

# Predicting the Acceptance of IoT Technologies: A Structural Equation Modeling Approach in the Smart Home Market

Jialiang Ni \*

Royal Holloway, University of London, Egham, UK

\*Corresponding Author: [nij563210@gmail.com](mailto:nij563210@gmail.com)

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## ABSTRACT

With the rapid advancement of IoT technologies, the smart home market has emerged as a crucial application domain within the IoT ecosystem. This study develops a theoretical framework employing SEM grounded in TAM and UTAUT, designed specifically to assess users' acceptance of smart home technologies. Core determinants, such as perceived usefulness, perceived ease of use, social influence, and perceived risk, are systematically identified, and corresponding hypotheses and measurement scales are proposed. The study further outlines a theoretical model designed to elucidate the intricate mechanisms underlying user acceptance intentions. Methodologically, this research contributes an integrated and comprehensive conceptual framework, blending TAM and UTAUT, thus providing a robust theoretical foundation and methodological roadmap for subsequent empirical research in this domain.

## KEYWORDS

Smart Home; IoT; TAM; UTAUT; SEM

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## 1. INTRODUCTION

In recent years, the swift proliferation of IoT technologies has driven the integration of diverse intelligent devices into daily human life. As a pivotal application scenario of IoT, smart homes have demonstrated substantial potential in areas including home automation, security monitoring, energy management, and remote control, positioning themselves as a critical growth sector within the broader IoT industry. However, a stark contrast persists between the rapid technological advancements and the relatively uneven user acceptance of smart home products, significantly hindering their widespread adoption. Thus, an in-depth exploration of users' motivations, psychological drivers, and decision-making mechanisms in adopting smart home technology is both practically vital and theoretically significant for enhancing the market penetration of such technologies.

Currently, the smart home market is undergoing rapid expansion and technological evolution. On one hand, the product landscape continually diversifies, with the emergence of smart speakers, intelligent locks, adaptive lighting, and household appliances reflecting increasingly sophisticated technological innovations. On the other hand, market competition has intensified as major enterprises actively establish IoT ecosystems through strategic platform development and ecosystem integration. Nevertheless, despite technological maturity, user adoption rates and overall market penetration of smart home technologies remain limited. This phenomenon is attributable not only to individual users' technological readiness but also to perceptions regarding security, privacy, economic costs, and operational convenience.

In view of these factors, this research addresses two central questions: What specific determinants influence users' intention to adopt smart home technologies? How do these determinants interrelate and influence user acceptance intentions? Drawing upon TAM and UTAUT, this study aims to construct a structural equation model (SEM) framework to systematically examine key variables, including perceived usefulness, perceived ease of use, social influence, and perceived risk, and their impact on user acceptance intentions. The goal is to pinpoint critical drivers influencing smart home adoption, thereby offering theoretical insights and practical recommendations for advancing the smart home industry.

## 2. THEORETICAL BACKGROUND

### 2.1. Overview of TAM and UTAUT

The Technology Acceptance Model (TAM), initially proposed by Davis [1], is a foundational theoretical framework used extensively to explain user acceptance behaviors toward information technologies. According to TAM, user behavior is primarily determined by Behavioral Intention (BI), which in turn is directly influenced by two pivotal constructs: Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). Specifically, PU denotes the degree to which an individual subjectively believes that utilizing a particular technology would enhance their productivity or effectiveness, whereas PEOU signifies the individual's perception of the technology as effortless to learn and use. The mathematical representation of the model is provided in Equation (1).

$$BI = \beta_1 PU + \beta_2 PEOU + \varepsilon \quad (1)$$

Where BI represents the behavioral intention to use the technology; PU and PEOU denote perceived usefulness and perceived ease of use, respectively;  $\beta$  indicates the path coefficients to be estimated, reflecting the direct impact of the perceptual variables on behavioral intention; and  $\varepsilon$  represents the error term, capturing unmeasured influences on behavioral intention.

Although TAM is widely embraced due to its conceptual simplicity and clarity, it is limited by its neglect of social and environmental influences on user behavior. In addressing this limitation, Venkatesh [2] proposed the Unified Theory of Acceptance and Use of Technology (UTAUT), synthesizing multiple theoretical perspectives, including planned behavior theory, innovation diffusion theory, and social cognitive theory, to enhance predictive capacity. UTAUT incorporates four principal constructs—Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), and Facilitating Conditions (FC)—and postulates their collective impact on behavioral intention. The formal equation of the UTAUT model is illustrated in Equation (2).

$$BI = \alpha_1 EE + \alpha_2 SI + \alpha_3 FC + \alpha_4 PU + \zeta \quad (2)$$

Where  $\alpha$  represents path coefficients reflecting the strength of influence exerted by each factor on behavioral intention, EE denotes effort expectancy, SI symbolizes social influence, FC indicates facilitating conditions, and  $\zeta$  is the random error term capturing other unspecified factors.

