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Do Smart Device Factors Play a Role in Affecting Consumers' Intention to Use Smart Home Devices

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Abstract

Rapid advancements in smart home technologies require understanding their current capabilities and predicting their future impact on our daily lives. Investigating consumers' use intention towards these smart home devices is crucial to improving understanding in this area. Numerous studies have been conducted empirically in this area, but these studies have explicitly focused on some specific smart devices and are very limited in the general smart home devices. Besides, the role of the smart device factors in the consumers' attitudes (ATT) and their adoption is minimal. Therefore, the present study aims to examine the role of three smart device factors on consumers' ATT and intention to use (IU) these devices. The technology acceptance model (TAM) is extended with three smart device factors and ATT in proposing a novel research framework. The partial least squares-structural equation modelling results on 186 usable responses indicated that perceived usefulness (PU), perceived intelligence (PInt), perceived interactivity (PI), and relative advantages (RA) significantly predict consumers' ATT. Besides, IU was significantly impacted by ATT, perceived ease of use (PEOU), and PU. Additionally, the results further found that ATT significantly mediates the connections between PU, PInt, PI, and RA on IU. These findings showed that the proposed smart device factors played a vital role in cultivating consumers' ATT and IU on smart home devices, either directly or indirectly, and it could further benefit the extant knowledge and also benefit the stakeholders in better understanding consumers' perspectives.

Keywords: Smart Home Devices, Intention to Use, Perceived Intelligence, Relative Advantages, Perceived Interactivity

Introduction

Traditional living environments have been transformed into inter-connected, intelligent ecosystems due to the rapid urbanisation and the integration of the Internet of Things (IoT). Smart home devices, including automated energy-saving climate systems and intelligent security monitors, to voice-assisted lighting and appliances, are no longer mere novelties; they offer tangible utility that directly elevates quality of life. For consumers, these smart devices offer greater convenience, enhanced home security, reduced energy consumption and remote monitoring capabilities that streamline daily routines. Despite these actionable benefits, the widespread adoption of smart home technology remains uneven globally and particularly sluggish in developing markets like Malaysia. Therefore, understanding consumer motivations to adopt these technologies is paramount to unlocking their daily utility and societal potential.

The global smart home market is expected to rise to $163.7 billion in 2028 (Markets and Markets, 2023), further showing the importance of smart home devices. In Malaysia, the smart home industry in 2020 is estimated to be valued at $132 million and is projected to rise further in the next few years (Rock et al., 2024). However, despite this economic trajectory, actual adoption among Malaysian households remains significantly lower than in neighbouring nations like Singapore (Rock et al., 2024).

A major contributor to this gap is the lack of empirical insight into how specific device characteristics (such as perceived intelligence and interactivity) shape consumer attitudes and actual usage intention. While prior research has predominantly examined single-purpose devices, including smart locks or smart speakers, only a few studies have addressed general smart home device adoption through a practical, utility-driven lens. Therefore, this study addresses this critical gap by examining how key smart device attributes drive consumer attitudes and adoption intentions, offering actionable insights for academics, industry stakeholders, and policymakers alike.

Academically, the adoption of smart technologies and devices adoption have extensively studied from different viewpoints. Most evidence is particularly evaluated on the determinant factors of different specific smart devices. For instance, Mamonov and Benbunan-Fich (2021) studied the IU smart lock in the United States by considering the salient factors and gender differences. Mamonov and Benbunan-Fich (2021) found that perceived advantage significantly affected adoption intention on smart locks for both males and females, but the significant effect of novel benefits was also found in the female sample. Besides, the acceptance of smart speakers in Germany was also studied by Kowalczuk (2018), who found that the IU smart speaker is significantly impacted by perceived usefulness (PU), perceived enjoyment and risk. Similarly, the IU smart speakers in Italy were further investigated by Aiolfi (2023), who found that consumers' ATT toward smart speakers is impacted by PU, perceived ease of use (PEOU), perceived enjoyment, and task technology fit. Moreover, the acceptance of smart home services in Korea was also studied by Yang et al. (2017), based on the theory of planned behaviour. Chouk and Mani (2019) further discovered the factors for and against resistance to the use of smart services in the banking sector in France. Unlike these studies that investigate the adoption intention of specific smart devices, limited studies have focused on general smart home devices. However, the requirement to

adopt general smart home devices may be different from the specific smart devices. Therefore, it requires further investigation in this area to bridge the research gap.

