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Determinants of Smart Home Products Adoption: Based on the Technology Acceptance Model

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Abstract. Smart home technologies have been revolutionizing people all over the world as they have proven to potentially increase convenience, security, energy efficiency and quality of life. With increasing trends, adoption rates in developing regions, especially West Africa, remain frustratingly low. Accordingly, this study seeks to examine the factors affectbeen ing smart home products adoption, based on the Technology Acceptance Model (TAM) and the inclusion of various other factors relevant to the smart home environment, namely Perceived Security, Hedonic Value, Functional Value, Subjective Norms, and Product Knowledge.

SPSS was used for an in-depth analysis to test the reliability and validity of the model. For measuring internal consistency between constructs, Cronbach's Alpha, EFA and CFA (Confirmatory Factor Analysis). We used multiple regression analysis to test the structural relationships, which provides an understanding of important predictors of smart home adoption. Results revealed that Hedonic Value, Functional Value, and Subjective Norms significantly influence Intention to Use, with Product Knowledge becoming significant when demographic controls are included. Mediation analysis indicated that Perceived Usefulness partially mediates the relationships of Hedonic and Functional Values with adoption intention, while fully mediating the effect of Perceived Risk. Perceived Risk mediates the influence of Subjective Norms but not Product Knowledge. These findings emphasize the roles of enjoyment, practicality, social influence, and awareness in driving smart home adoption, while highlighting the need to address perceived risks and enhance user

This study offers new insights for manufacturers, policymakers, and stakeholders to enhance smart home products penetration in less-studied markets. Text—Affordable pricing models, improved data security, and social influence-based marketing applications could facilitate further adoption of the technology. The paper addresses the lack of empirical studies on the adoption of smart home technologies in developing countries, and by providing an in-depth analysis of the context through the lens of West Africa, offers insights and policy recommendations that can contribute to future research and broader adoption of smart home technologies in developing areas.

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Keywords: Smart Home Adoption, Technology Acceptance Model (TAM), Perceived Risk, Product Knowledge, Internet of Things (IoT).

1. Introduction

Smart home products signify a dramatic change in how people engage with their homes. Connected devices allow the automation of household chores, improve energy management, boost home security, and even ensure convenience powered by the Internet of Things (IoT). Smart homes are equipped with a variety of functionalities that are built to make life easier and efficient, such as smart thermostats, automated lighting systems, and home security cameras [1]. But, while it is making significant headway in developed countries, especially in North America, as well as Europe, it is still at a very low penetration rate in many developing countries, including those in the West African region.

According to recent statistics, global growth in smart home adoption is expected; however, only 4.3% of West African households had adopted a smart home system as of 2024, while China 22% and the United States 30% were reported as having comparably higher adoption (Statista, 2024). These disparities lead to questions about whether smart home systems have been able to gain traction in developing regions of the world, which face hurdles like infrastructural constraints, lack of cost-effectiveness, and unawareness about their offerings. Additionally, these barriers are compounded by the large upfront costs, recurring maintenance costs, and fears of data privacy and security.

Both for academic research as well as practical activities, it is important to understand the factors that drive or impede the adoption of smart homes in these regions. Proposed by Davis [2] The Technology Acceptance Model (TAM) stands out as one of the most effective models in examining technology acceptance based on two practical constructs—Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). TAM suggests that when the potential user of a technology believes that a system will enhance their performance and is easy to use, they are more likely to accept it. However, the model has been expanded over the years to consider other factors leading to adoption, especially when it comes to emerging technologies such as smart homes [3]. Perceived security, Hedonic value, Functional value, Product knowledge, and Subjective norms have been significant across contexts in technology.

This study attempts to extend TAM to perceive the factors that influence the adoption of smart home product in West Africa. We seek to explore the factors that drive consumers' decisions to adopt or reject smart home systems and, in turn, offer actionable insights for manufacturers, policymakers, and other stakeholders. The adoption of smart homes product in less developed parts is comparatively lower than that of developed regions due to factors like internet penetration, infrastructural gaps, and economies of scale [4]. This study seeks to expand the insight obtained on barriers and drivers of smart home adoption in the West African context by integrating factors including social influence (subjective norms), perceived security, and product knowledge into the TAM framework. Technically, we utilized SPSS to critically evaluate the reliability and validity of our measurement model [5]. The internal consistency was determined by Cronbach's Alpha, and Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) were conducted to verify the validity of the constructs [6]. The correlation between independent variables [Perceived Usefulness (PU), Subjective Norms (SN), and Hedonic Value (HV)] and the dependent variable (intention to adopt smart home technologies) was visualized using multiple regression analysis.In focusing on the peculiarities and intricacies of the West African context, this research seeks to bridge a gap in the literature and offers a starting block for research in developing contexts. The data analyses in this study can provide useful information to manufacturers, who can design products more aligned with the needs of African end-users, as well as to policymakers who can provide supportive architectures and incentives for the adoption of smart home technologies by consumers. Furthermore, the research emphasizes the significance of utilizing social influence and implementing strong security measures to establish consumer faith and confidence in smart home systems.

2. Literature review

The adoption of information systems (IS) and emerging technologies has been a subject of extensive research, with scholars employing various theoretical models to explain user behavior. Among these, the Theory of Reasoned Action (TRA), developed by Martin Fishbein and Icek Ajzen [7], has played a foundational role in the fields of psychology and social sciences, particularly in understanding human behavior and decision-making processes. This theory was initially being developed as a response to the need for a more comprehensive and predictive model of human behavior. Prior to TRA, many psychological theories explained behavior using simpler models of instinct or external stimuli. However, Fishbein and Ajzen [7] sought to create a theory that could better account for volitional (intentional) behaviors, those actions that individuals can control and deliberate upon. In the early 1960s, Fishbein was researching attitude formation and change. He argued that attitudes are central to understanding behavior, and his early work focused on how attitudes influence decision-making. Attitude and the Prediction of Behavior, laid much of the groundwork for TRA by proposing that attitudes toward a behavior (and the underlying beliefs about that behavior) significantly shape the intention to perform it [8]. TRA is based on the idea that behavior is directly influenced by behavioral intentions, which are in turn influenced by two key factors: Attitude toward the behavior and Subjective norms. Muellerleile [9] Demonstrates how TRA has been instrumental in predicting safe-sex practices and guiding public health campaigns. Montano [10] Discusses TRA's application in health promotion, including its use in interventions aimed at reducing risky behaviors. While TRA was influential, it faced some criticisms, particularly in relation to behaviors that were not fully under an individual's control (e.g., involuntary behaviors or behaviors with external constraints). To address these limitations, Ajzen extended the Theory of Reasoned Action [11] by introducing the Theory of Planned Behavior (TPB), which incorporated an additional construct: Perceived Behavioral Control (PBC). This variable accounts for the perceived ease or difficulty of performing the behavior, recognizing that behaviors are not always fully volitional and can be influenced by external factors like resources, opportunities, and abilities. One of the most significant applications of TRA in the realm of technology adoption was the development of the Technology Acceptance Model (TAM) by Fred Davis [12].

