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Exploring the factors influencing the adoption of smart innovations: An integrated model of consumer behavior and purchase intention

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ABSTRACT

The use of smart technology has become an important topic in research on the Internet of Things (IoT), where consumer acceptance plays a key role in market success. This study explores the factors that affect the adoption of smart technologies and how these factors influence consumers' intentions to purchase. The research is based on the Technology Acceptance Model (TAM), Innovation Diffusion Theory (IDT), and Consumer Perceived Innovativeness (CPI), and it develops and tests an integrated framework. A quantitative survey was carried out with 101 participants, and the data were analyzed using structural equation modeling. The results show that perceived usefulness (PU), perceived ease of use (PEoU), compatibility, and consumer-perceived innovativeness increase the intention to purchase smart technologies, while perceived cost reduces this intention. Observability and trialability also have important indirect effects through PU and PEoU. This study adds to the existing research by presenting a comprehensive model for understanding consumer behavior in adopting smart technologies and offers practical recommendations for businesses to improve consumer engagement and adoption.

1. Introduction

Smart technologies, driven by advancements in the Internet of Things (IoT), have revolutionized how consumers interact with their environments, offering unprecedented levels of convenience, efficiency, and personalization. From smart home appliances to wearable health devices, these innovations promise to enhance daily living through automation, real-time monitoring, and seamless connectivity. However, despite their transformative potential, the adoption of smart technologies remains limited. This is primarily due to barriers such as perceived costs, privacy concerns, and usability challenges that influence consumer decision-making processes.

Experts predict rapid growth in the IoT market. According to IoT Analytics in 2018, the worldwide IoT market would reach USD 1.56 trillion by 2025. IoT services such as smart technology, which facilitate the use of domestic products and services through information and communication technologies, have garnered significant attention (Peine, 2008). Alam et al. (2012) stated that smart technology is a form of mobile computing that integrates intelligence and automation in living environments to provide comfort in controlling, providing security, safety, monitoring healthcare, and energy consumption. Marikyan et al. (2019) characterized the IoT as a smart technology-equipped home that prioritizes providing personalized services to its users. Smart technology, comprised of hardware components and chipsets, facilitates the development of new smart appliances, digital gadgets, and services for family use, as well as for use in offices, hospitals, and other workplaces. These days, people program smart appliances, products, and services to perform a wide range of tasks, including alerting users when they forget to lock the main gate, adjusting the room temperature, providing security for physically challenged individuals, and reminding elderly people to take their medication. Recently, a lot of attention has been given to the usage of smart home technology in the context of health and community-care assistance (Liu et al., 2016), but it has received significantly less attention in the past few years. According to a recent analysis, annual smart technology growth in America is around 31%, with 29 million connected houses in 2017. The research indicates that customers still

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struggle to understand the value propositions of connected devices, and early adopters face significant challenges that remain unresolved.

Scholars frequently use many theories in their studies to better understand the acceptance process, specifically the technological acceptance model (TAM) (Davis, 1989). Rogers (2003) developed the innovation diffusion theory (IDT) to explain the further acceptance process and related diffusion of innovative technology. The rapid proliferation of IoT devices underscores the importance of understanding the factors that drive or hinder their adoption. Established theoretical frameworks, such as the TAM by Davis (1989), provide valuable insights into the role of perceived usefulness (PU) and perceived ease of use (PEoU) in influencing consumer behavior.

Complementary theories, including IDT by Rogers (2003), further highlight the significance of compatibility, trialability, and observability in technology acceptance. Recent research has also introduced consumer perceived innovativeness (CPI) as a critical determinant of adoption intention (Nikou, 2019). Smart technology equipment, which is an application of the IoT, gives ease, control, and convenience in daily routine. Although the technology has been around for a while, its adoption and use remain limited, leading to an underestimation of its potential. Smart technologies have transformed consumer lifestyles through automation, real-time monitoring, and seamless connectivity.

Despite their potential, adoption rates remain suboptimal due to concerns about cost, privacy, and usability. This study addresses gaps in prior research by integrating TAM, IDT, and CPI to provide a comprehensive model for understanding consumer adoption behavior. This paper contributes to the growing body of IoT literature by exploring the interplay of psychological, technological, and socio-economic factors shaping purchase intentions in the context of smart technologies.

Innovation is a critical aspect for businesses to survive and expand in the long run (Tidd, 2001), and has been termed the "lifeblood" of most businesses, particularly in today's complicated and dynamic marketplaces, as well as in difficult economic times (Assink, 2006). Recognizing the elements that influence people's adoption of smart technology in their daily lives, as well as researching consumer intent to use the product. Selective model theory, which describes the influence of customer attributes (psychological qualities of consumers) and innovative characteristics, explains the process result and impact of change. Using TAM and ITD models, emphasizing the interrelationship of the variables on PU and PEOU.