Empirically, very limited studies have focused on general smart home usage or device adoption. For instance, Hubert et al. (2019) investigated smart home usage through an integrated framework of the technology acceptance model (TAM), innovation diffusion theory (IDT) and perceived risk theory, and found that the TAM constructs could mediate the indirect relationship between IDT and perceived risk theory on use intention. Furthermore, Mashal and Shuhaiber (2019) also studied the factors that affect Jordanians to buy smart home devices by focusing on social factors, personal factors, and smart home device factors, and the result revealed that residents' intention to buy is affected by social influence, trust, perceived cost, perceived enjoyment, awareness, and personalisation. However, the role of the smart device factors such as perceived intelligence (PInt), relative advantages (RA), and perceived interactivity (PI) on the consumers' ATT and smart home devices use intention is relatively limited. Undeniable, the influence of these smart device factors on consumers' or users' ATT and use intention is studied in other research contexts, such as chatbot adoption (Balakrishnan et al., 2022; Pillai & Sivathanu, 2020; Le, 2023), healthcare devices (Park et al., 2016), financial service devices (Haron & Barre, 2023; Krishanan et al., 2016; Zhu et al., 2023), not particularly in smart home devices. As documented in the literature, these smart device factors play a vital role in affecting consumers' ATT and IU in different technologies and devices. For example, Dixit et al. (2023) found that the RA of the new technology compared to the existing version tends to enhance the consumers' adoption intention. Similarly, the PInt could be the main reason for the adoption of artificial intelligence (AI) technology (Priya & Sharma, 2023), such as smart home devices. Moreover, the interactivity functions of smart devices are also found to be the essential determinant that influences individuals to adopt technologies, like social commerce (Dashti et al., 2019), mobile banking (Krishanan et al., 2016), and live streaming (Yu & Zhang, 2022). For that reason, the study wishes to evaluate the role of the smart device factors (PInt, RA, and PI) on consumers' attitudes (ATT) toward IU smart home devices.

The TAM has been used as the foundation of the study. However, due to the limitations of the TAM (Negm et al., 2023), this study further addressed this limitation by incorporating three smart device factors (PInt, RA and PI) and ATT into the TAM to propose the research framework that could investigate the subject matter comprehensively, as the crucial role of these additional factors on technology adoption in different contexts have been proven in literature (Balakrishnan et al., 2022; Balakrishnan & Dwivedi, 2024; Le, 2023; Mamonov & Benhunan-Fich, 2021; Pillai & Sivathanu, 2020). The research framework that extends the TAM framework is projected to offer more solid and robust evidence and further contribute to the subject area theoretically and practically. Investigating consumer adoption in this domain offers multi-stakeholder significance. For example, technology developers and manufacturers could better understand the specific device attributes that shape consumer perceptions, and this will allow them to design systems that are more intuitive, interactive, and aligned with user expectations. Besides, marketers and retailers could also identify the key decision drivers that enable them to formulate targeted campaigns to communicate functional advantages rather than focusing on complex technical specifications. Moreover, policymakers and urban planners could further promote smart device adoption directly to support national digital transformation agendas, energy management, and sustainable smart-

city frameworks. Lastly, for the end-users, bridging the adoption gap empowers consumers to utilise smart technologies that optimise home management, save time and lower living costs.

Literature Review and Hypotheses Development

Technology Acceptance Model (TAM)

TAM is a theoretical framework that Davis (1989) introduced to explain the individual's decision to adopt technology. As theorised by TAM, the intention of an individual to embrace a certain technology is affected by PEOU and PU. With the more remarkable predictive ability of TAM, this model has been used extensively in the literature in diverse areas, such as the financial industry (Leong et al., 2021; Shaikh et al., 2020; Teng et al., 2020), tourism industry (Berakon et al., 2023), retailing industry (Camoiras-Rodriguez & Varela, 2020), education industry (Pillai et al., 2024), and the like. However, some limitations are presented in the TAM (Negm et al., 2023), predominantly since it only consists of two factors (PEOU and PU). It does not consider the influence from other perspectives. This study extended the TAM with three smart device factors (PInt, RA, and PI) and ATT to form a more comprehensive research model for understanding consumers' IU smart home devices.

Perceived Usefulness on Attitudes and Intention to Use

PU is the perception of an individual towards performance enhancement by using technology (Davis et al., 1989). Generally, individuals perceive technology positively and use it if they expect it to enhance their performance. With that, the positive significant effect of PU on ATT and IU is postulated, and it is widely proven in previous studies. For instance, Pan et al. (2018) remarked on the substantial effect of PU on both ATT and the adoption intention of smart healthcare services. Similarly, Kim et al. (2021) also consistently found a similar influence of PU on ATT and behavioural intention in virtual reality. The important role of PU on ATT and intention to follow online advice is also documented by Shaker et al. (2023). Recently, Rahman et al. (2024) also documented the substantial effect of PU on ATT and continuance IU mobile wallets. Subsequently, the study formulated:

H1: PU is positively significant with ATT.
H2: PU is positively significant with IU.

