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ARTICLE

COMPETITIVE INTELLIGENCE AS A STRATEGIC FRAMEWORK FOR IOT SMART-HOME ADOPTION: EVIDENCE FROM SHENZHEN CONSUMERS

INTELIGÊNCIA COMPETITIVA COMO ESTRUTURA ESTRATÉGICA PARA A ADOÇÃO DE SISTEMAS RESIDENCIAIS INTELIGENTES COM IOT: EVIDÊNCIAS DE CONSUMIDORES DE SHENZHEN

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ABSTRACT

Purpose: This study develops a process-based Competitive Intelligence (CI) framework for IoT smart-home providers, examining which consumer perceptions are associated with adoption intention among surveyed Shenzhen consumers and how this consumer-derived evidence is transformed, through the complete CI cycle, into governed strategic decision support.

Methodology/Approach: A quantitative cross-sectional survey embedded within a process-based CI framework. A 106-response pilot supported instrument screening; a formal data set of 375 responses was analysed through reliability analysis (Cronbach's alpha), descriptive statistics, Pearson correlation, multiple regression with collinearity and robustness (HC3) diagnostics, and Personal-Innovativeness moderation analysis with multiple-testing correction. An additional Consumer-Derived Competitive Intelligence Actionability Index was developed to convert statistically supported consumer signals into ranked CI priorities for strategic decision support. CI is operationalized as an organizational process—planning, collection, analysis, dissemination, utilization, feedback and governance—rather than as a consumer-level scale.

Originality/Relevance: Existing smart-home adoption studies identify perceptual antecedents of adoption but rarely explain how consumer-derived evidence becomes product, communication and market decisions. The study addresses this gap by connecting consumer-adoption analytics with the complete CI cycle, a strategic-priority matrix and a governance and feedback protocol for the surveyed Shenzhen context.

Key Findings: The data were complete and clean (N = 375). All nine constructs showed good-to-excellent internal consistency (α = 0.876–0.946). All seven perception constructs correlated positively and significantly with adoption intention (r = 0.43–0.54) and remained significant in multiple regression, jointly explaining 57.9% of the variance (adjusted $R^2 = 0.571$; $F(7, 367) = 72.17$, $p < .001$), with Clear Interface ($\beta = 0.221$) and Consistency ($\beta = 0.200$) carrying the largest weights and Perceived Security ($\beta = 0.128$) the smallest significant weight. Personal Innovativeness significantly moderated five of the seven relationships in exploratory tests, most strongly for Information Completeness ($\Delta R^2 = 0.077$) and Information Accuracy ($\Delta R^2 = 0.064$).

Theoretical/Methodological Contributions: The study develops a process-based operationalization of Competitive Intelligence that connects consumer-derived market signals with intelligence planning, collection, analysis, dissemination, strategic utilization and feedback. Methodologically, it distinguishes the measured consumer-adoption constructs from the organizational CI process and demonstrates how regression and moderation evidence can be converted into a governed strategic decision-support framework.

Keywords: Competitive Intelligence. Competitive Intelligence Cycle. Intelligence Governance. Internet of Things. Smart-Home Systems. Adoption Intention. Sustainable Competitive Advantage.

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RESUMO

Objetivo: Este estudo desenvolve uma estrutura processual de Inteligência Competitiva (IC) para provedores de sistemas residenciais inteligentes com IoT. Examina quais percepções dos consumidores estão associadas à intenção de adoção de sistemas residenciais inteligentes com IoT entre os consumidores pesquisados de Shenzhen e demonstra como as evidências derivadas dos consumidores são transformadas, por meio do ciclo completo de IC, em apoio governado à decisão estratégica.

Metodologia/Abordagem: Estudo quantitativo transversal por questionário, incorporado a uma estrutura processual de Inteligência Competitiva. Um conjunto piloto de 106 respostas apoiou a triagem do instrumento e um conjunto formal de 375 respostas foi utilizado para as análises substantivas, incluindo análise de confiabilidade (alfa de Cronbach), estatísticas descritivas, correlação de Pearson, regressão linear múltipla com diagnósticos de colinearidade e robustez (HC3) e análise de moderação da Inovatividade Pessoal com correção para testes múltiplos. A IC é operacionalizada como um processo organizacionalplanejamento, coleta, análise, disseminação, utilização, feedback e governança e não como uma escala reflexiva no nível do consumidor. Foi desenvolvido também um Índice de Acionabilidade da Inteligência Competitiva Derivada do Consumidor para converter sinais estatisticamente sustentados dos consumidores em prioridades de IC ranqueadas para apoio à decisão estratégica.

Originalidade/Relevância: Os estudos existentes sobre adoção de residências inteligentes identificam antecedentes perceptuais da adoção, mas raramente explicam como as evidências derivadas dos consumidores são transformadas, por meio de um ciclo completo de Inteligência Competitiva, em decisões de produto, comunicação e mercado. O estudo aborda essa lacuna ao conectar a análise da adoção do consumidor ao processo organizacional de IC, a uma matriz de prioridades estratégicas e a um protocolo de governança e feedback para o contexto pesquisado de Shenzhen.

Principais Resultados: Os dados estavam completos e limpos ($N = 375$; sem valores ausentes, sem linhas duplicadas e todos os itens dentro do intervalo 1–5). Os nove construtos apresentaram consistência interna boa a excelente ($\alpha = 0{,}876$–$0{,}946$). Os sete construtos de percepção correlacionaram-se positiva e significativamente com a intenção de adoção ($r = 0{,}43$–$0{,}54$; $p < 0{,}001$). Na regressão múltipla, os sete preditores permaneceram significativos e explicaram conjuntamente 57,9% da variância da intenção de adoção (R^2 ajustado $= 0{,}571$; $F(7,\ 367) = 72{,}17$; $p < 0{,}001$), com Interface Clara ($\beta = 0{,}221$) e Consistência ($\beta = 0{,}200$) apresentando os maiores pesos padronizados e Segurança Percebida ($\beta = 0{,}128$) o menor peso significativo. A Inovatividade Pessoal moderou significativamente cinco das sete relações nos testes exploratórios, com maior intensidade para Completude da Informação ($\Delta R^2 = 0{,}077$) e Precisão da Informação ($\Delta R^2 = 0{,}064$).

Contribuições Teóricas/Metodológicas: O estudo desenvolve uma operacionalização processual da Inteligência Competitiva que conecta sinais de mercado derivados dos consumidores ao planejamento, coleta, análise, disseminação, utilização estratégica e feedback da inteligência. Metodologicamente, distingue os construtos mensurados de adoção do consumidor do processo organizacional de IC e demonstra como evidências de regressão e moderação podem ser convertidas em uma estrutura governada de apoio à decisão estratégica.

Palavras-chave: Inteligência Competitiva. Ciclo de Inteligência Competitiva. Governança da Inteligência. Internet das Coisas. Sistemas Residenciais Inteligentes. Intenção de Adoção. Vantagem Competitiva Sustentável.

1. INTRODUCTION

The Internet of Things (IoT) has dramatically changed the way that the home can be experienced, with everyday objects being able to sense, communicate and coordinate with each other and to and from integrated smart-home systems, which manage lighting, climate, security and entertainment. The reason behind consumer intention to adopt these systems has been a focal point in research and practice, as these systems diffuse (Aggarwal & Singh, 2024). The perceptual antecedents of intention are of particular interest to providers who are interested in predicting market response, and adoption intention is generally accepted as the closest predictor of actual use (Negm, 2023). This current research deals with these antecedents in the context of one clear-cut empirical situation.

The findings in this study support the conclusions of several decades of technology-acceptance studies, which suggest that an individual's perception of a system's usefulness and ease of use is a major factor in determining whether he or she will accept it (Mohd Thas Thaker et al., 2024; Ibrahim et al., 2025). In the smart-home environment, the perceptual drivers of intention are likely to include the clarity of the interface, its consistency across devices, visual appeal of the interface and the accuracy and completeness of the information provided by the system (Ferreira et al., 2023). Meanwhile, as smart-home systems gather and transmit home data that may be considered sensitive, security and privacy concerns are cited on numerous occasions as key factors (Gebsombut et al., 2025; Shuhaiber et al., 2023).

There are also general differences between consumers in terms of their attitudes toward new technologies. An individual's tendency to use new technologies before others, or personal innovativeness, has been found to moderate the role of perceptual factors in intention in various settings (Shetu et al., 2022; Wang et al., 2026). As in the original study framework, in the present study, personal innovativeness is not a directly postulated determinant of the perception–intention relationships but is instead placed as a moderator of the relationships.

This evidence is analyzed in relation to Shenzhen, one of the leading consumer-technology regions in China. The results are stated as evidence from the surveyed sample, and not as results of the entire population of consumers in Shenzhen or China. The study adopts Competitive Intelligence (CI) as its central process framework rather than as a consumer-level psychometric construct (Madureira et al., 2023; Maluleka & Chummun, 2023). Within this framework, the consumer survey constitutes the collection stage of the CI cycle, the statistical analysis constitutes the analytical stage, and the strategic-priority matrix developed in this study constitutes the dissemination and utilization stages, while governance and feedback complete the proposed cycle. Competitive Intelligence is therefore operationalized as an organizational process framework: the measured consumer-perception variables constitute intelligence inputs, while planning, collection, analysis, dissemination, strategic utilization, governance and feedback define the CI process through which those inputs become decision-relevant (Ju, 2024; Saracevic & Schlegelmilch, 2024).

The research gap is reformulated in view of this background. Existing smart-home adoption studies identify technological and perceptual antecedents of adoption, but they rarely explain how consumer-derived evidence is transformed through a complete Competitive Intelligence cycle into product, communication and market decisions (Mashal et al., 2023; Basarir-Ozel et al., 2022). Consequently, a gap remains between consumer-adoption analytics and the organizational processes of intelligence planning, analysis, dissemination, utilization, governance and feedback. Accordingly, the study addresses three research questions:

RQ1: Which interface, information, security and privacy perceptions are independently associated with IoT smart-home adoption intention among the surveyed Shenzhen consumers?

RQ2: How does Personal Innovativeness alter the relationships between consumer perceptions and adoption intention?

RQ3: How can the resulting consumer-derived evidence be structured through the Competitive Intelligence cycle to support governed strategic decisions and sustainable competitive advantage?

The study thus has four objectives: (i) to assess the reliability and empirical relationships among the measured consumer-perception constructs; (ii) to determine their relative contribution to adoption intention and to evaluate the moderating role of Personal Innovativeness; (iii) to operationalize a complete Competitive Intelligence process that converts consumer-derived evidence into intelligence priorities, dissemination outputs, decision rules, governance requirements and feedback indicators; and (iv) to explain how this process may support sustainable competitive advantage without making causal claims unsupported by the cross-sectional design. The study does not claim that Shenzhen is representative of China, nor does it present the cross-sectional evidence as causal proof.