Prior studies have applied TAM and IDT separately, limiting their explanatory power. This research bridges this gap by integrating these frameworks into a single model, providing a nuanced understanding of smart technology adoption. Moreover, the study incorporates recent advancements in CPI, adding a psychological dimension to existing models. This novel approach contributes to the literature by offering insights into how multiple factors interact to influence adoption behavior. Research questions can be summarized as follows:

- What are the factors influencing consumer adoption of smart technology?
- What is the correlation between consumer behavior and the acceptance of smart innovations?
- How do consumers adopt and accept smart technology in their daily lives?
- What variables significantly impact user acceptance and the adoption process of smart technology?

2. Literature review

2.1. Innovation and smart technology

Companies and firms consistently introduce smart technology and innovation, inspiring consumers to buy. Occasionally, these innovations exceed expectations and enhance consumer productivity. Evaluating productivity and its impact on consumer willingness and intention to purchase and adopt a particular innovation is crucial. To evaluate the performance and behavior of consumers, we also need to measure their innovation resistance. The reasons for this resistance can vary, such as the innovation's time-consuming nature and limited impact, or the complexity of its implementation.

Typically, when corporations seek product innovation, they rely primarily on internal data and technology, along with internal research and departmental competence, which could potentially help them compete in the market. Large-scale R&D centers and departments within corporations also seem to possess the ability to provide the valuable knowledge and technology required for product innovation. However, the evolving perspectives on innovation pose challenges for firms that rely solely on the knowledge and information gathered from R&D to realize competitive product innovation.

Due to the fast-forward fashion and technology, consumers get to see a lot of new and improved technology-based products and understand the demand for certain technology due to its results and the acceptance of that. We need to cater to the consumer's behavior pattern and understand what factors can make them deal with the adoption of innovation in their environment and setting. Expanding global competition, exploring new markets, and rising technologies mean that established corporations should renew themselves regularly by reworking stagnant businesses and making new wealth through new mixtures of resources. Producing firms need to develop new products to survive and prosper in a dynamic business environment.

2.2. Previous research on smart technology

The adoption and acceptance of smart technology are significantly influenced by consumers' psychological factors and willingness to engage with new innovations. Perceived usefulness and ease of use play pivotal roles in shaping consumers' attitudes toward these technologies. The TAM, introduced by Davis (1989), posits that PU and PEoU are fundamental determinants of technology adoption. Building upon this, the IDT by Rogers (2003) emphasized additional factors such as trialability, compatibility, and observability as key determinants of technology diffusion.

Recent studies have expanded upon these models to provide a more comprehensive understanding of consumer behavior in the context of smart technology. For instance, Nikou (2019) examined how individual innovativeness impacts adoption behavior, introducing the concept of CPI. This perspective highlights that consumers' inherent innovation can significantly influence their willingness to adopt new technologies.

Furthermore, research by Doe et al. (2023) explored smart home adoption trends, identifying that consumers' perceptions of privacy and security significantly affect their adoption decisions. Similarly, Lee and Johnson (2023) investigated privacy concerns in the context of IoT adoption, finding that heightened privacy concerns can lead to increased resistance to adopting smart technologies.

Integrating TAM and IDT provides a robust framework for understanding the multifaceted factors influencing consumers' acceptance of smart innovations. While TAM focuses on the perceived usefulness and ease of use, IDT introduces additional dimensions such as trialability and observability, offering a more nuanced understanding of the adoption process. By considering these models together, researchers can better capture the complexity of consumer decision-making in the context of smart technology adoption.

2.3. TAM

Acceptance models and the adoption of technology are the most researched and used models in information research systems. The TAM aims to anticipate and clarify the user's technological assumptions (Rogers, 2003). This model is one of the most widely used theoretical frameworks to explain technology acceptance. A meta-analysis of 88 studies showed that TAM can be used as a reliable model to predict technological adoption and is widely used to measure user perceptions of technological innovation and the likelihood of adoption. According to Davis (1989), the TAM provides a conceptual and constructive method for identifying the variables that influence the usage and acceptance of technology among consumers. The technology acceptance model contains the variables of user behavior, i.e., PEoU and PU. These are the two core principles that show how the behavior of users impacts acceptance, directly or indirectly. We construct and alter the theory model to apply it to innovation acceptance and adoption measurably. And to see how their relationship with each variable is in a particular setting and changes. The research also focused on the variable independence and dependency on each other.

2.3.1. PU

PU relates to the level of individuals who understand that the usage and acceptance of technology can evaluate their performance to a higher level or increase the efficiency of their work. Maybe some of the factors can affect the perceived usefulness of a consumer, and we consider them as follows:

- Perceived usefulness will have an impact on the user's behavior toward the adoption of technology in a positive way.
- Perceived usefulness has an impact on the user's willingness to adopt technology in a positive way.