Perceived Ease of Use on Attitudes and Intention to Use

PEOU is the individual’s level of belief in difficulties when using a certain technology (Davis et al., 1989). Practically, the individual tends to have a good feeling about the technology and eventually will cultivate it to use it if they think it doesn't require any additional effort or cost. An individual tends to have favourable ATT and IU smart home devices if they believe that it is user-friendly. The crucial role of PEOU on ATT and IU is also documented. For example, Karahoca et al. (2018) remarked on the important role of PEOU on ATT and adoption intention on IoT healthcare technology products. Similarly, Kampa (2023) also revealed a significant association between PEOU and ATT and IU in m-learning. Raj et al. (2024) also found that PEOU substantially influenced ATT and BI to adopt cashless transactions. Therefore, this study proposed that:

H3: PEOU is positively significant with ATT.
H4: PEOU is positively significant with IU.

Attitudes on Intention to Use

ATT is the individual's perception and feeling towards the entities or behaviour (Ajzen, 1985). It is also defined as an individual's favourable or unfavourable feelings towards technology (Ling et al., 2024a – Mobile Investment). Theoretically, individuals are more likely to use certain technologies with positive ATT (Ling et al., 2024b – Mobile Payment). With that, consumers are anticipated to have a high likelihood to adopt smart devices if they have positive ATT on them, and this is proven in the literature (Pan et al., 2018; Karahoca et al., 2018; Kampa, 2023; Raj et al., 2024; Sujood et al., 2022). For example, Kim et al. (2021) revealed that ATT predicts IU virtual reality technology significantly. Shaker et al. (2023) also found that ATT has a significant influence on the intention to follow online advice. The positively significant role of ATT on technology continuance adoption was also reported in the mobile wallets' context by Rahman et al. (2024). Hence, the study recommended:

H5: ATT is positively significant with IU.

Perceived Intelligence on Attitudes

PInt refers to the individual's perceived ability of certain technology to obtain and use the knowledge and skills in different situations (Bartneck et al., 2009). It also refers to the interactive, fast, knowledgeable, engaging, intelligent and dependable (Priya & Sharma, 2023). Smart home devices are a newly innovated technology that consists of AI features, and it is expected that these devices will be able to learn and solve associated problems. Therefore, these smart devices are expected to be more intelligent than conventional devices from the perspectives of usage and performance. Hence, consumers are expected to have a favourable ATT with smart home devices if they feel that these devices are intelligent. Numerous empirical studies have also supported this assumption, and the vital role of PInt on the ATT is widely documented. For example, Balakrishnan et al. (2022) found that PInt significantly affected ATT on chatbot-based services. Similarly, Priya and Sharma (2023) also found a remarkable effect of PInt on the utilitarian ATT on intelligent virtual assistants. Recently, Balakrishnan and Dwivedi (2024) also found that users' ATT is significantly affected by PInt. Accordingly, the study proposed:

H6: PInt is positively significant with ATT.

Relative Advantages on Attitudes

RA refers to how a technology is believed to be superior and outperforms what it supersedes (Dixit et al., 2023). An individual tends to have greater ATT toward a new technology if it outperforms the existing one. In this study context, the individual would have favourable ATT toward the smart home devices if these devices provide better value and benefits than traditional devices. With that, it is suggested that the RA would have a substantial effect on the consumers' ATT, as the more RA offered by the smart home devices, the more consumers tend to have positive and favourable ATT toward these smart devices. This supposition is paralleled with prior studies that also observed the positive significant association between RA and ATT (Liu et al., 2024; Wang et al., 2024; Dixit et al., 2023). For instance, Zhu et al. (2023) found that the RA of mobile payment is positively significant for ATT. Similarly, Ganjipour and Edrisi (2023) also remarked on the positive effect of RA on ATT in their study on delivery robots. Hence, the study formulated that:

H7: RA is positively significant with ATT.