2. THEORETICAL FRAMEWORK

2.1 Technology Acceptance and IoT Smart-Home Adoption

The emphasis of the technology-acceptance theory is on the conceptual framework that links perceptions of a system with the intent to adopt it. According to the TAM tradition, attitudes and behavioral intention are influenced by beliefs about a technology, and previous studies support the relevance of the model with digital products/services (Mohd Thas Thaker et al., 2024; Ibrahim et al., 2025). This study focuses on five interface and information related constructs – measured in the data directly in the IoT smart-home context – Clear Interface, Consistency, Attractiveness, Information Accuracy and Information Completeness.

The first three are related to the interaction surface of the system. A consistent interface ensures that working with connected devices will be straightforward, while the same interface elements on different devices and screens provide consistency in interaction, and beauty adds to the overall impression. The other two are related to the information that the system produces: accuracy refers to the reliability of the status reports and feedback, while completeness refers to whether the information is enough for them to be confident in using the system (Ferreira et al., 2023; Iqbal & Idrees, 2022). All these perceptions are potentially related to adoption intention. As this study focuses upon raw data, these five constructs are treated as individual constructs in this study, and not as some higher-order constructs of perceived ease of use and perceived usefulness are created in the model supplied.

2.2 Security, Privacy, and Personal Innovativeness

Security and privacy are key to smart-home system adoption, as these systems are constantly collecting data from the home. Perceived Security is about a consumer's trust that the system is secure and protects against unauthorised access and misuse, while Perceived Privacy is about a consumer's trust in the way personal data are handled. Previous smart-home studies have shown that this trust is correlated with a higher intention to adopt a smart home (Gebsombut et al., 2025; Basarir-Ozel et al., 2022; Shuhaiber et al., 2023) and that its lack is one of the most important obstacles. Perceived Security and Perceived Privacy are treated as two distinct measured constructs within the study’s scope of measurement. No separate trust variable or privacy-risk variable is introduced, because no such constructs were measured in the dataset.

Personal Innovativeness is defined as how likely a person is to try new technologies before others. It has shown to enhance the relationship between positive perceptions and intentions, which means that more innovative consumers are more receptive to the same perceptual cues (Shetu et al., 2022; Yuliawati et al., 2026; Wang et al., 2026). To examine the perception–intention relationships in the context of the original framework, Personal Innovativeness is explored as a moderator. All constructs are interpreted using the direction of the coded scores as reflected in the observed scores; when the direction of the scores is not reflected, or cannot be determined, with certainty in the coding, the interpretation does not make an unwarranted substantive claim but uses neutral language, e.g. “higher coded scores”.

2.3 Competitive Intelligence and Consumer-Derived Market Signals

Competitive Intelligence (CI) can be defined as the process of continuous collection, analysis and application of information for strategic decisions (Madureira et al., 2023; Ranjan & Foropon, 2021). It now has a significant focus on consumer-furnished and analytic data to predict the desires of consumers and competitors (Saracevic & Schlegelmilch, 2024; Sassi et al., 2022). In this study, consumer perceptions are treated as inputs to Competitive Intelligence rather than as CI itself. Consumer-derived information becomes intelligence only after it is directed by a strategic need, systematically collected, evaluated and analyzed, contextualized, disseminated to decision makers, used in a decision, and reviewed through feedback (Madureira et al., 2023; Ranjan & Foropon, 2021).

With this interpretation, consumer perception can be used to inform a number of strategic activities: uncovering barriers to adoption, differentiation of stronger vs weaker consumer perceptions, prioritizing product or information decisions, refining communication, and monitoring the market on an ongoing basis (Ju, 2024; Atkinson et al., 2022). The CI lens then complements rather than replaces the statistical analysis: the quantitative results identify those perceptions linked to the intention to adopt, and the CI lens allows the providers in the Shenzhen study context to contextualize the results.

2.4 The Competitive Intelligence Cycle

The complete Competitive Intelligence cycle comprises six connected stages: Planning → Collection → Analysis → Dissemination → Utilization → Feedback (Madureira et al., 2023; Ranjan & Foropon, 2021). Planning defines the strategic intelligence questions an organization must answer; collection acquires the information needed to answer them; analysis transforms the collected information into decision-relevant intelligence; dissemination delivers that intelligence to the relevant decision makers; utilization translates it into strategic actions; and feedback monitors outcomes and updates the intelligence priorities, closing the cycle.

Each stage applies directly to the present study. Planning corresponds to the strategic questions facing smart-home providers: which consumer perceptions most strongly relate to adoption intention, and which perceptions require strategic priority. Collection corresponds to the systematic survey of 375 Shenzhen consumers using 54 items across nine constructs. Analysis corresponds to the reliability, correlation, regression, robustness and moderation procedures reported in Section 3.4. Dissemination and utilization correspond to the strategic-priority matrix and decision rules developed in Sections 3.6 and 4.5, and feedback corresponds to the monitoring protocol proposed in Section 3.7. The empirically observed stages (planning, collection and analysis) are explicitly distinguished from the recommended organizational stages (dissemination, utilization and feedback), which were not directly measured.

2.5 Intelligence Governance, Strategic Intelligence and Information Asymmetry

Intelligence governance refers to the rules under which intelligence activities are conducted. It covers responsibility for intelligence activities, data ownership, analytical quality, access control, privacy compliance, ethical use, traceability, periodic review, and the avoidance of selective reporting (Madureira et al., 2023). Governance determines whether the intelligence an organization produces is credible enough to inform strategic decisions.

Strategic intelligence extends Competitive Intelligence beyond the reporting of statistical significance by connecting evidence with market positioning, product priorities, customer segmentation, risk communication, competitor monitoring and resource allocation (Atkinson et al., 2022; Sassi et al., 2022). A regression coefficient becomes strategic intelligence only when it is linked to a decision domain and a monitored organizational response.

The smart-home context also contains two important information asymmetries. Providers know more than consumers about technical capabilities, data collection and security; at the same time, providers may know less than consumers about consumer concerns, adoption barriers and information needs. Information accuracy, information completeness, privacy transparency and security communication can reduce these asymmetries, and the constructs measured in this study capture the consumer side of them directly.

2.6 Competitive Intelligence and Sustainable Competitive Advantage

The pathway from Competitive Intelligence to sustainable competitive advantage is presented cautiously as a theoretically grounded sequence: continuous market sensing → faster strategic response → improved product–market fit → stronger consumer trust → reduced adoption barriers → organizational learning → more sustainable competitive positioning (Atkinson et al., 2022; Ranjan & Foropon, 2021). The present cross-sectional data do not prove sustainable competitive advantage; the pathway is a theoretically grounded proposition that requires longitudinal organizational validation.

2.7 Integrated Conceptual Framework

Bringing these elements together, the conceptual framework specifies four connected layers. Layer 1 comprises the consumer-derived intelligence inputs: the seven measured perception constructs—Clear Interface, Consistency, Attractiveness, Information Accuracy, Information Completeness, Perceived Security and Perceived Privacy—as predictors of Intention to Adopt, together with Personal Innovativeness in its documented moderating role. Layer 2 comprises the Competitive Intelligence cycle—planning, collection, analysis, dissemination, utilization and feedback—surrounded by a governance layer covering ethics, privacy, information quality, accountability, access control and analytical transparency. Layer 3 comprises the strategic decisions supported by the intelligence: interface and product design, information strategy, security assurance, privacy communication, consumer segmentation and market positioning. Layer 4 comprises the strategic outcomes: reduced information asymmetry, improved decision responsiveness, trust development, adoption readiness, organizational learning and sustainable competitive advantage. The model does not draw causal arrows from Competitive Intelligence, nor does it include mediation paths, demographic paths or untested higher-order constructs. The structure is depicted in Figure 1.

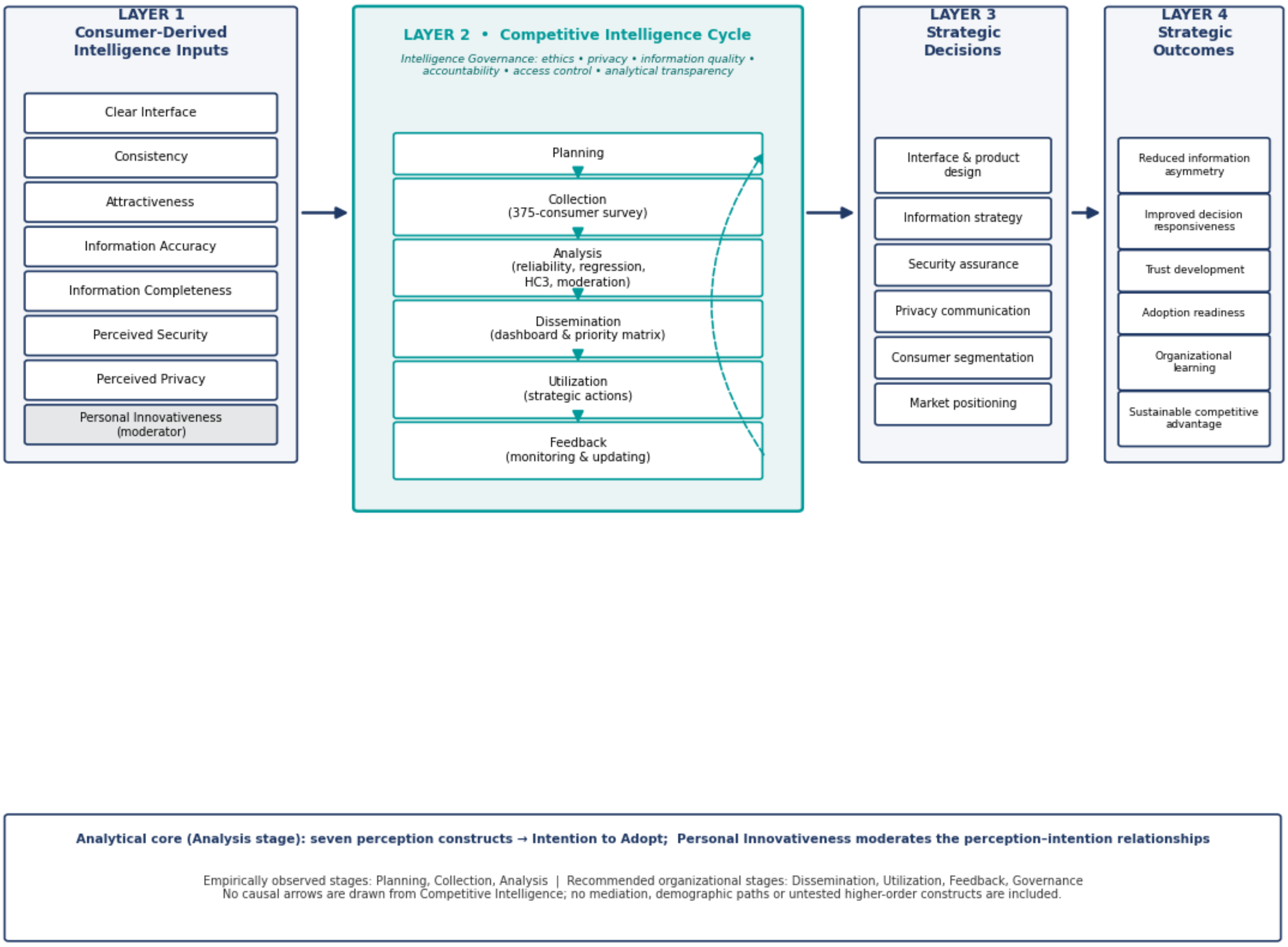

Figure 1. Process-Based Competitive Intelligence Framework Linking Consumer Perceptions, Strategic Decision Support and Sustainable Competitive Advantage.