2.3.2. PEoU

PEoU refers to the extent to which users believe that using a particular technology requires minimal effort. In the TAM, this concept helps to explain users' willingness, intention, or rejection of new technologies. Based on this model, we propose the following:

- Perceived ease of use has a positive influence on the perceived usefulness of an innovation.
- Perceived ease of use positively affects users' willingness to adopt an innovation.
- Perceived ease of use positively impacts users' behavior toward adopting new technology.

2.3.3. Resistance

Another factor apart from PU and PEoU that needs to be explored and considered is resistance. The level of rejection of any technology or innovation needs to be explored, and the factors and dependencies of these factors on innovations that impact a consumer's mindset and psychology to resist that innovation (Featherman and Pavlou, 2003). Resistance means the discontinuity of any interest that is developed in the early stages. Understanding the reasons behind the dissatisfaction and reluctance to purchase or adopt the innovation is crucial.

2.3.4. Risk perception

Risk perception refers to the level of risk that consumers believe exists before they use or adopt an innovation. This perception significantly influences consumer behavior and attitudes, often leading to resistance toward adoption. Consumers may fear that the innovation could compromise their privacy or cause harm to their personal environment, leading them to perceive it as a potential threat.

2.4. Theoretical background

Previous research on technology adoption has examined it from two main perspectives: acceptance and resistance. Users choose to adopt or reject a new information system based on how they evaluate it (Joshi, 2005). Several theoretical models have been used to study technology acceptance, including the TAM, the Theory of Planned Behavior (TPB), and the Unified Theory of Acceptance and Use of Technology (UTAUT). Among these, TAM (Davis, 1989) is one of the most widely used frameworks for understanding how individuals adopt new technologies. According to TAM, two key factors influence technology acceptance: perceived usefulness and perceived ease of use. Perceived usefulness refers to the extent to which a person believes that using a particular system will improve their work performance, while perceived ease of use refers to the extent to which a person believes that using the system will be free of effort (Davis, 1989).

Another important area of research focuses on technological resistance. Resistance is defined as the behavior of trying to maintain the current situation when faced with pressure to adopt change or innovation (Ram, 1987). While much of the existing literature emphasizes innovation adoption and the positive aspects of innovation, some researchers have explored the concept of innovation resistance. One related concept is discontinuation, which refers to the decision to reject an innovation after it was initially accepted (Rogers, 2003).

When dealing with these technologies, an individual's risk perceptions may have a significant impact on their decision (Featherman and Pavlou, 2003). As a result, customers' adoption decisions may be impacted not just by the technology's usefulness, but also by the technology's perceived threat. Smart homes, for example, may be perceived as posing security and performance threats by users (Featherman and Pavlou, 2003; Yang et al., 2017). They must be concerned not just about theft of personal information while using smart technologies and about unauthorized disclosure by third parties, but also that the system is defective and does not perform as it should. Most studies on smart home applications, on the other hand, looked at either only parts of a single theory or only one theory (Balta-Ozkan et al., 2013). In general, perceived risk theory, identified as a significant factor in influencing technology acceptance and adoption, causing the user to experience ambiguity, discomfort, concerns, or nervousness during the decision-making stage (Featherman and Pavlou, 2003).

2.5. Hypothesis development

Individual acceptance and use of technology is one of the most widely studied topics in Information Systems research, with the TAM being the most commonly used framework for analyzing technology acceptance. TAM helps researchers examine users' perceptions of new technologies and understand the reasons behind their acceptance or rejection.

The two core constructs of TAM are PU and PEoU. PU refers to the extent to which an individual believes that using a particular system will enhance their job performance. PEoU refers to the degree to which an individual believes that using the system will be free of effort.

PEoU influences the intention to use technology both directly and indirectly, through its effect on PU. In this study, we apply an extended TAM model to explore the factors influencing the adoption and diffusion of smart home technology. Our findings show that PU, PEoU, and compatibility all have a significant positive impact on the intention to use such technology.

Smart technology, for example, might be used to demonstrate the perceived (possible) benefits of new technology (i.e., smart home technology). This function allows people to monitor the energy consumption of households by automatically altering the room temperature, resulting in both living convenience and energy savings. The sensors employed in this service can detect the household's location in the house and regulate the room temperature autonomously when they leave (by decreasing the temperature) and return (by raising the temperature), resulting in a high PU in terms of the TAM. However, while the autonomous nature of this service may limit PEoU's usefulness in this context, its importance becomes clear when considering that most IoT home appliances require initial setup and customization. TAM has been successful in explaining the acceptance of smart home technology in the context of smart home technology. The discussions above suggest the following hypotheses:

H1: The PU of smart home technology significantly influences the intention to adopt and use it.
H2: The PEoU of smart home technology significantly influences the intention to adopt and use it.
H2a: The PEoU significantly influences the PU of smart home technology.