Perceived Interactivity on Attitudes

PI is defined as the users' subjective evaluation of the dynamic and responsive nature of their interactions with these smart technologies. This would determine if consumers would appreciate the technology more if it provided more interaction with the users. The consumers would have favourable ATT towards the technology as it could be cultivated by greater PI (Yu & Zhang, 2022). Therefore, this study further hypothesises the substantial influence of the PI on the consumers' ATT toward smart home devices, as the more interactivity provided by the devices, the more it would nurture positive ATT on the devices. This is consistent with the evidence in the literature, which also revealed the important effect of PI on ATT. For instance, Krishanan et al. (2016) concluded that PI substantially impacted ATT in mobile banking. Similarly, Dashti et al. (2019) also found that PI played important effect on ATT toward social commerce. Moreover, Yu and Zhang (2022) also found PI's positive and significant role in ATT in their study on live streaming. Hence, this study proposed the hypothesis below.

H8: PI is positively significant with ATT.

Mediating Role of Attitudes

The mediating effect of ATT on the association of the five predictors, consisting of two factors from TAM (PU and PEOU) and three smart device factors (PInt, RA, and PI), on the IU smart home devices. As Farani et al. (2017) mentioned, some other factors capture the unique feature that may influence the individual behavioural intention indirectly, through the TPB's constructs such as ATT. Besides, prior research also acknowledged the mediating effect of ATT on the predictors and outcome variables. For example, Himel et al. (2021) found that the associations between PU and PEOU on mobile financial services use intention are mediated by ATT. Similarly, Arli and Dakpayeu (2023) and Ganjipour and Edrisi (2023) also revealed the indirect impact of RA on IU mobile payment and delivery robots (respectively) through ATT. Thus, the indirect effect of the five predictors on the IU smart home devices is also proposed in this study and suggested that:

H9: PU indirectly influences IU through ATT.
H10: PEOU indirectly influences IU through ATT.
H11: PInt indirectly significantly influences IU through ATT.
H12: RA indirectly influences IU through ATT.
H13: PI indirectly influences IU through ATT.

Figure 1 demonstrates the proposed research model, whereas the three smart device factors (PInt, RA, and PI) and ATT are added to the TAM model.

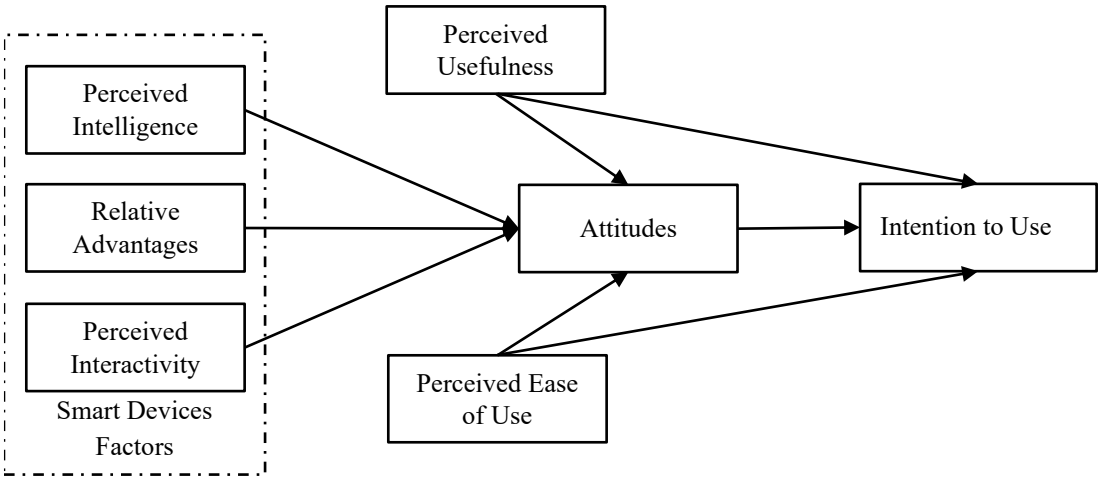

Figure 1: Research Model

Methodology

The study utilized quantitative research approach, whereas the primary responses were gathered from the general public in Malaysia using a convenience sampling technique. A total of 186 valid and usable responses were collected through Google Forms. The final sample of 186 fulfilled the required sample size suggestion of 138, determined by power analysis with the criteria of 0.15 effect size, 95% power level, and also five predictors (Memon et al., 2020).

A dual-language (English and Malay) questionnaire has been developed in this study by adapting the validated items from past research, such as Dong et al. (2017), Gao et al. (2022), Guerreiro et al. (2022), Lee and Pan (2023), and Sujood et al. (2022). Overall, 26 items from the past research were adapted. These items were assessed with the seven-point Likert-type scale that ranges from strongly disagree (1) to strongly agree (7).