The TAM, has been one of the most influential models in IS research. TAM extended TRA to explain why people accept or reject technology, with a focus on two key factors: perceived ease of use and perceived usefulness. These variables were influenced by attitudes toward the technology, which were in turn influenced by subjective norms (social influence) and individual perceptions of usefulness and ease. Its core constructs, Perceived Usefulness (PU) and Perceived Ease of Use (PEOU), provide a simple yet powerful explanation of user acceptance behavior. TAM posits that the degree to which a person believes a technology will enhance their performance (PU) and the effort required to use the technology (PEOU) are critical determinants of their behavioral intention to use the technology [13]. TAM has been extensively applied across diverse contexts, including marketing, consumer behavior, and education. Gefen et al [14] applied TAM to understand the factors that influence the adoption of online shopping. However, the simplicity of TAM has also been criticized for its inability to account for external factors influencing technology adoption. As a response, extended versions of TAM, such as TAM2 [3] By adding social influence and cognitive factors, TAM 2 provided a more comprehensive view of the factors affecting technology adoption, particularly in organizational settings where social pressure and performance expectations play an important role. TAM2 has been extensively validated across diverse domains, from corporate IT systems to consumer technologies: Researchers like Park [15] have applied TAM2 to assess students' acceptance of online learning platforms, where perceived relevance and social influence significantly affect adoption decisions. Lu [16] explored mobile Internet adoption, finding that TAM2 effectively captures the influence of both cognitive and social factors in shaping user intentions. Subsequently, the Unified Theory of Acceptance and Use of Technology (UTAUT) [17] synthesized TAM with other models such as the Theory of Planned Behavior (TPB) and the Diffusion of Innovations Theory (DOI). UTAUT introduced constructs such as Performance Expectancy, Effort Expectancy, Social Influence, and Facilitating Conditions, while also accounting for moderating variables like age, gender, experience, and voluntariness of use.

While TAM remained influential, UTAUT became a more comprehensive and universally applicable framework. As technology adoption continues to evolve, the original TAM and its extensions have been further refined to account for newer forms of technology and the changing nature of user behavior. TAM 3 [18], for example, introduced a more detailed exploration of the role of cognitive beliefs and emotions in technology adoption. TAM3, the most recent iteration, has demonstrated improved robustness in predicting technology adoption, especially in dynamic and complex environments [19]. Despite their robustness, neither TAM nor TPB alone can fully explain the complexities of technology adoption, particularly in niche fields like smart home technology (SHT). Scholars have argued that the core constructs of TAM and TPB do not adequately address critical factors like perceived security, trust, and automation [20]. Consequently, integrating these models with additional constructs has become essential to provide a more holistic understanding of adoption behavior. For example, TAM3 has been combined with variables such as Perceived Security, Trust, and Mobility to explore adoption behavior in the context of mobile banking and e-commerce. Similarly, extensions of TPB have incorporated cultural and contextual factors to understand adoption in developing regions. This integrative approach is particularly relevant for SHT, which involves concerns about data privacy, security, and the interoperability of devices—factors that are not explicitly addressed in the original TAM or TPB frameworks. To address emerging technologies and contexts, Venkatesh [21] proposed

UTAUT2, extending the model to consumer settings by introducing constructs such as: Hedonic Motivation: The fun or enjoyment derived from using technology. Price Value: The trade-off between the perceived benefits and costs of using the technology. Habit: The extent to which technology use becomes automatic due to repeated exposure. UTAUT2 has proven effective in consumer-focused studies, such as mobile app usage and smart device adoption, where emotional and cost-related factors play a larger role.

The adoption of IS, and specifically SHT, requires a nuanced understanding of user behavior that goes beyond traditional models. By combining elements of TAM3 and TPB with empirically verified variables like perceived security and trust, this study offers a comprehensive framework for understanding and predicting SHT adoption in developing regions. This integrative approach not only addresses theoretical gaps but also provides practical guidance for policymakers and businesses aiming to promote technology adoption in these contexts.

The application of TAM and its extensions to SHT adoption underscores the importance of adapting theoretical models to address the complexities of emerging technologies. Smart home technologies, which include automated lighting, smart thermostats, and virtual assistants, have unique adoption characteristics that make TAM highly applicable. For example, the Perceived Usefulness of these devices often relates to their ability to improve home energy efficiency, enhance security, and provide convenience. Studies such as Hubert [22] and Yang [20] have emphasized that these practical benefits directly influence user intention to adopt smart home systems. Perceived Ease of Use plays a critical role in reducing the perceived complexity of integrating smart home devices into daily routines. As IoT devices often require setup and interaction via apps or voice commands, ease of use is essential for ensuring widespread adoption [23]. Similarly, the simplicity of interacting with in-car technologies, such as touchscreens and voice-activated controls, is essential for fostering adoption in smart cars. Smart speakers like Amazon Echo and Google Home, which often serve as gateways to smart home ecosystems, illustrate how TAM can explain consumer behavior. In smart cars, Perceived Usefulness is linked to features like autonomous driving, fuel efficiency, and enhanced safety mechanisms. Similar to smart homes, Perceived Ease of Use affects consumer willingness to interact with advanced interfaces like heads-up displays and voice controlled dashboards. Wearable devices, such as fitness trackers and smartwatches, also benefit from TAM's applicability. For these devices, Hedonic Value and Functional Value often overlap, as users perceive them as both enjoyable gadgets and practical health monitoring tools [24] [25]. This dual appeal underscores the importance of integrating intrinsic and extrinsic motivations into TAM frameworks. Perceived Enjoyment, an intrinsic motivator, is a significant factor in the adoption of these devices. Users are often drawn to the novelty of interacting with voice assistants like Alexa and Google Assistant. This aligns with findings by Igbaria [26], who demonstrated that technologies perceived as enjoyable are more likely to be adopted. However, Trust and Perceived Security are also critical in this context, as smart speakers collect sensitive data. Users often question the ability of manufacturers to protect personal data from breaches, unauthorized access, or misuse. Yang [20] and Hubert [22] have emphasized that addressing these concerns through robust security measures, transparent data policies, and user education can significantly enhance user trust. Moreover, regulatory frameworks such as the General Data Protection Regulation (GDPR) in the European Union have heightened public awareness of data privacy issues, further influencing adoption patterns. For users in developing regions, concerns about security are often compounded by limited trust in local service providers, highlighting the need for context-specific solutions. Moreover, the integration of constructs like Subjective Norms reflects the influence of social dynamics, particularly in collectivist cultures where adoption decisions are heavily shaped by societal expectations. Studies like those by Gangwar [27] and Ajzen [11] highlight how subjective norms and social pressures impact technology adoption, making them indispensable in frameworks for developing regions

