Extending the Technology Acceptance Model to Explain Perceived Energy-Efficiency Improvement in Smart Homes: Evidence from Malaysia

Ooi Sue Yin [1], Aslina Siman [2], Adilah Mohd Din [2], Nur Atika Atan [3]

[1] Fakulti Pengurusan Teknologi dan Teknousahawanan, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian, Tunggal, Melaka, Malaysia

[2] Sekolah Asasi Teknikal dan Pengajian Diploma, Universiti Teknikal Malaysia Melaka, Hang Tuah Jaya, 76100 Durian Tunggal, Melaka, Malaysia

[3] School of Healthcare Management, KPJ Healthcare University, Lot PT 17010 Persiaran Seriemas, Kota Seriemas 71800 Nilai, Negeri Sembilan, Malaysia

DOI: https://doi.org/10.47772/IJRISS.2026.100900795

Received: 16 October 2026; Accepted: 21 October 2026; Published: 23 October 2026

ABSTRACT

Smart-home technologies are widely promoted as a pathway to residential energy efficiency, yet positive perceptions of such technologies do not by themselves demonstrate measured energy savings. Much of the existing literature explains adoption or usage intention rather than perceived energy-efficiency outcomes. This exploratory, cross-sectional study examined six factors from an extended Technology Acceptance Model, namely perceived ease of use (PEOU), perceived usefulness (PU), perceived security (PS), perceived enjoyment (PE), trust (TR) and energy-efficient devices (EED), as predictors of self-reported perceived energy-efficiency improvement (EEI) among 122 Malaysian smart-home users recruited through purposive sampling. All six factors correlated positively with EEI. In multiple regression ($R^2 = 0.543$), PE ($\beta = 0.205$, $p = 0.046$), TR ($\beta = 0.216$, $p = 0.043$) and EED ($\beta = 0.366$, $p < 0.001$) were significant, but only EED remained significant under heteroscedasticity-robust standard errors and bootstrapped confidence intervals. Collinearity was low (VIF 2.07–2.96), whereas Harman's test (first factor 51.3%) did not exclude common-method bias, and responses were concentrated at the top of the scale. The findings therefore indicate associations with perceived, not measured, energy efficiency: device-related beliefs were the most robust correlate, while enjoyment and trust remain tentative.

Keywords: Smart homes; Perceived energy-efficiency improvement; Technology Acceptance Model; Trust; Perceived enjoyment; Energy-efficient devices; Malaysia

I. INTRODUCTION

Smart-home technologies increasingly integrate Internet of Things (IoT) devices, sensors, automation and connected appliances to improve household convenience, security and resource management. Within residential energy management, such systems can support monitoring, automated control and more efficient operation of lighting, heating, cooling and appliances. However, the presence of smart technology alone does not guarantee energy savings: realised efficiency gains depend on how residents understand, trust, configure and continuously use these systems in everyday practice [12], [17]. A systematic review of motivations, barriers and risks in smart-home adoption identifies energy savings as a leading motivator of adoption, but the same evidence base highlights distrust, privacy concerns, technology anxiety and financial cost as persistent barriers to sustained use [15], underscoring that behavioural and technological factors jointly determine whether technical energy-saving potential is realised in practice.

The Technology Acceptance Model (TAM) remains a widely used lens for explaining technology adoption, in which perceived usefulness (PU) and perceived ease of use (PEOU) represent two basic user judgments: whether

a technology is beneficial and whether it can be used with little effort [6]. In smart-home environments, however, these two beliefs rarely operate in isolation, because connected home technologies also collect data, depend on networked infrastructure and interact continuously with users. Recent systematic reviews show that smart-home adoption research commonly extends TAM with constructs such as trust, perceived risk, security, compatibility and hedonic value to capture these additional dimensions [22], [31].

Evidence from Malaysia illustrates the relevance of these extended constructs. Users of IoT-based smart-home technology associate such systems with automation, convenience, security and energy conservation [26], while younger Malaysian consumers identify usefulness and ease of use as key motivators of usage intention, with trust moderating the strength of several relationships [4]. Yet findings are not always uniform: a recent Melaka Tengah study found perceived ease of use to significantly predict adoption intention while perceived usefulness did not remain significant once other predictors were controlled in a multivariate model [21]. The relevance of individual TAM constructs, in other words, seems to depend on the sample and on the outcome being measured.

Most smart-home studies stop at behavioural intention, adoption or continued use. Few ask whether users end up saving energy, and that matters because the technical potential of a device is only realised when residents use the relevant functions, keep sensible settings and trust automated decisions. Research on smart heating found that energy outcomes followed household competencies and everyday routines more closely than they followed installation alone [17], and adoption has been shown to differ across social groups in ways that do not map directly onto energy use [12]. Our study looks at perceived energy-efficiency improvement among existing users. Measured consumption data would be needed to verify realised savings, and we did not have them.

To address this gap, this study poses three research questions: (RQ1) what factors are associated with perceived energy-efficiency improvement in smart homes; (RQ2) what is the relationship between these factors and perceived energy-efficiency improvement; and (RQ3) which factors show the strongest association once considered jointly? Correspondingly, the study pursues three objectives: (RO1) to identify the user-perception and technology factors associated with perceived energy-efficiency improvement; (RO2) to examine the relationship between these factors and perceived energy-efficiency improvement; and (RO3) to determine which factors show the strongest association. These objectives are addressed through a cross-sectional quantitative survey of 122 smart-home users in Malaysia, analysed using descriptive statistics, Pearson correlation and multiple regression. Energy-efficiency improvement (EEI) is measured through respondents' self-reported perceptions, not metered household electricity data, and the findings are interpreted accordingly.

