Available at https://journalenrichment.com/index.php/jr/

Enrichment: Journal of Multidisciplinary Research and Development

Bim and AI Adoption in Construction Project Planning: Evaluation, Challenges, and Strategic Recommendations for Design Consultants

Ida Bagus Ari Suya Jnana*, I Gusti Agung Adnyana Putera, A.A. Gde Agung Yana
Universitas Udayana, Indonesia
Email: arisuya07@gmail.com*, apute@unud.ac.id, agungyana@unud.ac.id

Keywords
Building Information Modeling; Artificial Intelligence; construction planning; Technology Acceptance Model; Technology-Organization-Environment

Abstract

BIM and AI are becoming increasingly important in construction planning, although their adoption among design consultants remains uneven, particularly in developing construction markets. This research examines BIM-AI adoption through a combined assessment of BIM-AI maturity, technology acceptance, organizational and environmental readiness, and importance-performance priorities. The research was carried out in three design-consultant organizations in Bali, Indonesia: PT MBJ, Formata.id, and PT KASS. Data were obtained from 30 respondents through a Likert-scale questionnaire. The instrument was supported by content validation, pilot testing, and qualitative clarification. The results indicate that the three organizations had a high level of BIM-AI maturity, with a score of 3.97 out of 5.00. The overall TAM score reached 4.16, while adoption readiness scored 4.11, both of which were also in the high category. Respondents gave positive ratings to the TOE/implementation factors. The performance score was slightly higher than the importance score, 4.20 compared with 4.10, which indicates that the current implementation is already performing slightly above what respondents considered important. The reliability results also support the consistency of the instrument, with Cronbach's alpha values between 0.905 and 0.975. IPA identified five indicators in the Concentrate Here quadrant, mainly related to management support, workflow compatibility, system integration, human resource competence, and regulatory support. The study provides a practical basis for design consultants to strengthen their BIM-AI adoption. Rather than treating digital tools as separate or partial applications, the proposed structure helps organizations move toward more integrated, data-driven, and organization-wide use in construction planning.

INTRODUCTION

The construction industry is moving through a digital transition, with planning, coordination, and decision-making increasingly supported by data-driven and intelligent technologies. BIM is no longer limited to three-dimensional modeling but has developed into a broader information management system that can support scheduling, cost planning, sustainability analysis, and facility management (Bukunova & Bukunov, 2021; Rashidi et al., 2024; Tanne et al., 2025). At the same time, AI strengthens the use of project information by supporting pattern recognition, prediction, automation, and decision-making across the construction value chain (Attia, 2025; Khan et al., 2024). When BIM and AI are used together, they can improve design coordination, reduce errors, speed up planning processes, and support better decisions in complex construction projects (Pan & Zhang, 2021; Sacks et al., 2018, 2020)

Despite these potential benefits, the adoption of BIM and AI is still uneven, especially in developing construction markets. Previous studies have pointed to several challenges, including high initial costs, limited technical capability, weak data standards, lack of training, fragmented project workflows, and uncertain organizational readiness (Martilla & James, 1977; Oh, 2001; Oliveira & Fraga Martins, 2011; Succar, 2009). In Indonesia, BIM use has continued to grow, but it is often still focused on basic modeling and visualization. AI, meanwhile, is generally used in a more limited and experimental way. This issue is important for design consultants because decisions made during the planning stage shape the quality of project information, coordination between disciplines, design constructability, and the efficiency of later project stages.

Several studies have examined BIM adoption and AI applications in the construction industry. (Succar, 2009) developed a BIM maturity framework that helps organizations understand whether BIM use remains isolated at the individual level or has become integrated into organizational processes. Sacks et al., (2018) emphasized that BIM provides a collaborative information environment that improves visualization, multidisciplinary coordination, and design documentation. Chan et al. (2019) identified perceived benefits and barriers to BIM implementation, including high costs, lack of standards, and resistance to change (Anh et al., 2023; Mtya & Windapo, 2017; Van Roy & Firdaus, 2020). In the Indonesian context, Van Roy and Firdaus (2020) found that BIM knowledge and implementation are still developing, with barriers related to training, software costs, and client demand.

