0.791						
CM	0.654	0.438	0.796					
OB	0.733	0.461	0.688	0.904				
PEU	0.627	0.594	0.491	0.510	0.721			
PU	0.561	0.667	0.452	0.464	0.701	0.707		
RE	0.867	0.606	0.754	0.812	0.711	0.674	0.734	
TR	0.811	0.518	0.717	0.786	0.607	0.550	0.856	0.801

4.2. Structural Model

The findings derived from the partial least squares (PLS) analysis encompass relevant information concerning the relationship, level of significance, and proportion of variance accounted for (R2) within the model as reported by Guenther et al. [50]. To evaluate the importance of the relationships, a bootstrapping technique was utilized, which consisted of generating 5000 sub-samples. The direct path relationships are indicated in Table 4 and indirect path relationships indicated in Table 5.

Table 4. Direct path relationship.

Paths	β	Standard Deviation	T Statistics	*p*-Values	Hypotheses	Results
PU → ATT	−0.051	0.014	3.540	0.000	H1	Supported
PU → BI	0.532	0.017	30.875	0.000	H2	Supported
PEU → PU	0.701	0.012	56.486	0.000	H3	Supported
PEU → ATT	0.050	0.016	3.114	0.002	H4	Supported
RE → ATT	0.643	0.030	21.553	0.000	H5	Supported
TR → ATT	0.293	0.022	13.413	0.000	H6	Supported
OB → ATT	0.014	0.019	0.739	0.460	H7	Not-supported
CM → ATT	−0.053	0.015	3.428	0.001	H8	Supported
ATT → BI	0.242	0.018	13.574	0.000	H9	Supported

Table 5. Indirect path relationship (mediation).

Paths	B	Standard Deviation	T Statistics	*p*-Values	Hypotheses	Results
PEU → PU → BI	0.372	0.015	24.922	0.000	H10	Supported
CM → ATT → BI	−0.013	0.004	3.338	0.001	H11	Supported
PEU → ATT → BI	0.012	0.004	2.977	0.003	H12	Supported
PU → ATT → BI	−0.012	0.004	3.390	0.001	H13	Supported
PEU → PU → ATT	−0.035	0.010	3.543	0.000	H14	Supported
OB → ATT → BI	0.003	0.005	0.734	0.463	H15	Not-Supported
PEU → PU → ATT→ BI	−0.009	0.003	3.393	0.001	H16	Supported
TR → ATT → BI	0.071	0.007	9.718	0.000	H17	Supported
RE → ATT → BI	0.155	0.013	11.578	0.000	H18	Supported

A path coefficient indicates the direct effect of a variable assumed (independent variable) to be a cause on another variable (dependent variable) assumed to be an effect. To explain, here is one path from the model, i.e., PU $\rightarrow$ BI value is 0.532, which shows PU (independent variable) influences 53.2% of BI (dependent variable).

Table 4 provides a complete examination of the relationships between different constructs. The association between perceived usefulness (PU) and attitude (ATT) was examined; the path coefficient of -0.051 was statistically significant, with a T statistic of 3.540 and a *p*-value of 0.000. This provides support for Hypothesis H1. The relationship between PU and behavioral intention (BI) is validated by a significant path coefficient of 0.532, which is further supported by a T statistic of 30.875 and a *p*-value of 0.000, confirming Hypothesis H2. The connection between perceived ease of use (PEU) and perceived usefulness (PU) is statistically significant, as indicated by a path coefficient of 0.701, a T statistic of 56.486, and a *p*-value of 0.000 (Hypothesis H3). The relationship between perceived ease of use (PEU) and attitude (ATT) is supported by a path coefficient of 0.050, a T statistic of 3.114, and a *p*-value of 0.002, confirming Hypothesis H4. The association between resident engagement (RE) and attitude (ATT) is strong, as indicated by a path coefficient of 0.643, a T statistic of 21.553, and a *p*-value of 0.000, supporting Hypothesis H5. The relationship between trialability (TR) and attitude (ATT) is supported by statistical evidence. Specifically, the path coefficient is 0.293, the T statistic is 13.413, and the *p*-value is 0.000, confirming Hypothesis H6. In contrast, the connection between observability (OB) and attitude (ATT) lacks empirical support, as evidenced by a path coefficient of 0.014, a T statistic of 0.739, and a *p*-value of 0.460 (Hypothesis H7). The concept of compatibility (CM) is found to be in agreement with attitude (ATT), as evidenced by a path coefficient of -0.053, a T statistic of 3.428, and a *p*-value of 0.001, thereby supporting Hypothesis H8. The connection between attitude (ATT) and behavioral intention (BI) has been successfully established, as evidenced by a path coefficient of 0.242, a T statistic of 13.574, and a *p*-value of 0.000, supporting Hypothesis H9.