### 2.2. Structural Equation Modeling

Structural Equation Modeling (SEM) is a robust multivariate statistical analysis technique widely employed for theoretical verification and model evaluation in fields such as psychology, management, and marketing. SEM integrates the advantages of Path Analysis and Factor Analysis, enabling simultaneous assessment of relationships between latent variables and observed variables, as well as

direct and indirect effects among constructs. Consequently, SEM is particularly suited to validate hypothesized structural relationships within frameworks such as TAM and UTAUT [3].

Typically, SEM comprises two distinct models: the measurement model and the structural model. The measurement model specifies the relationships between latent constructs and their corresponding observed indicators, as expressed mathematically in Equation (3).

$$X = \Lambda_x \xi + \delta, Y = \Lambda_y \eta + \epsilon \quad (3)$$

Where  $X$  denotes observed variables associated with exogenous latent variables, and  $Y$  denotes observed variables linked to endogenous latent variables;  $\xi$  represents exogenous latent variable vectors,  $\eta$  represents endogenous latent variable vectors;  $\Lambda_x$  and  $\Lambda_y$  symbolize factor loading matrices for exogenous and endogenous latent variables, respectively;  $\delta$  and  $\epsilon$  are error terms representing measurement inaccuracies in observed variables.

The structural model defines causal or predictive relationships between latent constructs, as formally represented in Equation (4).

$$\eta = B\eta + \Gamma\xi + \zeta \quad (4)$$

In Equation (4),  $\eta$  is the vector of endogenous latent variables (variables being explained),  $\xi$  denotes the vector of exogenous latent variables (explanatory variables),  $B$  denotes the matrix of path coefficients among endogenous latent variables,  $\Gamma$  represents the path coefficient matrix linking exogenous to endogenous latent variables, and  $\zeta$  reflects residual errors indicating unmodeled influences.

Through these two systems of equations, SEM delineates both direct and indirect structural relationships among constructs and assesses the overall model fit using various statistical criteria. Employing SEM to construct and validate a theoretical model of technology acceptance within the smart home context allows for comprehensive exploration of complex internal mechanisms underlying users' technology adoption, thus significantly enhancing the academic rigor and practical applicability of the findings.

### 3. RESEARCH MODEL AND HYPOTHESIS DEVELOPMENT

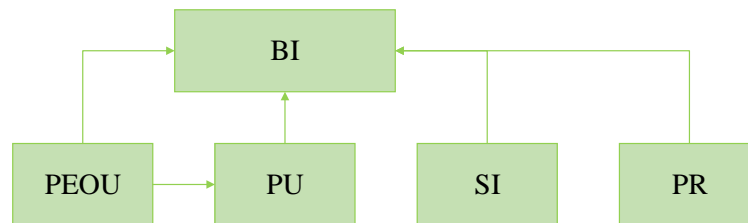
#### 3.1. Research Framework and Overall Approach

This study constructs a theoretical framework for examining user acceptance of smart home technologies using SEM based on TAM and UTAUT. The research framework systematically identifies key latent variables and elucidates their intrinsic logical relationships influencing users' acceptance intentions. Specifically, the model integrates PU and PEOU derived from TAM to analyze how subjective perceptions of smart home technologies shape users' behavioral intentions. Additionally, SI and PR, conceptualized within UTAUT, are incorporated into the model as critical extension constructs, providing a more comprehensive depiction of user decision-making complexity in the smart home market.

The proposed framework hypothesizes that PEOU positively influences PU, and both collectively impact BI. Moreover, SI is expected to exert a significant positive effect on BI, whereas PR is anticipated to negatively influence BI. Clarifying these core relationships will yield targeted recommendations for advancing smart home technology adoption.