Regarding AI, Pan and Zhang (2021) provided a critical review of AI roles in construction engineering and management, highlighting applications in prediction, optimization, and safety monitoring. Na et al. (2023) used the Technology Acceptance Model (TAM) to examine AI adoption in the construction industry across multiple countries, finding that perceived usefulness and ease of use significantly influence adoption intentions. Sadiq et al. (2021) developed an AI maturity model, noting that organizational learning, data management, and leadership support are critical for successful AI integration. However, most of these studies examined BIM and AI separately rather than as an integrated system, and few focused on design-consultant organizations in developing construction markets (Ahuja et al., 2020; Chan et al., 2019; Memon et al., 2014; Na et al., 2023).

Previous studies have discussed BIM maturity, AI applications, and technology acceptance in the construction industry. However, limited attention has been given to how BIM and AI are adopted together within design-consultant organizations. A purely technical assessment is not enough, since digital adoption is influenced not only by the availability of software but also by user acceptance, management support, organizational culture, data readiness, and external demands. To address this issue, this study uses a combined evaluation approach that brings together BIM-AI maturity assessment, TAM, TOE, and IPA. The purpose of this study is to understand the current level of BIM and AI implementation and acceptance among design consultants, identify the main barriers they face, and develop practical priorities for improving digital construction planning.

The benefits of this research are both theoretical and practical. Theoretically, this study contributes to the literature on digital transformation in construction by integrating four complementary perspectives—BIM-AI maturity assessment, the Technology Acceptance Model (TAM), the Technology-Organization-Environment (TOE) framework, and Importance-Performance Analysis (IPA)—within a single empirical evaluation (Sadiq et al., 2021; Tornatzky & Fleischer, 1990; Yusoff, 2019). This integrated approach provides a more comprehensive understanding of BIM-AI adoption than studies that focus on only one dimension, particularly in the context of developing construction markets. Practically, the findings offer actionable insights for design consultants to prioritize their digital investments, strengthen management support, improve workflow compatibility, develop human resource competence, and align with regulatory requirements. The proposed staged implementation roadmap helps organizations move from basic BIM use toward integrated, data-driven, and organization-wide adoption of BIM and AI in construction planning. Furthermore, the evaluation framework can serve as a self-assessment tool for other design-consultant firms seeking to benchmark their digital readiness and plan strategic improvements (Davis, 1989; Venkatesh et al., 2003).

BIM provides a collaborative information environment that improves visualization, multidisciplinary coordination, clash detection, quantity take-off, and design documentation. BIM maturity models help organizations understand whether BIM use remains isolated at the individual or project level or has become integrated into organizational processes, standards, and information exchange mechanisms. In construction planning, higher BIM maturity is associated with improved design coordination, reduced rework, and better alignment between design, cost, and schedule information.

AI can support various construction activities, including prediction, optimization, classification, image recognition, natural-language processing, design automation, safety monitoring, and project-risk analysis. However, its adoption depends on several conditions, such as the quality of available data, digital infrastructure, staff capability, understanding of algorithms, organizational trust, and proper governance of data privacy and security [18,19]. For this reason, AI maturity is not only about having advanced tools. It also requires organizational learning, good data management, leadership support, and alignment with existing work processes.

TAM is used to understand technology acceptance through two main aspects: perceived usefulness and perceived ease of use. In this study, TAM helps explain whether users see BIM and AI as tools that can improve their work and whether they find these technologies easy enough to understand and apply. TOE complements this by looking at adoption from a broader perspective, including technological readiness, organizational capability, and external environmental pressure. IPA is then used to compare importance and performance so that the results can be translated into practical improvement priorities. By combining TAM, TOE, maturity assessment, and IPA, this study not only describes the current level of BIM-AI adoption but also identifies which areas should be prioritized to support digital transformation in construction planning.

Table 1. Synthesis of selected literature used to develop the BIM-AI adoption framework

Reference stream	Main emphasis	Implication for this study
BIM maturity and information management [2,8,9]	BIM evolves from isolated modeling into coordinated information management and multi-dimensional project support	Maturity indicators must capture workflow integration, not only software use
BIM benefits and barriers [16–19]	Benefits include coordination and quality improvement, while barriers include cost, skill, standards, and fragmented processes	The questionnaire should measure both perceived value and implementation constraints
AI in construction [4–7,20]	AI supports prediction, automation, and decision support, but it depends on data quality and organizational learning	AI items should be operationalized around practical planning tasks rather than abstract technological capability
Technology acceptance [10,20,23]	Perceived usefulness and ease of use influence user intention and acceptance of digital tools	User acceptance should be analyzed separately from organizational maturity
TOE adoption theory [11,21]	Technology adoption is affected by technological readiness, organizational support, and the external environment	Barriers should be grouped into technology, organization, and environment dimensions
IPA priority analysis [12,13]	Importance-performance gaps translate stakeholder perception into action-oriented quadrants	The final output should identify high-importance/low-performance priorities for strategic intervention