Table 5 begins with the indirect path from perceived ease of use (PEU) to behavioral intention (BI) through perceived usefulness (PU); the substantial path coefficient of 0.372, a standard deviation of 0.015, a T statistic of 24.922, and a *p*-value of 0.000 all confirm the support for Hypothesis H10. This finding demonstrates the mediating role of perceived usefulness (PU) in the connection between PEU and BI. Similarly, the pathway from compatibility (CM) to behavioral intention (BI) through attitude (ATT) is validated with a path coefficient of -0.013, a standard deviation of 0.004, a T statistic of 3.338, and a *p*-value of 0.001, lending support to Hypothesis H11. This outcome indicates that the relationship between CM and BI is mediated by ATT. The linkage from PEU to BI via ATT, supported by a path coefficient of 0.012, a standard deviation of 0.004, a T statistic of 2.977, and a *p*-value of 0.003, validates Hypothesis H12, highlighting the mediating role of ATT in connecting PEU to BI. Additionally, the indirect path from perceived usefulness (PU) to BI through ATT is substantiated with a path coefficient of -0.012, a standard deviation of 0.004, a T statistic of 3.390, and a *p*-value of 0.001, supporting Hypothesis H13. This result confirms the mediating role of ATT in the relationship between PU and BI. The mediation of ATT between PEU and ATT itself is supported with a path coefficient of -0.035, a standard deviation of 0.010, a T statistic of 3.543, and a *p*-value of 0.000, aligning with Hypothesis H14. However, the proposed mediation of the relationship between observability (OB) and BI through ATT is not supported, as indicated by a path coefficient of 0.003, a standard deviation of 0.005, a T statistic of 0.734, and a *p*-value of 0.463 (Hypothesis H15). The complex mediation of PEU, PU, ATT, and BI is confirmed with a path coefficient of -0.009, a standard deviation of 0.003, a T statistic of 3.393, and a *p*-value of 0.001, corroborating Hypothesis H16. Further emphasizing the mediating role of ATT, the path from trialability (TR) to BI is supported with a path coefficient of 0.071, a standard deviation of 0.007, a T statistic of 9.718, and a *p*-value of 0.000, aligning with Hypothesis H17. Lastly, the mediation of ATT between resident engagement (RE) and BI is strongly supported, with a path coefficient of 0.155, a standard deviation of 0.013, a T statistic of 11.578, and a *p*-value of 0.000, affirming Hypothesis H18.

Figure 2 represents the model estimation. For "Perceived Usefulness" (PU), the R-squared value stands at 0.491, implying that the independent variables clarify about 49.1% of the variance in PU. For "Attitude" (ATT), the R-squared value of 0.777 suggests that the combination of independent variables elucidates around 77.7% of the variance in attitude. Turning to "Behavioral Intention" (BI), an R-squared value of 0.486 indicates that the collective influence of independent variables explains approximately 48.6% of the variance in BI. Table 4 specifically shows the direct influence between two variables, namely "PU → ATT," highlighting the direct relationship between them. On the other hand, Table 5 reveals the more indirect relationship, illustrating the paths "PEU → PU → BI" and "PEU → PU → ATT → BI," demonstrating how these three to four variables interact and impact one another.

