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Development of an AI-Based Prototype for Integrating Design and Cost Estimation in the Early Stages of Residential Construction: A Design Thinking Approach and Adoption Validation

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Abstract

Small and medium-sized construction businesses are increasingly required to provide faster, clearer, and integrated early-stage services for residential clients. However, many SME contractors still manage design briefing, preliminary cost estimation, and proposal preparation through sequential handovers, informal knowledge, and manual coordination. This article examines how artificial intelligence (AI)-based design-to-cost prototypes can support early-stage decision-making in SME residential construction. The research used an applied design research approach with Design Thinking for the development of prototypes and UTAUT3 models adapted for adoption validation. Qualitative data is collected through a focus group discussion with homeowners and the internal functions of the construction, then translated into problem formulations, How Might We question, and prototype needs. The resulting prototype integrates guided briefing, AI-based layout creation, historical cost estimates per square meter, and a design-cost compromise dashboard. The survey of 105 respondents was analyzed using PLS-SEM. The model explains a 67.8% variation in adoption intent. Social Influence and Personal Innovation significantly affect Adoption Intentions, while Performance Expectations, Business Expectations, and Enabling Conditions are insignificant. The findings show that the early adoption of AI in SME residential construction depends not only on the perception of usability, but also on organizational support and individual openness to innovation.

INTRODUCTION

Residential construction is a service environment that is very loaded with decision-making (Da Silva et al., 2020; Elavarasan & Regina, 2026; Karamoozian & Hong, 2023; Motaghifard et al., 2020; Wang et al., 2025). Before a project enters the detailed design or construction stage, homeowners and contractors need to align expectations regarding space needs, design preferences, budget ranges, material quality, timeframes, and communication processes. This early stage is economically important because the initial decision affects the cost at the later stage, clarity of scope, client trust, and the efficiency of the proposal drafting. However, this stage also has a high level of uncertainty, especially when the client is a non-technical homeowner and not an institutional buyer.

For small and medium-sized construction businesses, residential workflows in the early stages can be difficult to manage. SME contractors often have experience in project execution, but they don't necessarily have a mature digital platform, an integrated cost database, a formalized customer journey, or a dedicated pre-construction service team. As a result, initial design discussions, preliminary estimates, and proposal revisions can depend on sequential handovers between design, estimation, and management functions. This condition can lead to long proposal cycles, repeated revisions, budget ambiguity, and low confidence in decision-making.

Digital transformation and artificial intelligence have been extensively discussed in construction research, including their application to design support, cost prediction, scheduling, safety, building information modeling, and decision-making support (Abioye et al., 2021; Ahuja et al., 2017; Baduge et al., 2022; Li et al., 2019; Xu et al., 2021). Nonetheless, most of the literature is oriented towards large-scale projects, institutional clients, mature data environments, or technical prediction models. Attention to how SME residential contractors translate clients' practical problems and internal workflow limitations into AI-based service flows that are user-acceptable and feasible to implement at an early stage are still limited.

This research addresses this gap by developing and validating an AI-based design-to-cost prototype for SME residential contractors. The research uses SME contractors in Indonesia as an empirical case context. The company has historically operated in the B2B and B2G construction markets and is working to strengthen B2C residential services. The initial occupancy process still relies heavily on manual coordination between the design, estimation, and project management functions, making it a relevant case to examine design-to-cost alignment and technology adoption in resource-constrained contractor environments.

This research aims to conceptualize early-stage residential service delivery as a design-to-cost alignment issue requiring integrated decision support, to develop an AI-based prototype using Design Thinking to address homeowner uncertainty and internal coordination barriers, and to validate adoption intention using the adapted UTAUT3 framework to identify key drivers of technology acceptance in SME construction contexts.

This article makes three contributions to construction management and economics. First, this research conceptualizes the delivery of early-stage residential services as a design-to-cost alignment issue, not solely a technical problem of design or estimation. Second, this study shows how Design Thinking can be used to translate homeowner uncertainty and internal coordination barriers into a proof-of-concept digital workflow. Third, this study validates the intention of adoption using the adapted UTAUT3 framework and shows that Social Influence and Personal Innovation are more decisive than the perception of usability in the context of early-stage prototypes.

METHOD

Research design

This research used an applied design research approach that combines qualitative problem exploration, prototype development, and quantitative adoption validation. The unit of analysis is the initial phase of residential construction workflow at one SME contractor as a case (Yin, 2018), specifically the process from the initial question of the homeowner to the preliminary design, initial cost orientation, and proposal discussion.

