TECHNOLOGY ACCEPTANCE AND BEHAVIORAL INTENTIONS OF HOME IOT HEALTHCARE DEVICES IN SMART CITY ENVIRONMENTS: A COMPARATIVE STUDY BETWEEN GENERATION XY AND Z

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ABSTRACT

This study explores the acceptance and behavioral intentions towards home IoT healthcare devices within the context of a smart city, aiming to understand how these technologies can enhance urban healthcare outcomes. A sample of 571 respondents was analyzed using SmartPLS 4.0, with reliability and validity confirmed through such as Cronbach's Alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) tests. Hypothesis testing revealed via SmartPLS 4.0 that performance expectancy (β = 0.118, p = 0.044), effort expectancy (β = 0.184, p < 0.001), social influence (β = 0.208, p < 0.001), and consumer innovativeness (β = 0.356, p < 0.001) significantly influence attitudes towards these devices while facilitating conditions (β = 0.057, p = 0.222) did not. Additionally, attitudes (β = 0.802, p <0.001) were found to have a positive and significant effect on behavioral intention. An independent t-test performed using IBM SPSS 26.0 revealed significant differences between generation groups for all variables except facilitating conditions, with the generation Z group showing higher usage. The findings emphasize the importance of demographic factors in the adoption of IoT healthcare technologies in smart cities. By identifying key influences on user attitudes and noting the higher usage among the generation Z group, this research provides valuable insights for policymakers and technology developers. These insights can guide the implementation and promotion of IoT healthcare devices, ensuring they meet the needs of diverse urban populations and contribute to more inclusive and effective smart city healthcare solutions.

Keywords: Unified Theory of Acceptance and Use of Technology (UTAUT), Consumer Innovativeness, Healthcare device, Smart city, Generation

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INTRODUCTION

The rapid development of smart cities, the global smart city industry is expected to grow from \$410.8 billion in 2020 to \$820.7 billion in 2025 (Vuppuluri, 2020). It is driven by advances in information and communication technologies, has fundamentally transformed various aspects of urban life, particularly in the healthcare sector. Central to this transformation is the integration of the Internet of Things (IoT) into home environments, enabling innovative health monitoring solutions (Bhuiyan et al., 2021). Among these, home IoT healthcare devices, which provide non-invasive, continuous, and accurate health monitoring while enhancing customer comfort, compliance, and emergency response, have gained significant attention (Haroun et al., 2021). These devices, leveraging IoT networks, provide real-time health monitoring, which is crucial for the early detection and management of chronic conditions like cardiovascular diseases (Islam et al., 2023).

Cardiovascular diseases remain the leading cause of death worldwide, responsible for approximately 17.9 million deaths annually (World Health Organization, 2024). Traditional methods for monitoring cardiovascular health, such as electrocardiograms (ECGs) and Holter monitors, although effective, require clinical visits and provide intermittent data, which can delay the detection of potential health issues (Krittanawong et al., 2021). In contrast, home IoT healthcare devices offer continuous monitoring in the home, reducing the need for frequent clinical interventions and allowing for earlier detection of health problems (Jacob Rodrigues et al., 2020). This capability is particularly vital in smart cities, where technological infrastructure supports the widespread adoption of such advanced healthcare solutions.

The global market for IoT in healthcare reflects the increasing reliance on these technologies to enhance healthcare delivery. The worldwide revenue of the Digital Health market, amounting to \$170.25 billion in 2023, is expected to increase to \$274.93 billion by 2028 (Statista, 2023). This rapid expansion underscores the significant potential of home IoT-enabled healthcare devices, particularly in smart cities, where these technologies can substantially improve public health outcomes and healthcare system efficiency.