The Technology Acceptance Model offers a robust foundation for understanding the adoption of smart technologies, but its explanatory power is enhanced when combined with additional factors such as perceived security, hedonic and functional value, social influence, and user knowledge. These factors interact dynamically with TAM's core constructs (PU and PEOU) to shape behavioral intentions and adoption outcomes.

For developing regions like West Africa, addressing barriers such as economic constraints, infrastructural limitations, and low digital literacy is critical for fostering adoption. By identifying and addressing these challenges, researchers, policymakers, and practitioners can develop strategies to promote the widespread adoption of smart technologies, thereby unlocking their potential to enhance quality of life and drive economic growth.

3. Conceptual framework

3.1. Extended technology acceptance model for analyzing adoption of smart home services

The conceptual framework for this study explores the adoption of smart home technologies (SHT) in developing regions by integrating the Technology Acceptance Model (TAM), the Theory of Planned Behavior (TPB), and specific constructs like Perceived Security, Hedonic Value, Functional Value, Subjective Norms, and Product Knowledge. These additions address the limitations of traditional models in understanding adoption behaviors for emerging technologies. TAM, introduced by Davis [12], highlights Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) as key drivers of adoption. To better fit the SHT context, constructs like Hedonic Value (enjoyment) and Functional Value (practical benefits) are added, following Venkatesh [18] recommendations to extend TAM for specific technologies. TPB [11] adds Perceived Behavioral Control (PBC) to account for external constraints. Gangwar [27] found Subjective Norms play a critical role in collectivist cultures, making them relevant for SHT adoption in developing regions. Product Knowledge is also integrated to address gaps in user understanding of SHT functionalities. Additional constructs, such as Perceived Security, which addresses privacy concerns [20], and Hedonic Value, which captures emotional appeal [28], are included to better explain adoption behavior. Functional Value reflects the practical benefits of SHT, such as energy efficiency, aligning with Rogers [29] Diffusion of Innovation Theory. This integrative framework offers a more comprehensive view of SHT adoption by combining traditional models with region-specific variables. It is particularly relevant for developing regions, where infrastructural, economic, and cultural factors influence technology adoption. The study aims to provide insights for overcoming barriers to SHT adoption in these regions.

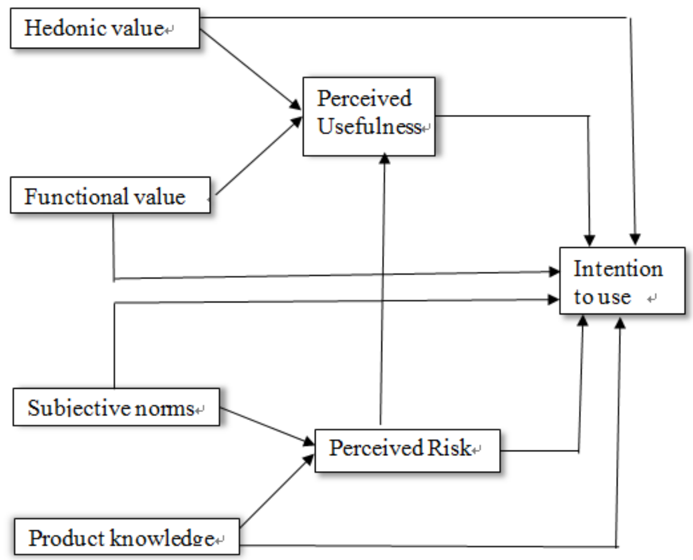

Figure 1: Conceptual model

3.2. Research hypothesis

3.2.1. Hypothesis main effect

(1) Perceived Usefulness (PU)

Perceived Usefulness (PU) in the context of smart refers to the degree to which users believe that smart home technologies enhance their daily lives by offering practical and valuable benefits. These benefits include automation of routine tasks, improved household security through surveillance and alarm systems, and energy efficiency. In particular, systems such as smart thermostats and security cameras are valued for their ability to solve practical problems [23]. Davis [13] originally established PU as a critical factor in technology adoption, asserting that the more useful users perceive a system to be, the more likely they are to adopt it. Subsequent studies (e.g., Yang[20]) have reaffirmed PU's significance, particularly in the context of smart technologies, where functional advantages directly influence user satisfaction and adoption decisions. Consequently, the perception of these technologies as indispensable tools for modern living strengthens behavioral intentions to adopt them.

H1: Perceived Usefulness (PU) positively influences the intention to adopt smart home technology.

(2) Hedonic Value

Hedonic Value refers to the enjoyment and intrinsic satisfaction users derive from interacting with technology. Unlike PU, which focuses on functional benefits, hedonic value emphasizes the intrinsic satisfaction associated with the experience of using the technology. Igbaria [26] and Sheth [30] have demonstrated that technologies perceived as engaging, entertaining, or fun significantly enhance users' motivation to adopt them.