The collected responses were first processed through the data preparation process, then ready to be analysed using statistical tests. The dataset was first analysed using Mardia's multivariate coefficient procedures to assess the normality of the dataset. The kurtosis coefficient (76.32) is greater than 20, which shows that the data is non-normally distributed (Byrne, 2013; Kline, 2011). With that, partial least squares-structural equation modelling (PLS-SEM) is an adequate technique (Hair et al., 2019).

Results

The respondents' characteristics are provided in Table 1, which indicates that males (52%) were slightly greater than females (48%). Besides, over 80% of the respondents were aged 35 years and below, and approximately 57% were employees, while 23% and 17% were students and self-employed, respectively. Most respondents received tertiary education (85%) regarding the highest education level.

Table 1
Characteristics of Respondents

Category	Group	Frequency	Percentage
Gender	Male	96	51.61
	Female	90	48.39
Age Range	25 YO and Below	73	39.25
	26 – 35 YO	92	49.46
	36 – 45 YO	18	9.68
	46 YO and Above	3	1.61
Occupation	Employee	106	56.99
	Housewife / Househusband	6	3.23
	Self-Employed	31	16.67
	Students	43	23.12
Education Level	Primary and Secondary School	28	15.05
	Certificate and Diploma	33	17.74
	Bachelor Degree	112	60.22
	Master Degree	11	5.91
	Doctor of Philosophy	2	1.08

Table 1 shows the outcome of the outer measurement assessment, and it indicates that convergent validity of the study is achieved as all 26 measurement items were retained as their outer loading value were greater than 0.7080 (Hair et al., 2017), while the average variance extracted (AVE) value for all constructs also exceeds 0.50 (Bagozzi & Yi, 1988). Besides, the study also confirmed internal consistency, as all constructs have a composite reliability value that is greater than 0.7000 (Gefen et al., 2000). Additionally, the heterotrait-monotrait ratio of correlation in Table 3 further indicated that the study also has no discriminant validity issue, as the HTMT value is below the 0.85 level (Kline, 2011).

Moreover, Harman's single-factor test proved that only 47.17% of the variance in a first factor can be explained by all items, which is less than the 50% level (Podsakoff et al., 2003), and indicated the absence of single-source bias. Besides, the full collinearity test result in Table 2 also proved that all constructs have the variance inflation factor (VIF) value below the 3.30 level (Kock, 2015), and further confirmed the absence of common method bias.

Table 2
Results of Outer Measurement Assessment

Constructs	Items	Loading	AVE	CR	VIF
Perceived	PInt1	0.8439	0.7307	0.8161	2.7250
Intelligence	PInt2	0.8678			
	PInt3	0.8527			
Relative	RA1	0.8874	0.7969	0.8728	2.4810
Advantages	RA2	0.8948			
	RA3	0.8958			
Perceived	PI1	0.7847	0.6633	0.8303	2.3360
Interactivity	PI2	0.7764			
	PI3	0.8298			
	PI4	0.8637			
Attitudes	ATT1	0.8966	0.7254	0.8716	3.1630

	ATT2	0.8910			
	ATT3	0.8698			
	ATT4	0.7398			
Perceived Usefulness	PU1	0.8407	0.7368	0.8808	3.0320
	PU2	0.8916			
	PU3	0.8664			
	PU4	0.8337			
Perceived Ease of Use	PEOU1	0.9061	0.8204	0.9269	1.8440
	PEOU2	0.8770			
	PEOU3	0.9257			
	PEOU4	0.9135			
Intention to Use	IU1	0.9001	0.8026	0.9170	2.1900
	IU2	0.9454			
	IU3	0.9207			
	IU4	0.8118			

Table 3
Result of Discriminant Validity Test

	PInt	**RA**	**PI**	**ATT**	**PU**	**PEOU**	**IU**
PInt							
RA	0.8387						
PI	0.8082	0.6740					
ATT	0.8091	0.7533	0.8192				
PU	0.6767	0.7057	0.7102	0.8085			
PEOU	0.5518	0.4764	0.5330	0.6115	0.7116		
IU	0.5912	0.6236	0.5295	0.7072	0.7584	0.5973	

The PLS-SEM structural model assessment was used to test the proposed hypotheses. The R^2 result first showed that around 66.81% of the variance in ATT is predicted by the five predictors, and three predictors explain 53.03% of the variation in IU. Besides, the Q^2 values for both ATT (0.4734) and IU (0.4169) are greater than zero, which further indicates the predictive validity (Hair et al., 2017). Additionally, based on the guidelines of Cohen (1988), the f^2 result in Table 4 indicated that PU, Pint, RA, and PI have a small effect size on ATT, while PEOU has no effect on ATT. Similarly, a small effect size was also reported for PU, PEOU, and ATT toward IU.