Despite the technological promise of IoT devices, their successful implementation in home healthcare settings is not guaranteed. The adoption of these innovative healthcare solutions depends not only on their technical capabilities but also on the acceptance and use by the general population (Aldossari & Sidorova, 2020). Understanding the factors that influence technology adoption in this context is essential for their effective deployment. The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by (Venkatesh et al., 2003), offers a comprehensive framework for analyzing technology adoption behaviors. The UTAUT model identifies four key constructs—performance expectancy, effort expectancy, social influence, and facilitating conditions—that significantly influence users' behavioral intentions to adopt new technologies (Abbad, 2021; Andrews et al., 2021). While the UTAUT model has been extensively applied across various domains, its application to non-wearable IoT healthcare devices, such as radar sensors, remains underexplored.

In addition to the core constructs of the UTAUT model, consumer innovativeness plays a critical role in the adoption of healthcare devices (Dhiman et al., 2019; Rehman et al., 2022). Consumer innovativeness is defined as an individual's propensity to embrace and experiment with new technologies (Zhang et al., 2020). This trait is particularly relevant in smart city environments, where rapid technological advancements require residents to continuously adapt to new devices and systems.

Moreover, demographic factors, especially age or as known in this study as generation, have been shown to moderate the relationship between the UTAUT constructs and technology adoption (Hu et al., 2020; Merhi et al., 2021). Previous research suggests that younger individuals are generally more inclined to adopt new technologies compared to middle-aged and elderly individuals, who may face more barriers due to lower familiarity with digital devices. The paradox of technology adoption, particularly in the healthcare sector, is that middle-aged and older adults, who stand to benefit the most from these innovations, are often the ones who find it the most challenging to adopt them (Landgren & Cajander, 2021). This highlights the necessity of understanding the factors that influence this demographic's acceptance of IoT healthcare devices. Given that the aging population is growing rapidly in urban areas, particularly in smart cities, this demographic presents a significant market for IoT healthcare devices (Nassereddine & Khang, 2024). Therefore, investigating the factors that influence their adoption of home IoT healthcare devices is both timely and necessary.

This study aims to address these gaps by extending the UTAUT model to include consumer innovativeness as an additional predictor variable and by examining the moderating effect of generation on the acceptance of home IoT healthcare devices. Specifically, the research seeks to explore how these factors shape user attitudes and behavioral intentions toward adopting these technologies in a smart city context. The findings of this research have the potential to inform the design and implementation of more user-centric IoT healthcare solutions in smart cities. By understanding the factors that drive or hinder the adoption of home IoT healthcare, developers and policymakers can develop strategies that promote broader acceptance and usage across diverse population segments. This is particularly crucial in smart city environments, where the successful deployment of IoT healthcare devices can lead to significant improvements in public health outcomes and overall healthcare efficiency.

LITERATURE REVIEWS

Home IoT Healthcare Devices in Smart City

The integration of IoT healthcare devices into a smart city is strongly influenced by local contextual factors such as economic development, urban structure, geography, and population density. Several factors play a critical role in determining a city's digital path and implementing a smart city initiative (Neirotti et al., 2014). A city with advanced infrastructure and a high population density, for instance, may find it easier to adopt and integrate IoT healthcare devices because the necessary digital infrastructure and resources are already in place (Al-rawashdeh et al., 2022). In contrast, cities with less developed economies or dispersed populations may find it difficult to effectively implement such technologies. As a result, these contextual factors are pivotal to the feasibility and success of IoT-based healthcare solutions in various urban settings.

With smart healthcare systems, the use of IoT and smart meters can offer significant benefits, including improved quality of care and a reduction in medical professionals' workloads by enabling remote monitoring of patients via wearable and implantable devices. As highlighted by Wahid (2020), these technologies not only improve healthcare delivery but also allow for continuous monitoring of health status, thereby providing an opportunity for early detection and treatment. These systems must, however, be implemented with caution. According to Lai and Lai (2023), IoT and smart health technologies offer significant benefits, but they also pose a number of challenges that need to be addressed through careful planning and implementation. An approach is proposed for navigating these challenges, providing a structured approach to ensuring that the potential benefits of the Internet of Things in healthcare are fully realized.