Based on the theoretical foundations of TAM, this study proposes the following relational hypotheses: (1) PEOU positively and significantly influences PU, suggesting users perceiving technology as easy to use are more inclined to regard it as useful; (2) PU positively and significantly influences BI; and

(3) PEOU directly and positively influences BI. Furthermore, grounded in UTAUT, the study introduces two additional hypotheses regarding SI and PR: (4) SI positively and significantly influences BI, indicating peer opinions and recommendations enhance users' willingness to adopt smart home technologies; and (5) PR negatively and significantly affects BI, implying that heightened perceptions of risk diminish user adoption intentions. The SEM theoretical model is presented in Figure 1.



**Figure 1.** SEM Theoretical Model

### 3.2. Definition and Measurement of Key Variables

The core latent variables included in the SEM for this research are PU, PEOU, SI, PR, and BI. To ensure robust measurement quality, the conceptualization and operationalization of each latent variable are rigorously derived from the literature review.

PU reflects users' subjective beliefs regarding the extent to which smart home technologies can enhance their life efficiency and effectiveness. Measurement items include statements such as "I believe using smart home devices improves my living efficiency," and "Using smart home technology helps me manage household affairs more conveniently," designed explicitly to assess users' subjective evaluations of technological utility. Secondly, PEOU captures users' subjective perceptions of the ease of understanding, simplicity, and accessibility associated with smart home technologies. Representative measurement items encompass statements like "Learning to operate smart home technology is effortless for me," and "The operational methods for smart home devices are clear, enabling me to quickly master them," effectively quantifying user perceptions of usability. Thirdly, SI signifies the extent to which users perceive their decisions are influenced by social contexts and peer recommendations. Relevant measurement items include "My family or friends think I should adopt smart home technology," and "The growing adoption of smart home products among people around me encourages me to consider adopting such technologies," capturing the social dynamics influencing technology acceptance. Fourthly, PR is introduced to capture users' concerns regarding security, privacy, and economic costs when considering smart home adoption. Measurement items reflecting risk perceptions include "I am concerned smart home devices could compromise my personal information," and "High prices of smart home technology make me hesitant," accurately assessing users' risk-related concerns. Finally, BI characterizes users' subjective intention and likelihood to adopt smart home technologies [4-6]. Measurement items include "I intend to try smart home devices within the next six months," and "If given the opportunity, I will prioritize purchasing smart home products," directly capturing users' purchase intentions and willingness to use such technologies.

All latent variables are assessed through five-point Likert scales, ranging from 1 ("strongly disagree") to 5 ("strongly agree"), to effectively quantify users' subjective perceptions. The key latent variables and representative measurement items are summarized in Table 1.

**Table 1.** Core Latent Variables and Measurement Items

Latent Variable	Measurement Dimension	Representative Measurement Item
PU	Efficiency Improvement	Using smart home devices improves my living efficiency
PEOU	Ease of Use	Learning how to use smart home devices is effortless for me
SI	Social Environment	My friends think I should adopt smart home technology
PR	Privacy and Economic Risk	I worry smart home devices may compromise my personal data
BI	Adoption Intentions	I will prioritize purchasing smart home products

### 3.3. Hypotheses Formulation and Theoretical Justification

This study's hypotheses are derived by integrating insights from TAM and UTAUT and contextualizing them within smart home adoption research. Specifically, the following hypotheses are proposed:

Based on TAM, PEOU is frequently considered an antecedent to PU, meaning that users who perceive technology as easy to operate are more likely to view it as beneficial. Hence, we propose:

H1: PEOU positively and significantly influences PU.

According to the foundational premise of TAM, BI is directly influenced by both PU and PEOU. When users perceive the practical utility of smart home technologies and their ease of use, their intention to adopt these technologies increases. Therefore, this study proposes:

H2: PU positively and significantly influences BI.

H3: PEOU directly and positively influences BI.

Drawing from UTAUT, SI is conceptualized as the influence of significant others or societal groups on individuals' adoption intentions. Users often rely on advice or recommendations from friends, family, or opinion leaders during adoption decisions. Thus, we hypothesize:

H4: SI positively and significantly influences BI.

Furthermore, although TAM and UTAUT primarily emphasize positive drivers of technology acceptance, negative perceptions such as security, privacy, and cost-related risks substantially influence user adoption decisions, particularly within smart home contexts. Incorporating PR as an important construct, informed by Featherman and Pavlou (2003), we propose:

H5: PR negatively and significantly influences BI.

The hypotheses and corresponding theoretical foundations are summarized in Table 2.