This exploratory study contributes in three ways. It moves TAM from explaining adoption toward explaining a perceived energy-efficiency outcome, while keeping the model's behavioural logic. It places perceived security, enjoyment and trust in the same model as energy-efficient devices, so that perceptual and technological correlates of perceived EEI can be compared directly. And it adds Malaysian residential evidence to a literature that has mostly examined adoption, with the caveat that our outcome is perceptual.

The rest of the article is organised as follows. Section II reviews the literature and develops six hypotheses. Section III describes the design, sampling, instrument and analysis. Section IV reports and discusses the results, and Section V sets out implications, limitations and recommendations before Section VI concludes.

II. LITERATURE REVIEW

A. Smart Homes and Energy-Efficiency Improvement

Smart homes combine networked sensors, control devices, appliances and software to automate or support household activities, including occupancy-responsive lighting, adaptive temperature control and real-time energy monitoring. Their energy-management value stems from the ability to observe consumption, coordinate device operation and automate decisions that would otherwise require continuous user attention. Malaysian users have reported energy conservation as a practical benefit of IoT-based smart-home technology, alongside convenience, security and improved environmental conditions [26].

Nevertheless, the relationship between smart-home technology and energy efficiency is not purely technical. A broad review of smart-home adoption identifies distrust, privacy concerns and cost as major barriers that can

limit sustained, energy-efficient use even where devices are installed [15], while a critical review of end-user behaviour concludes that occupant behaviour, rather than technology alone, is a major determinant of the household energy-performance gap [19]. Recent energy-practice research similarly shows that expected efficiency gains depend on how technologies are integrated into everyday routines and on users' competence in configuring and managing them [17], and adoption and energy consumption have been found to be socially differentiated, indicating that ownership of smart technology should not be treated as equivalent to energy-efficient use [12]. In this study, EEI is operationalised as respondents' perceived energy-efficiency improvement, that is, their perceptions of smart homes' contribution to saving energy and supporting sustainability. It is treated as a perceptual indicator that may be influenced by both technical capability and user engagement, not as a measure of verified reductions in household electricity consumption.

B. Extended Technology Acceptance Model in the Smart-Home Context

TAM proposes that perceived usefulness and perceived ease of use are fundamental beliefs shaping technology acceptance [6]. The model has been repeatedly extended to accommodate contextual factors relevant to particular technologies, and smart homes are a strong example of such a context because they combine physical devices, software interfaces, remote connectivity, personal data and automated decision-making. Systematic reviews show that smart-home adoption research frequently draws on TAM while adding constructs such as perceived risk, trust, compatibility, cost, social influence and hedonic value [1], [22], [31]. This study adopts an extended TAM-oriented framework rather than a pure adoption model. PEOU and PU retain their original behavioural interpretation, while perceived security, perceived enjoyment and trust capture additional perceptions that may shape willingness to engage with connected domestic technologies. Energy-efficient devices are added as a practical technology factor because behavioural acceptance alone cannot generate lower energy use without devices or systems capable of delivering energy-saving functions. The resulting model links user beliefs and technological capability to a downstream outcome, perceived energy-efficiency improvement.

C. Perceived Ease of Use and Energy-Efficiency Improvement

Perceived ease of use refers to the degree to which a person believes that using a technology requires relatively little effort [6]. In smart homes, ease of use concerns the simplicity of device installation, configuration, control interfaces and interpretation of feedback; complexity can discourage users from activating advanced functions or maintaining energy-saving settings. Recent smart-home literature continues to identify ease of use as an important determinant of adoption or usage intention [4], and Malaysian evidence has found PEOU to be a significant predictor of adoption intention in some samples [21]. This study therefore proposes:

H1: Perceived ease of use has a positive relationship with perceived energy-efficiency improvement in smart homes.

D. Perceived Usefulness and Energy-Efficiency Improvement

Perceived usefulness is the belief that using a technology will improve valued outcomes [6]. In smart homes, these outcomes may include convenience, control, reduced electricity expenditure and more effective energy management. Malaysian smart-home evidence identifies usefulness as an important motivator of usage intention [4], although other studies show that its effect can weaken once competing predictors are entered simultaneously [21]. In the present study, PU is expected to influence EEI because users who believe smart technologies provide meaningful energy-management benefits may be more willing to rely on automated controls and maintain energy-saving routines. Accordingly:

H2: Perceived usefulness has a positive relationship with perceived energy-efficiency improvement in smart homes.

E. Perceived Security and Energy-Efficiency Improvement

Perceived security reflects users' belief that connected systems can protect data, prevent unauthorised access and operate without unacceptable security threats, an issue that is especially salient for smart homes because sensors, cameras and connected appliances collect data about routines and occupancy. Recent smart-home security

research shows that perceived security contributes to users' attitudes toward adopting security technologies and indirectly to usefulness and intention [10]. Security may also matter for energy efficiency indirectly, through willingness to keep devices connected, share data with energy-management platforms, or enable automation; a user who distrusts system security may disable remote access or avoid integrated monitoring functions, reducing the potential for coordinated energy management. Nevertheless, perceived security may be more proximal to adoption and trust than to the energy outcome itself. Thus:

H3: Perceived security has a positive relationship with perceived energy-efficiency improvement in smart homes.