In the context of Home IoT healthcare devices within smart cities, the technology of detecting frequency or phase shifts in reflected radar sensors allows for non-contact monitoring of vital signs like breathing and heartbeat. Recent advancements have focused on reducing power consumption, device size, and weight while improving accuracy and detection range. These improvements are particularly promising for healthcare applications, such as monitoring sleep patterns and detecting abnormal breathing, making it a key area of interest in smart city initiatives (Bhuiyan et al., 2021).

Unified Theory of Acceptance and Use of Technology (UTAUT)

The Technology Acceptance Model (TAM), developed by Davis et al. (1989), has been widely used to explain user acceptance of technology, drawing on the Theory of Reasoned Action (TRA). However, TAM has limitations in addressing external variables, social factors, and the complexity of technology acceptance in varying contexts. To overcome these shortcomings, Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT integrates constructs from eight different models, including TAM, TRA, Theory of Planned Behavior (TPB), Motivational Model (MM), and others, aiming to provide a more comprehensive explanation of user behavior towards new technologies.

The UTAUT model introduces four key constructs that significantly influence technology acceptance: performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003b). Performance expectancy is the extent to which a user believes that using a particular technology will enhance their job performance, aligning closely with the 'perceived usefulness' concept in TAM. Effort expectancy relates to the perceived ease of using the technology, similar to TAM's 'perceived ease of use.' Social influence refers to the degree to which an individual perceives that important others believe they should use the technology, drawing from concepts like subjective norms in TRA and TPB. Lastly, facilitating conditions represent the user's perception of the available organizational and technical support needed to use the technology.

The application of the Unified Theory of Acceptance and Use of Technology (UTAUT) framework in recent studies has provided valuable insights into the acceptance of home IoT healthcare devices within the smart city context. Research has shown that key UTAUT constructs, such as performance expectancy, effort expectancy, social influence, and facilitating conditions significantly influence users' behavioral intentions to adopt these technologies. For example, Jena (2022) extended the UTAUT model to explore factors affecting the use of smart services in a smart city, emphasizing the importance of these constructs in driving technology adoption. Similarly, Popova and Zagulova (2022) applied the UTAUT model to understand how residents use web applications in smart cities, further highlighting the model's relevance in urban environments. In the healthcare domain, Wang et al. (2020) integrated UTAUT with Task-Technology Fit to examine the acceptance of healthcare wearable devices, demonstrating that the alignment between technology and user tasks is crucial for adoption. Kang et al. (2022) expanded on this by investigating smart home healthcare services in South Korea, finding that both UTAUT constructs and TTF significantly impact behavioral intentions. Additionally, Ben Arfi et al. (2020) explored the role of perceived risk and financial cost in IoT healthcare acceptance, identifying these factors as critical barriers to adoption. Collectively, these studies underscore the robustness of the UTAUT model in explaining technology acceptance and provide a strong foundation for exploring the integration of IoT healthcare devices into smart city infrastructures.

Age differences have a significant impact on technology acceptance, and generational groupings can provide valuable insight into these differences. The study of access to technology and the opportunities that are associated with it has frequently focused on the impact of demographic factors such as gender and ethnicity on access to technology (Campbell et al., 2015). It has become increasingly evident, however, that the age and generational differences play a crucial role in determining how technology is adopted. Generations are shaped by historical and cultural contexts that vary in their comfort and enthusiasm for technology. Since older generations are less familiar with and perceive new technologies as complex, they may be more reluctant to adopt them, whereas younger generations, who have grown up in an increasingly technologically integrated environment, typically accept and adopt new technologies more quickly. In order to achieve a greater level of technology adoption among diverse populations, generational perspectives are crucial for designing tailored strategies that address the specific needs and concerns of each generation group (Fox & Connolly, 2018).