Hedonic motivation is defined by Venkatesh [21] as the fun or pleasure derived from using a technology. This definition has been supported by a number of scholars who regarded hedonic motivation (otherwise known as entertainment value, fun, and enjoyment) as the performance of certain transaction without any form of benefit other than the process of performing it [31]. For example, smart lighting systems that allow users to create personalized ambiance or virtual assistants capable of engaging in humorous interactions contribute to the hedonic appeal of these technologies. Shuhaiber [23] validated that enjoyment is a primary motivator for smart home users, especially in contexts where novelty plays a role in adoption decisions. A higher perception of enjoyment leads to a stronger intention to adopt smart homes.

H2: Hedonic Value positively influences the intention to adopt smart home technologies.

(3) Functional Value

Functional Value pertains to the practical utility offered by smart home devices. Sheth [30] and Yang [20] emphasized that consumers are more likely to adopt technologies that provide clear, measurable benefits, such as enhanced security, energy savings, or convenience. Devices like smart locks often appeal due to their ability to simplify and improve daily tasks. Smart thermostats capable of adjusting temperatures based on user preferences or occupancy patterns exemplify high functional value, which directly influences adoption intentions.

H3: Functional Value positively influences the intention to adopt smart home technologies.

(4) Perceived Risk

Perceived reflects the uncertainties or negative consequences users associate with adopting smart home technologies. In an era of increasing digital vulnerability, security concerns have become a significant barrier to the adoption of Internet of Things (IoT) devices. Since smart home systems is configured to collect data about the lifestyles of its residents with respect to energy usage, movement, and purchase preferences for the purpose of supporting them effectively, the residents may be wary about the safety of their personal data (Balta-Ozkanet [32]. Similarly, Hubert[22] emphasized that trust in system security significantly influences user confidence and adoption intentions. For instance, smart home devices equipped with encrypted communication protocols, regular software updates, and user-controlled privacy settings can alleviate fears of data breaches. Moreover, the perception of security directly influences user confidence, which in turn fosters a willingness to adopt the technology.

H4: Perceived Risk negatively influences the intention to adopt smart home technologies.

(5) Subjective Norms

Subjective Norms refer to the social pressure to adopt a particular technology. It is the degree to which an individual think that referent group influences his/her decision. Such influence which is felt on the belief, attitude and behaviors of the individual, comprises of three major processes of conformance, identification and internalization [33] [34]. An individual conforms to the opinion of others based on the objective that either a reward will be earned or punishment will be avoided. According to Rogers' Diffusion of Innovations Theory [35] and Venkatesh [17], subjective norms play a crucial role in shaping behavioral intentions, particularly in communal or collectivist cultures. For example, in collectivist societies, observing friends or family members using smart home systems often prompts adoption Yang [20]. In developing countries, where financial, informational, and infrastructural barriers may exist, subjective norms act as a catalyst for smart home technology adoption, subjective norms help bridge the gap between awareness and action, thereby contributing to the growth of smart technologies in these regions. For smart home technologies, observing others successfully using these systems can reduce uncertainty and build confidence in their utility. Additionally, the perception of social acceptance or status associated with owning smart technologies further reinforces adoption intentions.

H5: Subjective Norms positively influence the intention to adopt smart home technologies.

(6) Product Knowledge

Product Knowledge refers to the level of familiarity a user has with smart home technologies. reduces perceived risks and enhances user confidence. Gao [36] emphasize that greater knowledge reduces uncertainty, builds confidence, and mitigates perceived risks, thereby fostering adoption. In smart home contexts, users with greater knowledge of the technology are more likely to perceive its usefulness and security positively [23]. Users who are well-informed about smart technologies are better equipped to appreciate their functional and hedonic benefits, making them more likely to adopt these systems. Conversely, a lack of knowledge often leads to skepticism or fear of potential drawbacks, such as technical failures or hidden costs. Therefore, educating users through marketing campaigns, product demonstrations, and user-friendly manuals is essential for promoting adoption

H6: Product Knowledge positively influences the intention to adopt smart home technologies.

3.2.2. Hypotheses of mediation effects

(1) Mediating Role of Perceived Usefulness

Perceived Usefulness mediates the relationship between Hedonic Value (HV), Functional Value (FV), and adoption intention. When users perceive enjoyment or practical utility, they are more likely to see the system as beneficial, thereby strengthening their intention to adopt. Shuhaiber [23] validated this pathway for smart homes, showing that PU links emotional and functional drivers to adoption. Hubert [22] highlight that PU acts as a critical link between users' experiences and their behavioral intentions, reinforcing the importance of designing technologies that deliver both utility and satisfaction. Martins [37] demonstrated that perceived risk (performance, financial, time, social, and privacy) had a negative impact on perceived usefulness of internet banking. These studies suggest that when individuals perceive the higher risks associated with using smart technology, they are more likely to view the technology as less useful, potentially due to the challenges and difficulties of integrating it into their daily lives and routines. The perceived risk of the domestication of the technology can undermine its perceived benefits and usefulness. This reduced perception of usefulness, in turn, negatively impacts the user's intention to use the smart technology

H7: Perceived Usefulness mediates the relationship between Hedonic Value and adoption intention.

H8: Perceived Usefulness mediates the relationship between Functional Value and adoption intention.

H9. Perceived usefulness mediates the relationship between perceived risk and intention to use.

(2) Mediating Role of Perceived Risk

Perceived risk mediates the relationship between Subjective Norms (SN), Product Knowledge (PK), and adoption. n. Social endorsements and knowledge reduce uncertainty and increase trust, thus increasing the likelihood of adoption. Salim [38] investigated the role of privacy concerns in mediating the relationship between reputation and the intention to adopt mobile health (mHealth) services among non-users. Their findings suggest that even with a strong reputation, privacy concerns can hinder adoption intentions, highlighting the importance of addressing privacy issues in regions sensitive to data security. Familiarity with a product reduces perceptions of risk by providing clarity about its benefits and limitations. Gao [36] argue that reducing perceived risk is essential for fostering user confidence and encouraging adoption, particularly in contexts where trust is a key determinant of behavior.

H10: Perceived Risk mediates the relationship between Subjective Norms and intention to adopt smart home technologies.

H11: Perceived Risk mediates the relationship between Product Knowledge and intention to adopt smart home technologies.

4. Research methodology

This research adopts an extended version of the Technology Acceptance Model (TAM) to explore the determinants of smart home technology adoption in West Africa, a region with limited existing research in this area. The methodology includes data collection, measurement model assessment, reliability and validity tests, and regression analysis, all conducted using SPSS. The goal is to systematically evaluate relationships between core variables and understand factors influencing smart home adoption.