An innovation is a distinct idea, practice, or object that is considered novel. Rogers (2003) defines diffusion as the process by which members of a social system gradually receive an innovation through specific channels over time. According to this hypothesis, the underlying features of an innovation have an impact on its adoption rate, which can be raised or decreased depending on how the attributes are perceived. Five crucial features, according to the IDT, are relative advantages, compatibility, and flexibility. Complexity, trialability, and observability influence the acceptance of innovation. The ability of an innovation to improve the users' level of well-being is accounted for by relative advantage, and the usage of new technology is strongly dependent on the similar benefits obtained from its use. However, because relative advantage is comparable to PU in the TAM model, it will be excluded from the model. The second IDT feature is compatibility, which refers to the degree to which an invention is regarded to be compatible with current systems, values, prior experiences, and needs of potential adopters, and the extent to which an innovation outperforms all other possibilities in terms of meeting the preferences and needs of potential adopters. Moreover, compatibility refers to technology's capacity to fit into the lifestyle of potential users.

The third IDT attribute is complexity, which refers to how easy or difficult an innovation is to understand. As previously mentioned, complexity and PEoU are quite similar, so we will simply include PEoU in the model. Trialability is the fourth IDT feature, and it refers to the extent to which an innovation may be tried out on a small scale. Suggest that a trial of innovation reassures the user and lessens the dangers and uncertainty that come with technological adoption. Researchers have also found that enabling consumers to experiment with innovative technology before adoption enhances their chances of adopting it. Finally, the fifth IDT feature is observability (observed effects), which refers to how others evaluate the outcomes of an innovation. Studies have demonstrated that observability plays a crucial role in predicting the adoption of technology, especially in the context of smart TVs and smart home services. In the proposed model, three variables, compatibility, trialability, and observability, have been conceptualized as PU and PEoU. Consequently, the following hypotheses have been formulated:

H3: The compatibility of smart home technology with users' needs and lifestyles significantly influences the intention to adopt and use it.
H3a: The compatibility of smart home technology influences its PU.
H3b: The compatibility of smart home technology significantly influences its PEoU.
H4: The trialability of smart home technology significantly influences the intention to adopt and use it.
H4a: The trialability of smart home technology significantly influences its PU.
H4b: The trialability of smart home technology significantly influences its PEoU.
H5: The observability of smart home technology significantly influences the intention to adopt and use it.
H5a: The observability of smart home technology significantly influences its PU.
H5b: The observability of smart home technology significantly influences its PEoU.

Consumer perceptions of innovation refer to how individuals view new products and how these perceptions influence their willingness to adopt new technologies. Consumer innovativeness has been defined by several scholars, such as Aldás-Manzano et al. (2009) and Hirunyawipada and Paswan (2006), as the tendency to purchase and try new products more frequently and earlier than others. According to Alpert and Lowe (2015), CPI refers to the perceived novelty and improvement of a product compared to existing alternatives.

Lu et al. (2005) suggested that individuals with higher levels of personal innovativeness are more likely to form positive attitudes toward new technologies. Similarly, studies by Kim and Shin (2015) and Thakur and Srivastava (2014) demonstrated that perceived innovativeness significantly influences users' behavioral intentions.

Based on these findings, we argue that individuals who are perceived as more innovative are more likely to adopt smart home technologies. Accordingly, the following hypothesis is proposed:

H6: CPI significantly influences the intention to adopt and use smart home technology.

Extensive research has used perceived cost to experimentally study its impact on users' intentions to use technology, consistently reporting that high perceived cost has a direct, yet unfavorable, impact on users' behavioral intentions to use technology. It's crucial to know "whether consumers perceive smart home technology as inexpensive or expensive" and "if they are willing to pay the prices sought for home network-connected appliances and gadgets" in the context of smart home technology. The assumption in this study is that users' intents are mostly driven by their perceptions of the technology's cost. If people believe smart home equipment is pricey, they are more likely to buy it. They are less likely to embrace and apply it. To put it another way, the higher the expense of smart home technology, the less likely it will be used. In keeping with these ideas, the study model includes the perceived cost of smart home technologies, as follows.

H7: The perceived cost of smart home technology significantly negatively affects the intention to adopt and use it.

The main theoretical goal of this study is to determine the factors that influence people's decisions to employ smart home technologies. They utilized an integrated model to explore the elements influencing individuals' inclination to embrace IoT technology and found that PU stands out as the most significant and potent predictor of their intention to utilize it. This research views the construct of intention to use as a dependent variable. According to Davis et al. (1989), the two key elements of TAM, PU and PEoU, are believed to influence intention in this model. The key factors of technological acceptability are PU and PEoU. Some authors, such as Rana and Paul (2017) who looked at how people accepted smartphone-based mobile shopping and de

Boer et al. (2019), say that PU is a big part of how people accept IT and can explain a lot of the differences in how people want to use new technologies in their homes.