As shown in Figure 1, the consumer-derived intelligence inputs feed the governed Competitive Intelligence cycle. Within the analytical stage of that cycle, the seven perception constructs are modelled as direct predictors of adoption intention and Personal Innovativeness moderates the predictor–intention relationships. The governed cycle then converts the empirical evidence into strategic decisions and, through repeated sensing, response and learning, into the proposed strategic outcomes, including a pathway toward sustainable competitive advantage.

3. METHODOLOGY

3.1 Study Design

The study adopts a quantitative, cross-sectional, questionnaire-based consumer-survey design embedded within a process-based Competitive Intelligence framework, comprising two stages: a pilot stage and a formal survey stage. The survey constitutes the empirical component of the study, while Competitive Intelligence provides the process framework within which the resulting evidence is planned, collected, analysed, disseminated, utilized and monitored. The pilot stage supported instrument screening, and the formal stage provided the data for all substantive analyses. The design is not experimental, longitudinal, nationally representative or causal; accordingly, the findings are interpreted as associations and observed predictive relationships within the surveyed sample rather than as proof of causal mechanisms.

3.2 Data Source and Characteristics

Two workbooks underpin the study. The pilot/pre-research dataset contains 106 respondent rows and 79 variables organised into the same principal item blocks as the formal survey. The formal survey dataset contains 375 respondent rows before any justified screening, again with 79 columns, of which 54 are psychometric items organised into nine construct blocks measured on a 1–5 coded response scale. The 106 pilot responses and the 375 formal responses are kept strictly separate; they are not combined, and no aggregate sample of 481 or 750 is reported. The nine constructs, their item codes and their analytical roles are summarised in Table 1.

Table 1. *Raw-Data Constructs, Item Codes, and Analytical Roles.*

Construct	Item codes	No. of items	Analytical role
Clear Interface	PECI1–PECI5	5	Predictor
Consistency	PEC1–PEC5	5	Predictor
Attractiveness	PEA1–PEA5	5	Predictor
Information Accuracy	PUIA1–PUIA5	5	Predictor
Information Completeness	PUIC1–PUIC5	5	Predictor
Perceived Security	PSP1–PSP9	9	Predictor
Perceived Privacy	PP1–PP7	7	Predictor
Personal Innovativeness	PI1–PI7	7	Moderator
Intention to Adopt	ITA1–ITA6	6	Outcome

Note. N = 375 (formal dataset). Total items = 54. All items use a 1–5 coded response scale. Coded background variables were excluded from the substantive analysis because verified category meanings were unavailable.

3.3 Data Preprocessing

Only checks that can be done on the raw workbook provided are done in the preprocessing. CPS data was checked for missing cells, exact duplicate rows, and data falling outside the response range and item distributions were reviewed, along with corrected item–total correlations and internal consistency and multicollinearity diagnostics. The data does not contain any fields for the IP address, who is the respondent, completion time, geographic coordinates and device identifiers, so they were not evaluated. No respondent was dropped; no observation being excluded because inclusion of these observations made a coefficient weaker or affected the significance of a hypothesis.

3.4 Analytical Framework

A conservative analytical strategy was deliberately adopted, and was fully reproducible. It included Cronbach's alpha for internal consistency, composite mean score calculated on the original 1 to 5 scale, Pearson correlation (Spearman correlation when the Pearson assumptions were materially unsuitable) and moderation regression (documented) for Personal Innovativeness. No structural equation modelling or machine-learning was performed as this is not necessary given the data provided to answer the research question.

The principal regression model is used to explain the mean Intention to Adopt score, which is a linear function of the seven mean perception scores:

$$ITAi = \beta_0 + \beta_1 PECIi + \beta_2 PECi + \beta_3 PEAi + \beta_4 PUIAi + \beta_5 PUICi + \beta_6 PSPi + \beta_7 PPi + \varepsilon i$$

where β_0 is the intercept, β_1 - β_7 are the regression coefficients for the seven perception predictors and εi is the error term. Personal Innovativeness (PI) were mean-centred and the predictor (X) was mean-centred prior to the creation of the interaction term X × PI and the model $ITAi = \beta_0 + \beta_1 Xi + \beta_2 PIi + \beta_3 (Xi \times PIi) + \varepsilon i$ was estimated for each verified moderation path. As there is no defined a moderated path, the full set of interactions was considered exploratory and corrected for multiple testing. Within the Competitive Intelligence framework, the regression coefficients, confidence intervals, robustness tests and moderation results are treated as analytical intelligence outputs—decision-relevant evidence produced by the analysis stage of the CI cycle—rather than merely as statistical findings.

3.5 Process-Based Operationalization of the Competitive Intelligence Cycle

Competitive Intelligence is operationalized as an organizational process framework rather than as a consumer-level reflective scale. The measured consumer-perception variables constitute intelligence inputs, while planning, collection, analysis, dissemination, strategic utilization, governance and feedback define the CI process through which those inputs become decision-relevant. Table 2 shows how each stage of the CI cycle is operationalized in this study, explicitly distinguishing the empirically observed stages (planning, collection and analysis) from the recommended organizational stages (dissemination, utilization, feedback and governance).

Table 2. Process-Based Operationalization of the Competitive Intelligence Cycle in This Study.

CI stage	Operational meaning in this study	Evidence or output
Planning	Definition of the strategic intelligence questions facing smart-home providers	Which consumer perceptions most strongly relate to adoption intention? Which perceptions require strategic priority?
Collection	Systematic acquisition of consumer-derived market information	Survey of 375 Shenzhen consumers using 54 items across nine constructs
Analysis	Transformation of collected information into decision-relevant intelligence	Reliability analysis, correlation, multiple regression, HC3 robustness tests, moderation analysis and coefficient ranking
Dissemination	Delivery of results to relevant organizational decision makers	Proposed CI dashboard and strategic-priority matrix for product, UX, information, privacy, security and marketing teams
Utilization	Translation of analytical results into strategic actions	Interface redesign, information-quality improvement, privacy communication, security assurance and segment-specific messaging
Feedback	Monitoring outcomes and updating intelligence priorities	Periodic tracking of adoption intention, customer complaints, interface usability, trust indicators and post-adoption behaviour
Governance	Rules governing data quality, ethics, privacy, access and accountability	Defined responsibility, data-validation procedures, privacy protection, documented interpretation rules and audit trails

Note. Planning, collection and analysis are empirically observed stages; dissemination, utilization, feedback and governance are recommended organizational stages that were not directly measured in this study.

To address the empirical boundary between consumer-adoption measurement and Competitive Intelligence operationalization, the study additionally develops a Consumer-Derived Competitive Intelligence Actionability Index (CI-AI). The CI-AI does not treat Competitive Intelligence as a consumer attitude or reflective psychometric scale. Instead, it operationalizes the analytical output of the CI cycle by converting empirically measured consumer signals into ranked intelligence priorities. For each measured perception construct, actionability is assessed through four criteria: internal reliability, independent predictive contribution to adoption intention, robustness of the coefficient under diagnostic checks, and strategic relevance within the CI cycle. In this way, the measured consumer variables remain adoption constructs, while the CI-AI represents the empirically derived intelligence output produced by the analysis stage and prepared for dissemination and utilization.

Only statistically supported results are translated into strategic implications, and the translation remains restrained: coefficient magnitude and confidence intervals, scale reliability, model fit and residual uncertainty are all considered. No single variable is identified as the “most important driver”; relative importance is presented via the standardized-coefficient ranking, and the Competitive Intelligence reading is limited to the surveyed sample and is presented as a list of priorities for additional validation rather than as guaranteed effects.

3.6 Intelligence Dissemination and Strategic Decision Matrix

To operationalize the dissemination stage of the CI cycle, explicit rules are used to translate statistical evidence into strategic priorities. A variable must be statistically supported before it can enter the strategic decision matrix; its coefficient magnitude and confidence interval must be considered jointly, and priority ranking must not rely solely on p-values. All results remain bounded to the Shenzhen sample, and the resulting strategic actions are treated as recommendations for further validation rather than as guaranteed effects. The dissemination outputs comprise a proposed CI dashboard and the strategic priority matrix reported in Section 4.5, which delivers the analytical intelligence to product, UX, information, privacy, security and marketing teams.

3.7 Intelligence Governance and Feedback Protocol

A governance and feedback protocol is specified for continued organizational use of the intelligence. The findings should be received by product, UX, information, privacy, security and marketing decision makers, whom they support in interface and product design, information strategy, privacy communication, security assurance and segmentation decisions. Intelligence priorities should be updated periodically (for example, quarterly or after major product releases), subject to defined data-quality standards, privacy protection, documented interpretation rules, access control and audit trails. Monitoring indicators include adoption intention tracking, customer complaints, interface usability measures, trust indicators and post-adoption behaviour, and a reanalysis is required whenever these indicators shift materially, the product portfolio changes, or new consumer segments are targeted.

3.8 Tools and Techniques

Data handling: pandas, NumPy, statistical estimation: SciPy, statsmodels, visualisation: Matplotlib were used in the Python programming environment for all analyses. Reliability analysis, descriptive statistics, correlation analysis, multiple regression with collinearity and residual diagnostics, and moderation regression were carried out with these tools. Other statistical software were not used.

3.9 Ethical Considerations

This study received approval from Universiti Utara Malaysia research institutional review board (UUM/OYAGSB/R-4/4/1). The study was done in compliance with the Helsinki Declaration. Respondents who filled out survey forms gave informed consent for their participation. None of those under the age of 16 were surveyed.

4. RESULTS and DISCUSSION

The formal information was checked to be of high quality before the substantive analyses were conducted. It consisted of 375 respondent rows and 79 columns, it had no missing cells, no exact duplicate rows, and all item responses were within the range of 1–5, which was the valid range. The reported sample size is consistent for each procedure, since there was no imputation of missing data, due to complete data.

4.1 Descriptive Statistics

Cronbach's alpha was used to determine the internal-consistency reliability of each construct with the use of corrected item–total correlations. As indicated in Table 3 and Figure 2, all the nine constructs had an alpha score above 0.70, ranging from a minimum of 0.876 (Attractiveness and Information Completeness) to a maximum of 0.946 (Personal Innovativeness). All corrected item–total correlation values were greater than 0.40 (ranging from a minimum of 0.666). The original item sets were thus left intact and no item was removed from the sets nor was there one found that was reverse-worded as evidenced by the documentation provided.