4.1. Measurement development

This research involves seven variables: functional value, product knowledge, subjective norms, hedonic value, perceived usefulness, intention to use and perceived risk. The observed variables of all variables are all extracted from the previous study, and the specific content and related references are shown in Table 1. All the survey variables are required to measure the items on the 5-point Likert scale which is scored from 1–5, where “1” is “strongly disagree”, “2” is “disagree”, “3” is “neutral”, “4” is “agree”, and “5” is “strongly agree”.

Table 1: Measurement table for the variables

Construct	Measure Items
	HV1: I have fun using smart technology
	HV2: Interacting with smart home products is fun

Hedonic value(HV)	HV3: Interacting with smart home products is entertaining HV4: Interacting with smart home products is enjoyable HV5: The actual process of interacting would be pleasant
Perceived Usefulness (PU)	PU1: The use of smart home products can improve your efficiency
	PI2: Using smart home products can give you freedom PU3: Using smart home products can save your time PU4: The use of smart home products can bring you a lot of convenience PU5: Using smart home products can improve your living standards
Intention to Use (ITU)	ITU1: It is worthwhile to use smart home products
	ITU2: I would like to use smart home products as much as I can from now on ITU3: I will continue using smart home products or expect to use smart home products in the future ITU: 4: I will recommend smart home facilities to others
Functional Value(FV)	FV1: Smart home has convenience in environmental control
	FV2: Smart home has convenience in remote monitoring FV3: Smart home is secure in terms of visitor monitoring FV4: Smart home is safe in terms of leak detection FV5: Smart home provides effective management in terms of energy conservation FV6: Smart homes are reliable in air quality monitoring FV7: Smart home can provide medical assistance in emergency
Perceived Risks(PR)	PR1: I have security concerns associated with smart homes PR2: I have privacy concerns associated with smart homes PR3: I am anxious about my personal data by using Smart Homes PR4: I am anxious about the data security of the Smart Homes
Subjective Norms(SN)	SN1: People who influence my behavior think that I should use smart home products

	SN2: People who are important to me think that I should use smart home products
	SN3: People whose opinions are valued to me would prefer that I should use smart home products
Product Knowledge (PK)	PK1: I have a lot of knowledge about how smart home technologies work
	PK2: I am very familiar with the features and capabilities of smart home products.
	PK3: Compared to most people, I know a lot about smart home technologies

4.2. Sample characteristics

The target respondents for this study are primarily Gambian individuals who have knowledge or an understanding of smart home technology. This focus is necessary because respondents unfamiliar with the concept of smart homes would not find the designed questionnaire suitable. Respondents who are familiar with smart home technology can provide more accurate and reliable data compared to those who are not. To ensure clarity, examples and explanations accompany the questionnaire to help respondents understand the questions. A usability test is conducted to confirm that the questionnaire's format and content are appropriate before it is manually distributed.
Convenience sampling and snowball sampling methods are employed in this study. Convenience sampling allows the researchers to easily access respondents, while the snowball method facilitates the recruitment of additional participants within the target population through referrals, increasing the potential to reach qualified respondents.

4.3. Data collection

Data were collected through an online survey targeting respondents in West Africa. The survey was designed to capture key constructs: Perceived Usefulness (PU), Hedonic Value (HV), Functional Value (FV), Perceived Risk (PR), Product Knowledge (PK), and Subjective Norms (SN). These constructs were measured using a 5-point Likert scale, with options ranging from "Strongly Disagree" (1) to "Strongly Agree" (5).

To ensure a diverse sample, demographic variables such as age, education level, income, and occupation were included. Responses were obtained from 261 participants, representing a cross-section of early adopters and general consumers. Data collection was facilitated through social media platforms, email lists, and personal networks to achieve regional diversity and inclusivity.

4.4. Demographic information

In the demographic information part, the study uses descriptive statistical analysis to obtain statistics on the basis information of the valid samples, including gender, age, education background, monthly income, etc. Among the 261 samples, 164 are males, accounting for 62.8% of the total sample; 97 are females, accounting for 37.2%. The detailed results are shown in Table 2.

Table 2: Demographic information

Attributes	Value	Frequency	Attributes	Value	Frequency
Gender	Male	164	Income(Dalasi)	<D5000	38
	Female	97		D5000-D10,000	49
Age	20-	3		D10,100-D15,000	39
	21-30	148		D15,100-D30,000	64
	31-40	71		D30,000+	71
	41-50	22	Degree Major	Science and Engineering	93
	51+	17		Economics and Management	66
Education	High school	23		Humanities and Arts	56
	Certificate	61		Others	46
	Bachelor's degree	117	Housing	Apartment	98
	Masters	60		Non Apartment	163

5. Results and findings

The model analysis results mainly consist descriptive analysis, reliability, validity and regression analysis. The following will discuss the relevant data and results in detail.

5.1. Reliability and validity analysis

The measurement model evaluates the reliability and validity of constructs, ensuring they accurately represent the intended variables. The data that is collected from the online questionnaire survey is analyzed using a Confirmatory Factor Analysis (CFA) to test our research model. The convergent validity of the constructs is tested by using the CFA. Cronbach’s alpha measures are used for checking the internal consistency of the questionnaire. The results are presented in TABLE 3. It is observed that all the constructs have high Cronbach’s alpha values (more than 0.7) (39). Therefore, a high degree of internal reliability has been achieved. The highest alpha value = 0.95 has been obtained for the hedonic construct, while the lowest one = 0.89 corresponds to the perceived risk construct. Mean scores suggest moderate to high agreement, indicating general awareness and attitudes toward smart home technologies in the target region.

Results for the test of convergent validity have been reported in Table 4. Regarding the convergent validity, we verified two conditions. The factor loading of every item measuring a particular construct was calculated and found to be greater than 0.6. This is the first minimum requirement for the convergent validity test to pass. Convergent validity refers to the extent to which a measure correlates, or converges, with other measures of the same construct [39]. Convergent validity is demonstrated when the Average Variance Explained (AVE) value between the constructs is equal to, or exceeds, 0.5 [[39],]. As seen in TABLE 4, The average variance extracted (AVE) value was also calculated for every construct and found to be greater than 0.5, which is the second test for convergent validate ([39], [40]), which meets the first requirement of achieving convergent validity. An alternative approach to assess the convergent validity of the constructs is to examine the composite reliability of the constructs [40]. All constructs exhibited acceptable to high scores of composite reliability by exceeding the 0.60 threshold recommended by Ref [39]. Therefore, the mean variance shared between the latent variable (construct) and its indicators (items) is greater than 50%. When AVE is greater than this threshold, the variance explained by the items is greater than the variance arising from the measurement error.