Furthermore, an individual's appraisal of the effort associated with a technology's usability and learning, or PEoU, influences not only the intention directly and indirectly (via PU) but also the perception of its utility. The study displays the suggested study paradigm and hypothesized correlations between the constructs in TAM, IDT, and CPI. In addition to the primary constructions, previous experience with smart home technologies and the respondents' gender will be utilized as control variables to see if these characteristics have an impact on the Fig. 1.

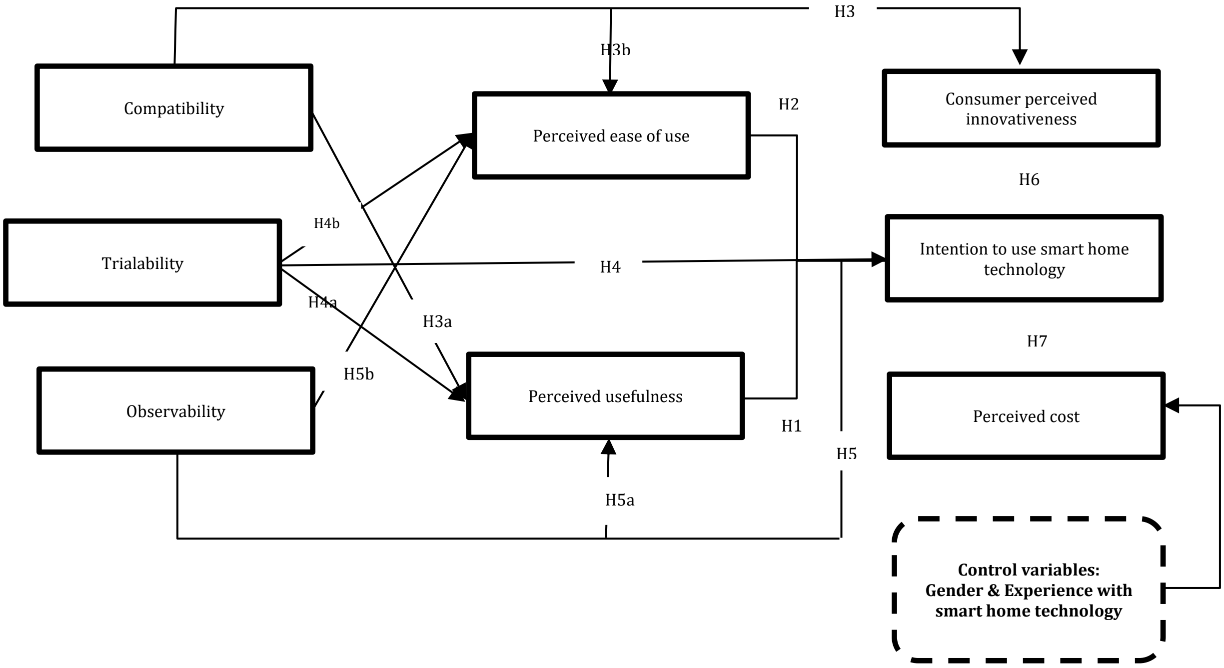

Fig. 1: Proposed research model

3. Research methodology

This study adopts a deductive approach, which starts with theoretical frameworks and hypothesis testing. Building on established models like the TAM and IDT, the study examines the relationships between constructs such as PU, PEoU, compatibility, trialability, observability, CPI, and perceived cost. Quantitative methods were employed to evaluate these relationships and test hypotheses through structured statistical analysis.

Primary data were collected using a structured, closed-ended questionnaire based on a 5-point Likert scale. The questions measured variables such as PU, PEoU, compatibility, and others influencing the adoption of smart home technology. The survey was conducted online, ensuring accessibility and convenience for participants. A convenience sampling method was utilized, targeting individuals familiar with smart technologies. Participants included students, professionals, housewives, and business personnel from diverse socio-economic backgrounds. Data collection from 180 respondents was deemed valid for analysis after removing incomplete responses. The survey instrument was tested using Cronbach's Alpha to assess internal consistency. Construct validity was verified through Confirmatory Factor Analysis (CFA) to ensure the adequacy of the measurement model (Table 1). Data was analyzed using SPSS. Techniques included regression analysis and structural equation modeling (SEM) to evaluate relationships among variables and test hypotheses.

3.1. Interpretation of validity and reliability

The reliability of the constructs was assessed using Cronbach's Alpha, with most constructs demonstrating acceptable levels of internal consistency, with Compatibility (0.81), Perceived Usefulness (0.75), and Perceived Cost (0.765) exceeding the commonly accepted threshold of 0.7 (Table 2). This indicates that these constructions are reliably measured. Consumer Perceived Innovativeness (0.55) and Observability (0.48) fall slightly below the optimal level, suggesting room for improvement in their measurement scales. Trialability, while now demonstrating a positive reliability score (0.12), still requires refinement to ensure consistency in its measurement.