Source: Author's compilation based on literature review [1–23]

The literature synthesis indicates that the adoption of BIM and AI should be examined as a socio-technical transformation process. From the technical perspective, BIM and AI require interoperable software, reliable data, model quality, and secure information exchange. At the user level, BIM and AI adoption depends on the practical value that users experience in their daily tasks. The technologies are more likely to be accepted when they help speed up work, reduce repetitive activities, improve coordination, and make project information easier to access. Ease of use is also important, since tools that are difficult to learn may discourage regular use. At the organizational level, successful adoption requires management support, training, budget commitment, and readiness to adapt work processes. External factors also play a role, including market pressure, client requirements, regulations, and professional standards. These different viewpoints support the use of TAM, TOE, maturity assessment, and IPA as an integrated evaluation approach in this study.

METHOD

Research design, case context, and sampling

In this research, survey responses were used as the main basis for understanding BIM and AI adoption in construction planning services. Qualitative input was added to help explain the survey results more clearly. The analysis focused on how mature the implementation is, how users perceive the technologies, what barriers are still faced, and which indicators need more attention based on the importance-performance gap. Qualitative input is then used to refine the indicators, explain the survey results in more detail, and develop recommendations that are realistic for management to apply. This design is relevant because adopting BIM and AI is not only about introducing software but also about preparing users, adjusting workflows, improving data readiness, gaining management support, and responding to client and industry expectations.

The study was conducted in three design-consultant organizations involved in construction planning: PT MBJ, Formata.id, and PT KASS. These organizations were chosen because BIM has already been introduced or is being developed in their work processes, while AI-related practices are beginning to appear in activities such as document review, design support, data processing, automation, and decision support. The respondents were professionals involved in construction planning, including architects, engineers, BIM modelers, BIM coordinators, project managers, and management representatives. They were selected purposively so that the data came from people who were familiar with planning workflows and the use of digital technology in their work. The main survey involved at least 30 respondents and was complemented by semi-structured interviews with key informants who had knowledge of BIM, AI, and organizational decision-making.

Table 2. Consolidated research design, data sources, and outputs

Research objective	Evidence and data source	Analytical technique	Main output
Evaluate BIM and AI implementation and acceptance	Survey responses from planning professionals; interview clarification from managers, architects, engineers, and BIM-related roles	Descriptive statistics using BIM-AI maturity indicators and TAM constructs	Profile of current implementation maturity, perceived usefulness, and perceived ease of use
Identify adoption barriers	Importance and performance scores for technological, organizational, environmental, and user-acceptance indicators	TOE-based grouping, mean comparison, gap analysis, and IPA preparation	Barrier profile across technology readiness, organizational support, external environment, and user acceptance
Prioritize strategic improvement	Integrated survey results, IPA quadrants, and qualitative interpretation from interviews	Importance-Performance Analysis and strategic synthesis	Priority improvement areas and practical recommendations for design consultants

Source: Author's elaboration (2025)

Instrument development and measurement structure

The questionnaire was developed by drawing on four related areas of literature. The first relates to BIM and AI maturity, which was used to assess how far digital tools have become part of everyday planning work. Second, the Technology Acceptance Model (TAM) is used to measure perceived usefulness and perceived ease of use because user acceptance influences whether a technology becomes part of routine work. Third, the Technology-Organization-

Environment (TOE) framework is used to classify implementation barriers into technological readiness, organizational capacity, and external environmental pressure. Fourth, Importance-Performance Analysis (IPA) is used to convert stakeholder perception into prioritized action by comparing the importance and performance level of each indicator.

The instrument uses a five-point Likert scale. For implementation maturity and acceptance, respondents assess the level of agreement or condition reflected by each item. For the barrier and prioritization analysis, each indicator is assessed using two dimensions: importance and performance. The importance score reflects how critical the indicator is for successful BIM-AI implementation, while the performance score reflects how well the organization currently performs on that indicator. This dual-scale structure enables the study to distinguish between issues that are merely weak and issues that are both weak and strategically important.