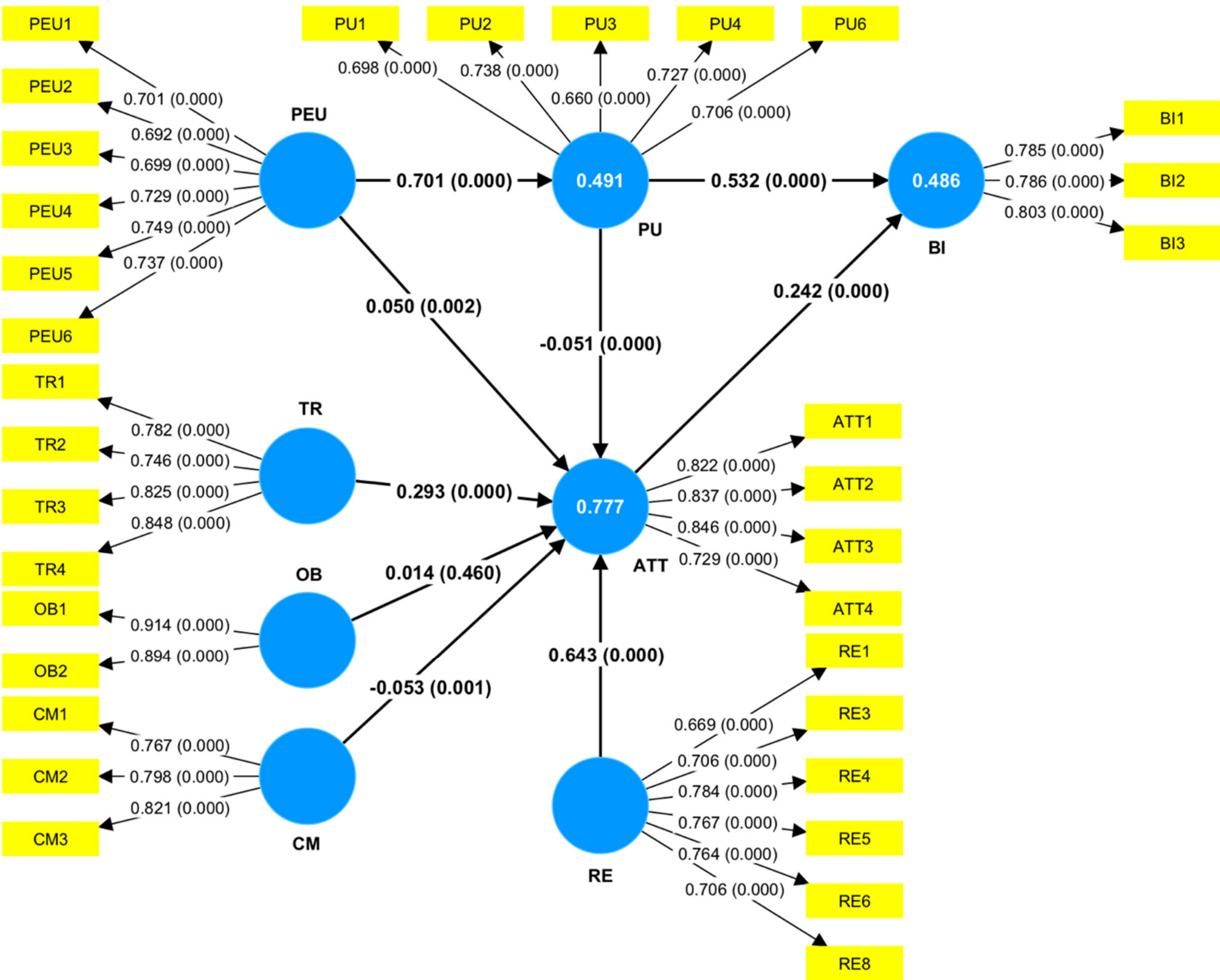

Figure 2. Model estimation. Notes: Path coefficients are denoted on the lines of the arrows, and significant values are enclosed within brackets. R-squared values are represented within circles on the arrows, with corresponding significant values enclosed in brackets.