Table 5 and Figure 2 provided the path coefficient and hypothesis testing results. The results showed that seven out of eight direct hypotheses were supported, except for H3. This indicated that, PU (β = 0.2893), PInt (β = 0.2002), RA (β = 0.1525) and PI (β = 0.2678) significantly affected ATT, and thus supporting H1, H6, H7, and H8. Besides, H2, H4, and H5 are also supported as IU is significantly influenced by PU (β = 0.4046), PEOU (β = 0.1401) and ATT (β = 0.2742). However, ATT is insignificantly affected by PEOU (β = 0.0708, p > 0.05).

Furthermore, the result of the mediation analysis on the five indirect hypotheses was provided in Table 5 and revealed that PU (β = 0.0793), PInt (β = 0.0549), and PI (β = 0.0734) have indirect significant influence on IU on smart home devices through ATT. As such, H9, H11, and H13 were supported. However, PEOU (β = 0.0194, p > 0.05) and RA (β = 0.0418) insignificantly affect IU via ATT, and H10 and H12 were unsupported.

Table 4
Path Coefficients and Hypotheses Testing for Direct Hypotheses

Hypo.	Path	Coef.	T-value	P-value	BCI-LL	BCI-UL	f^2	Results
H1	PU -> ATT	0.2893	4.0958	0.0000	0.1729	0.4062	0.1024	Supported
H2	PU -> IU	0.4046	5.1115	0.0000	0.2612	0.5257	0.1413	Supported
H3	PEOU -> ATT				-			**Not**
		0.0708	1.2380	**0.1079**	0.0251	0.1632	0.0085	**Supported**
H4	PEOU -> IU	0.1401	1.7423	0.0408	0.0056	0.2703	0.0237	Supported
H5	ATT -> IU	0.2742	3.5149	0.0002	0.1459	0.4018	0.0780	Supported
H6	PInt -> ATT	0.2002	2.7413	0.0031	0.0789	0.3210	0.0464	Supported
H7	RA -> ATT	0.1525	2.2371	0.0127	0.0465	0.2677	0.0296	Supported
H8	PI -> ATT	0.2678	4.6278	0.0000	0.1738	0.3637	0.1031	Supported