Table 3. Measurement constructs and operational use in the analysis

Construct	Representative indicators	Operational use
BIM and AI implementation maturity	BIM modeling, multidisciplinary coordination, clash detection, information exchange, AI-based review, automation, design-support use cases	Measures the actual level of digital implementation in planning workflows
Perceived usefulness	Efficiency, work quality, speed, decision support, error reduction, added value for planning outputs	Explains whether users consider BIM and AI beneficial for their work performance
Perceived ease of use	Ease of learning, usability, compatibility with daily tasks, workload effect, confidence in using digital tools	Explains whether users perceive BIM and AI as manageable and acceptable
TOE technology factors	Software availability, hardware, interoperability, data quality, security, digital infrastructure	Identifies technical readiness and data-related constraints
TOE organizational factors	Management support, training, human-resource competence, workflow standards, culture, budget, leadership commitment	Identifies internal organizational enablers and barriers
TOE environmental factors	Client demand, regulation, industry standards, market pressure, competitor adoption, supply-chain readiness	Identifies external drivers and constraints influencing adoption

Source: Author's elaboration based on TAM [10,23], TOE [11,21], and IPA [12,13] frameworks

Validation, survey implementation, and analytical procedure

Before the main survey, the instrument is reviewed through content validation. Expert judgment is used to assess whether each item is relevant, clear, and consistent with the intended construct. The Content Validity Index (CVI) was used to measure the level of agreement among experts. The CVI score for each item helped determine whether a statement could be kept, revised, or removed. Once the content validation was completed, the questionnaire was tested through a pilot study to review item clarity, respondent understanding, and early internal consistency. In the main data set, item validity was checked using item-total correlation, and reliability was examined with Cronbach's alpha. Any item or construct that did not meet the required standard was refined before the results were interpreted.

The main analysis proceeds in four steps. First, respondent characteristics are summarized to describe the professional background of the sample. Second, descriptive statistics are calculated for each construct and indicator to identify the current level of BIM-AI maturity, perceived usefulness, perceived ease of use, and adoption barriers. Third, Importance and performance scores were calculated for each indicator and then plotted to form the IPA quadrants. The results from the survey were further supported by interview findings, which helped explain the meaning behind the numerical scores. By combining both sources of evidence, the final recommendations were developed not only from ranking results but also from the practical context experienced by professionals in design-consultant environments.

Table 4. Analytical protocol and quality-control criteria

Analysis phase	Input data	Quality-control criterion	Reported output
Content validation	Expert rating of item relevance and clarity	I-CVI used to identify items requiring revision or retention	Validated item structure for the main questionnaire
Pilot and main survey testing	Pilot responses and main survey responses	Item-total correlation and Cronbach's alpha were used to check validity and reliability	Reliable constructs and refined indicators
Descriptive analysis	Likert-scale scores for maturity, TAM, and TOE indicators	Mean, standard deviation, frequency, and percentage interpretation	Implementation and acceptance profile
IPA prioritization	Mean importance and performance values for each indicator	Quadrant classification based on overall mean values	Priority map: concentrate here, keep up the good work, low priority, possible overkill
Strategic synthesis	IPA priorities supported by interview evidence and document review	Consistency between quantitative priority and qualitative explanation	Actionable recommendations and implementation roadmap

Source: Author's elaboration based on Creswell (2014) and Yusoff (2019)

Strategy formulation and methodological integration

The final stage uses the analytical results as the basis for developing strategic recommendations for construction planning consultants. Indicators that fall into the high-importance and low-performance quadrant are placed as immediate priorities, since they show areas that are considered important but still need improvement. Indicators with both high importance and high performance are treated as strengths that should be maintained.

Meanwhile, low-importance indicators are interpreted more carefully, so that organizations do not allocate too much effort or investment to areas with limited influence on adoption. The recommendations are grouped into four managerial areas: digital infrastructure and data governance, workflow standardization, user capability development, and organizational policy support.

The method combines quantitative and qualitative evidence so that the results are not based only on survey scores. The survey shows the general pattern across respondents, while the interviews help explain why the pattern appears and what kind of improvement is realistic within the organization. This is especially important for AI adoption. Some organizations may already use BIM in a more structured way, but still face uncertainty about how AI should be applied, what data are needed, who is responsible, how ethical issues should be managed, and how benefits can be measured. For this reason, the method is designed not only to describe the current level of adoption but also to support a staged implementation plan. The process can begin with stabilizing BIM workflows, improving data readiness, testing AI through limited pilot projects, and gradually integrating AI into wider organizational practices.