Table 3. Descriptive Statistics and Reliability of the Measured Constructs (N = 375).

Construct	Mean	SD	Min	Max	Skew	Kurt.	α
Clear Interface	3.40	0.89	1.00	5.00	-0.15	-1.03	**0.893**
Consistency	3.39	0.86	1.00	5.00	-0.17	-0.79	**0.890**
Attractiveness	3.47	0.81	1.60	5.00	-0.14	-0.97	**0.876**
Information Accuracy	3.41	0.85	1.00	5.00	-0.21	-0.79	**0.885**
Information Completeness	3.44	0.82	1.20	5.00	-0.23	-0.78	**0.876**
Perceived Security	3.44	0.83	1.33	4.89	-0.26	-0.84	**0.934**
Perceived Privacy	3.40	0.86	1.14	4.86	-0.30	-0.86	**0.922**
Personal Innovativeness	3.27	1.18	1.00	5.00	-0.34	-1.29	**0.946**
Intention to Adopt	3.43	0.81	1.17	5.00	-0.20	-0.75	**0.896**

Note. All scores are mean composites on the original 1–5 scale. SD = standard deviation; Kurt. = kurtosis; α = Cronbach's alpha. α ≥ .70 acceptable, ≥ .80 good, ≥ .90 excellent; all corrected item–total correlations exceeded .40.

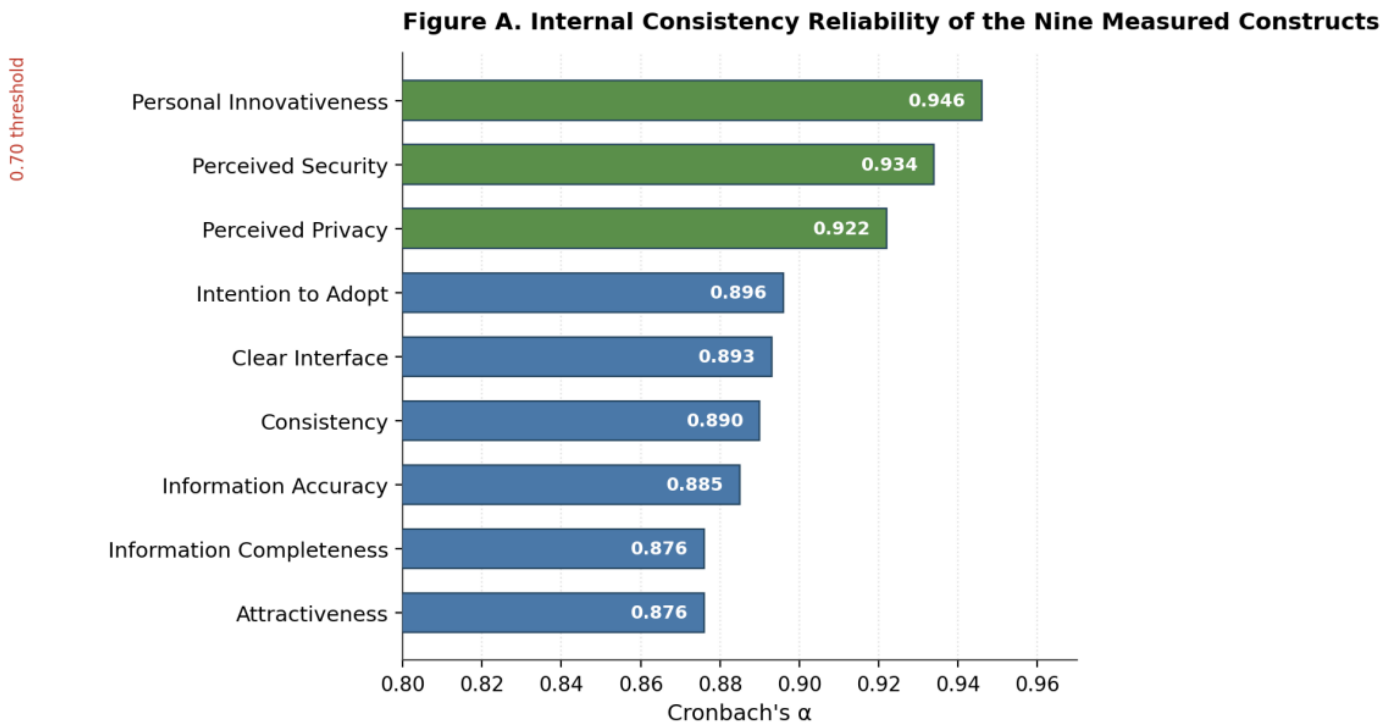

Figure 2. Internal-consistency reliability (Cronbach's α) of the nine measured constructs. The dashed line marks the 0.70 acceptability threshold.

Turning to the construct scores, all means fell modestly above the scale midpoint of 3.0, indicating generally moderate-to-favourable perceptions across the sample. Attractiveness recorded the highest mean (3.47) and Personal Innovativeness the lowest (3.27); the outcome, Intention to Adopt, averaged 3.43. Personal Innovativeness also showed the widest dispersion (SD = 1.18), reflecting greater heterogeneity in respondents' general openness to new technology. Skewness and kurtosis values fell within conventionally acceptable bounds (approximately ±1 and ±2 respectively), supporting the use of parametric methods. The construct means and their standard deviations are displayed in Figure 3.

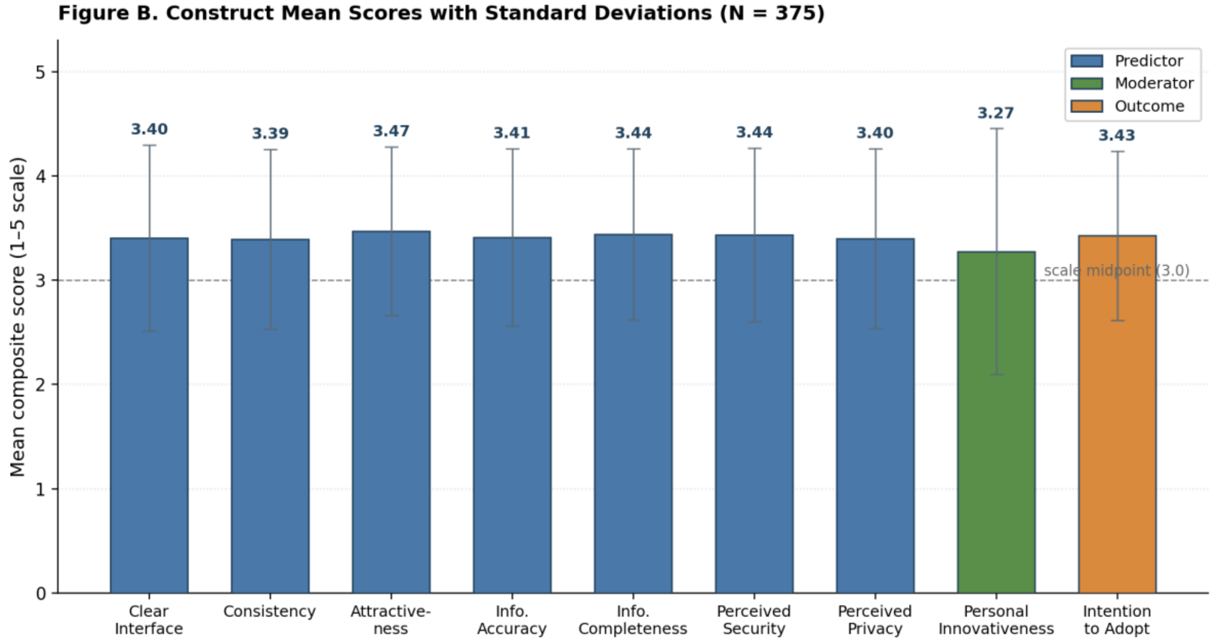

Figure 3. Construct mean scores with standard-deviation bars. The dashed line marks the scale midpoint (3.0); bars are coloured by analytical role.

4.2 Correlation Analysis

All nine constructs were correlated, and these correlation coefficients indicate association instead of causation, due to cross-sectional data. Table 4 and Figure 4 show that all of the seven perception constructs were positively and significantly correlated with Intention to Adopt with values ranging from r = 0.43 (Attractiveness) to r = 0.54 (Consistency and Perceived Privacy) (all at p<0.001). The strongest bivariate links with the adoption intention were for Consistency and Perceived Privacy, followed closely by Clear Interface (r = 0.53) and Information Completeness (r = 0.52). Inter-predictor correlations were moderate and positive, and no high correlations were seen that may indicate excessive redundancy. Personal Innovativeness, which was coded in the raw data, was negatively correlated with adoption intention (r = −.18) and with the other perception constructs and is reported as such rather than as a substantive claim about personal innovativeness.

Table 4. *Correlations Among the Measured Study Constructs (N = 375).*

Construct	1	2	3	4	5	6	7	8	9
1. Clear Interface	1								
2. Consistency	.28***	1							
3. Attractiveness	.24***	.30***	1						
4. Info. Accuracy	.42***	.33***	.31***	1					
5. Info. Completeness	.35***	.45***	.28***	.34***	1				
6. Perceived Security	.30***	.32***	.20***	.37***	.36***	1			
7. Perceived Privacy	.40***	.50***	.28***	.36***	.44***	.32***	1		
8. Personal Innov.	-.17***	-.12*	-.25***	-.18***	-.17***	-.18***	-.17***	1	
9. Intention to Adopt	.53***	.54***	.43***	.50***	.52***	.44***	.54***	-.18***	1

Note. N = 375. * p < .05, ** p < .01, *** p < .001. Header numbers correspond to the construct numbers in the first column. Leading zeros omitted.