The research process follows Design Thinking. The Empathize stage gathers the perspective of the homeowner and internal parties. The Define stage translates the findings into problems, root causes, and How Might We question. The Ideate stage produces process, service, and technology solutions. The Prototype stage develops an AI-based design-to-cost workflow. The Test Stage validated user acceptance using an adapted UTAUT3 questionnaire and PLS-SEM analysis (Figure 1).

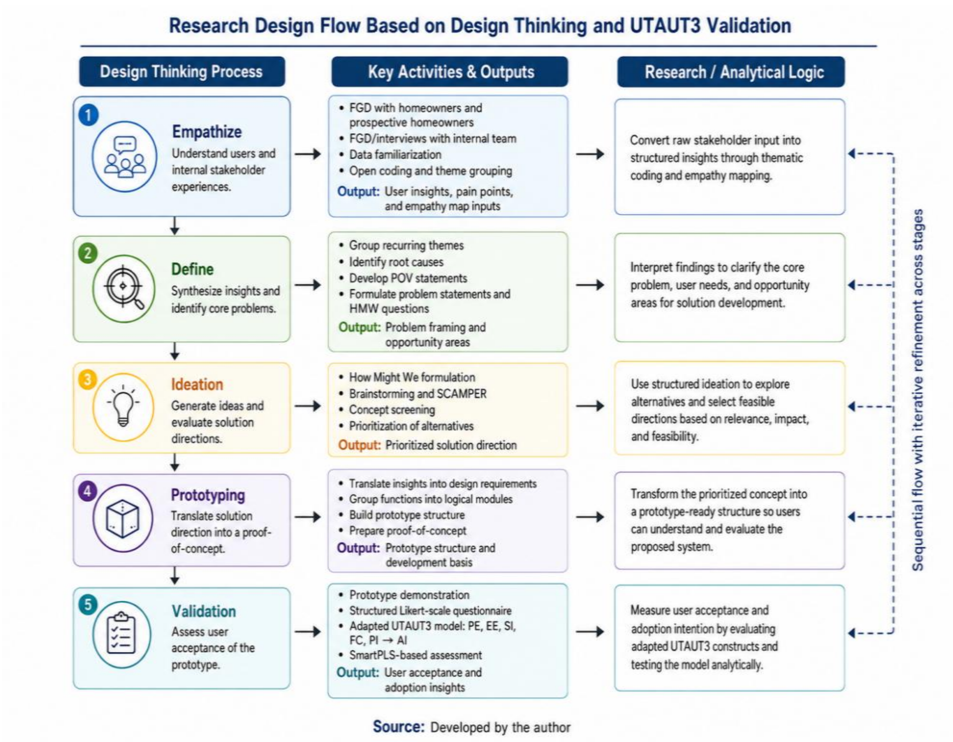

Figure 1. Research Process Flow Using Design Thinking Approach
Source: Compiled by the researcher based on the Design Thinking framework (Brown, 2008; Doorley et al., 2018), 2026

Qualitative data collection and analysis

Two focus group discussions (FGDs) were conducted under the guidance of semi-structured discussions (Kallio et al., 2016; Krueger & Casey, 2015). The homeowner's FGD involved four participants, namely two residential clients with previous project experience and two residential clients with ongoing projects. Participants with previous experience provided retrospective insights into previous construction service experience, while clients undergoing a project provided current expectations and concerns during the active planning process. The internal and management FGD involved four participants from the case contractor, namely the director, project manager, engineer, and estimator. These roles were chosen because they directly affect the preparation of early-stage proposals, design coordination, technical feasibility, and initial cost estimates. Qualitative data were analyzed using thematic coding (Braun & Clarke, 2006).

Qualitative data were analyzed using thematic coding. The analysis began with familiarizing yourself with discussion notes and transcript snippets, followed by open coding, grouping code into themes, and translating themes into empathy maps, root causes, How Might We questions, and design needs. The goal is not to produce qualitative findings that can be generalized statistically, but rather to identify actionable design needs for prototypes.

Table 1. Data sources and analytical roles.