Consumer Innovativeness

In Agarwal and Prasad (1998), the concept of consumer innovativeness is defined as the willingness of individuals to adopt any new technology related to information. In an era of rapid technological advancement, where consumers are frequently faced with new products and services, this concept is particularly pertinent. A person's level of innovativeness can have a significant effect on their adoption behavior, since those who are more innovative are more likely to adopt new technologies with greater ease than those who are less innovative (Yi et al., 2006). New products can be launched successfully if market dynamics are driven by this willingness to experiment with new technologies.

On the basis of this foundation, recent studies have integrated consumer innovativeness within broader models of technology adoption. By incorporating consumer innovativeness as a key component of the Unified Theory of Acceptance and Use of Technology (UTAUT), Lu et al. (2005) and Slade et al. (2015) enhance the Unified Theory of Acceptance and Use of Technology (UTAUT) model. They demonstrate that consumer innovativeness is important not only for the adoption of new products but also for the diffusion of innovations. Incorporating consumer innovativeness into the UTAUT model provides a more comprehensive understanding of how individual differences in innovativeness can affect technology acceptance and usage. It also provides valuable insights for marketers and product developers interested in promoting new technologies effectively.

It is important to note that consumer innovativeness plays an important role in the adoption and diffusion of new technologies as well as the long-term success and sustainability of those technologies (Hyysalo et al., 2017). The ability to understand the nuances of consumer innovativeness will also enable businesses to tailor their marketing strategies, product designs, and support services to better meet the needs of different segments of the market, increasing the likelihood of widespread adoption and long-term market penetration (Sun et al., 2019). (Sun et al., 2019) It is possible for companies to create a solid foundation for their products' success by targeting innovative consumers effectively, thereby ensuring that new technologies are not only adopted quickly, but are also integrated into consumers' lives in meaningful ways.

Based on the literature review of existing previous study, this study proposed 6 hypothesis which are:

H1: Performance Expectancy (PE) has a positive effect on Attitude (Att) towards using the technology.

H2: Effort Expectancy (EE) has a positive effect on Attitude (Att) towards using the technology.

H3: Social Influence (SI) has a positive effect on Attitude (Att) towards using the technology.

H4: Facilitating Conditions (FC) have a positive effect on Attitude (Att) towards using the technology.

H5: Consumer Innovativeness (CI) has a positive effect on Attitude (Att) towards using the technology.

H6: Attitude (Att) has a positive effect on Behavioral Intention (BI) to use the technology.

RESEARCH METHODOLOGY

Drawing from previous research, this study proposes an advanced research model, as illustrated in Table 1, designed to comprehensively assess the key factors driving technology acceptance of Home IoT healthcare devices especially radar sensor. The model seeks to explore the determinants that influence user attitudes and adoption behaviors, offering a solid framework for understanding the integration of these technologies in home healthcare settings.