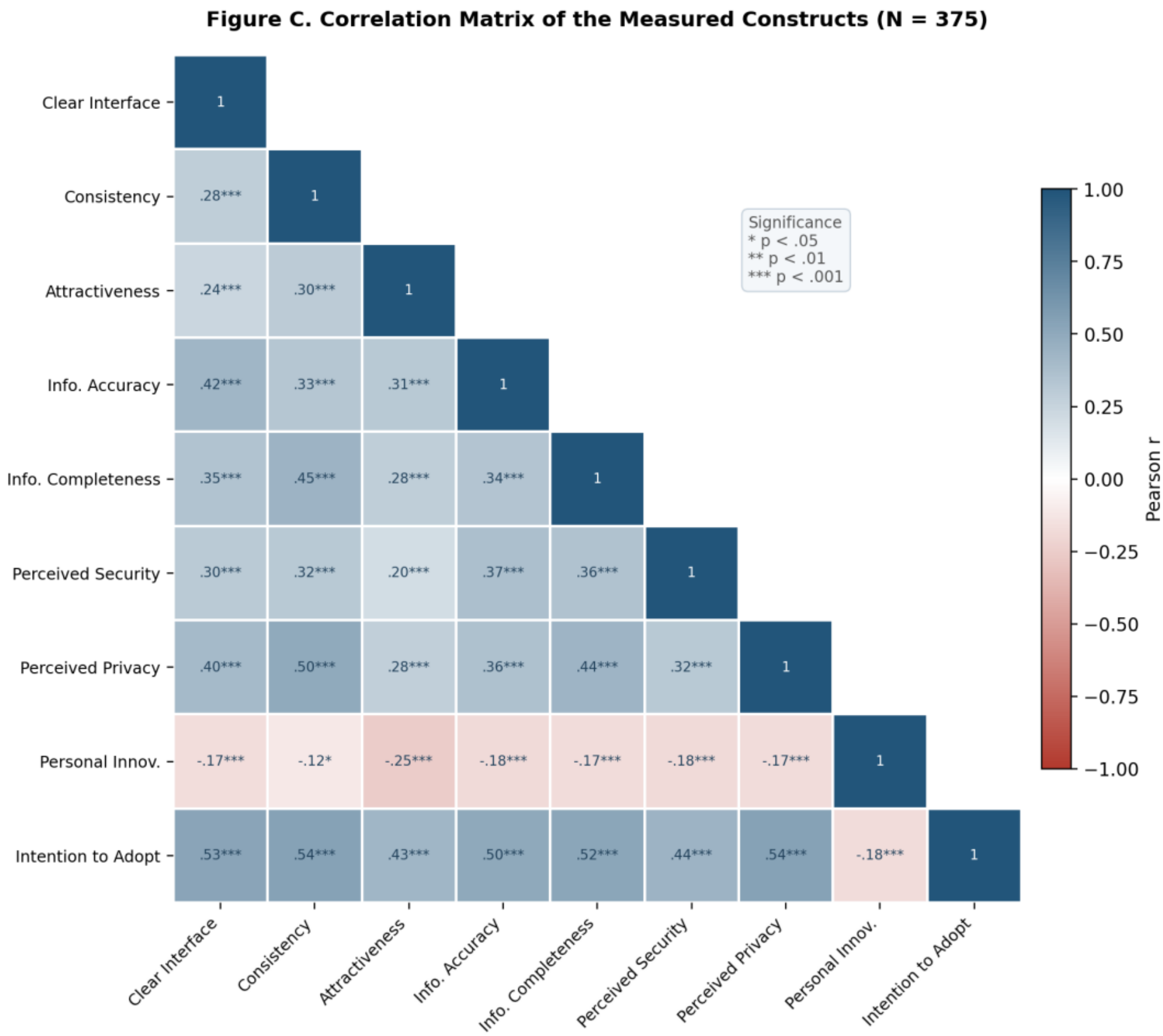

Figure 4. Correlation heatmap of the nine constructs. Blue denotes positive and red negative associations; intensity reflects magnitude (* p < .05, ** p < .01, *** p < .001).

4.3 Regression Analysis

The dependent variable was Intention to Adopt, and the seven perception constructs were simultaneous independent variables in the multiple linear regression. The model proved to be statistically significant, and accounted for a significant proportion of variance in adoption intention $R^2 = 0.579$, adjusted $R^2 = 0.571$, $F(7, 367) = 72.17$, $p < .001$. This seven measured perceptions therefore explain about 58% of the variance in respondents' intention to adopt IoT smart-home systems. Complete results are displayed in Table 5.

Table 5. *Predictors of Intention to Adopt IoT Smart-Home Systems (N = 375).*

Predictor	B	SE	β	t	95% CI	VIF
(Constant)	-0.330	0.174	—	-1.90	[-0.673, 0.012]	—
Clear Interface	0.200	0.036	**0.221*****	5.54	[0.129, 0.272]	1.38
Consistency	0.189	0.039	**0.200*****	4.79	[0.111, 0.266]	1.52
Attractiveness	0.160	0.037	**0.160*****	4.31	[0.087, 0.233]	1.20
Information Accuracy	0.132	0.039	**0.138*****	3.40	[0.056, 0.208]	1.43
Information Completeness	0.151	0.041	**0.153*****	3.72	[0.071, 0.231]	1.48
Perceived Security	0.125	0.038	**0.128****	3.31	[0.051, 0.199]	1.29
Perceived Privacy	0.141	0.040	**0.150*****	3.52	[0.062, 0.220]	1.58

Note. B = unstandardized coefficient; β = standardized coefficient; CI = confidence interval; VIF = variance inflation factor. ** $p < .01$, *** $p < .001$. $R^2 = 0.579$, adjusted $R^2 = 0.571$, $F(7, 367) = 72.17$, $p < .001$, Durbin–Watson = 1.855.

All seven predictors were positive and statistically significant, and each perception contributed to adoption intention, independently of the others. All VIFs were substantially less than 2.0, meaning there is no concern about multicollinearity, and the Durbin–Watson statistic (1.855) suggested that there was no serious autocorrelation of residuals. All the seven predictors remained significant even after applying the heteroscedasticity-consistent (HC3) standard errors, as obtained after the assumption check suggested that there was mild heteroscedasticity; this further substantiated the stability of the findings.

The standardized coefficients of the predictors give a sense of the relative importance of these predictors in the sample. Clear Interface (β = 0.221) and Consistency (β = 0.200) had the greatest weights, followed by Attractiveness (β = 0.160), Information Completeness (β = 0.153), Perceived Privacy (β = 0.150) and Information Accuracy (β = 0.138), while Perceived Security (β = 0.128) had the least of the significant effects. In Figure 5, the standardized ranking is shown and in Figure 6 the unstandardized coefficients and their 95% confidence intervals are shown – all of which are not crossing zero.

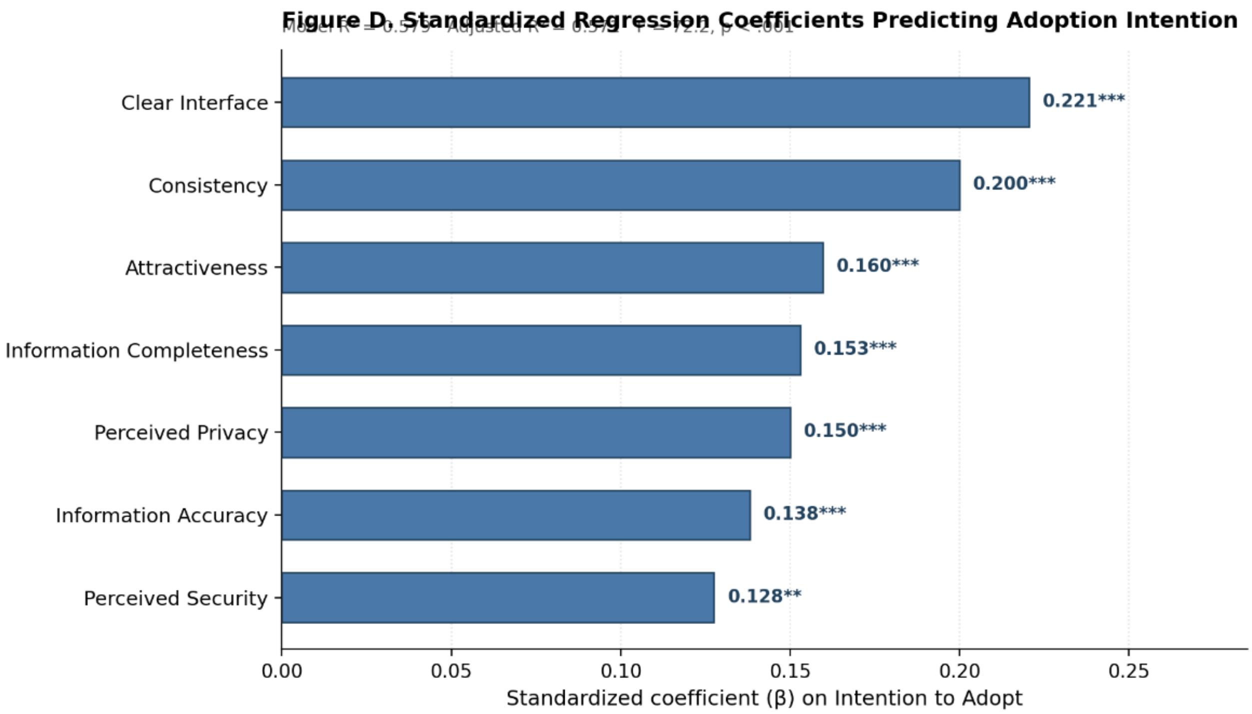

Figure 5. Standardized regression coefficients (β) of the seven predictors on Intention to Adopt, ordered by magnitude (** $p < .01$, *** $p < .001$).

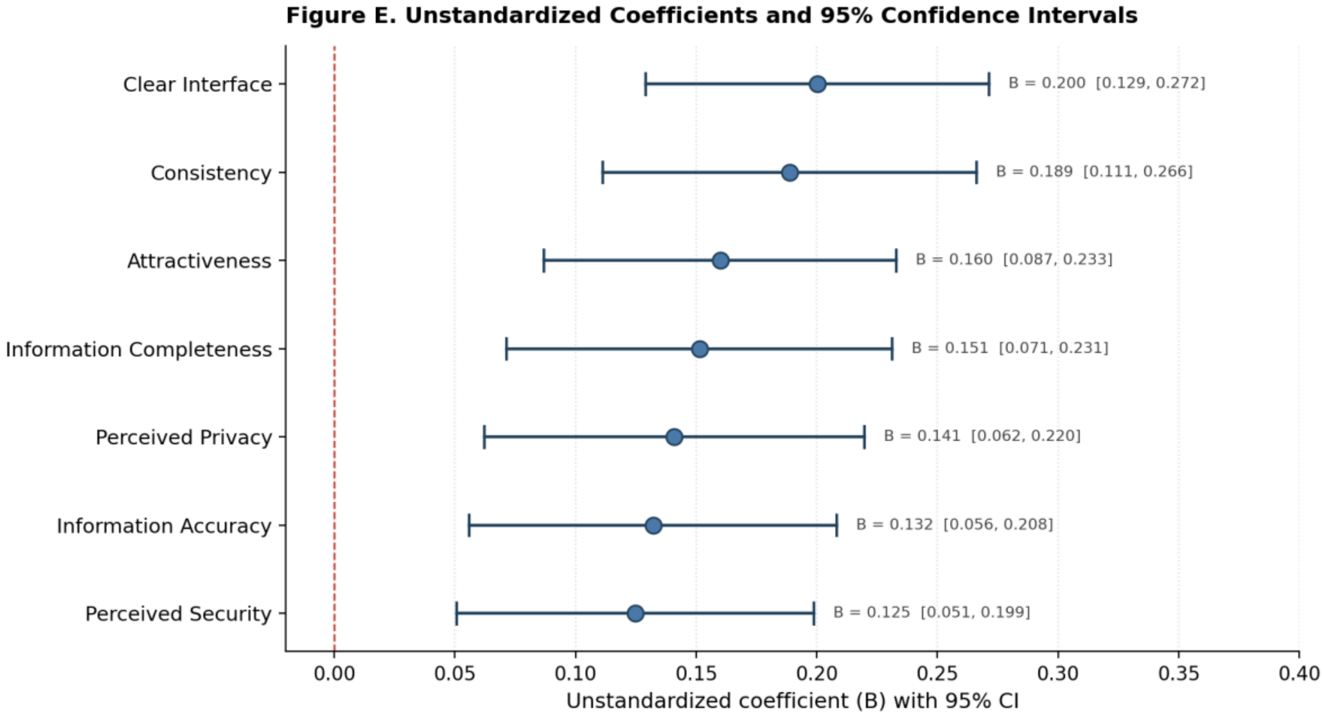

Figure 6. Unstandardized coefficients (B) with 95% confidence intervals. The dashed line marks zero; all intervals lie entirely above it.