**Table 2.** Summary of Hypotheses and Their Content

Hypothesis	Description of Hypothesis
H1	PEOU positively influences PU
H2	PU positively influences BI
H3	PEOU positively influences BI
H4	SI positively influences BI
H5	PR negatively influences BI

## 4. RESEARCH METHODOLOGY

### 4.1. Sampling Criteria and Data Collection

To guarantee generalizability and representativeness, the study employs strict sampling criteria. Considering the unique attributes and target demographics of smart home technologies, respondents are primarily urban residents with sufficient economic resources, familiarity with technological innovations, and potential purchasing power. Furthermore, stratified random sampling will be employed, considering demographic characteristics such as age, gender, educational background, and occupational categories, to ensure balanced representation across diverse user segments.

Data collection will adopt an integrated approach, utilizing both online and offline methods. Online data collection will be facilitated through digital questionnaire platforms to broaden geographical coverage and enhance collection efficiency. Concurrently, offline surveys will be conducted face-to-face to improve response rates and data quality, mitigating issues commonly associated with online surveys, such as superficial or inattentive responses. During face-to-face interactions, detailed explanations concerning the research context and questionnaire completion instructions will be provided, thereby promoting respondents' cooperation and ensuring accurate responses.

Furthermore, a two-stage data collection process, encompassing a pilot survey and a subsequent formal survey, will be implemented to enhance the reliability and validity of collected data. The pilot phase, involving a smaller-scale sample, aims to evaluate the clarity, relevance, and reliability of measurement items. Based on feedback and analysis derived from the pilot study, necessary adjustments will be implemented. In the formal phase, questionnaires will be distributed on a broader scale, aiming for a minimum sample size of 300 respondents to satisfy SEM analysis requirements regarding sample adequacy and model robustness [7]. The integrated approach of rigorous quality control procedures and diversified data collection methods ensures the reliability, validity, and representativeness of the data collected, thus laying a solid empirical foundation for the subsequent analyses.

### 4.2. Analytical Methods and Procedures

The data analysis phase comprises a three-step methodological approach: reliability and validity analysis, exploratory and confirmatory factor analyses, and structural equation modeling.

Reliability indicates the internal consistency of measurement instruments, whereas validity examines the degree to which instruments accurately measure theoretical constructs. Cronbach's alpha coefficient will be employed to measure internal consistency, with values exceeding 0.7 indicating adequate reliability. Composite reliability (CR), as expressed in Equation (5), will also be utilized for comprehensive reliability assessment.

$$CR = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum \text{Var}(e_i)} \quad (5)$$

Where  $\lambda_i$  represents standardized factor loadings, and  $\text{Var}(e_i)$  represents the variance of measurement error terms. A CR value exceeding 0.7 denotes sufficient reliability.

Validity analysis encompasses content validity, convergent validity, and discriminant validity. Content validity will be ensured through expert consultations and pilot testing. Convergent validity will be evaluated via Average Variance Extracted (AVE), calculated as shown in Equation (6).

$$AVE = \frac{\sum \lambda_i^2}{n} \quad (6)$$

Where  $\lambda_i$  signifies factor loading values, and  $n$  represents the number of measurement items. An AVE greater than 0.5 indicates strong convergent validity. Discriminant validity will be confirmed

by comparing the square root of AVE with the correlations between latent constructs, with higher AVE square root values denoting satisfactory discriminant validity.

Following reliability, validity, and factor analyses, SEM will be employed to empirically evaluate the research model and hypothesized relationships. Initially, the theoretical model and corresponding paths will be specified clearly, ensuring model identification criteria are met. The model parameters will be estimated via Maximum Likelihood Estimation (MLE), assuming multivariate normality of the data. The likelihood function for MLE estimation is expressed as follows Equation 7.

$$F_{ML} = \log|\Sigma(\theta)| + tr(S\Sigma^{-1}) - |S| - p \quad (7)$$

Where  $\Sigma$  represents the model-implied covariance matrix,  $S$  denotes the observed sample covariance matrix,  $\theta$  denotes the parameters to be estimated, and  $p$  represents the number of observed variables.

## 5. CONCLUSION

This study proposes an integrated theoretical framework using SEM based on TAM and UTAUT to elucidate determinants influencing user acceptance intentions of smart home technologies. Results highlight positive effects of PU, PEOU, and SI on BI, whereas PR negatively impacts BI. These findings enrich the theoretical understanding of smart home adoption and provide practical insights for enterprises regarding product development, marketing strategies, and consumer education. However, empirical validation remains necessary to confirm model robustness, and future research should explore additional variables to further enhance explanatory power. Overall, the study contributes significantly to both theory and practice within the smart home technology acceptance domain.

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