Data source	Participants	Objectives in the research
FGD homeowners	Four participants: two clients with previous project experience and two clients with ongoing projects	Identify homeowner problems, decision uncertainty, budget concerns, communication expectations, and trust issues.
Internal and management FGDs	Four participants: director, project manager, engineer, and estimator	Identify workflow bottlenecks, repetitive revisions, cost estimation issues, technical coordination issues, and implementation constraints.
Basic conditions of internal operations	Experience in drafting proposals and revisions from case contractors	Support problem definitions using early-stage workflow indicators, such as proposal time, revision rounds, and initial cost deviations.
Prototype demonstrations and surveys	105 responds	Validate the perception and intention of adoption of the developed prototype.

Source: Compiled by the researcher based on FGD design and case contractor data, 2026

Logic of prototype development

The ideation process is carried out through How Might We questions, brainstorming, SCAMPER, and concept screening (Doorley et al., 2018; Eberle, 2023). Ideas considered include a customer journey guide, a structured needs briefing checklist, a material grade catalog, an assumption transparency template, an early-stage consultation flow, a library of layout archetypes, a case reference filter, a parametric cost range estimator, a compromise dashboard, an AI-based layout generator, and a project status tracker.

The selected concept combines process-oriented and technology-oriented ideas. Process features are retained because they directly address homeowner ambiguity and can be implemented quickly. The technology feature is retained because it addresses the core problem of design-to-cost alignment by linking the initial layout exploration and budget orientation. The final prototype consists of three modules, namely an AI-based layout module, a parametric cost module, and a customer journey and compromise dashboard (Figure 2).

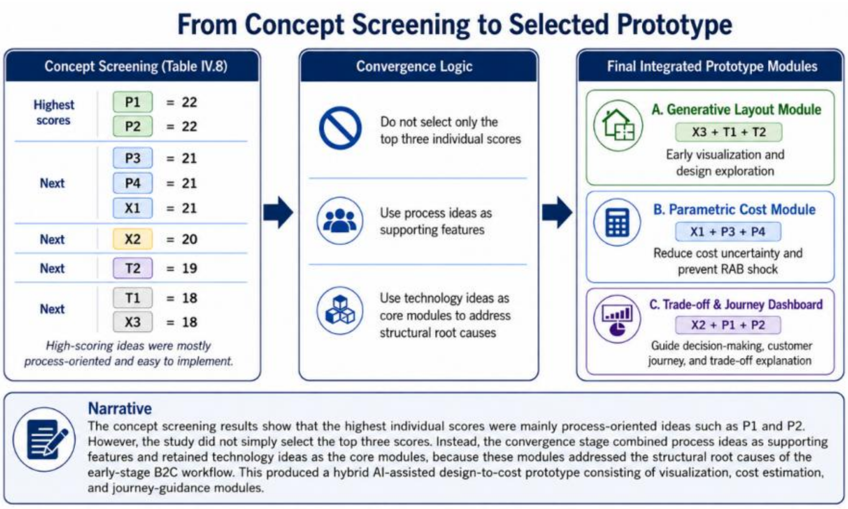

Figure 2. Prototype Architecture and Module Integration
Source: Designed by the researcher based on Design Thinking ideation and concept screening results, 2026

Quantitative validation and PLS-SEM

The prototype was evaluated using a structured questionnaire based on the adapted UTAUT3 framework. Respondents were first shown a prototype demonstration to assess the same object. Each item uses a five-point Likert scale. The questionnaire consisted of 19 indicators in six constructs, namely Performance Expectations, Business Expectations, Social Influences, Facilitating Conditions, Personal Innovation, and Adoption Intentions.

Data were analyzed using SmartPLS 4 (Ringle et al., 2024). The model evaluation follows the general guidelines of PLS-SEM (Hair et al., 2022; Hair et al., 2011; Wong, 2013). The analysis evaluates the reliability of indicators, the reliability of internal consistency, convergent validity, and structural relationships. Because the prototype is still in the proof-of-concept stage and has not yet been implemented as a routine system, the model is interpreted as an exploratory adoption validation, not as a prediction of actual usage behavior.

Table 2. Adapted UTAUT3 construct and measurement focus.

Construct	Item	Role in validation
Performance Expectations	PE1-PE4	Usability perception to accelerate initial design, improve cost consistency, connect design and budget, and improve communication with clients.
Business Expectations	EE1-EE3	Perception of ease of understanding and clarity of user flow.
Social Influence	SI1-SI3	Perception of organizational support and the work environment towards the use of the system.
Enabling Conditions	FC1-FC3	Perception of data readiness, company capabilities, and workflow suitability.
Personal Innovation	PI1-PI3	An individual's openness, interest, and willingness to learn AI-based systems.
Adoption Intention	AI1-AI3	Willingness to use, further develop, and support prototypes in residential projects.