4.3.1 Regression diagnostics

Model assumptions were examined graphically, as shown in Figure 7. The residuals-versus-fitted plot in Figure 7(a) shows residuals scattered around zero without a strong systematic pattern, and the normal Q–Q plot in Figure 7(b) shows residuals lying close to the reference line across most of the distribution. Together with the acceptable Durbin–Watson value, the low VIFs, and the preservation of every result under robust (HC3) re-estimation, these diagnostics indicate that the regression provides a dependable description of the relationships in the data.

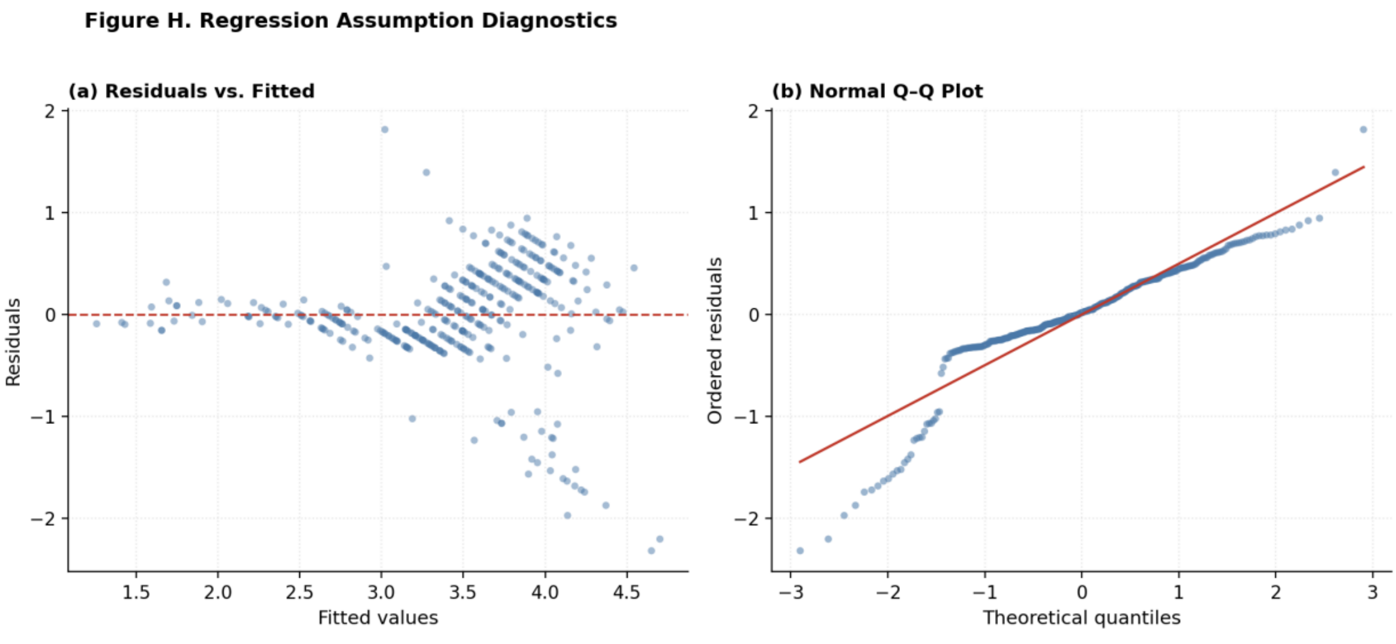

Figure 7. Regression assumption diagnostics: (a) residuals versus fitted values; (b) normal Q–Q plot of residuals.

4.4 Moderation and Cross-Sectional Pattern Analysis

Because the data are cross-sectional and contain no time variable, no temporal trends are presented; this subsection reports cross-sectional score and coefficient patterns only. Two patterns are salient. First, the construct-mean pattern (Figure 3) shows uniformly moderate-to-favourable perceptions clustered just above the scale midpoint, with adoption intention (3.43) situated among the perception means. Second, the predictor-coefficient pattern (Figures 5 and 6) shows interface-related perceptions carrying the largest standardized weights and security the smallest of the significant weights.

The study framework positions Personal Innovativeness as a moderator of the perception–intention relationships but does not specify a single moderated path. Accordingly, a complete set of seven interaction models was estimated as an exploratory analysis, with each predictor and Personal Innovativeness mean-centred before forming the interaction term and a Holm–Bonferroni correction applied across the seven tests. All results, including non-significant ones, are reported in Table 6. After correction, the interaction was statistically significant for five predictors—Consistency, Information Accuracy, Information Completeness, Perceived Security and Perceived Privacy—and non-significant for Clear Interface and Attractiveness. In every significant case the interaction coefficient was positive, meaning that the predictor–intention association was stronger among respondents reporting higher Personal-Innovativeness scores. The largest incremental effects were for Information Completeness ($\Delta R^2 = 0.077$) and Information Accuracy ($\Delta R^2 = 0.064$). These cross-sectional moderation patterns are summarised in Figure 8.

Table 6. Personal-Innovativeness Moderation of the Predictor–Intention Relationships (N = 375).

Predictor × Personal Innov.	b (interaction)	SE	ΔR^2	Holm p	Result
Information Completeness	+0.238	0.036	0.077	< .001	**Significant**
Information Accuracy	+0.202	0.034	0.064	< .001	**Significant**
Perceived Privacy	+0.180	0.034	0.051	< .001	**Significant**
Perceived Security	+0.177	0.037	0.045	< .001	**Significant**
Consistency	+0.124	0.035	0.023	0.001	**Significant**
Clear Interface	+0.069	0.034	0.008	0.078	Not sig.
Attractiveness	+0.004	0.041	0.000	0.915	Not sig.

Note. Predictors and Personal Innovativeness mean-centred before forming interaction terms. Holm p = Holm–Bonferroni-corrected p-value across seven tests; significance threshold = .05. These interaction results are exploratory.

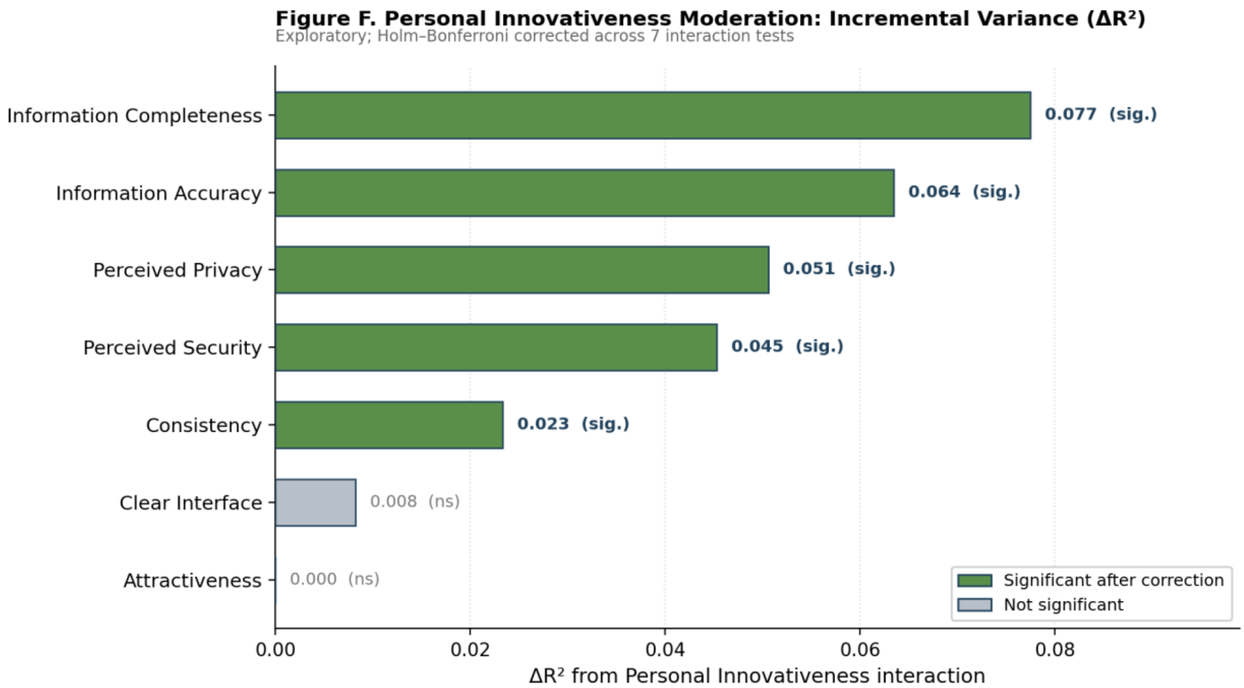

Figure 8. Cross-sectional patterns in smart-home adoption intention: incremental variance (ΔR^2) contributed by each Personal-Innovativeness interaction, with significance after Holm–Bonferroni correction.

To illustrate the form of a significant interaction, Figure 9 plots the simple slopes for the strongest case, Information Completeness, at low (−1 SD) and high (+1 SD) levels of Personal Innovativeness. The steeper line for high-innovativeness respondents indicates that, for this group, stronger perceptions of information completeness are associated with more sharply increasing adoption intention, whereas for low-innovativeness respondents the relationship is comparatively flat. Consistent with the exploratory status of the moderation tests, these patterns are interpreted with corresponding caution.