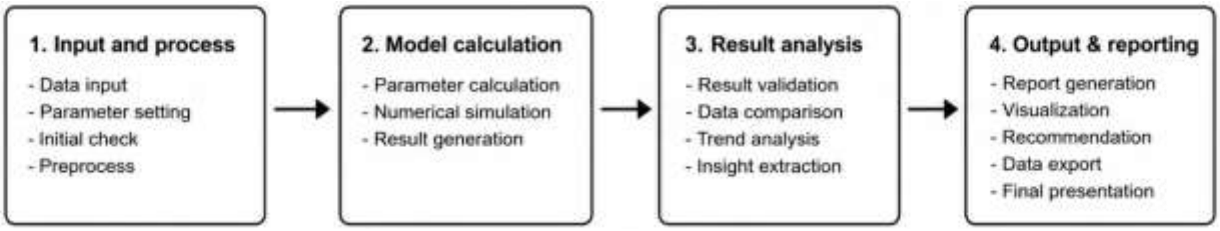

Figure 1. Integrated methodological framework linking TOE, TAM, BIM-AI maturity, and IPA-based strategy formulation

Source: Author's elaboration (2025)

Confidentiality was maintained by reporting the data at the group level rather than at the individual level. Respondent identities, project details, and sensitive company information were not included in the results. The study was also limited to evaluating BIM and AI adoption and preparing strategic recommendations for planning-consultant organizations. It did not develop AI models or directly assess construction-site performance. With this scope, the framework can be used as an internal review tool and repeated as BIM and AI practices become more established.

RESULTS AND DISCUSSION

Integrated evaluation framework and interpretation logic

The survey involved 30 respondents from design-consultant organizations and resulted in an overall BIM-AI maturity score of 3.97 out of 5.00, or 79.44%. This indicates that digital technology has already been used in construction planning activities, although its maturity varies between BIM and AI applications. BIM-related functions showed stronger implementation, particularly clash detection (X1.3 = 4.23), interdisciplinary BIM coordination (X1.2 = 4.10), and design modeling (X1.1 = 4.00). AI adoption appears to be less mature than BIM adoption. This can be seen from the lower scores for AI use in design analysis or data processing (X1.4 = 3.73), integrated BIM-AI planning (X1.6 = 3.87), and AI's contribution to planning efficiency (X1.5 = 3.90). In other words, BIM has become a more familiar part of daily planning work, whereas AI is still developing as a practical tool within the organizations.

Technology acceptance is also high. The overall TAM score is 4.16 out of 5.00, with perceived usefulness (4.23) higher than perceived ease of use (4.09). The highest acceptance scores are related to work efficiency (X2.1.1 = 4.30), making work easier (X2.2.4 = 4.30), accelerating work processes (X2.1.3 = 4.27), and adding value to work (X2.1.5 = 4.27). The score for ease of learning was 3.80, which shows that this area still needs attention. Respondents may already see the benefit of BIM-AI, but learning how to use the tools in daily planning work is not always simple. This means that practical training, clearer guidance, and easier user support are still needed before BIM-AI can be used more regularly. This is consistent with the technology acceptance perspective, which explains that people are more likely to use digital tools when they find them useful and easy to apply in daily work [10,20,23]. Therefore, training, user guidance, and practical usability support are still needed so that positive perceptions can develop into consistent adoption.

Table 5. Summary of BIM-AI maturity, TAM, TOE, and readiness scores

Construct / metric	Mean score	Score %	Category	Cronbach alpha	Interpretation
BIM-AI maturity	3.97	79.44	High	0.905	BIM use is stronger than AI and BIM-AI integration.
Perceived usefulness	4.23	84.67	Very high	0.947	Users perceive BIM-AI as beneficial for work performance.
Perceived ease of use	4.09	81.73	High	0.920	Ease of learning and use still requires support.
Overall TAM acceptance	4.16	83.20	High	0.960	Overall acceptance is high.
TOE/ implementation importance	4.10	81.93	High	0.967	Implementation factors are considered important.
TOE/ implementation performance	4.20	84.04	Very high	0.975	Current performance slightly exceeds importance overall.
Overall adoption readiness	4.11	82.23	High	-	The organization-level readiness profile is high.

Source: Primary survey data analysis using SPSS (2025)

TOE implementation factors and reliability interpretation

The TOE-related implementation factors show a balanced pattern between importance and performance. The overall importance score is 4.10, while the overall performance score is 4.20. This indicates that respondents perceive technology, organizational, environmental, usefulness-related, and ease-of-use-related factors as important, while also reporting that organizational performance on these factors is generally adequate. Among the performance results, perceived usefulness had the highest score at 4.32. This was followed by perceived ease of use at 4.23, environmental pressure at 4.18, technology readiness at 4.17, and organizational capability at 4.15. The pattern shows that respondents already recognize the practical value of BIM-AI. However, organizational capability still needs closer managerial attention, especially in relation to internal support, resources, and readiness to manage change.