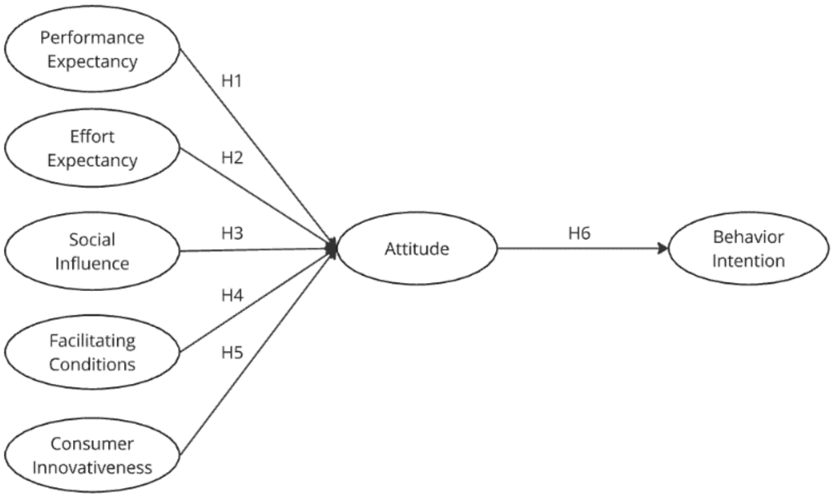

Figure 1 Research Model

This study employed a structured research design, consisting of four key steps: Data Collection, Data Refining, Data Analysis, and Additional Analysis as shown in Figure 2. The data collection was conducted from June 10th to July 21st, utilizing an online survey distributed through Google Forms with convenience sampling. A total of 593 responses were initially gathered. To ensure the integrity of the data, a data refining process was implemented. During this process, responses with missing data and those regarded as insincere were removed, resulting in a final dataset comprising 571 valid responses.
The refined dataset underwent a comprehensive data analysis process. Firstly, a socio-demographic analysis was performed using SPSS 26.0 to assess the demographic profile of the respondents. Subsequently, the reliability and validity of the constructs were tested using SmartPLS 4.0 to ensure the robustness of the measurement model. Hypothesis testing was also conducted within the SmartPLS 4.0 to evaluate the proposed relationships in the research model. To further explore potential differences in responses across demographic variables, an additional t-test analysis was carried out specifically for generation using SPSS 26.0. This multi-step methodology ensured a rigorous examination of the data, leading to reliable and valid conclusions that support the study's objectives.

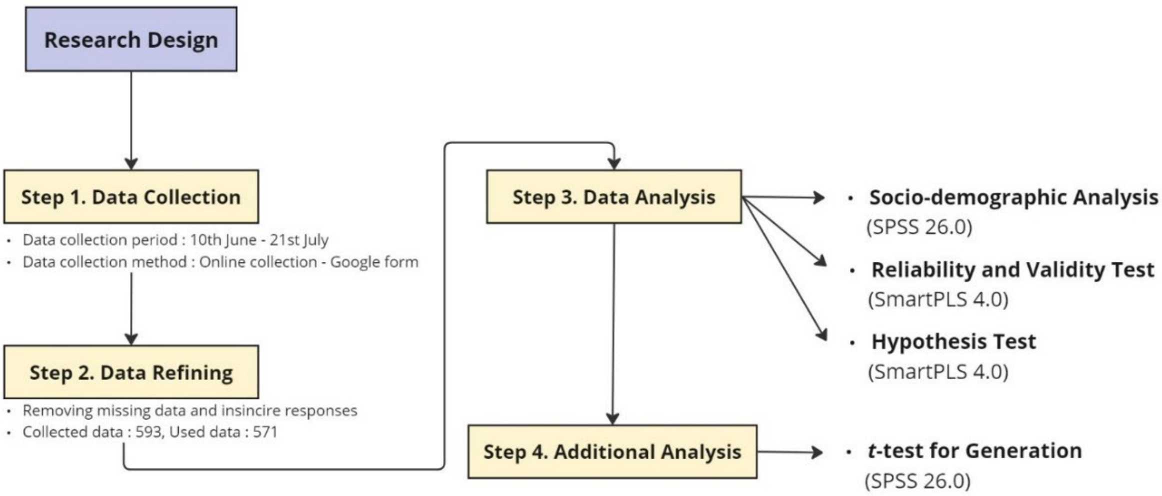

Figure 2 Research Flow

RESEARCH RESULTS

Demographic Information

The demographic profile of the respondents as shown in Table 1 reveals a balanced gender distribution, with 49% male and 51% female participants. The majority of respondents are in their 20s (52.2%), followed by those in their 30s (32.6%), with a smaller representation of individuals under 20 (2.9%) and over 40 (12.1%). Nationality-wise, the largest group is Indonesian (52.2%), followed by Chinese (32.6%), and Vietnamese (11.7). In terms of education, the majority have a Bachelor's degree (60.8%), with smaller segments having completed postgraduate studies (15.7%), a 3-year college (14.9%), or high school and below (8.6%). The income distribution shows that nearly half of the respondents earn between $1,000 and $1,999 monthly (48.2%), with others earning less than $1,000 (22.5%), between $2,000 and $2,999 (22.5%), and over $3,000 (6.9%). Marital status indicates that 43.2% are married, 39.6% are not married, and 17.3% are divorced. Regarding household size, most respondents live in households with three (26.9%) or more than four members (27.6%), while 20.7% live alone and 24.7% live in two-person households.