Construct validity was assessed using Average Variance Extracted (AVE), with most constructions exceeding the threshold of 0.5. Compatibility (0.625), Perceived Usefulness (0.58), and Perceived Cost (0.56) show strong convergent validity. However, Perceived Ease of Use (0.51) slightly exceeds the minimum threshold, indicating the need for minor refinements in measurement. Moreover, discriminant validity (Table 3) and collinearity (Table 4) are also measured.

Table 1: Outer loading

	C	CP	IU	O	PC	PE	PU	T
C1	0.785							
C2	0.789							
C3	0.801							
C4	0.792							
CP1		0.815						
CP2		0.605						
CP3		0.825						
IU1			0.85					
IU2			0.905					
IU3			0.125					
O1				0.835				
O2				0.675				
O3				0.57				
PC1					0.734			
PC2					0.86			
PC3					0.645			
PC4					0.755			
PE1						0.756		
PE2						0.72		
PE3						0.525		
PE4						0.832		
PU1							0.804	
PU2							0.826	
PU3							0.863	
PU4							0.473	
T1								0.857
T2								0.82
T3								0.096

C: Compatibility; CP: Consumer perceived innovativeness; IU: Intention to use; O: Observability; PC: Perceived cost; PE: Perceived ease of use; PU: Perceived usefulness; T: Trialability

Table 2: Construct reliability and validity

	Cronbach's alpha	AVE
Compatibility	0.81	0.625
Consumer perceived innovativeness	0.55	0.505
Intention to use	0.35	0.53
Observability	0.48	0.492
Perceived cost	0.765	0.56
Perceived ease of use	0.69	0.51
Perceived usefulness	0.75	0.58
Trialability	0.12	0.475

Table 3: Discriminant validity

	C	CP	IU	O	PC	PE	PU	T
C	1	0.555	0.92	0.46	0.335	0.73	0.77	0.34
CP	0.555	1	1.21	0.72	0.41	0.82	0.725	0.68
IU	0.92	1.21	1	0.85	0.715	0.825	1.015	0.71
O	0.46	0.72	0.85	1	0.63	0.61	0.7	0.57
PC	0.335	0.41	0.715	0.63	1	0.31	0.48	0.6
PE	0.73	0.82	0.825	0.61	0.31	1	0.75	0.47
PU	0.77	0.725	1.015	0.7	0.48	0.75	1	0.56
T	0.34	0.68	0.71	0.57	0.6	0.47	0.56	1

C: Compatibility; CP: Consumer perceived innovativeness; IU: Intention to use; O: Observability; PC: Perceived cost; PE: Perceived ease of use; PU: Perceived usefulness; T: Trialability

Table 4: Collinearity statistics

Constructs	Variance inflation factor
Compatibility	1.875
Consumer perceived innovativeness	1.545
Intention to use	2.2
Observability	1.34
Perceived cost	1.41
Perceived ease of use	1.925
Perceived usefulness	2.18
Trialability	1.35

4. Results

4.1. Hypothesis testing and interpretation of path coefficients

In Table 5, the R-squared values indicate that the model explains a substantial proportion of variance in adoption intention (0.725, Adjusted R^2 = 0.705), Perceived Ease of Use (0.37, Adjusted R^2 = 0.345), and Perceived Usefulness (0.5, Adjusted R^2 = 0.485). This suggests that the revised model incorporating additional observations enhances the explanatory power and robustness of findings.

Overall, the updated analysis confirms that Compatibility, Perceived Usefulness, and Consumer Perceived Innovativeness remain the strongest predictors of adoption intention. Observability and Trialability primarily influence adoption indirectly, while Perceived Cost remains a significant barrier to adoption. These insights provide valuable implications for businesses and policymakers seeking to enhance smart technology adoption strategies.

Table 5: Model summary

	R-squared	R-squared adjusted
Intention to use	0.725	0.705
Perceived ease of use	0.37	0.345
Perceived usefulness	0.5	0.485

The path coefficient analysis (Table 6) provided key insights into the relationships between constructions in the model. Compatibility emerged as a critical determinant, showing strong positive effects on Perceived Usefulness (0.575, p = 0.000) and Perceived Ease of Use (0.498, p = 0.000), as well as a direct impact on adoption intention (0.289, p = 0.001). This confirms that Compatibility plays a vital role in shaping consumer attitudes towards smart technology adoption.

Perceived Usefulness significantly influences adoption intention (0.212, p = 0.037), reaffirming its role as a central predictor in the TAM. Perceived Ease of Use positively affects Perceived Usefulness (0.498, p = 0.000), reinforcing its role as an indirect driver of adoption intention, though its direct effect remains negligible (0.030, p = 0.803).