F. Perceived Enjoyment and Energy-Efficiency Improvement

Perceived enjoyment captures the intrinsic pleasure or satisfaction experienced when using a technology, arising in smart homes from personalised automation, interactive interfaces and the sense of control created by responsive systems. Smart-home acceptance research has incorporated perceived enjoyment as a meaningful predictor of intention to use [25]. At the same time, comparative evidence indicates that utilitarian value (such as energy-cost or waste reduction) can outweigh hedonic value in household technologies, although enjoyment still contributes for some users [20]. Enjoyment may be particularly relevant to sustained engagement: energy-management systems require repeated interaction with dashboards, alerts and automated routines, and technologies that users find pleasant may be used more consistently, providing a theoretical pathway from enjoyment to energy efficiency through sustained interaction with energy-saving features. Hence:

H4: Perceived enjoyment has a positive relationship with perceived energy-efficiency improvement in smart homes.

G. Trust and Energy-Efficiency Improvement

Trust concerns confidence that a smart-home system or service provider is reliable, competent, predictable and able to protect users from unacceptable harm. Trust is especially important when users delegate control to automated systems or permit technologies to collect and process household data; empirical evidence on voice-enabled smart-home systems shows that trust is a central mechanism for overcoming uncertainty and perceived risk in smart-home use [16]. Malaysian evidence shows that trust can moderate relationships between technology perceptions and usage intention [4]. In an energy-management context, trust may determine whether users accept automated recommendations or continue using system-generated feedback; a trusted system is more likely to remain enabled and integrated into daily routines, increasing the chance that its energy-saving functions operate as designed. Therefore:

H5: Trust has a positive relationship with perceived energy-efficiency improvement in smart homes.

H. Energy-Efficient Devices and Energy-Efficiency Improvement

Energy-efficient devices represent the practical technological capability through which smart homes can reduce or better manage energy consumption, including smart thermostats, intelligent lighting, smart appliances and energy-monitoring systems. Malaysian evidence from a national smart-home pilot shows that such implementations can support conservation of energy and other resources consistent with sustainability goals [13], while acceptance research on IoT-based smart meters shows that electricity-saving knowledge and environmental awareness strengthen the link between acceptance and actual use behaviour [2]. Detailed appliance-level consumption feedback has similarly been shown to support user engagement and reduction in energy use [3]. In this study EED is measured through respondents' beliefs about how effectively such devices save energy, not through ownership or metered use, so it is conceptually the closest predictor to the outcome; moreover, even technically efficient devices depend on correct installation, interoperability and appropriate use, so the strongest conceptual argument is that devices provide the functional capacity for energy savings while user perceptions determine whether that capacity is effectively used. Thus:

H6: The use of energy-efficient devices has a positive relationship with perceived energy-efficiency improvement in smart homes.

I. Research Gap and Conceptual Synthesis

The literature leaves three gaps. Most acceptance studies stop at adoption or behavioural intention and do not treat energy-efficiency improvement as the outcome. Behavioural and technical factors are also studied apart: acceptance research looks at perceptions, while engineering work looks at devices and system performance. Malaysian evidence is growing but scattered across adoption, smart-meter and qualitative usage studies [14], [21], and few studies model extended TAM perceptions and an energy-efficiency outcome together.

The present study therefore treats PEOU and PU, together with perceived security, perceived enjoyment, trust and energy-efficient devices, as parallel predictors of EEI. Fig. 1 shows the framework and the six hypothesised paths (H1–H6). Section IV reports that energy-efficient devices was the only predictor significant in every check, that enjoyment and trust were significant in the standard regression only, and that PEOU, PU and PS were not significant once all six variables were assessed simultaneously.