Source: Compiled by the researcher based on the adapted UTAUT3 framework (Venkatesh et al., 2003; Venkatesh et al., 2012), 2026

RESULTS AND DISCUSSION

Definition of the problem based on qualitative findings

Qualitative findings show that the problems of early-stage residential construction are experiential as well as operational. Homeowners report difficulty envisioning the final design, budget uncertainty, confusion about project stages, and limited confidence in technical information. Some homeowners use social media references as a reference for their initial budget, but they often don't connect to actual material specifications, design complexity, and site conditions.

Internal participants describe repetitive design-cost iterations, inconsistent initial cost assumptions, and sequential handoffs between design and estimation functions. The basic experience of the case contractor shows that the preparation of the proposal takes about two to four weeks, there are five to seven rounds of revision, the initial cost deviation can reach 150-200% of the client's informal reference, and the entire early-stage process can take about three to seven months in complex cases. This problem confirms that the issue faced is not only the lack of design ideas, but also the lack of structured decision support.

Table 3. The translation of qualitative themes into prototype needs.

Theme	Construction management interpretation	Implications for prototypes
Design visualization uncertainty	Homeowners do not easily translate preferences and references into viable space choices.	Provides guided input, layout archetypes, and AI-based initial layout output.
Budget ambiguity	Homeowners need a budget orientation before committing to a detailed design, but initial estimates are often unclear.	Use historical cost data per square meter and material class assumptions to present preliminary cost ranges.
Unclear customer journey	The client does not always understand what happens after the initial question, the briefing of needs, the design, and the discussion of the proposal.	Add structured customer journeys, checklists, and decision stages.
Separation of design and cost	Design and cost estimation are often done sequentially, resulting in rounds of revisions.	Synchronize layout choices with the initial cost range and compromise explanations.
Professional trust and assessment	AI can speed up onboarding, but clients still need human confidence for high-value decisions.	Positioning AI as a decision supporter and maintaining human consultation as a mandatory layer.

Source: Compiled by the researcher based on FGD findings with homeowners and internal participants, 2026

Prototype architecture and cost estimation logic

The prototype was developed as a semi-functional application interface called PrimaBuild. The prototype consists of an input layer, a processing layer, and a data layer (Figure 3). The input layer collects homeowner identity, existing land or building information, space needs, lifestyle preferences, reference images, and material class preferences. The processing layer uses AI-based logic to generate initial layout-oriented outputs and relate them to the assumption of the cost range. The data layer stores user feedback, project parameters, selected choices, and interaction history to support a more structured customer journey.

The cost estimation module is deliberately designed as a preliminary parametric estimator, rather than as a detailed work quantity list system. The logic uses the project's historical data and the internal cost assumptions per square meter as a basis. These assumptions are adjusted based on the area of the building, the number of floors, the class of materials, the intensity of the wet area, the complexity of the layout, and the project-specific risk factors. Outputs are presented in low, medium, and high cost ranges (Figure 5). This format supports early decision-making without overdoing precision. The final price should still be reviewed by a professional estimator as well as take into account the site conditions, detailed drawings, and specifications of the final material.