The reliability check showed that the questionnaire items worked consistently across the main scales. Cronbach's alpha reached 0.905 for BIM-AI maturity, 0.960 for TAM, 0.967 for TOE/implementation importance, and 0.975 for TOE/implementation performance. These results show that the items within each scale were strongly related to one another. Therefore, the data can be used for descriptive interpretation and for identifying improvement priorities through IPA.

Table 6. TOE group scores and reliability summary

Group/ scale	Importance mean	Performance mean	Gap (I-P)	Interpretation
X3.1 Technology readiness	4.14	4.17	-0.03	High performance
X3.2 Organizational capability	4.06	4.15	-0.09	High performance
X3.3 Environmental pressure	4.09	4.18	-0.09	High performance
X3.4 Perceived usefulness drivers	4.08	4.32	-0.24	Very high performance
X3.5 Perceived ease-of-use drivers	4.12	4.23	-0.11	Very high performance
Reliability: BIM-AI maturity	-	-	-	Cronbach alpha = 0.905
Reliability: overall TAM	-	-	-	Cronbach alpha = 0.960
Reliability: implementation importance	-	-	-	Cronbach alpha = 0.967
Reliability: implementation performance	-	-	-	Cronbach alpha = 0.975

Source: Primary survey data analysis using SPSS (2025)

IPA quadrant results and priority ranking

The IPA mapping used the grand mean scores for importance and performance as the quadrant cut-off points, with values of 4.10 and 4.20, respectively. Based on this mapping, five indicators were placed in Quadrant I, or the Concentrate Here quadrant. Nine indicators were categorized in Quadrant II, four in Quadrant III, and one in Quadrant IV. Since the average performance score was slightly higher than the average importance score, the results do not point to a major implementation gap. Instead, the IPA results highlight specific areas that still need attention because their performance remains slightly below the overall benchmark, even though respondents considered them important.

The five Concentrate Here indicators are management support (X3.2.1), compatibility between BIM-AI technology and existing work systems (X3.1.3), integration of BIM and AI systems in the company workflow (X3.1.4), government regulatory support for BIM implementation (X3.3.3), and human-resource competence in BIM-AI use (X3.2.3). These indicators should not be interpreted as weak in absolute terms because their mean scores remain high. Rather, they represent relative priority areas that require further strengthening to ensure that current digital practices can develop into systematic organizational capability. IPA is useful in this context because it translates perception-based importance and performance scores into managerial priorities.

Table 7. IPA priority ranking for Concentrate Here indicators

Rank	Code	Indicator	Importance	Performance	Gap (I-P)	Recommended response
1	X3.2.1	Management support	4.20	4.20	0.00	Strengthen formal management commitment, budget allocation, and BIM-AI governance.
2	X3.1.3	Compatibility with existing workflow	4.10	4.10	0.00	Improve interoperability and align BIM-AI tools with existing planning workflows.
3	X3.1.4	Integrated BIM-AI systems in workflow	4.10	4.13	-0.03	Develop integrated BIM-AI workflow protocols and shared data procedures.
4	X3.3.3	Government regulatory support	4.10	4.13	-0.03	Align internal standards with government BIM guidance and digital-deliverable requirements.
5	X3.2.3	Human-resource competence	4.10	4.20	-0.10	Provide role-based training in BIM coordination, AI literacy, and data management competence.

Source: Primary survey data analysis (2025)

Discussion and strategic implications for design consultants

The empirical results show that BIM-AI adoption among the observed design consultants is not starting from a low baseline. Respondents report high maturity, high acceptance, high implementation importance, and high implementation performance. However, the pattern of results also shows that BIM is more mature than AI. BIM is already used for modeling, coordination, and clash detection, while AI-related planning applications still require clearer use cases, stronger data readiness, and user capability development. This finding suggests that BIM can serve as the main foundation for managing project information. AI, on the other hand, still depends on reliable digital data and organizational learning before it can function consistently as a decision-support tool.