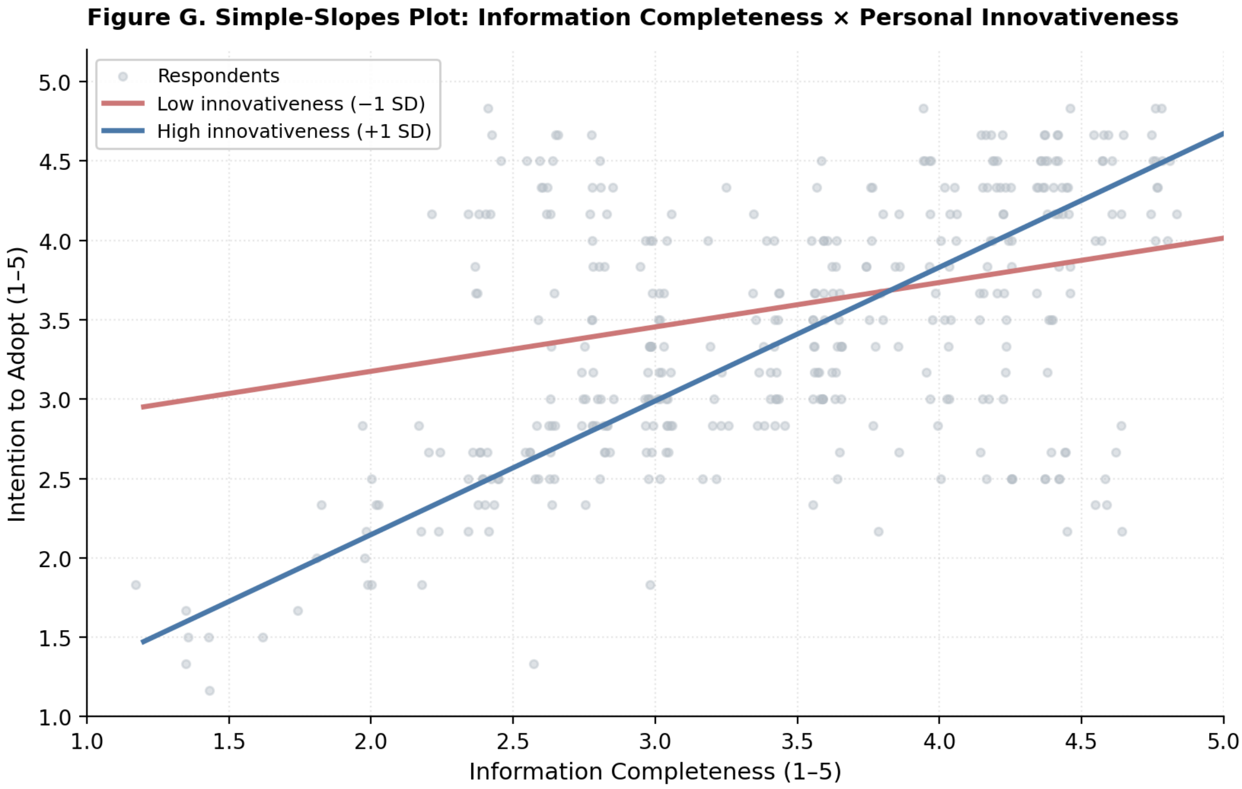

Figure 9. Simple-slopes plot for Information Completeness × Personal Innovativeness. Lines show predicted Intention to Adopt at −1 SD and +1 SD of Personal Innovativeness; points are individual respondents.

4.5 Integrated Findings

Drawing the analyses together, the observed formation pattern of adoption intention within this sample can be summarised concisely. The measurement instrument is reliable, the data are clean, and the relationships are stable across correlation, standard regression and robust re-estimation. All seven perception constructs are positively and significantly associated with adoption intention; none of the seven direct relationships was unsupported. Jointly, the seven perceptions explain 57.9% of the variance in adoption intention (adjusted R^2 = 0.571). Within the sample, Clear Interface and Consistency carry the largest standardized weights, while Perceived Security carries the smallest of the significant weights. Personal Innovativeness significantly moderates five of the seven relationships in the exploratory tests, most strongly for Information Completeness and Information Accuracy. No single variable is described as the universal “most important driver”; relative emphasis is expressed through the standardized-coefficient ranking, and all conclusions are bounded to the surveyed sample.

To complete the dissemination and utilization stages of the Competitive Intelligence cycle, the statistically supported findings are translated into a strategic priority matrix (Table 7), which links each intelligence finding to a decision domain, a proposed strategic response and governance/feedback indicators. Consistent with the decision rules in Section 3.6, these strategic responses are recommendations for further validation, bounded to the surveyed Shenzhen sample, rather than guaranteed effects.

Table 7. *Competitive Intelligence Strategic Priority Matrix Derived from the Regression and Moderation Evidence.*

Intelligence finding	Decision domain	Proposed strategic response	Governance/feedback indicator
Clear Interface has the largest standardized weight	UX and product design	Simplify navigation, setup and device control	Usability tests, task completion, interface complaints
Consistency has the second-largest weight	Cross-device architecture	Standardize terminology, controls and interaction logic	Cross-device error rate and usability consistency
Information Completeness shows strong moderation	Information strategy	Provide complete device status, explanations and guidance	Information-related queries and abandonment
Information Accuracy is significant and moderated	Data and content quality	Improve status accuracy and error reporting	Accuracy audits and customer-reported discrepancies
Privacy positively predicts adoption intention	Privacy communication	Provide concise data-use disclosures and user controls	Privacy concerns, consent withdrawals and trust measures
Security positively predicts adoption intention	Security assurance	Communicate authentication, updates and incident response	Security complaints, update compliance and trust measures
Innovativeness changes several relationships	Segmentation	Use detailed technical messaging for innovative consumers and clearer reassurance for cautious consumers	Segment-specific response and adoption indicators

Note. Each row translates a statistically supported analytical result into a governed dissemination and utilization output of the Competitive Intelligence cycle.

Table 8. Empirical Operationalization of Consumer-Derived Competitive Intelligence Actionability.

Intelligence signal	Empirical basis	CI actionability level	CI interpretation
Clear Interface	$\beta = 0.221$; $\alpha = 0.893$	Very High	Primary intelligence signal for UX redesign and adoption-support strategy
Consistency	$\beta = 0.200$; $\alpha = 0.890$	Very High	Core intelligence signal for cross-device standardization
Attractiveness	$\beta = 0.160$; $\alpha = 0.876$	High	Design-related intelligence signal for interface appeal
Information Completeness	$\beta = 0.153$; $\alpha = 0.876$; strongest moderation $\Delta R^2 = 0.077$	High	Priority intelligence signal for information strategy and innovative-user segmentation
Perceived Privacy	$\beta = 0.150$; $\alpha = 0.922$	High	Trust-related intelligence signal for privacy communication
Information Accuracy	$\beta = 0.138$; $\alpha = 0.885$; moderation $\Delta R^2 = 0.064$	Medium-High	Intelligence signal for status accuracy, error reporting, and product-information quality
Perceived Security	$\beta = 0.128$; $\alpha = 0.934$	Medium-High	Intelligence signal for security assurance and risk-reduction messaging

Note. CI-AI = Consumer-Derived Competitive Intelligence Actionability Index. Actionability levels are based on standardized regression weight, reliability, robustness, moderation evidence where applicable, and strategic relevance to the CI cycle. The index is not a validated CI maturity scale; it is an empirically derived decision-support output that converts measured consumer evidence into Competitive Intelligence priorities.

The CI-AI results provide the empirical operationalization of the analytical intelligence output. Clear Interface and Consistency receive the highest actionability level because they combine strong reliability with the two largest standardized regression weights. Information Completeness and Information Accuracy also receive elevated intelligence priority because their effects are strengthened among more innovative consumers, indicating segment-sensitive intelligence value. Privacy and Security remain strategically relevant because they represent trust-related adoption signals in the IoT smart-home context. Therefore, Competitive Intelligence is empirically represented in this study not as a consumer-level scale, but as a ranked actionability output generated from reliable, statistically supported consumer-derived market signals.

4.6 Discussion

4.6.1 Consumer-Adoption Findings

The finding that interface- and information-related perceptions are positively associated with adoption intention is consistent with the broad technology-acceptance literature, in which beliefs about how a system can be used and what it offers shape intention (Mohd Thas Thaker et al., 2024; Negm, 2023). The prominence of Clear Interface and Consistency aligns with smart-home studies emphasising ease and predictability of interaction (Ferreira et al., 2023; Iqbal & Idrees, 2022), while the significant roles of Perceived Security and Perceived Privacy echo work identifying data-handling confidence as a salient adoption consideration (Gebsombut et al., 2025; Basarir-Ozel et al., 2022; Shuhaiber et al., 2023). The moderating role of Personal Innovativeness is consistent with studies in which more innovative consumers respond more strongly to favourable perceptions (Shetu et al., 2022; Yuliawati et al., 2026). In line with good practice, no external study's numerical result is used as evidence from the present sample; comparisons are qualitative.

There are several possible explanations for the pattern that has been observed. The level of the interface-related perceptions is in line with the notion that meaningful and predictable interaction will reduce perceived effort to use a connected device, which will facilitate intention (Ladeira et al., 2025). The information accuracy and completeness is a significant contribution, which is consistent with the idea that during use, uncertainty can be mitigated when the information in the system is dependable and adequate. More innovative consumers might be more likely to consider information quality and data-handling cues when making intentions, which may explain the positive moderation found for the information and security/privacy predictors. These interpretations are provided as potential causal mechanisms that are consistent with the data rather than as established mechanisms.

The coded background variables had no verified categories meaning and as such there was no demographic subgroup analysis performed and diversity is treated only as a contextualization and limition, and not directly tested. Although the SD is high (1.18), the results show that there exists a meaningful variation among respondents' general innovativeness; the moderation results show that, in some cases, the relationship between several perceptions and intention is moderated by situational differences in innovativeness (Strzelecki, 2024). Remainder of the evidence does not address differences related to background categories that are not labeled.

4.6.2 Consumer Evidence as Competitive Intelligence

The statistical results become decision-relevant intelligence when they are read through the dissemination and utilization stages of the CI cycle and the strategic priority matrix (Table 7). Because Clear Interface and Consistency have the highest standardized weights, smart-home providers and interface designers can rightfully focus on interface clarity and cross-device consistency in product design and onboarding. Because Information Accuracy and Information Completeness are significant predictors and are strongly moderated, information content teams can increase the accuracy and scope of information and status reporting in the app. Since Perceived Security and Perceived Privacy are positive and significant, security and privacy teams should make their communications explicit and easy to comprehend. Finally, because Personal Innovativeness strengthens multiple relationships, messaging can be differentiated: detailed technical information cues for more innovative consumers and clearer reassurance for the more cautious (Saracevic & Schlegelmilch, 2024). These are intelligence-based priorities for further validation, bounded to the sampled population, rather than guaranteed effects.

The Consumer-Derived Competitive Intelligence Actionability Index further clarifies the empirical status of Competitive Intelligence in the study. The index does not claim that respondents personally measure or evaluate CI. Rather, it shows how organizational intelligence is produced from reliable consumer-derived market signals after these signals are analysed, ranked, governed and translated into decision priorities. This strengthens the epistemological alignment of the study with Competitive Intelligence because the empirical contribution lies in the intelligence output generated by the CI cycle, not in relabelling adoption perceptions as CI constructs.

4.6.3 Application of the Complete Competitive Intelligence Cycle

Each stage of the CI cycle is applied in this study. Planning defined the strategic intelligence questions: which consumer perceptions most strongly relate to adoption intention and which require strategic priority. Collection acquired consumer-derived market information through the survey of 375 Shenzhen consumers. Analysis transformed that information into decision-relevant intelligence through reliability assessment, correlation, multiple regression, HC3 robustness testing, moderation analysis and coefficient ranking. Dissemination is operationalized through the proposed CI dashboard and the strategic priority matrix (Table 7), which deliver the findings to product, UX, information, privacy, security and marketing teams. Utilization translates these outputs into interface redesign, information-quality improvement, privacy communication, security assurance and segment-specific messaging. Feedback closes the cycle through periodic tracking of adoption intention, customer complaints, interface usability, trust indicators and post-adoption behaviour, under the governance protocol of Section 3.7. The dissemination, utilization, feedback and governance stages are thereby specified as proposed applications of the analytical evidence rather than as empirically observed organizational processes.