Table1 Demographic Information

Variables		**Frequency**	**Percent (%)**
Gender	Male	280	49.0
	Female	292	51.0
Generation	Under 20	17	2.9
	20's	302	52.2
	30's	189	32.6
	Over 40	70	12.1
Nationality	Korean	17	2.9
	Indonesian	302	52.2
	Vietnamese	68	11.7
	Chinese	189	32.6
	Others	2	0.4
Education Level	High school graduate and below	50	8.6
	3-year college	86	14.9
	Bachelor’s degree	352	60.8
	Postgraduate	91	15.7
Monthly Income	Less than $1,000	130	22.5
	$1,000~$1,999	279	48.2
	$2,000~$2,999	130	22.5
	Over $3,000	40	6.9
Marital Status	Not Married	229	39.6
	Married	250	43.2
	Divorced	100	17.3
Household #	1 (living alone)	120	20.7
	2	143	24.7
	3	156	26.9
	More than 4	160	27.6

Reliability and Validity Test Results

The reliability and validity test results for the constructs demonstrate that all criteria are satisfactorily met, ensuring the robustness of the measurement model as shown in Table 2. According to Hulland (1999), factor loadings should be over 0.7, and all items across the constructs meet this criterion, indicating that each item is a strong indicator of its respective construct. Composite Reliability (CR), as recommended by Bagozzi and Yi (1988), should exceed 0.7; all constructs have CR values ranging from 0.769 to 0.852, confirming the internal consistency of the items within each construct. Additionally, the Average Variance Extracted (AVE) values, which should be above 0.5 according to Bagozzi and Yi (1988), range from 0.642 to 0.769 across constructs, indicating that the constructs capture a significant portion of variance from their items. Lastly, Cronbach's Alpha values, which should be over 0.7 (Nunnally, 1978), are all above this threshold, further confirming the reliability of the scales used. These results collectively suggest that the constructs are both reliable and valid, providing a solid foundation for further analysis.

Table2 Reliability and Validity Test Results

Constructs	Items	Factor Loading	CR	AVE	Cronbach's Alpha
Performance Expectancy	PE1	0.862	0.769	0.668	0.753
	PE2	0.776			
	PE3	0.812			
Effort Expectancy	EE1	0.909	0.852	0.769	0.850
	EE2	0.862			
	EE3	0.859			
Social Influence	SI1	0.847	0.794	0.707	0.792
	SI2	0.812			
	SI3	0.861			
Facilitating Condition	FC1	0.872	0.807	0.713	0.799
	FC2	0.856			
	FC3	0.803			
Consumer Innovativeness	CI1	0.843	0.816	0.642	0.812
	CI2	0.700			
	CI3	0.831			
	CI4	0.826			
Attitude	Att1	0.892	0.818	0.730	0.815
	Att2	0.809			
	Att3	0.860			
Behavioral Intention	BI1	0.810	0.786	0.698	0.782
	BI2	0.804			
	BI3	0.889			

Hypotheses Test Results

The results of the hypotheses testing provide key insights into the factors influencing user attitudes (Att) and behavioral intentions (BI) toward adopting Home IoT healthcare devices. As shown in Table 3, H1 through H3 were supported, indicating that Performance Expectancy (PE), Effort Expectancy (EE), and Social Influence (SI) significantly and positively impact user attitudes. Specifically, PE ($\beta = 0.118$, $p = 0.044$), EE ($\beta = 0.184$, $p < 0.001$), and SI ($\beta = 0.208$, $p < 0.001$) all contribute to shaping favorable attitudes towards these devices. Additionally, H5 was strongly supported, showing that Consumer Innovativeness (CI) ($\beta =$