The improvement process should begin with the systems that are already used in daily work. BIM workflows need to be made more consistent first, for example through agreed modeling rules, coordination routines, revision control, and regular model checks. The organization can then focus on making project data clearer and easier to access by setting consistent naming rules, using shared data environments, preparing object libraries, and defining access and editing rights for specific information. Once the BIM workflow and project data are more stable, AI can be tested in limited but useful areas, such as checking documents, searching design standards, supporting quantity reviews, or finding lessons learned from past projects. Over time, these practices should be supported by clear responsibilities, regular training, management review, and IPA-based monitoring. In this way, BIM-AI adoption can grow gradually with the organization's routines and external requirements, as suggested by the TOE perspective.

Table 8. Updated staged BIM-AI implementation roadmap based on questionnaire results

Stage	Empirical basis	Main action	Performance signal
1. BIM workflow stabilization	BIM indicators are stronger than AI indicators	Standardize modeling, coordination, clash detection, and revision-control procedures	Consistent BIM outputs across projects and disciplines
2. Data readiness and interoperability	X3.1.3 and X3.1.4 fall into Concentrate Here	Develop shared data environment, naming rules, object libraries, and interoperability standards	Reusable and reliable digital information for planning and analytics
3. User capability and AI literacy	Ease of learning is the lowest TAM item and HR competence is a priority	Provide role-based BIM-AI training, mentoring, internal use-case demonstrations, and helpdesk support	Higher confidence, lower learning difficulty, and broader daily use
4. Governance and management support	Management support is the first IPA priority	Assign responsible roles, approve implementation budgets, and monitor BIM-AI KPIs	Digital adoption becomes organizational rather than individual
5. Regulatory and client alignment	Regulatory support appears in Concentrate Here	Align internal deliverables with public BIM guidance, client requirements, and contractual digital standards	Better readiness for digital-deliverable requirements

Source: Author's synthesis based on questionnaire results (2025)

Implications and limitations

For construction-management practice, the findings offer a practical basis for setting BIM-AI adoption priorities. Since the overall performance score is slightly higher than the importance score, the main issue is no longer awareness of digital technology, but how to make its use more consistent within the organization. This means that design consultants should not treat BIM-AI adoption simply as a matter of purchasing or introducing software. The more important task is to turn positive user acceptance into standard workflows, reliable data structures, clear governance, and practical AI applications that can support daily planning work.

This study involved 30 respondents from three design-consultant organizations in Bali, so the results should be understood within that specific context. The findings give insight into the selected firms, rather than representing all construction-planning consultants. Future studies could include more organizations, compare firms with different levels of digital maturity, and see whether the same maturity–TAM–TOE–IPA framework produces similar priorities in other regions, project types, or organizational settings.

CONCLUSION

This study evaluated BIM and AI adoption in construction planning by integrating BIM-AI maturity assessment, TAM, TOE, and IPA. Based on questionnaire data from 30 respondents, the overall BIM-AI maturity score is 3.97, the overall TAM score is 4.16, and the overall adoption-readiness score is 4.11, indicating a high level of readiness among the observed design consultants. The implementation-factor results were positive, with importance and performance scores of 4.10 and 4.20. The slightly higher performance score suggests that current BIM-AI practices are generally in line with, or slightly above, what respondents considered important. The instrument also showed strong reliability, with Cronbach's alpha values above 0.90 across the main scales. Based on the IPA results, five indicators need priority attention: management support, workflow compatibility, integrated BIM-AI systems, regulatory support, and human-resource competence. These findings indicate that the next phase of BIM-AI adoption should place more attention on governance, system interoperability, data readiness, role-based training, and alignment with digital-deliverable requirements. The maturity–TAM–TOE–IPA framework can therefore be used as a practical basis for assessing digital readiness and planning BIM-AI implementation in stages for design consultants.

REFERENCES

Ahuja, R., Sawhney, A., Jain, M., Arif, M., & Rakshit, S. (2020). Factors influencing BIM adoption in emerging markets-the case of India. *Smart and Sustainable Built Environment*. https://doi.org/10.1108/SASBE-07-2019-0090

Anh, P. X., Toan, N. Q., Nam, T. P., Long, H. D., & Thang, D. D. (2023). BIM competency in personnel recruitment in Vietnam construction enterprises. *Archives of Civil Engineering*, *69*, 381–397. https://doi.org/10.24425/ace.2023.145274

Attia, A. R. (2025). The impact of integrating artificial intelligence and Building information modeling (BIM) systems on the development of construction methodologies. *Journal of Umm Al-Qura University for Engineering and Architecture*. https://doi.org/10.1007/s43995-025-00193-2

Bukunova, O., & Bukunov, A. (2021). Building Information Modeling for Sustainable Construction. *IOP Conference Series: Materials Science and Engineering*, *1079*, 32080. https://doi.org/10.1088/1757-899x/1079/3/032080

Chan, D. W. M., Olawumi, T. O., & Ho, A. M. L. (2019). Perceived benefits of and barriers to Building Information Modelling (BIM) implementation in construction: The case of Hong Kong. *Journal of Building Engineering*, *25*. https://doi.org/10.1016/j.jobe.2019.100764

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 319–340.