4.6.4 Intelligence Governance and Information Asymmetry

Data quality, privacy protection, transparency and defined responsibility directly influence the credibility of the intelligence and its legitimate strategic use. Without governance—data-validation procedures, access control, documented interpretation rules, audit trails and the avoidance of selective reporting—even statistically sound evidence can be misused or mistrusted inside the organization. The findings also speak to the two information asymmetries of the smart-home market: providers know more than consumers about technical capabilities, data collection and security, yet may know less about consumer concerns, adoption barriers and information needs. The significant roles of Information Accuracy, Information Completeness, Perceived Privacy and Perceived Security indicate that accurate and complete information, privacy transparency and clear security communication can reduce both asymmetries, strengthening intelligence credibility and consumer trust simultaneously.

4.6.5 Sustainable Competitive Advantage

Sustainable competitive advantage is not produced by a single survey. It arises from an organization's repeated ability to sense changes, interpret market signals, coordinate responses, learn from outcomes, and update its intelligence priorities (Atkinson et al., 2022; Ranjan & Foropon, 2021). The governed CI process developed here supports this repeated capability: continuous market sensing enables faster strategic response, improved product–market fit and stronger consumer trust, which reduce adoption barriers and feed organizational learning. This pathway is theoretically grounded rather than empirically established by the present cross-sectional data and requires longitudinal organizational validation.

4.6.6 Theoretical and Methodological Contributions

The study connects consumer-adoption analytics with a process-based Competitive Intelligence architecture. Its theoretical contribution lies in distinguishing consumer information from organizational intelligence while explaining how the former can become strategically actionable through planning, analysis, dissemination, utilization, governance and feedback. Its methodological contribution is the integration of reliability assessment, multivariable prediction, robust inference, moderation analysis and a transparent decision-translation protocol (Madureira et al., 2023; Ju, 2024).

4.6.7 Limitations and Future Research

Several limitations bound the results. Competitive Intelligence was not measured as a consumer-level reflective construct or as a full organizational CI maturity score; rather, it was empirically operationalized as a consumer-derived intelligence actionability output generated from the planning, collection and analysis stages of the CI cycle. The dissemination, utilization, governance and feedback stages were specified as organizational applications requiring future validation with managers, CI professionals and smart-home providers. Actual adoption behaviour was not measured; reported intentions are analysed instead. The design is cross-sectional, so the analysis supports associations and observed predictive relationships rather than causal explanations, and the absence of a time variable precludes temporal claims. The sample cannot represent all Shenzhen or Chinese consumers, and verified meanings of the coded background variables were unavailable, preventing demographic subgroup analysis. Sustainable competitive advantage was theoretically inferred rather than empirically established. Future studies could add a second empirical phase with smart-home managers, marketing and product managers and market-intelligence professionals to observe the organizational CI stages directly, adopt longitudinal or behavioural designs to validate the relationships explored here, and incorporate contextual factors such as social influence or perceived cost that were not measured in this study (Mashal et al., 2023; Aggarwal & Singh, 2024).

5. CONCLUSION

This study develops a process-based Competitive Intelligence framework for transforming Shenzhen consumer evidence into strategic decision support for IoT smart-home providers. Within this framework, the consumer survey constitutes the collection stage of the CI cycle, the statistical analysis constitutes the analytical stage, the strategic priority matrix constitutes the dissemination and utilization stages, and the proposed governance and feedback protocol completes the cycle.

The collected consumer intelligence proved reliable and complete: the measurement instrument showed good-to-excellent internal consistency (Cronbach's alpha range 0.876–0.946) and the formal data set of 375 responses was clean, with no missing values or duplicate rows. All seven perception constructs (Clear Interface, Consistency, Attractiveness, Information Accuracy, Information Completeness, Perceived Security and Perceived Privacy) were positively and significantly associated with adoption intention, and all were significant predictors in a multiple regression model accounting for 57.9% of the variance in adoption intention (adjusted $R^2 = 0.571$); no direct relationship was unsupported. Within the sample, the standardized weights were highest for Clear Interface and Consistency and lowest, among the significant weights, for Perceived Security. In exploratory, multiplicity-corrected tests, Personal Innovativeness significantly moderated five of the seven relationships, with stronger predictor–intention connections for more innovative respondents, particularly for Information Completeness and Information Accuracy.

The study therefore provides an empirical CI output through the Consumer-Derived Competitive Intelligence Actionability Index, which ranks the measured market signals according to their reliability, predictive contribution, robustness and strategic relevance.

These analytical results are disseminated through the strategic priority matrix, which links each supported finding to interface and product design, information strategy, security assurance, privacy communication and consumer segmentation, while the governance and feedback protocol specifies the data-quality, privacy, accountability and monitoring requirements for continued intelligence use. Through repeated sensing, analysis, response and learning, this governed process establishes a pathway through which organizations may strengthen sustainable competitive advantage; the results provide decision support that may contribute to such advantage but do not directly demonstrate it. The main limitations remain the cross-sectional design, which supports associations rather than proven causal mechanisms, and the absence of directly observed organizational evidence; the findings are bounded to the surveyed sample and are not claimed to generalize beyond it.

REFERENCES

Aggarwal, N., & Singh, S. (2024). Embracing the future by unlocking the door to smart living: A systematic review of consumers' adoption and acceptance of smart home devices. *Management and Labour Studies*. https://doi.org/10.1177/0971102324131028

Atkinson, P., Hizaji, M., Nazarian, A., & Abasi, A. (2022). Attaining organisational agility through competitive intelligence: The roles of strategic flexibility and organisational innovation. *Total Quality Management & Business Excellence, 33(3–4), 297–317.* https://doi.org/10.1080/14783363.2020.1842188

Basarir-Ozel, B., Turker, H. B., & Nasir, V. A. (2022). Identifying the key drivers and barriers of smart home adoption: A thematic analysis from the business perspective. *Sustainability, 14(15), 9053.* https://doi.org/10.3390/su14159053

Ferreira, L., Oliveira, T., & Neves, C. (2023). Consumer's intention to use and recommend smart home technologies: The role of environmental awareness. *Energy, 263, 125814.* https://doi.org/10.1016/j.energy.2022.125814

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).* https://doi.org/10.1177/21582440251358967

Ibrahim, F., Münscher, J.-C., Daseking, M., & Telle, N.-T. (2025). The technology acceptance model and adopter type analysis in the context of artificial intelligence. *Frontiers in Artificial Intelligence, 7, 1496518.* https://doi.org/10.3389/frai.2024.1496518

Iqbal, J., & Idrees, M. (2022). Understanding the IoT adoption for home automation in the perspective of UTAUT2. *Global Business Review.* https://doi.org/10.1177/09721509221132058

Ju, X. (2024). A social media competitive intelligence framework for brand topic identification and customer engagement prediction. *PLOS ONE, 19(11), e0313191.* https://doi.org/10.1371/journal.pone.0313191

Ladeira, W., Perin, M. G., & Santini, F. (2025). Consumer adoption of internet of things: A meta-analytic structural equation modeling approach. *Journal of Consumer Behaviour, 24(2).* https://doi.org/10.1002/cb.2427

Madureira, L., Popovič, A., & Castelli, M. (2023). Competitive intelligence empirical validation and application: Foundations for knowledge advancement and relevance to practice. *Journal of Information Science.* https://doi.org/10.1177/01655515231191221

Maluleka, M. L., & Chummun, B. Z. (2023). Competitive intelligence and strategy implementation: Critical examination of present literature review. *Journal of Contemporary Management, 20(2).* https://doi.org/10.4102/sajim.v25i1.1610

Mashal, I., Shuhaiber, A., & Al-Khatib, A. W. (2023). User acceptance and adoption of smart homes: A decade long systematic literature review. *International Journal of Data and Network Science, 7(2), 533–548.* https://doi.org/10.5267/j.ijdns.2023.3.012

Mohd Thas Thaker, H., Subramaniam, N. R., Qoyum, A., & Iqbal Hussain, H. (2024). Marketing research trends using technology acceptance model (TAM): A comprehensive review of researches (2002–2022). *Cogent Business & Management, 11(1), 2329375.* https://doi.org/10.1080/23311975.2024.2329375

Negm, E. (2023). Internet of Things (IoT) acceptance model – assessing consumers' behavior toward the adoption intention of IoT. *Arab Gulf Journal of Scientific Research, 41(4).* https://doi.org/10.1108/AGJSR-09-2022-0183

Ranjan, J., & Foropon, C. (2021). Big data analytics in building the competitive intelligence of organizations. *International Journal of Information Management, 56, 102231.* https://doi.org/10.1016/j.ijinfomgt.2020.102231

Saracevic, S., & Schlegelmilch, B. B. (2024). Voice of the professional: Acquiring competitive intelligence from large-scale professional generated contents. *Journal of Business Research, 181, 114712.* https://doi.org/10.1016/j.jbusres.2024.114719

Sassi, D. B., Frini, A., Chaieb, M., & Karaa, W. B. A. (2022). A rough set-based competitive intelligence approach for anticipating competitor's action. *Expert Systems with Applications, 204, 117523.* https://doi.org/10.1016/j.eswa.2022.117523

Shetu, S. N., Islam, M. M., & Promi, S. I. (2022). An empirical investigation of the continued usage intention of digital wallets: The moderating role of perceived technological innovativeness. *Future Business Journal, 8, 43.* https://doi.org/10.1186/s43093-022-00158-0

Shuhaiber, A., Alkarbi, W., & Almansoori, S. (2023). Trust in smart homes: The power of social influences and perceived risks. In *Intelligent Sustainable Systems (LNNS Vol. 578). Springer.* https://doi.org/10.1007/978-981-19-7660-5_27

Strzelecki, A. (2024). Exploring the factors driving smart home adoption: An extension of the unified theory of acceptance and use of technology. In *Lecture Notes in Networks and Systems. Springer.* https://doi.org/10.1007/978-981-97-3698-0_19

Wang, J., Li, Y., & Chen, H. (2026). Configurational effects of personal innovativeness, self-efficacy, and perceived risk on AI adoption in media students. *Scientific Reports, 16.* https://doi.org/10.1038/s41598-026-36538-7

Yuliawati, A. K., Rahayu, A., Wibowo, L. A., & Disman. (2026). Determinants of e-wallet adoption among Generation Z in Indonesia: An extended UTAUT3 model integrating personal innovativeness and perceived security. *Journal of Risk and Financial Management, 19(6), 421.* https://doi.org/10.3390/jrfm19060421