Table 3: Descriptive statistics and internal consistency of the used Questionnaire

Construct	**Mean**	**Standard Deviation**	**Cronbach's Alpha**
Perceived Usefulness	3.67	1.01	0.91
Hedonic Value	3.64	0.95	0.95
Functional Value	3.67	0.97	0.91
Perceived Risk	3.45	1.04	0.89
Product Knowledge	3.10	1.02	0.90
Subjective Norms	3.12	1.07	0.90
Intention to Use	3.71	1.05	0.92

Table 4: Test for convergent validity

Construct	Item		Factor loading	Composite reliability	Average variance extracted
Intention to use	ITU1		0.792	0.794	0.614
	ITU2		0.767		
	ITU3		0.796		
	ITU4		0.778		
Perceived Usefulness	PU1		0.587	0.812	0.500
	PU2		0.764		
	PU3		0.683		
	PU4		0.754		
	PU5		0.637		
Hedonic value	HV1		0.723	0.887	0.612
	HV2		0.794		
	HV3		0.819		
	HV4		0.801		
	HV5		0.770		

Functional Value	FV1		0.679	0.882	0.517
	FV2		0.667		
	FV3		0.744		
	FV4		0.772		
	FV5		0.786		
	FV6		0.736		
	FV7		0.634		
Perceived Risk	PR1		0.775	0.83	0.698
	PR2		0.860		
	PR3		0.852		
	PR4		0.852		
Subjective Norms	SN1		0.848	0.905	0.76
	SN2		0.902		
	SN3		0.866		
Product Knowledge	PK1		0.881	0.907	0.765
	PK2		0.879		
	PK3		0.864		

5.2. Regression analysis

Prior to the regression, a reliability analysis was conducted for the dependent variables consisting of multiple scales. For reliability, the internal consistency reliability was examined based on Cronbach's alpha, and its value was measured at 0.861. In general, a Cronbach's alpha of 0.6 or higher can be considered to represent internal consistency and indicates that the reliability of the results is relatively high. To test the hypotheses, regression analysis was performed to study the effects of independent variables on intention to use after controlling for demographic characteristics. The results analysis on the effects of demographic characteristics are reported in Table 5. Model 1 examined whether and how the independent variables affect the intention to use. Model 2 examined whether and how the independent variables affect the intention to use by employing demographic characteristics as the control variables. The dependent variable is the intention to use smart home product. The independent variables are perceived usefulness, Function value, Hedonic value, Usefulness, Privacy, Product Knowledge and Subjective Norms. In Model 1, demographic variables are not controlled, so the effects of the independent variables are tested directly on the intention to adopt smart home technologies. For H2, we can see that hedonic value was significant. It indicates that the enjoyment or pleasure derived from smart home products strongly influences adoption. This is consistent with the notion that people in developing regions may prioritize experiences that improve quality of life or provide entertainment, particularly as smart technologies may be perceived as novel or luxurious. For H3, we can see that functional value was significant. It suggests that the practicality and utility of smart home products (e.g., energy efficiency, automation) are critical to adoption. People likely value solutions that directly address their daily needs. For H5, we can see that the significance of subjective norms highlights the influence of social expectations or peer pressure on adoption. In West Africa, communal values and societal norms often play a strong role in shaping individual decisions. There are also some hypotheses that not got supported. For example, H1 isn't satisfied. This result may indicate that while usefulness is a key factor in TAM, it may not be the most immediate driver of adoption in this context. Potential adopters might require more awareness or demonstration of the practical benefits of smart home technologies before usefulness becomes influential. H4 isn't satisfied. The non-significance suggests that perceived risks, such as concerns about privacy or security, may not strongly deter adoption in this region. This could be due to limited awareness of such risks or a perception that they are manageable compared to the benefits. H6 isn't satisfied. Product Knowledge Non-Significant Indicates that understanding smart home technologies does not significantly affect adoption intention. Limited exposure to these products may lead to adoption decisions being influenced more by external factors like social norms than internal factors like knowledge. In Model 2, demographic variables (income, gender, age, housing, education) were included as controls. This allows a clearer view of how the independent variables function when demographic influences are accounted for. *Significant* Hypotheses include H2 (Hedonic Value), H3 (Functional Value), and H5 (Subjective Norms): These remained significant, reinforcing their strong influence on adoption even after controlling for demographic factors.H6 (Product Knowledge): The addition of demographic controls reveals that product knowledge is significant. This suggests that awareness and understanding of smart home technologies are crucial, especially in a developing context where such products are not widespread. Changes in results is likely because demographic factors (e.g., education) correlate with knowledge. Once these are accounted for, the unique contribution of product knowledge to adoption becomes evident. Product knowledge likely mitigates uncertainties and builds confidence in the technology. *Non-Significant* Hypotheses: H1 (Perceived Usefulness): Even after controlling for demographics, usefulness remains non-significant. This may indicate that potential users prioritize other attributes (e.g., enjoyment or social influence) over pure utility in their adoption decisions. H4 (Perceived Risk): The continued non-significance of perceived risk could reflect a low awareness of privacy and security issues or a cultural context where risks are seen as secondary to benefits. The shift in significance between models emphasizes the importance of demographic factors in shaping smart home technology adoption. Future studies should explore the interplay between these controls and other predictors. Multicollinearity measured by the variance inflation factor (VIF) index was less than 10 in all. Therefore, it is hard to find any related problem in Multicollinearity. The results of hypothesis testing are described in Table 5 below.