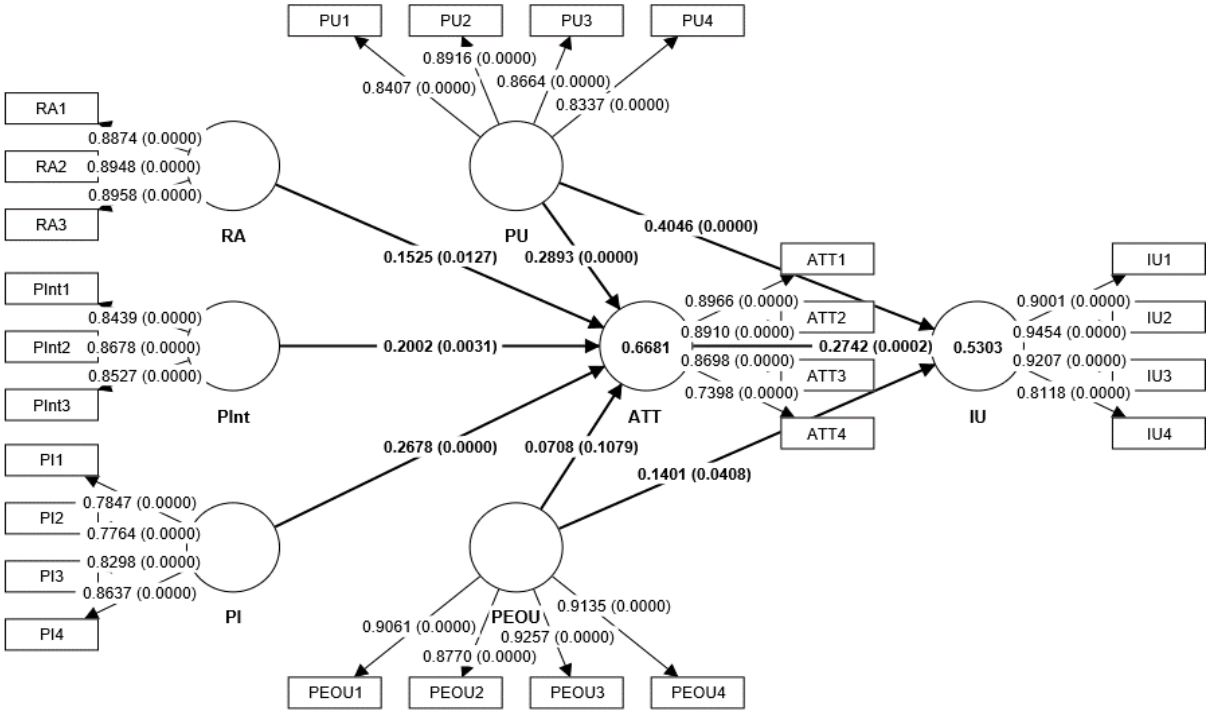

Figure 2 Research Model with Path Coefficients and P-values

Table 5
Path Coefficients and Hypotheses Testing for Indirect Hypotheses

Hypo.	Path	Coef.	T-value	P-value	BCI-LL	BCI-UL	Results
H9	PU -> ATT -> IU	0.0793	2.7369	0.0062	0.0339	0.1522	Supported
H10	PEOU -> ATT -> IU				-		**Not**
		0.0194	1.1767	**0.2394**	0.0081	0.0588	**Supported**
H11	PInt -> ATT -> IU	0.0549	2.0689	0.0386	0.0148	0.1206	Supported
H12	RA -> ATT -> IU						**Not**
		0.0418	1.8447	**0.0651**	0.0086	0.0997	**Supported**
H13	PI -> ATT -> IU	0.0734	2.7393	0.0062	0.0306	0.1371	Supported

Discussions

This study aimed to bridge the existing research gap by investigating the role of the smart device factors on the consumers' ATT and IU through an extended TAM model. The three smart device factors (PInt, RA, and PI) and ATT were integrated into the TAM model. The results from 186 valid responses revealed that all three smart device factors and PU significantly affect ATT, and PU, PEOU, and ATT predict IU. The findings also showed that all predictors indirectly affect IU, except PEOU.

Parallel to Kim et al. (2021), Pan et al. (2018), Rahman et al. (2024), and Shaker et al. (2023), PU has a positively significant effect on ATT and IU. This signified that consumers tend to have favourable ATT and high IU when they perceive that smart home devices are more advantageous and provide more benefits than traditional devices.

However, mixed findings were observed for PEOU on ATT and IU, as PEOU only significantly affects IU but not ATT. This finding is somewhat opposed to the empirical evidence from Kampa (2023), Karahoca et al. (2018), and Raj et al. (2024). This suggests that consumers' IU on smart home devices would be enhanced if consumers perceived that smart home devices required less effort and ease of use. However, this perception doesn't significantly establish favourable ATT toward these devices.

The current study also further added new evidence on the substantial effect of ATT on the IU in smart home devices, which supports the findings of Kim et al. (2021), Rahman et al. (2024), Shaker et al. (2023) and others. Consumers are likelier to use smart home devices if they have good and positive ATT.

The substantial influence of the PInt on ATT is also identified in this study, which further enriches the literature in the area. This result is consistent with Balakrishnan et al. (2022) and Priya and Sharma (2023) in the context of Chatbot-based services and intelligent virtual assistants. Consumers tend to have favourable ATT on smart home devices if they believe these devices can gather and apply their knowledge and skills to solve problems.

Parallel to Dixit et al. (2023), Ganjipour and Edrisi (2023), Zhu et al. (2023), and others, the significant association of RA on the ATT was also confirmed in this study. This implies that the superior and better features of the smart home devices, compared to the traditional devices, would form the positive and good ATT of the consumers.

The study also further remarked on the crucial role of the PI on ATT, and this indicates that the interaction features of the smart home devices would provide a favourable and good ATT to the consumers. The substantial role of PI in ATT is consistent with Dashti et al. (2019), Krishanan et al. (2016), and Yu and Zhang (2022), who also found that consumers' ATT is significantly affected by PI.

Furthermore, the study also found the indirect role of the PU, PInt, and PI on the IU through the mediator of ATT. This signified that the two smart device factors (PInt and PI) and PU significantly affect consumers' ATT and indirectly influence consumers' IU. The significant mediating role of ATT aligns with Himel et al. (2021). This finding further enriched the

literature on the effects of the three smart device factors on consumers' ATT and IU on smart home devices, either directly or indirectly.