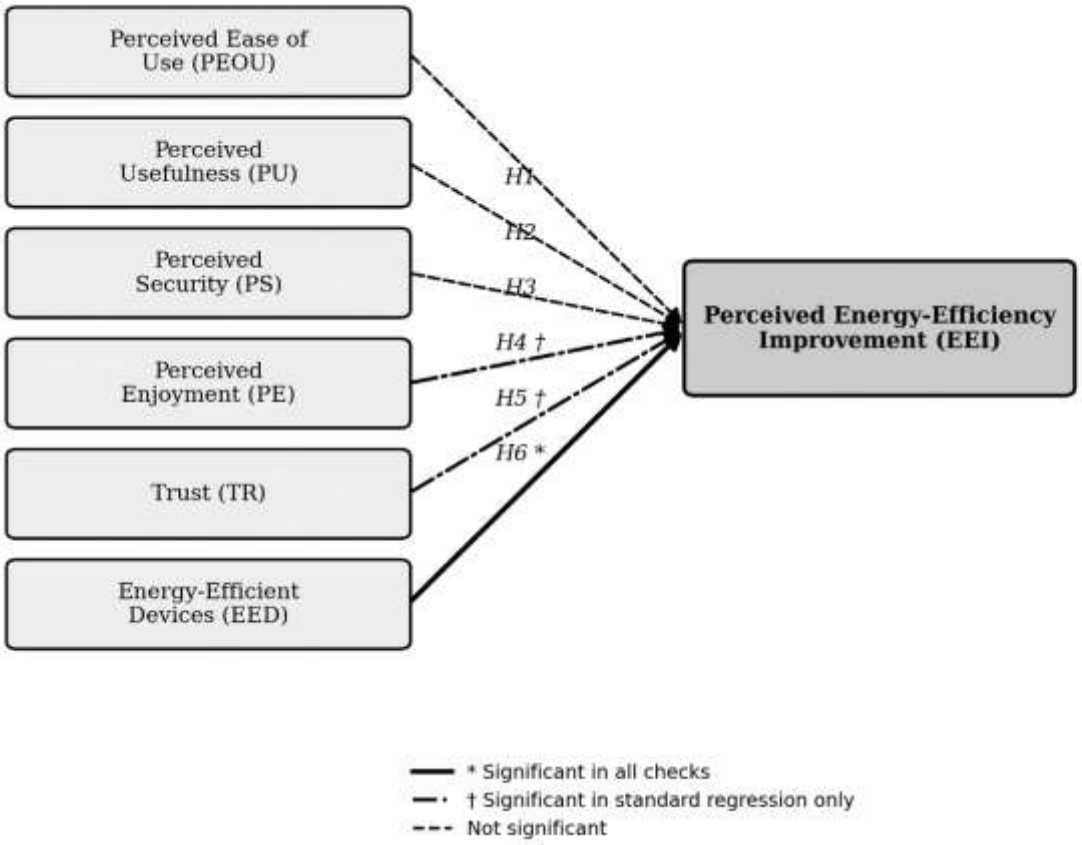


Fig. 1 Conceptual framework of the study, showing six hypothesised paths (H1–H6) from PEOU, PU, PS, PE, TR and EED to perceived energy-efficiency improvement (EEI). Solid line (*): significant in all checks (H6); dash-dot lines (†): significant in the standard regression only (H4, H5); dashed lines: not significant (H1–H3).

III. METHODOLOGY

A. Research Design and Approach

This study adopted a deductive, quantitative research approach, selected because the six predictors and their hypothesised relationships with EEI were derived from an existing theoretical framework (extended TAM) rather than generated inductively from the data; deductive designs are recommended when hypotheses can be specified in advance from prior theory and tested against new evidence [5]. A descriptive research design was used because the study's primary aims were to characterise respondents' perceptions on each construct and to quantify the strength and direction of their association with EEI, rather than to establish causal mechanisms [27], [28].

B. Population, Sampling and Sample Size

The target population comprised Malaysian residents with direct experience of smart-home technologies. A non-probability purposive sampling technique was used to recruit respondents from smart-home user communities who had direct experience with smart-home systems, using an online Google Forms questionnaire. This approach ensured that participants could meaningfully evaluate the six constructs, while minimizing the inclusion of individuals lacking relevant experience. This choice prioritises the relevance of respondents over random selection and limits statistical generalisability, as discussed in Section V. The minimum sample size was determined a priori using G*Power at a statistical power of 0.80 [7], which indicated a minimum of 92 respondents. Data collection, including the pilot test and the preparatory steps before the main survey, was completed within six weeks. The 122 valid main-survey responses.

C. Instrument and Data Collection

Primary data were collected through a structured, self-administered online questionnaire with two sections: respondent demographics (Section A) and the study constructs (Section B). Section B comprised 29 five-point Likert items (1 = strongly disagree to 5 = strongly agree): PEOU (4 items), PU (4), PS (4), PE (4), TR (4), EED (5) and EEI (4). Items were adapted from prior studies: PEOU, PU, PE and TR from Shuhaiber and Mashal [29]; PS from Pavlou [24], Malhotra et al. [18] and Featherman and Pavlou [8]; and EED from prior smart-home energy research. Example items are “I feel using Smart Homes would be easy” (PEOU), “Using Smart Homes would be fun” (PE), “I feel Smart Homes are trustworthy” (TR), “Smart thermostats save energy effectively” (EED) and “Smart home technologies save energy” (EEI). The EEI items are attitudinal statements about the energy and sustainability benefits of smart-home technologies (for example, “Smart homes support sustainable energy use”); they do not ask respondents to report their own household electricity consumption or measured savings. EEI is therefore a perceptual outcome and is referred to as perceived EEI throughout. A pilot test with 30 respondents preceded the main survey. Pilot Cronbach's alpha was 0.800 for the full instrument and 0.841 (PEOU), 0.841 (PU), 0.888 (PS), 0.665 (PE), 0.645 (TR), 0.414 (EED) and 0.394 (EEI) by construct (Table II). No items were deleted after the pilot, so the pilot values for PE, TR, EED and EEI remained below the conventional 0.70 threshold, and the main-survey reliability should be read with this in mind. Content validity relied on the adaptation of previously used items; construct validity was assessed after data collection from the respondent-level file (Section IV-B).

D. Data Analysis Techniques

Primary analyses were run in SPSS version 27. Descriptive statistics (frequencies, percentages, means, standard deviations) summarised respondent demographics and construct scores. Cronbach's alpha assessed internal consistency against the conventional 0.70 threshold [23]. Pearson correlation examined the bivariate association between each predictor and EEI, and multiple linear regression tested the unique contribution of each predictor while controlling for the other five [30], [9], [11]. After reviewer comments, the author re-analysed the respondent-level file in Python (pandas, statsmodels, SciPy), which reproduced the SPSS reliability and regression results exactly, and added four sets of checks. Collinearity was assessed with the variance inflation factor (VIF) and tolerance. Common-method bias was assessed with Harman's single-factor test on the unrotated principal components of all items. Construct validity was assessed with the Kaiser–Meyer–Olkin (KMO) index and Bartlett's test, within-construct component loadings, average variance extracted (AVE), composite reliability (CR), the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT); because these were calculated from single-factor principal-component loadings and not from confirmatory factor analysis, they approximate the usual structural-equation values. Robustness was checked with heteroscedasticity-consistent (HC3) standard errors, 5,000-sample bootstrap confidence intervals, Spearman correlations and a sensitivity analysis that excluded one duplicated item (Section IV-D).