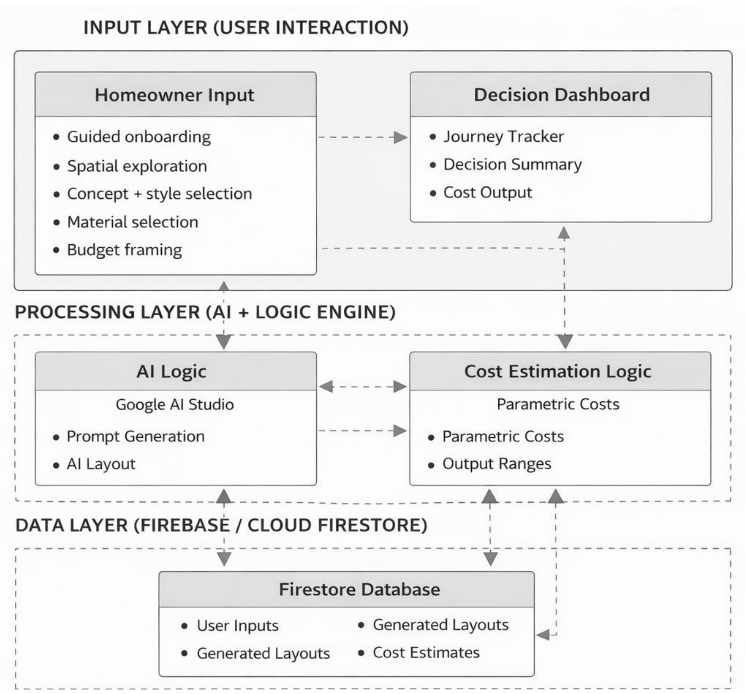

Figure 3. Prototype Architecture of PrimaBuild

Source: Designed by the researcher based on Design Thinking ideation and concept screening results, 2026

Changes to front-end service workflows and internal processes

From a homeowner's perspective, the prototype transforms the front-service journey from an open consultation to a guided decision-making process. Homeowners provide structured information, choose preferences, review the direction of the resulting design, compare cost implications, and identify compromises. This process reduces ambiguity and supports more informed discussions with contractors (Figure 4).

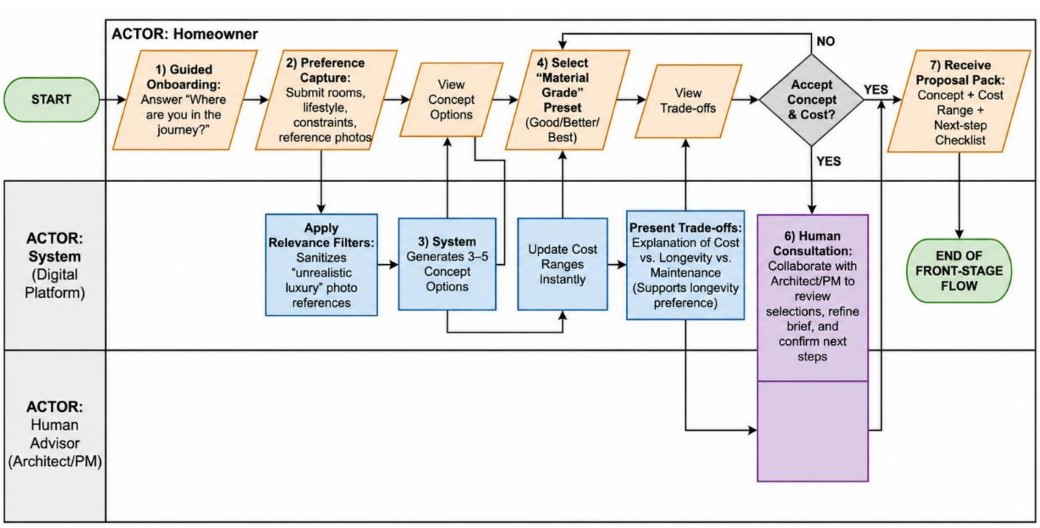

Figure 4. The front-stage customer journey through prototypes

Source: Compiled by the researcher based on FGD findings and Design Thinking workflow design, 2026

From a contractor's perspective, prototyping changes internal workflows by reducing the separation between design and estimation. Instead of preparing the design first and making estimates later, the initial layout and cost range alternatives are generated in parallel. This design-to-cost workflow doesn't eliminate design work or professional estimation, but it improves the quality of the first conversation and reduces the actual round of revisions that could have been avoided.

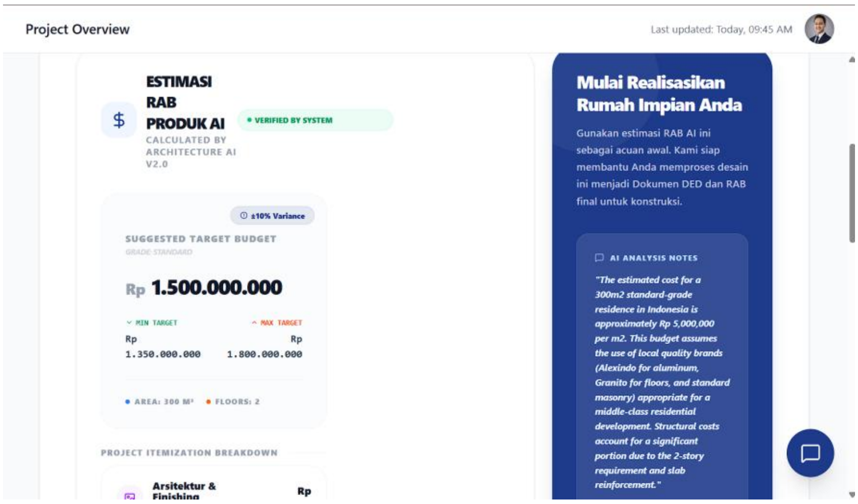

Figure 5. Cost Range Dashboard Output

Source: Developed by the researcher based on historical cost data and internal assumptions of the case contractor, 2026