Table 5: The results of regression analysis

Variable	Model 1					Model 2				
	B	β	t	p	VIF	B	β	t	p	VIF
(Constant)	0.691		3.211	0.001		.499		1.549	.123	
Function value	0.182	0.196	2.902	**0.004**	2.230	.182	.197	2.864	**.005**	2.302
Hedonic value	0.228	0.248	3.589	**0.000**	2.338	.232	.253	3.608	**.000**	2.392

Usefulness	0.116	0.126	1.734	0.84	2.592	.115	.125	1.679	.094	2.691
Privacy	0.44	0.047	0.926	0.355	1.270	.045	.048	.924	.356	1.330
Product Knowledge	0.70	0.82	1.634	0.103	1.239	.092	.108	2.006	**.046**	1.403
Subjective Norms	0.231	0.266	5.422	**0.000**	1.173	.224	.258	5.211	**.000**	1.193
Gender						.093	.055	1.146	.253	1.124
Age						.052	.057	1.095	.275	1.332
Income						-.029	-.051	-.946	.345	1.392
Education						-.001	-.001	-.015	.988	1.207
Housing						-.086	-.051	-1.088	.278	1.080
R adj. R2 R2 F	0.693 0.467 0.480 39.024					0.699 0.466 0.489 21.667				

Note: * p < 0.05, ** p <0.01, *** p < 0.001

5.3. Mediation effects

The mediation analysis (shown in table 6) revealed the following results. The study assessed the mediating role of Perceived Usefulness on the relationship between Hedonic Value and Intention to use. The results revealed a significant indirect effect of Hedonic Value on Intention to Use (b= 0.175, t= 5.5004). Furthermore, the direct effect of hedonic on intention to use in presence of the mediator was also found significant (b = 0.355, P < 0.001). This implies that users not only enjoy smart technologies but also see them as useful in improving their lives. Another results revealed a significant indirect effect of functional value on Intention to Use (b= 0.194, t= 5.0710), the direct effect of functional value on intention to use in presence of the mediator was also found significant (b = 0.318, P < 0.001). The partial mediation indicates that users appreciate the practical benefits of smart home products and see their usefulness, both directly influencing their intention to use. There is also a significant indirect effect in the relationship among Perceived Risk, Perceived Usefulness and Intention to Use (b= 0.214, t=1.3216), but the direct effect of Perceived Risk on intention to use in presence of the mediator was non-significant (b = 0.072, P >0.001). Full mediation was found, perceived risk negatively affects perceived usefulness, which in turn impacts adoption intention. The full mediation suggests that the influence of perceived risk on adoption intention is entirely channeled through its effect on perceived usefulness. Users are less likely to adopt smart home technologies if they perceive them as risky, particularly if these risks diminish the perceived utility of the products. Finally, the mediating role of Perceived Risk on Product Knowledge and Subjective Norms to intention to use was tested. The results revealed a significant indirect effect of Subjective Norms on Intention to Use (b= 0.032, t= 7.4632). When subjective norms reduce perceived risks, users are more likely to adopt the technology. Whiles the results for Product Knowledge revealed non-significant indirect effect on Intention to Use (b= 0.016, t= 5.626), but the direct effect of Product Knowledge on intention to use in presence of the mediator was significant (b = 0.016, P >0.001). While product knowledge impacts adoption intention directly, its effect is not significantly mediated by perceived risk. This suggests that knowing about the technology reduces uncertainties and enhances confidence, leading to direct adoption, but this knowledge does not strongly influence users' risk perceptions. In other words, users may recognize potential risks but still adopt the technology due to their understanding of its functionality. These results support H7, H8, H9, and H10. H11 was not supported.

Table 6: The Result of Mediating Effect

	Effect	Boot SE	Boot LLCI	Boot ULCI	Percentage	Conclusion
Ind 1: HV → PU → ITU	0.175	0.578	0.662	0.292	37%	Partial
Ind 2: FV → PU → ITU	0.194	0.551	0.884	0.304	36%	Partial
Ind 3: PR → PU → ITU	0.214	0.046	0.124	0.308	30%	Full
Ind 4: SN → PR → ITU	0.032	0.20	0.001	0.078	25%	Partial
Ind 5: PK → PR → ITU	0.016	0.019	-0.013	0.061	19%	Non

6. Conclusions

6.1. Managerial implications

This study provides significant insights for managers, marketers, and policymakers aiming to enhance the adoption of smart home technologies in developing regions, particularly West Africa, The Gambia. The findings indicate that hedonic value, functional value, and subjective norms are key factors driving adoption, while perceived risks and lack of product knowledge act as barriers. These insights suggest specific strategies to address the challenges and leverage the opportunities presented by the growing interest in smart home technologies.

The role of hedonic value highlights the emotional appeal of smart home products. Consumers are drawn to the enjoyment and convenience these technologies provide. Managers should capitalize on this by crafting marketing campaigns that showcase the pleasure of using smart home devices. For instance, advertisements could depict scenarios where smart home products simplify daily life or add an element of entertainment. Interactive in-store demonstrations can also provide hands-on experiences, helping consumers connect emotionally with the technology. Functional value further underscores the importance of communicating practical benefits. Consumers need to see how smart home devices can improve their lives, whether through energy savings, enhanced security, or automated convenience. Marketers should emphasize these advantages in their messaging, using real-world examples such as reduced energy bills from smart thermostats or improved home safety with smart locks. Collaborations with energy providers and security firms can reinforce these benefits and build trust among consumers. Subjective norms reveal the powerful influence of social networks on consumer behavior. Many individuals look to peers, family members, or community leaders when deciding whether to adopt new technologies. Managers can harness this influence by engaging trusted influencers or local figures to endorse smart home products. Organizing community-based workshops or events can also foster a sense of collective learning and acceptance, making the technology more relatable and accessible. Addressing perceived risks is another critical consideration. Security and privacy concerns remain significant barriers to adoption. Companies must be transparent about their privacy policies and security protocols, ensuring consumers feel their data is protected. Displaying security certifications prominently in marketing materials can build consumer trust, as suggested by Hubert et al. (2019). Features like end-to-end encryption and user-controlled permissions should be prominently highlighted. Certifications from credible organizations or endorsements from independent reviewers can further build trust and reduce apprehension.

Finally, the importance of product knowledge underscores the need for educational initiatives. Many potential adopters may not fully understand what smart home technologies can do or how to use them. Companies should invest in user-friendly resources, including instructional videos, detailed manuals, and training sessions. These efforts can bridge knowledge gaps and foster confidence, particularly in developing regions (Gao and Bai, 2014). Partnerships with community organizations and educational institutions can also help spread awareness and build confidence among users.