E. Ethical Considerations

Participation in the survey was voluntary, and respondents were informed of the study's purpose before completing the questionnaire. No personally identifying information (e.g., name, contact details or exact address) was collected, and responses were analysed only in aggregate or de-identified form.

IV. RESULTS AND DISCUSSION

This section presents the demographic profile of respondents, the reliability and validity of the measurement instrument, bivariate correlations, and the regression results and diagnostic checks used to test H1–H6, before discussing the pattern of findings against the literature reviewed in Section II.

A. Respondent Profile

Every one of the 122 respondents reported already using smart-home technology, a detail that says as much about who the sampling reached as it does about the sample's characteristics (Table I). Beyond this near-total prior exposure, 59.8% of respondents were female, 50.8% were aged 41–50, and Chinese respondents formed the largest ethnic group (57.4%), followed by Malay (29.5%) and Indian (13.1%) respondents. Most were self-employed (74.6%) and reported a monthly household income of RM2,000–RM4,999 (50.8%). This profile is a direct consequence of the purposive sampling strategy described in Section III-B, which deliberately targeted respondents with existing smart-home experience; the regression results reported below therefore describe an already-engaged, comparatively narrow segment of Malaysian smart-home users rather than the general population, a point revisited in Section V.

TABLE I. RESPONDENT PROFILE (N = 122)

Demographic	Category	%
Gender	Female	59.8
Age	41–50 years	50.8
Race	Chinese	57.4
Occupation	Self-employed	74.6
Monthly income	RM2,000–RM4,999	50.8
Uses smart tech.	Yes	100

B. Reliability and Validity

Cronbach's alpha in the main survey exceeded 0.70 for all seven constructs [23], ranging from 0.806 (PU) to 0.931 (PS) (Table II). This is a marked improvement on the pilot values (n = 30) for PE, TR, EED and EEI, which had fallen below 0.70.

TABLE II. CRONBACH'S ALPHA: PILOT AND MAIN SURVEY

Construct	Items	Pilot α (n=30)	Main α (n=122)
PEOU	4	0.841	0.905
PU	4	0.841	0.806
PS	4	0.888	0.931
PE	4	0.665	0.92
TR	4	0.645	0.921
EED	5	0.414	0.901
EEI (DV)	4	0.394	0.816

Validity was examined with the respondent-level data. Two items, PS2 and PS3, received identical responses from all 122 respondents (r = 1.00), which makes the 29-item correlation matrix singular; PS3 was therefore excluded from KMO and Bartlett's test but retained in the primary analyses for consistency with the original thesis, and a sensitivity analysis is reported in Section IV-D. The 28-item matrix was suitable for factor analysis (KMO = 0.881; Bartlett's $\chi^2 = 3{,}048.9$, df = 378, $p < 0.001$). Within-construct component loadings ranged from 0.64 to 0.96, AVE from 0.645 to 0.830 and CR from 0.878 to 0.951 (Table III), above the usual 0.50 and 0.70 benchmarks and supporting convergent validity. For discriminant validity, the square root of each construct's

AVE exceeded its correlations with every other construct, and the highest HTMT value was 0.818 (PS and TR), below the 0.85 criterion. Several HTMT values for PU, PS and TR were above 0.80, however, so these constructs overlap noticeably. The HTMT between EED and EEI was 0.774, so the two are statistically distinguishable even though their items are conceptually close.

TABLE III. CONVERGENT AND DISCRIMINANT VALIDITY

Construct	AVE	CR	√AVE	Max HTMT
PEOU	0.782	0.935	0.884	0.807
PU	0.645	0.878	0.803	0.816
PS	0.83	0.951	0.911	0.818
PE	0.807	0.944	0.899	0.771
TR	0.81	0.945	0.9	0.818
EED	0.717	0.927	0.847	0.774
EEI	0.646	0.879	0.803	0.774

C. Correlation Analysis

At the bivariate level, all six predictors correlated positively and significantly with EEI ($p < 0.01$): EED ($r = 0.664$), PE ($r = 0.631$), TR ($r = 0.602$), PS ($r = 0.561$), PEOU ($r = 0.553$) and PU ($r = 0.546$). Taken alone, these figures make all six factors look equally relevant. They do not stay that way. Once the predictors enter the same model (Table IV), several of the bivariate correlations turn out to reflect variance shared with stronger predictors, which is why we rely on multiple regression rather than correlation to test H1–H6. The predictors were also correlated with one another ($r = 0.54$ to 0.75), which raises the question of multicollinearity examined in Section IV-D.

D. Regression and Diagnostic Checks

When all six predictors compete in a single model, only half survive. The model was statistically significant, $F(6, 115) = 22.814$, $p < 0.001$, with $R = 0.737$, $R^2 = 0.543$, adjusted $R^2 = 0.520$ and a standard error of the estimate of 0.243. $R^2 = 0.543$ corresponds to Cohen's $f^2 = R^2 / (1 - R^2) \approx 1.19$ for the whole model, a large effect by conventional benchmarks. Individual effect sizes were small: $f^2 = 0.142$ for EED, 0.036 for PE and TR, 0.021 for PEOU, 0.002 for PU and 0.000 for PS.