Descriptive results

The descriptive results show a positive perception of the prototype. The average of the entire construct exceeds 4.50 on a five-point scale. Personal Adoption and Innovation Intentions obtained the highest average scores, followed by Performance Expectations, Business Expectations, Social Influence, and Enabling Conditions. These findings show that respondents generally view prototypes as a useful, easy to understand, and worthy of further development.

Table 4. Descriptive results at the construct level.

Construct	Average	Interpretation
Performance Expectations	4.610	Respondents view prototypes as beneficial for early-stage design-cost communication.
Business Expectations	4.565	Respondents view the interface and its flow relatively easy to understand.
Social Influence	4.530	Respondents viewed organizational support and the work environment positively.
Enabling Conditions	4.527	Respondents viewed data readiness and workflow feasibility positively, but slightly lower than other constructs.
Personal Innovation	4.622	Respondents showed a high openness to try and learn AI-based systems.
Adoption Intention	4.622	Respondents expressed willingness to use and support further development of prototypes.

Source: Primary data processed using SmartPLS 4, 2026

Measurement model

The measurement model shows internal consistency and acceptable convergent validity. The Alfa Cronbach exceeded 0.70 for the entire construct, the composite reliability exceeded 0.85, and the AVE exceeded 0.50, thus meeting the recommended threshold (Hair et al., 2022; Hair et al., 2011).

Table 5. Summary of convergent reliability and validity.

Construct	Alfa Cronbach	Composite reliability	AVE
Adoption Intention	0.818	0.892	0.733
Business Expectations	0.812	0.888	0.726
Enabling Conditions	0.749	0.857	0.666
Performance Expectations	0.858	0.904	0.702
Personal Innovation	0.837	0.902	0.754
Social Influence	0.770	0.867	0.685

Source: Primary data processed using SmartPLS 4, 2026.

An SRMR value of 0.0719 indicates an approximate model fit that is acceptable for exploratory PLS-SEM studies. Since the prototype is still in the proof-of-concept stage, the structural pathway is interpreted as exploratory evidence of adoption trends, rather than as a conclusive causal estimate.

Structural Model

The structural model explains 67.8% variation in Adoption Intent (Figure 6). Social Influence and Personal Innovation are significant predictors of Adoption Intention. Performance Expectations, Business Expectations, and Enabling Conditions are not significant even though they have a high descriptive average value. This pattern suggests that in the context of early-stage prototypes, respondents may like the concept and find it useful, but their intentions to support adoption are stronger shaped by organizational or social support and individual openness to innovation.

Table 6. Structural line results.

Hypothesis	Steps	Coefficients	t-value	p-value	Results
H1	Performance Expectations -> Adoption Intent	0.017	0.094	0.925	Not supported
H2	Business Expectations - > Intention to Adopt	-0.062	0.461	0.645	Not supported
H3	Social Influence - > Adoption Intent	0.381	2.607	0.009	Supported
H4	Conditions That Facilitate -> Intention of Adoption	0.216	1.530	0.126	Not supported
H5	Personal Innovation - > Intention to Adopt	0.332	2.617	0.009	Supported

Source: Primary data processed using SmartPLS 4, 2026.