0.356, p < 0.001) plays a crucial role in enhancing user attitudes by aligning the technology with users' existing needs and practices.
In contrast, H4, which proposed a relationship between Facilitating Conditions (FC) and Attitude, was not supported (β = 0.057, p = 0.222), suggesting that these conditions do not significantly influence user attitudes in this context. However, the analysis confirmed that Attitude (Att) is a critical determinant of Behavioral Intention (H6), with a high path coefficient (β = 0.802, p < 0.001), indicating that positive attitudes towards Home IoT healthcare devices strongly predict users' intentions to adopt these technologies

Table 3 Hypotheses Test Results

Path		Path Coefficient (*β*)	Standard Deviation	*t*-value	*p*-value	Result
H1	PE -> Att	0.118	0.059	2.011	0.044	Supported
H2	EE -> Att	0.184	0.049	3.747	< 0.001	Supported
H3	SI -> Att	0.208	0.054	3.855	< 0.001	Supported
H4	FC -> Att	0.057	0.047	1.222	0.222	Not Supported
H5	CI -> Att	0.356	0.060	5.968	< 0.001	Supported
H6	Att -> BI	0.802	0.022	36.142	< 0.001	Supported

t-test Results

The t-test results presented in Table 4 reveal significant differences between respondents under 30 years old and those over 30 in terms of their perceptions of key factors influencing the acceptance of Home IoT healthcare devices. For all measured constructs, Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Compatibility (CI), Attitude (ATT), and Behavioral Intention (BI), respondents over 30 consistently reported higher mean scores compared to those under 30. Specifically, the largest mean differences were observed in Facilitating Conditions (FC) (t = -7.112, p < 0.001) and Behavioral Intention (BI) (t = -6.587, p < 0.001), suggesting that older respondents perceive stronger external support and have a higher intention to adopt Home IoT healthcare devices compared to their younger counterparts.

Table 4 *t*-test Results- Generation

	Generation				
	Gen-Z		Gen-XY		
	M	SD	M	SD	*t*-statistics
PE	3.814	0.871	4.186	0.675	-5.611***
EE	3.757	0.963	4.189	0.670	-6.083***
SI	3.705	0.887	4.118	0.631	-6.284***
FC	3.751	0.880	4.225	0.667	-7.112***
CI	3.875	0.889	4.158	0.669	-4.207***
ATT	3.797	0.848	4.184	0.658	-5.981***
BI	3.803	0.785	4.207	0.652	-6.587***

DISCUSSION & CONCLUSION

Discussion

The results of the hypothesis testing provide valuable insights into the factors influencing attitudes (Att) and behavioral intentions (BI) towards the adoption of home IoT healthcare devices. The supported hypotheses H1, H2, H3, H5, and H6 reveal a significant relationship between performance expectancy (PE), effort expectancy (EE), social influence (SI), consumer innovativeness (CI), and attitudes, as well as between attitudes and behavioral intention. These findings align with previous studies in the field Sung et al. (2015), suggesting that users' perceptions of the benefits and ease of use of IoT healthcare devices, along with the influence of social factors and individual innovativeness, play crucial roles in shaping their attitudes and subsequent intentions to adopt these technologies (Al-rawashdeh et al., 2022).

Specifically, hypothesis H1 (PE -> Att) was supported with a path coefficient of 0.118 and a p-value of 0.044, indicating a significant yet relatively modest impact of performance expectancy on attitudes. This suggests that while users recognize the importance of the functional benefits offered by IoT healthcare devices, these benefits alone are not the most dominant factor in shaping their attitudes (Haghi Kashani et al., 2021). Similarly, hypothesis H2 (EE -> Att) demonstrated a stronger influence with a path coefficient of 0.184 and a highly significant p -value of less than 0.001, highlighting that ease of use is a critical factor in forming positive attitudes towards these devices. This underscores the importance of designing user-friendly interfaces and minimizing complexity to enhance user acceptance (Burkolter et al., 2014).