6.2. Limitations

Despite its valuable insights into the determinants of smart home technology adoption, this study has several limitations that must be acknowledged. These limitations provide important context for interpreting the findings and highlight areas where further research is needed to deepen our understanding of the topic.

One significant limitation is the regional focus of the study, which was confined to West Africa, The Gambia. While this focus allows for an in-depth analysis of the specific socio-economic and cultural factors influencing smart home adoption in this region, it limits the generalizability of the findings to other developing regions. Different areas may face unique challenges, such as variations in technological infrastructure, cultural attitudes toward technology, or differing levels of economic development. For example, what works in West Africa might not be applicable in Southeast Asia or South America due to differences in market conditions and consumer behavior. Future research should explore these differences by replicating the study in other developing regions to draw comparisons and identify universal versus region-specific trends.

Another limitation stems from the reliance on self-reported data collected through surveys. While surveys are an efficient way to gather large amounts of data, they are subject to biases such as social desirability bias, where respondents might answer in ways they think are socially acceptable rather than reflecting their true thoughts and behaviors. Additionally, recall bias may affect the accuracy of responses, especially when participants are asked about past experiences or behaviors. This can lead to inaccuracies that skew the results. Future studies could complement self-reported data with observational or behavioral data to gain a more accurate understanding of adoption behavior.

The study’s cross-sectional design also poses a limitation. By collecting data at a single point in time, the research cannot capture changes in attitudes, perceptions, or adoption behaviors over time. For instance, as smart home technology becomes more accessible or as public awareness increases, user intentions and behaviors may evolve. A longitudinal study design, which tracks participants over an extended period, would provide deeper insights into how these factors interact and change, offering a more dynamic understanding of adoption processes.

Moreover, the study did not include certain variables that could play a significant role in smart home technology adoption, such as cost and technological infrastructure. Cost is a critical factor in developing regions, where the affordability of smart home devices can significantly impact adoption rates. Similarly, the availability of reliable internet connectivity and power supply—essential for operating smart home technologies—can either facilitate or hinder adoption. By excluding these factors, the study provides an incomplete picture of the challenges and enablers of smart home technology adoption. Future research should aim to incorporate these variables to develop a more comprehensive understanding of the adoption process.

Lastly, the study does not delve deeply into the role of specific demographics within the sample population. While demographic characteristics such as income, gender, age, housing, and education were controlled for, their unique impacts on adoption intentions were not fully explored. Different demographic groups may face distinct barriers or exhibit varying motivations for adopting smart home technologies. For example, younger consumers might prioritize hedonic and functional values, while older consumers might be more concerned about ease of use and reliability. Understanding these nuances could help tailor marketing and policy interventions more effectively to the needs of specific groups.

6.3. Future research

This study provides a foundational understanding of the factors influencing smart home technology adoption in developing regions, specifically West Africa. However, it also opens avenues for further research that can deepen our knowledge of this subject and address some of the limitations inherent in the current study. By exploring these areas, future research can provide a more comprehensive and globally applicable understanding of smart home technology adoption.

One important direction for future research is to expand the geographical scope of the study. While this research focuses on West Africa, other developing regions, such as Southeast Asia, South America, and other parts of Africa, have different socio-economic, cultural, and infrastructural dynamics that may affect the adoption of smart home technologies in unique ways. For instance, Southeast Asia has witnessed rapid technological advancements and urbanization, which could present a different set of challenges and opportunities compared to West Africa. Similarly, South America might prioritize issues like political stability or energy infrastructure, which influence technology adoption. By conducting comparative studies across multiple developing regions, researchers can identify universal factors that drive adoption as well as those specific to local contexts. This broader perspective will enhance the applicability of the findings and inform more effective regional policies and business strategies.

Another critical avenue for exploration is the use of longitudinal study designs. The current study captures a snapshot of attitudes and behaviors at a single point in time, which limits the ability to understand how these factors evolve. Adoption of new technologies often involves a process that unfolds over time, influenced by changing perceptions, market penetration, and external events. For example, as more people in a community adopt smart home technologies, social influence may play a more prominent role in encouraging others to follow suit. Similarly, as public awareness of privacy and security measures increases, perceived risks may diminish. Longitudinal studies could track participants over several years to observe these dynamic changes and provide insights into the long-term drivers and barriers to adoption.

Future research should also consider incorporating additional variables that were not examined in this study but are likely to influence adoption decisions. One such variable is cost, which is a critical factor in developing regions. The affordability of smart home devices can be a major barrier to adoption, particularly in areas where disposable income is limited. Another important variable is technological infrastructure, including the availability of reliable internet connectivity and electricity, which are essential for the operation of smart home devices. In many developing regions, infrastructure constraints may significantly hinder the adoption of these technologies, regardless of their perceived usefulness or enjoyment. By including these factors, future studies can offer a more comprehensive understanding of the challenges to adoption.

Another promising area for future research is the exploration of demographic differences in adoption behavior. While this study controlled for demographic characteristics such as age, gender, income, housing, and education, it did not examine how these characteristics uniquely influence adoption decisions. For instance, younger individuals might be more inclined to adopt smart home technologies due to greater familiarity with digital tools and a preference for innovative products, while older individuals may prioritize ease of use and reliability. Similarly, gender differences might play a role, with men and women potentially valuing different aspects of smart home technologies. Understanding these demographic nuances can help businesses and policymakers develop targeted interventions that cater to the specific needs and preferences of various groups.

Finally, future research could explore the interplay between cultural values and technology adoption. Cultural factors such as collectivism versus individualism, attitudes toward privacy, and openness to change may significantly influence how people perceive and adopt smart home technologies. For example, in collectivist cultures, decisions about adopting new technologies may be influenced more by family or community norms than in individualist cultures, where personal preferences might take precedence. Studying these cultural dimensions can provide valuable insights for designing culturally sensitive marketing and education campaigns.

By addressing practical needs, security concerns, and the enjoyment derived from smart home systems, this study provides a roadmap for increasing adoption in developing regions. Extending TAM with variables such as Hedonic Value, Functional Value, and Subjective Norms captures the multifaceted nature of adoption decisions. The findings highlight the importance of tailoring strategies to local contexts, ensuring that technologies align with consumer preferences and lifestyles. These insights can guide stakeholders in promoting the widespread adoption of smart home technologies, ultimately improving living standards and fostering sustainable development in West Africa.

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