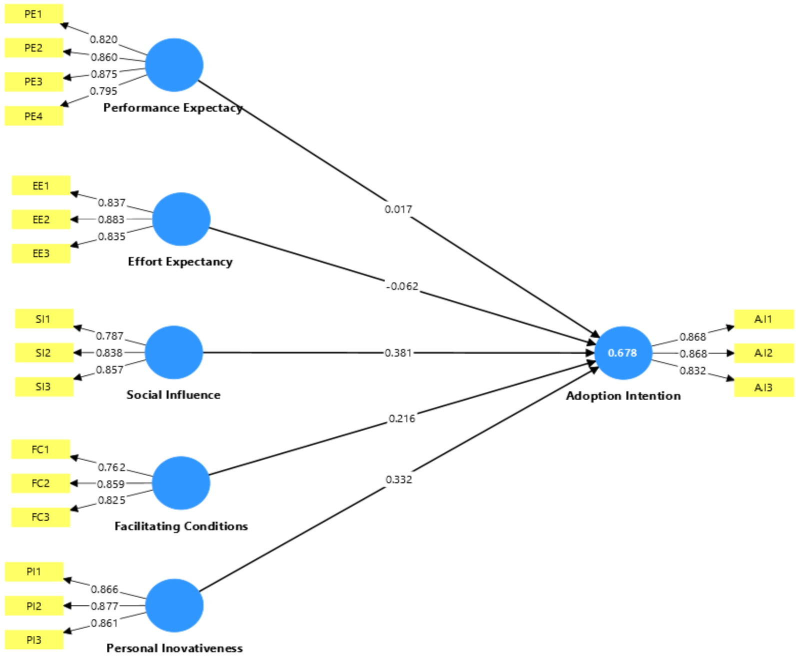

Figure 6. Structural Model Results (PLS-SEM)
Source: Primary data processed using SmartPLS 4, 2026.

Design-to-cost alignment as an early-stage management issue

The findings suggest that early-stage residential construction needs to be understood as a matter of design-to-cost alignment. Homeowners need not only an attractive layout or low estimate, but also a guided process that connects design preferences, budget consequences, and decision stages. For SME contractors, this is a management challenge because early decisions require cross-functional coordination between design, estimation, engineering, and client communication.

The prototype addresses these issues by integrating client needs briefing, AI-based layout exploration, and cost range orientation. Thus, the value of the prototype lies not only in the function of AI, but also in the way the system restructures the contractor's early-stage service processes. This is important for the field of economics and construction management because it connects digital technology with the economics of proposal preparation, revision efforts, speed of client decision-making, and the use of pre-construction resources.

Why the usability is not enough to encourage the intention of adoption

Although Performance Expectations have a high average value, the construct does not significantly predict Adoption Intent. This does not mean that usability is irrelevant. Instead, these findings suggest that respondents may have equally rated the prototype as a useful solution, so the variation available to explain adoption intentions is limited. In addition, because the prototype is not yet ready for production, respondents may need evidence of accuracy, implementation readiness, data quality, and managerial support before translating usability perceptions into adoption intent.

The significant influence of Social Influence shows that adoption in the SME construction environment is socially and organizationally embedded. Users may be more willing to support a prototype when management, colleagues, and the work environment see it as important to the quality of service. These findings are in line with the practical reality of

SME contractors, where the use of technology is often shaped by leadership commitments and norms at the team level, rather than just by individual evaluations.

Personal innovation and digital transformation of SMEs

Personal Innovation is also a significant predictor of Adoption Intent. These findings highlight the role of early adopters in the digital transformation of SMEs. In resource-constrained enterprises, new technologies often rely on a small number of individuals willing to experiment, learn, and translate digital devices into practical workflows. In AI-driven prototypes, such individuals can act as internal drivers who bridge management intent, technical experimentation, and operational use.

The influence of insignificant Facilitating Conditions needs to be interpreted carefully. The descriptive mean value is positive, but the path is not significant. This can indicate that respondents view enabling conditions as part of a broader set of readiness and overlap with usability, ease of use, and social support. However, for implementation, the conditions that facilitate it are still important. Data governance, cost database maintenance, human review procedures, and workflow integration are required before a prototype can move from proof of concept to routine use.

CONCLUSION

This article examines how AI-based design-to-cost prototypes can support early-stage decision-making in SME residential construction. Using Design Thinking, the research translated homeowner issues and internal workflows into a prototype that integrates guided needs briefing, AI-based layout exploration, historical cost estimates per square meter, and design-cost compromise dashboards. The prototype reframes the initial residential construction process as a structured decision journey, rather than as a separate set of design and estimation tasks. Adoption validation shows that the model explains 67.8% variation in Adoption Intent. Social Influence and Personal Innovation significantly affect Adoption Intent, whereas Performance Expectations, Business Expectations, and Enabling Conditions are not significant in the structural model. These findings suggest that early-stage AI adoption in SME construction relies not only on usability perception, but also on social support, leadership support, and innovative user presence. For SME residential contractors, the managerial lesson is clear: AI devices are more likely to create value when embedded into credible design-to-cost workflows, supported by historical cost data, and controlled by human professional judgment.

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