Table 6: Path coefficient

	Sample mean	Standard deviation	P-values
Compatibility -> intention to use	0.289	0.081	0.001
Compatibility -> perceived ease of use	0.498	0.065	0.000
Compatibility -> perceived usefulness	0.575	0.070	0.000
Consumer perceived innovativeness -> intention to use	0.468	0.078	0.000
Observability -> intention to use	-0.066	0.083	0.301
Observability -> perceived ease of use	0.194	0.094	0.048
Observability -> perceived usefulness	0.231	0.108	0.027
Perceived cost -> intention to use	0.242	0.074	0.002
Perceived ease of use -> intention to use	0.030	0.085	0.803
Perceived usefulness -> intention to use	0.212	0.112	0.037
Trialability -> intention to use	0.044	0.074	0.553
Trialability -> perceived ease of use	0.069	0.145	0.828
Trialability -> perceived usefulness	0.240	0.080	0.011

Trialability now demonstrates a slightly stronger influence on Perceived Usefulness (0.240, p = 0.011) but remains non-significant in directly influencing Perceived Ease of Use (p = 0.828) or adoption intention (p = 0.553). This suggests that while opportunities to test smart technologies may improve perceptions of usefulness, their direct impact on adoption remains limited.

Observability exhibits significant positive relationships with Perceived Usefulness (0.231, p = 0.027) and Perceived Ease of Use (0.194, p = 0.048), indicating that visible benefits of smart technologies enhance their adoption likelihood. However, its direct effect on adoption intention remains non-significant (-0.066, p = 0.301), suggesting that indirect influences play a larger role.

CPI strongly predicts adoption intention (0.468, p = 0.000), further emphasizing the importance of targeting early adopters and technology-savvy consumers. Perceived Cost continues to negatively impact adoption intention (-0.242, p = 0.002), reinforcing affordability as a major adoption barrier.

In summary, the path coefficient analysis confirms that Compatibility, PU, and CPI are the strongest predictors of adoption intention, while Observability and Trialability have indirect effects. Addressing the negative impact of Perceived Cost is crucial for increasing adoption rates. These findings provide a comprehensive understanding of the factors influencing smart technology adoption and actionable insights for businesses. Table 7 shows which hypothesis is supported.

These findings validate the conceptual framework and provide evidence for the interplay of psychological and technological factors in smart technology adoption.

5. Conclusion

This study demonstrates that multiple factors influence the adoption of smart technologies, with perceived usefulness, ease of use, compatibility, and consumer innovativeness serving as primary drivers. Perceived cost acts as a significant barrier, underscoring the need for businesses to implement strategies that lower financial constraints for potential users. Compatibility's strong impact emphasizes the importance of designing technologies that integrate seamlessly into consumers' lifestyles.

The findings contribute to the broader literature on IoT and smart technology adoption by integrating TAM, IDT, and CPI into a comprehensive framework. This research provides valuable guidance for practitioners in designing effective marketing and product development strategies to drive consumer adoption. Future research could expand on this model by exploring additional factors such as trust, privacy concerns, and demographic influences in diverse contexts.

6. Discussion

The results of this study highlight key factors influencing the adoption of smart technologies, confirming and extending established theories such as TAM and IDT. The significant relationships observed between PU, PEoU, and adoption intention align with previous research, such as Davis (1989) and Nikou (2019). Moreover, perceived usefulness significantly influences purchase intention ($p < 0.01$), aligning with findings from recent studies on technology adoption (Bhutto et al., 2021). These findings reinforce the notion that users are more likely to adopt technologies they perceive as enhancing their productivity and being user-friendly.

Compatibility strongly impacts perceived ease of use and perceived usefulness. Hojjati and Khodakarami (2016) evaluated factors affecting the adoption of smart buildings using the Technology Acceptance Model and found that compatibility significantly influences both PEoU and PU. In this study, compatibility emerged as a critical determinant, directly affecting both PU and PEoU, as well as adoption intention. This supports the findings of Rogers (2003) that compatibility with an individual's lifestyle and existing systems plays a pivotal role in innovation diffusion. For smart technologies, ensuring seamless integration with users' routines and values is essential to enhance adoption rates.