TABLE IV. MULTIPLE REGRESSION COEFFICIENTS (DV = EEI; * P < 0.05)

Predictor	B	β	t	p
PEOU	0.104	0.143	1.545	0.125
PU	−0.042	−0.047	−0.441	0.66
PS	−0.014	−0.022	−0.199	0.843
PE	0.159	0.205	2.021	0.046*
TR	0.164	0.216	2.041	0.043*
EED	0.303	0.366	4.036	<0.001*

The unstandardised regression equation, based on the coefficients in Table IV, is:

$$EEI = 1.588 + 0.104(PEOU) - 0.042(PU) - 0.014(PS) + 0.159(PE) + 0.164(TR) + 0.303(EED) + \varepsilon$$

Table IV shows which predictors survive. Perceived ease of use ($B = 0.104$, $t = 1.545$, $p = 0.125$), perceived usefulness ($B = -0.042$, $t = -0.441$, $p = 0.660$) and perceived security ($B = -0.014$, $t = -0.199$, $p = 0.843$) have no statistically significant unique effect on EEI once the other five predictors are controlled. Perceived enjoyment ($B = 0.159$, $\beta = 0.205$, $t = 2.021$, $p = 0.046$), trust ($B = 0.164$, $\beta = 0.216$, $t = 2.041$, $p = 0.043$) and energy-efficient devices ($B = 0.303$, $\beta = 0.366$, $t = 4.036$, $p < 0.001$) remain significant positive predictors, with energy-efficient devices the strongest of the six, more than double the standardised effect of either PE or TR. The p values for

PE (0.046) and TR (0.043) lie just below the 0.05 threshold, and the robustness checks reported below show that these two effects do not hold up as well as that for EED.

Collinearity statistics computed from the respondent-level data are shown in Table V. VIF ranged from 2.07 (EED) to 2.96 (PS) and tolerance from 0.34 to 0.48, well within the conventional limits of VIF below 5 and tolerance above 0.20, which indicates moderate but not severe overlap among predictors.

TABLE V. COLLINEARITY STATISTICS

Predictor	VIF	Tolerance
PEOU	2.15	0.46
PU	2.91	0.34
PS	2.96	0.34
PE	2.59	0.39
TR	2.81	0.36
EED	2.07	0.48

The regression residuals were not normally distributed (Shapiro–Wilk W = 0.887, $p < 0.001$; skewness = −1.22), which reflects the ceiling in the data, so robustness was checked (Table VI). Only EED was significant in every check. PE and TR were significant in the standard model (p = 0.046 and 0.043) but not with HC3 standard errors (p = 0.126 and 0.064), their bootstrap confidence intervals included zero, and they lost significance when the duplicated item PS3 was excluded from the PS composite (p = 0.061 and 0.071). In that sensitivity analysis R^2 (0.544) and the pattern for PEOU, PU and PS were unchanged. Spearman correlations between the predictors and EEI ranged from 0.476 to 0.664.

TABLE VI. ROBUSTNESS OF THE REGRESSION RESULTS

Predictor	OLS p	HC3 p	Bootstrap 95% CI of B	p without PS3
PEOU	0.125	0.182	[−0.050, 0.249]	0.126
PU	0.66	0.746	[−0.261, 0.241]	0.598
PS	0.843	0.857	[−0.176, 0.138]	0.81
PE	0.046	0.126	[−0.025, 0.378]	0.061
TR	0.043	0.064	[−0.017, 0.338]	0.071
EED	<0.001	<0.001	[0.137, 0.468]	<0.001

Harman's single-factor test, applied to the unrotated principal components of the 28 items, showed that the first component explained 51.3% of the variance (51.4% with all 29 items), slightly above the 50% guideline. The test is a weak diagnostic, but the result means that common-method bias cannot be excluded in this single-source, self-reported survey. Responses were also concentrated at the top of the scale: 97.7% of all item responses were 4 or 5, no respondent's EEI score was below 4.0, and 83.6% scored 4.5 or higher.

E. Hypothesis Testing Summary

Table VII translates these results into hypothesis outcomes. H1–H3 are not supported, and H6 is supported under every specification. H4 and H5 are only partly supported: the paths are significant in the standard regression but not robust to HC3 standard errors, bootstrapping or the exclusion of the duplicated PS item. The one robust path involves the construct conceptually closest to the outcome, which raises the item-overlap concern discussed below. These interpretations are exploratory.

TABLE VII. SUMMARY OF HYPOTHESIS TESTING

Hypothesis	Path	Result
H1	PEOU → EEI	Not supported

H2	PU → EEI	Not supported
H3	PS → EEI	Not supported
H4	PE → EEI	Partly supported
H5	TR → EEI	Partly supported
H6	EED → EEI	Supported

F. Discussion

PEOU and PU both correlated significantly with EEI on their own, but neither kept a significant unique effect once PE, TR and EED were in the model. Malaysian evidence points the same way: PEOU predicted adoption intention while PU dropped out of a multivariate model [21]. We see two possible reasons, and these data cannot fully separate them. One is construct overlap. Respondents who find smart homes enjoyable, trustworthy and well equipped with energy-saving devices may also rate them easy to use and useful, so PEOU and PU would share variance with PE, TR and EED and add little of their own. The VIF values (2.07–2.96; Table V) show moderate rather than severe overlap, and the HTMT values above 0.80 among PU, PS and TR point the same way. The other reason lies in who answered. All 122 respondents already used smart-home technology, 97.7% of item responses were 4 or 5, and EEI scores never fell below 4.0, leaving little variation for PEOU and PU to explain.