Khan, A. M., Alrasheed, K. A., Waqar, A., Almujibah, H., & Benjeddou, O. (2024). Internet of things (IoT) for safety and efficiency in construction building site operations. *Scientific Reports*, *14*. https://doi.org/10.1038/s41598-024-78931-0

Martilla, J. A., & James, J. C. (1977). Importance-performance analysis. *Journal of Marketing*, *41*(1), 77–79. https://doi.org/10.1177/002224297704100112

Memon, A. H., Rahman, I. A., Memon, I., & Azman, N. I. A. (2014). BIM in Malaysian construction industry: Status, advantages, barriers and strategies to enhance the implementation level. *Research Journal of Applied Sciences, Engineering and Technology*, *8*, 606–614. https://doi.org/10.19026/rjaset.8.1012

Mtya, A., & Windapo, A. (2017). *Drivers And Barriers To The Adoption Of Building*

Information Modelling (BIM) By Construction Firms In South Africa.
Na, S., Heo, S., Choi, W., Kim, C., & Whang, S. W. (2023). Artificial Intelligence (AI)-Based Technology Adoption in the Construction Industry: A Cross National Perspective Using the Technology Acceptance Model. *Buildings*, *13*. https://doi.org/10.3390/buildings13102518
Oh, H. (2001). Revisiting importance-performance analysis. *Tourism Management*, *22*(6), 617–627. https://doi.org/10.1016/S0261-5177(01)00036-X
Oliveira, T., & Fraga Martins, M. (2011). Literature Review of Information Technology Adoption Models at Firm Level. *The Electronic Journal Information Systems Evaluation*, *14*, 110.
Pan, Y., & Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Automation in Construction*, *122*. https://doi.org/10.1016/j.autcon.2020.103517
Rashidi, A., Chan, D. W. M., Ravanshadnia, M., Sarvari, H., & Tajaddini, A. (2024). Applying Building Information Modelling (BIM) Technology in Pre-Tender Cost Estimation of Construction Projects: A Case Study in Iran. *Buildings*, *14*. https://doi.org/10.3390/buildings14051260
Sacks, R., Eastman, C. M., Lee, G., & Teicholz, P. M. (2018). *BIM Handbook: A Guide to Building Information Modeling for Owners, Designers, Engineers, Contractors, and Facility Managers*. Wiley.
Sacks, R., Girolami, M., & Brilakis, I. (2020). Building Information Modelling, Artificial Intelligence and Construction Tech. *Developments in the Built Environment*, *4*. https://doi.org/10.1016/j.dibe.2020.100011
Sadiq, R. B., Safie, N., Abd Rahman, A. H., & Goudarzi, S. (2021). Artificial intelligence maturity model: A systematic literature review. *PeerJ Computer Science*, *7*, 1–27. https://doi.org/10.7717/peerj-cs.661
Succar, B. (2009). Building information modelling framework: A research and delivery foundation for industry stakeholders. *Automation in Construction*, *18*, 357–375. https://doi.org/10.1016/j.autcon.2008.10.003
Tanne, Y. A., Rivana, D., Ramadan, R., & Farhani, S. (2025). BIM for efficiency and sustainability in construction: a case study in Indonesia. *Discover Civil Engineering*, *2*. https://doi.org/10.1007/s44290-025-00228-6
Tornatzky, L. G., & Fleischer, M. (1990). *The Processes of Technological Innovation*. Lexington Books.
Van Roy, A. F., & Firdaus, A. (2020). Building Information Modelling in Indonesia: Knowledge, Implementation and Barriers. *Journal of Construction in Developing Countries*, *25*, 199–217. https://doi.org/10.21315/jcdc2020.25.2.8
Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 425–478.
Yusoff, M. S. B. (2019). ABC of Content Validation and Content Validity Index Calculation. *Education in Medicine Journal*, *11*(2), 49–54. https://doi.org/10.21315/eimj2019.11.2.6