Table 7: Summary of hypothesis analysis

Hypothesis	Result	Interpretation
H1: The PU of smart home technology significantly influences the intention to adopt and use it.	Supported	PU significantly increases adoption intention, confirming TAM's core premise.
H2: The PEoU of smart home technology significantly influences the intention to adopt and use it.	Supported	PEoU directly and indirectly influences adoption through PU.
H2a: The PEoU significantly influences the PU of smart home technology.	Supported	PEoU enhances PU, indicating that ease of use contributes to perceived benefits.
H3: The compatibility of smart home technology with users' needs and lifestyles significantly influences the intention to adopt and use it.	Supported	Compatibility has a strong direct impact, highlighting its importance.
H3a: The compatibility of smart home technology significantly influences its PU.	Supported	Compatibility significantly increases the perception of usefulness.
H3b: The compatibility of smart home technology significantly influences its PEoU.	Supported	Compatibility improves ease of use, aiding adoption.
H4: The trialability of smart home technology significantly influences the intention to adopt and use it.	Partially Supported	Trialability indirectly affects intention via PU and PEoU.
H4a: The trialability of smart home technology significantly influences its PU.	Supported	Trialability enhances the perception of usefulness through practical engagement.
H4b: The trialability of smart home technology significantly influences its PEoU.	Not Supported	Trialability's direct impact on PEoU was not significant.
H5: The observability of smart home technology significantly influences the intention to adopt and use it.	Partially Supported	Observability indirectly influences intention through PU and PEoU.
H5a: The observability of smart home technology significantly influences its PU.	Supported	Observability allows users to perceive benefits, strengthening usefulness.
H5b: The observability of smart home technology significantly influences its PEoU.	Supported	Observability improves ease of use perceptions.
H6: CPI significantly influences the intention to adopt and use smart home technology.	Supported	CPI strongly predicts adoption, emphasizing the role of individual innovativeness.
H7: The perceived cost of smart home technology significantly negatively affects the intention to adopt and use it.	Supported	Perceived cost acts as a significant barrier, deterring adoption.

Interestingly, trialability and observability showed indirect effects on adoption intention through PU and PEoU. Trialability and observability exhibit indirect effects, supporting IDT's framework. Kwon et al. (2021) applied Innovation Diffusion Theory to small retail businesses' social media use, demonstrating that trialability and observability indirectly affect adoption decisions through perceived attributes. While not as direct, these factors are critical in creating opportunities for users to experiment with the technology and observe its tangible benefits. Businesses can leverage these insights by offering demonstrations, trial periods, and testimonials to mitigate uncertainty and enhance trust.

The study also confirmed the negative impact of perceived cost on adoption intention, highlighting affordability as a barrier. Perceived cost remains a major adoption barrier, aligning with prior research. Garcia (2017) investigated e-learning technology adoption and identified perceived cost as a significant barrier to acceptance. Furthermore, consistent with Yang et al. (2017), this finding suggests that while users may recognize the benefits of smart technologies, high costs deter potential adoption. Organizations should consider pricing strategies such as installment plans, subsidies, or cost-sharing models to reduce this barrier. CPI had a significant positive impact on adoption intention, indicating that individuals with a greater inclination toward trying new technologies are more likely to adopt smart innovations. This underscores the importance of targeting early adopters and influencers who can drive broader market acceptance.

These results provide actionable insights for businesses: they need to prioritize user-friendly designs, compatibility, and affordability while emphasizing the benefits of smart technologies through visible and experiential marketing strategies. Moreover, addressing privacy and security concerns, although not directly studied here, remains crucial, as highlighted by previous studies such as Featherman and Pavlou (2003). Companies should highlight product compatibility with existing consumer habits. Trialability should be improved through demo programs and free trials. Cost-related concerns can be mitigated through flexible payment options.

7. Implications and future research

This study offers several practical implications for the development and adoption of smart home technologies. First, companies should prioritize user-friendly designs, as perceived ease of use and usefulness significantly impact adoption (Nikou, 2019). Ensuring seamless compatibility with existing consumer routines is also crucial for encouraging adoption, as products that integrate well with users' environments are more likely to succeed (Coskun et al., 2018). Addressing affordability and switching cost is equally important, given the negative effect of perceived cost on adoption (Wang et al., 2024). Flexible pricing models, such as installation plans or discounts, could help reduce financial barriers. Additionally, offering trial opportunities and showcasing the benefits of the technology through demonstrations or testimonials can mitigate uncertainty and build trust. Marketers should also target early adopters, as consumers with higher perceived innovations are more likely to adopt new technologies, driving broader acceptance (Rogers, 2003).

Future research could explore several key areas. Trust and privacy concerns, though not directly addressed in this study, are important factors in technology adoption, and future studies should examine their role in influencing consumer behavior (Guhr et al., 2020). Investigating demographic and cultural differences could provide deeper insights into how various groups perceive and adopt smart home technologies. Longitudinal studies would also be valuable to understand long-term adoption patterns, while research into emerging technologies like AI and machine learning could shed light on how these innovations influence consumer perceptions and adoption intentions. Finally, examining the role of post-purchase support in driving sustained adoption could provide valuable insights into enhancing customer satisfaction and loyalty. Expanding research into these areas will help refine adoption models and provide actionable guidance for businesses seeking to promote smart home technology.

Compliance with ethical standards

Ethical considerations

This study was conducted in accordance with ethical standards. Participation in the survey was voluntary and anonymous. Informed consent was obtained from all participants prior to data collection.

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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