Perceived security was not significant either. Security shapes smart-home attitudes and trust formation [10], so it may act upstream of trust and adoption and reach perceived energy outcomes only through trust, but we did not test this. PE and TR were significant in the standard regression, which fits earlier work showing that trust supports sustained smart-home use [16] and that hedonic engagement can keep people interacting with system features [20]. Their effects did not survive the robustness checks, however, so we treat them as tentative. EED was the only robust predictor, in line with evidence that device-level capability and feedback are tied to lower energy use [3], [13], [2]. It also needs the most caution. The EED and EEI items are both beliefs about smart-home energy savings (for example, “Smart thermostats save energy effectively” and “Smart home technologies save energy”), so part of the strong EED–EEI association may be conceptual overlap and shared method variance, not a separate contribution of devices.

The results show that perceived device effectiveness is the factor most consistently associated with favourable perceptions of smart homes' energy-efficiency benefits. Enjoyment and trust are associated with those perceptions in the standard model but not reliably, and ease of use, usefulness and security show no unique association. None of this shows that these factors cause measurable energy savings. That would take electricity-consumption records and longitudinal designs, and Section V sets out the limits.

V. IMPLICATIONS, LIMITATIONS AND RECOMMENDATIONS

Theoretically, the study extends TAM beyond PEOU and PU by adding perceived security, perceived enjoyment, trust and energy-efficient devices as parallel correlates of perceived energy-efficiency improvement, which gives a multidimensional account of the outcome rather than of adoption intention alone.

Practically, perceived device effectiveness was the most consistent correlate of perceived energy-efficiency improvement, so manufacturers and developers should be able to show convincingly that their hardware saves energy. Enjoyment and trust were significant only in the standard model, so engaging and reliable user experiences are a reasonable but less certain priority. For policymakers, awareness programmes and incentives for energy-efficient devices have the firmest support in these data, with trust-building and digital-literacy initiatives as plausible complements. Because these associations are perceptual, such measures should be accompanied by consumption monitoring to verify actual savings.

The study has limits that readers should weigh before using the findings. The most important concerns the outcome. EEI was measured with four attitudinal items about the energy and sustainability benefits of smart homes, not with metered or bill-based electricity consumption, so the results describe perceived improvement and cannot be read as evidence of actual savings. Ratings were also uniformly high (97.7% of item responses were 4 or 5, and no EEI score was below 4.0), which creates a ceiling effect that restricts variance and leaves

the regression residuals non-normal, and the EED and EEI items are conceptually close. The sample raises a second set of problems. It is small (122 users), purposive and non-probability, it is not representative of Malaysian smart-home users, and it is concentrated in particular groups (74.6% self-employed; 50.8% aged 41–50; 50.8% in one income band), so findings should be generalised with caution. All 122 respondents already used smart-home technology, which restricts the range of familiarity and gives an alternative explanation for the non-significant effects of PEOU, PU and PS. The measurement checks also qualify the results. Harman's test did not exclude common-method bias (first component 51.3%), and procedural remedies were limited to anonymous, voluntary participation. Items PS2 and PS3 were identical for every respondent, and the significance of PE and TR depended on that duplicated item and on the standard error estimator. AVE, CR and HTMT were calculated from principal-component loadings, not from confirmatory factor analysis, and pilot alphas for PE, TR, EED and EEI were below 0.70. Finally, the cross-sectional design cannot establish causality. Future research should link survey responses to household electricity bills or smart-meter data, use longitudinal designs, and draw probability or stratified samples across more varied occupations, ages and income groups. It should also check the source data for the duplicated PS items, test the measurement model with confirmatory factor analysis, use a marker variable or a separate source for the outcome, and replicate the model in a larger sample.

VI. CONCLUSION

This study set out to identify the factors associated with perceived energy-efficiency improvement (EEI) among Malaysian smart-home users, examine their relationships with EEI, and determine which show the strongest association (RO1–RO3). Based on a survey of 122 users, perceived device effectiveness was the strongest predictor and the only one that stayed significant in every check. Enjoyment and trust were significant in the standard regression but not under robust standard errors or bootstrapping, and ease of use, usefulness and security showed no unique association. In this sample, favourable perceptions of smart homes' energy-efficiency benefits are therefore most consistently associated with device-related beliefs. Because EEI was self-reported, responses were concentrated at the top of the scale, and common-method bias could not be excluded, these results are associations, not evidence of verified energy savings.

These conclusions should be read within the limits set out in Section V: a small purposive sample, uniformly high ratings, a single self-reported source, an attitudinal outcome measure and a cross-sectional design. The most useful next step is to link survey responses from a larger, probability-based sample to household electricity bills or smart-meter records, so that perceived and measured efficiency can be compared, and to test the measurement model with confirmatory factor analysis. If measured savings track the device-related beliefs identified here, developers, energy-service providers and policymakers would have a firmer basis for prioritising effective energy-efficient devices, with enjoyable and trustworthy user experience as a secondary consideration.

ACKNOWLEDGMENT

The authors would like to acknowledge and extend special gratitude to the Center of Technopreneurship Development, Universiti Teknikal Malaysia Melaka, for the support.