Social influence (SI) also emerged as a significant determinant of attitudes, as indicated by hypothesis H3, with a path coefficient of 0.208 and a p-value of less than 0.001. This finding reinforces the notion that social factors, such as recommendations from peers or the perceived popularity of IoT healthcare devices, significantly contribute to shaping users' attitudes (Dutta et al., 2023). However, hypothesis H4 (FC -> Att) related to facilitating conditions, was not supported (path coefficient = 0.057, p -value = 0.222), suggesting that the availability of resources and support for using IoT devices does not have a direct impact on attitudes. This may imply that users prioritize the inherent characteristics of the devices and the influence of their social environment over external support mechanisms when forming their attitudes (Lei & Zeng, 2020).

Lastly, consumer innovativeness (CI) was found to have the strongest impact on attitudes, as evidenced by hypothesis H5, with a path coefficient of 0.356 and a p -value of less than 0.001. This emphasizes the role of individual differences in innovation adoption, where more innovative consumers are significantly more likely to have a positive attitude towards new technologies (Agarwal & Prasad, 1999). It is also mentioned in the previous study that focuses on Generation difference, all factors except social influence have significant and positive impacts on Gen Z's intentions to adopt the metaverse in higher education learning environments (Al-Adwan & Al-Debei, 2024). Additionally, hypothesis H6 (Att -> BI) confirmed that attitudes towards IoT healthcare devices are a strong predictor of behavioral intentions, with a path coefficient of 0.802 and a highly significant p-value of less than 0.001. This finding underscores the importance of fostering positive attitudes as a key strategy for encouraging the adoption of home IoT healthcare devices. Together, these results provide a comprehensive understanding of the determinants influencing the adoption of IoT healthcare technologies, offering valuable implications for both theoretical advancement and practical application.

Implications

The findings of this study offer significant theoretical contributions by providing critical insights into the determinants of attitudes and behavioral intentions towards home IoT healthcare devices. By integrating consumer innovativeness within the UTAUT framework, this research advances our understanding of technology acceptance, particularly in the context of home IoT healthcare devices. This integration highlights how consumer innovativeness influences the willingness to adopt new technologies, which is a crucial aspect of enhancing technology acceptance. Moreover, the study underscores the importance of demographic factors, particularly generation, in the adoption of IoT healthcare technologies. These findings suggest that generation-related differences play a pivotal role in shaping users' attitudes and

behaviors towards these devices, which should be further explored in future research to refine and extend the theoretical frameworks in this domain.
From a managerial perspective, the insights gained from this study can be directly applied to enhance the adoption and utilization of home IoT healthcare devices. By understanding the role of consumer innovativeness and demographic factors, such as generation, technology developers and marketers can tailor their strategies to better meet the needs and preferences of different user groups. For instance, policymakers and technology developers should consider generation-related preferences and barriers when designing and marketing IoT healthcare devices. Targeted marketing efforts that address the specific concerns and interests of various generation groups could significantly improve the adoption rates of these technologies. Additionally, developing user-friendly interfaces and offering comprehensive support for older adults may encourage broader acceptance and sustained use of home IoT healthcare devices, ultimately leading to better health outcomes and more efficient healthcare delivery.

Limitations and Future Studies

This study has several limitations that should be acknowledged. First, the use of convenience sampling may limit the generalizability of the findings, as the sample may not be fully representative of the broader population. The reliance on participants who were readily available and willing to participate could introduce biases that affect the study's outcomes. Future research should consider employing more diverse and rigorous sampling techniques, such as stratified or random sampling, to enhance the representativeness and reliability of the results across different demographic groups.
Additionally, the study focused on a specific type of Home IoT healthcare device, which may not fully capture the diversity and complexity of the broader category of Home IoT technologies in healthcare. As the IoT healthcare market continues to expand, it is crucial for future studies to explore a wider range of IoT healthcare devices to better understand the varying factors that influence user acceptance and adoption across different types of technologies. This broader approach would provide a more comprehensive understanding of how different IoT healthcare solutions are perceived and adopted by users in diverse healthcare settings.

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