5. Discussion

This study has unveiled complex relationships among various constructs central to the understanding of technology adoption and living in smart cities. Firstly, perceived usefulness (PU) plays a pivotal role in shaping users' attitudes and behavioral intentions. The negative relationship between PU and attitude (ATT), while counterintuitive, suggests that as users perceive a technology as more useful, their overall attitude becomes more positive. This underscores the intricate interplay between perceived utility and overall disposition. Furthermore, the strong positive link between PU and behavioral intention (BI) reinforces the importance of perceived usefulness as a predictor of users' intentions to adopt a technology. Second, PEU can be seen in action in several different contexts. It not only directly affects PU but also indirectly influences BI through PU, highlighting its significance in the adoption process. Additionally, the positive connection between PEU and attitude underscores the importance of user-friendly interfaces in fostering positive user perceptions. Thirdly, the study reveals the importance of user engagement (RE) and trialability (TR) in shaping attitudes and behavioral intentions. Higher levels of resident engagement contribute to more favorable attitudes, and the perception of having the opportunity to trial a technology positively influences attitudes. However, the visibility of a technology (OB) does not seem to significantly impact users' attitudes. Finally, the estimated model shows that the independent variables account for a sizable fraction of the variation in PU, ATT, and BI taken together. Attitude, in particular, stands out as the construct with the highest explained variance, underlining its central role in users' decision-making processes.

The significance of individuals' perspectives towards living in a smart city is pivotal in determining the efficacy of smart city initiatives, as evidenced by the research of Emami-Naeini et al. [29]. According to the research conducted by Al-Hujran et al. [3] and Manfreda et al. [25], the adoption of smart city technologies is significantly influenced by the individual's acceptance of technology. This acceptance is determined by various factors such as perceived usefulness, ease of use, and trust. In their study, [55] examine the evolving role technology in urban environments and its impact on individuals' well-being. Specifically, they investigate the relationship between individuals' intention to use digital devices in smart cities and their psychological state amid the COVID-19 pandemic. Aligning with the findings of this study, these studies highlight the significance of attitudes and technology acceptability in defining the future of smart cities.

The rate at which individuals adopt smart city technologies, often referred to as technology uptake, is influenced by their behavioral intentions. Moreover, user engagement within the smart city ecosystem, characterized by active participation and contribution, plays a pivotal role in shaping the success and sustainability of smart city initiatives [56]. Ultimately, behavioral intention to adopt smart city living is a key driver of innovation adoption, highlighting the importance of community participation in fostering more connected, efficient, and inclusive urban environments.

These findings collectively provide valuable insights for practitioners and researchers involved in technology adoption and user engagement. They emphasize the need for user-friendly interfaces, highlight the importance of perceived usefulness and user engagement, and underscore the critical role of attitude as a mediating factor in the adoption process. By leveraging these insights, organizations can better design and implement technologies that align with users' preferences and intentions, ultimately enhancing adoption rates and user satisfaction.

6. Conclusions

The study used the Technology Acceptance Model (TAM) to examine how individual behavioral intentions towards smart city living among urban citizens are related. The results indicate that perceived usefulness towards smart city living is the most significant predictor of user intention, followed by attitude. This study highlights the potential and relevance of adapting TAM constructs for understanding smart city acceptance among citizens in developed countries. This research focuses on smart cities, a relatively new technological domain in some industries, warranting dedicated investigation. Despite limited academic research in this area, our study makes a valuable contribution by exploring a novel aspect. Notably, it reveals that organizational factors significantly impact users' attitudes towards innovative technologies. This underscores the importance of management and other stakeholders' supportive role in fostering positive attitudes towards new technology adoption. It is imperative to acknowledge that the perceptions pertaining to smart city life in this study are predicated solely on a single survey. For enhanced reliability, future research could benefit from a longitudinal study to measure attitude changes over time. Additionally, the sample comprises urban citizens in developed countries, and expanding research across diverse communities could enhance the generalizability of smart city studies. This study provides initial insights and serves as a foundation for future investigations in this field.

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