REFERENCES

1. Al-Husamiyah, A., & Al-Bashayreh, M. G. (2022). A comprehensive acceptance model for smart home services. International Journal of Data and Network Science, 6(1), 45–58.
2. Alkawsi, G., Ali, N., & Baashar, Y. (2020). An empirical study of the acceptance of IoT-based smart meter in Malaysia: The effect of electricity-saving knowledge and environmental awareness. IEEE Access, 8, 42794–42804.
3. Caldera, M., Hussain, A., Romano, S., & Re, V. (2023). Energy-consumption pattern-detecting technique for household appliances for smart home platform. Energies, 16(2), 824.
4. Chin, C.-H., Wong, W. P. M., Cham, T.-H., Thong, J.-Z., & Ling, J. P.-W. (2023). Exploring the usage intention of AI-powered devices in smart homes among millennials and zillennials: The moderating role of trust. Young Consumers, 25(1), 1–27.
5. Creswell, J. W., & Creswell, J. D. (2018). Research Design: Qualitative, Quantitative, and Mixed Methods Approaches (5th ed.). Sage.

6. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319–340.
7. Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. Behavior Research Methods, 39(2), 175–191.
8. Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: A perceived risk facets perspective. International Journal of Human-Computer Studies, 59(4), 451–474.
9. Field, A. (2018). Discovering Statistics Using IBM SPSS Statistics (5th ed.). Sage.
10. Gebsombut, N., Naruetharadhol, P., Chaiwong, P., & Hengboriboon, L. (2025). Smart home security: Factors affecting consumer intention to put smart home security in place. SAGE Open, 15(3).
11. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). Multivariate Data Analysis (8th ed.). Cengage.
12. Hansen, A. R., Trotta, G., & Gram-Hanssen, K. (2024). Smart home technology adoption in Denmark: Diffusion, social differences, and energy consumption. Energy Efficiency, 17(3).
13. Kee, K.-K., Ting, H.-Y., Lim, Y.-S., Ting, J.-T.-W., Peter, M., Ibrahim, K., & Show, P. L. (2022). Feasibility of UTS Smart Home to support Sustainable Development Goals of United Nations (UN SDGs): Water and energy conservation. Sustainability, 14(19), 12242.
14. Lau, J. S., Lau, J. L., & Harun, Z. (2022). Factors influencing the intention to adopt smart home technology among households in Johor Bahru, Malaysia. International Journal of Academic Research in Business and Social Sciences, 12(12).
15. Li, W., Yiğitcanlar, T., Erol, I., & Liu, A. (2021). Motivations, barriers and risks of smart home adoption: From systematic literature review to conceptual framework. Energy Research & Social Science, 80, 102211.
16. Liu, Y., Gan, Y., Song, Y., & Liu, J. (2021). What influences the perceived trust of a voice-enabled smart home system: An empirical study. Sensors, 21(6), 2037.
17. Madsen, L. V., Hansen, A. R., & Larsen, S. P. A. K. (2023). Embodied competencies and smart home technology in energy use: Three ways users integrate smart heating systems in everyday practices. Energy Efficiency, 16(6).
18. Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). Internet users' information privacy concerns (IUIPC): The construct, the scale, and a causal model. Information Systems Research, 15(4), 336–355.
19. Marchi, L., & Gaspari, J. (2023). Energy conservation at home: A critical review on the role of end-user behavior. Energies, 16(22), 7596.
20. Marikyan, D., Papagiannidis, S., & Alamanos, E. (2021). "Smart Home Sweet Smart Home." International Journal of E-Business Research, 17(2), 1–24.
21. Mohamed, N. H., Mohd Sam, M. F., Aris, A., Alias, S. N. A., & Mohamed, N. H. (2025). Consumer perception, innovativeness, and readiness in smart home technology adoption: Evidence from Malaysia. International Journal of Research and Innovation in Social Science, 9(28), 103–111.
22. Nascimento, D. R., & Fettermann, D. C. (2023). The acceptance of smart home technologies. Contemporary Management Research, 19(2), 107–129.
23. Nunnally, J. C., & Bernstein, I. H. (1994). Psychometric Theory (3rd ed.). McGraw-Hill.
24. Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. International Journal of Electronic Commerce, 7(3), 101–134.
25. Pliatsikas, P., & Economides, A. A. (2022). Factors influencing intention of Greek consumers to use smart home technology. Applied System Innovation, 5(1), 26.
26. Rock, L. Y., Tajudeen, F. P., & Chung, Y. W. (2022). Usage and impact of the Internet-of-Things-based smart home technology: A quality-of-life perspective. Universal Access in the Information Society.
27. Saunders, M., Lewis, P., & Thornhill, A. (2020). Research Methods for Business Students (8th ed.). Pearson.
28. Sekaran, U., & Bougie, R. (2019). Research Methods for Business: A Skill-Building Approach (8th ed.). Wiley.
29. Shuhaiber, A., & Mashal, I. (2019). Understanding users' acceptance of smart homes. Technology in Society, 58, 101110.
30. Tabachnick, B. G., & Fidell, L. S. (2019). Using Multivariate Statistics (7th ed.). Pearson.

31. Valencia-Arías, A., Cardona-Acevedo, S., Gómez-Molina, S., González-Ruíz, J. D., & Valencia, J. (2023). Smart home adoption factors: A systematic literature review and research agenda. PLOS ONE, 18(10), e0292558.