Implications

The study offers certain important theoretical and practical implications and is expected to enrich the existing knowledge and benefit the stakeholders. Theoretically, the outcomes of the study enrich the extant knowledge on AI device adoption, especially in smart home devices. Through the extended TAM framework, the study acknowledged the crucial effect of the proposed smart device factors and ATT in decisive the consumers' IU smart home devices. This would further provide a better understanding of this area. The study also advocated that the existing TAM framework should be extended with some other elements that may have been ignored in the TAM framework to capture the unique setting of the study, such as smart device factors in this study. More precisely, this study proved that the three smart device factors (PInt, RA, and PI) and ATT played vital roles directly or indirectly in consumers' ATT and IU. By extending the TAM model, it is expected that this novel extension model will be capable of predicting consumers' ATT and IU on smart home devices comprehensively, as it included the technological factors from TAM (PU and PEOU), smart device factors (PInt, RA, and PI), and the personal factor of ATT.

Practically, the findings could offer some important implications for the stakeholders in articulating and implementing strategies to increase the usage of smart home devices. Main stakeholders in this area, such as governments, manufacturers, and businesses, should emphasise PU, PEOU, and ATT as these factors significantly affect consumers of IU smart home devices. For instance, the manufacturers of smart devices should improve their usefulness by offering more features or functions that could further enhance their efficiency and effectiveness in their daily routines. Besides, the way to use or operate these devices should be simplified and require less learning effort when adopting these devices. Including more languages to command the devices would be one of the focuses, as it would be more applicable if national languages like Malay could be used to command these devices instead of other international common-use languages like English and Chinese. Additionally, the stakeholders should improve consumers' ATT on the smart devices through some marketing and promotional materials and campaigns, as it would further deepen the consumers' understanding of the benefits and advantages of the smart devices. Consumers tend to have favourable ATT on these smart devices if they positively perceive them.

Furthermore, the three smart device factors (PInt, RA, and PI) must be prioritised. They would further enhance the consumers' ATT and indirectly impact consumers' IU on the smart home devices. The intelligence functions of the smart devices should be further improved and enhanced as they boost consumers' favourable ATT and further influence consumers' IU through ATT. Similarly, the advantages of smart devices over traditional ones also have to be emphasised in the marketing and promotional materials, as consumers will understand the advantages and benefits of adopting smart devices. As revealed in the study, consumers tend to have positive and good ATT on smart devices, which will eventually affect their IU through ATT. Compared with traditional devices, one of the unique features of smart devices is the interaction with the users. Users need to interact with these smart devices, like giving commands or using mobile devices to give instructions. Therefore, the smart devices'

interactivity function must be further focused on as it will form favourable ATT on consumers and further enhance their IU on the devices via ATT.

In conclusion, the study proved that the IU on smart home devices is not solely dependent on technological features like PU and PEOU. Still, it is also significantly influenced by smart device factors (PInt, RA, and PI) and personal factors like ATT, directly or indirectly.

Conclusions

This study endeavours to fill the existing research gap by investigating the effect of the smart device and personal factors on the IU smart home devices. A novel research framework based on the TAM was developed by integrating three smart device factors (PInt, RA, and PI) and ATT as personal factors to provide a more inclusive understanding of this subject area. The results from 186 valid responses proved that PU, PEOU and ATT significantly influenced consumers' IU on smart home devices. Besides, ATT has also been found to be substantially impacted by PU, PInt, RA, and PI, except for PEOU. Moreover, the indirect relationship via ATT further found that PU, PInt, and PI indirectly influenced consumers' IU on smart home devices, except for PEOU and RA. The study's findings provide some important implications. It is expected to benefit the relevant stakeholders in promoting the usage of smart home devices and further offer new empirical evidence to the extant knowledge on the direct and indirect role of three smart device factors in adopting smart home devices.

Limitations and Suggestions for Future Study

A few limitations are present in the study, and they should be considered in upcoming studies. The generalizability could be one of the limitations, as the data was focused on a single country. With that, it would be better if upcoming studies could enlarge the scope to other countries, or perhaps a comparative study on different countries could be focused on providing more valuable understandings. Besides, the study only focuses on the general consumers in Malaysia, whether they have used or never used smart home devices before. This may have some biases, as users' perspectives may not be the same as those of non-users. Therefore, it is suggested that forthcoming research gather responses from both groups (users and non-users), and a comparison study could be one of the exciting ideas for exploring the constructs that affect them to adopt smart home devices. Moreover, this study only included three smart device factors and one personal factor to develop the research framework. However, the study did not consider other factors influencing the consumers' ATT and IU on smart home devices, like the cost, privacy risk, trust, etc. Valuable insights might be produced if future research could comprehensively include these constructs in their study.

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