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Integrating the Artificial Intelligence Technology Acceptance Model (AI-TAM) and Task-AI Technology Fit (TATF) to Improve Construction Project Success

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ABSTRACT : Construction projects are complex because they involve many activities, many parties, uncertainty, and interdependent relationships between work packages. The development of artificial intelligence offers opportunities to support these needs. However, technological potential does not automatically guarantee optimal utilization, because the results obtained also depend on user readiness and on the fit of the technology with work requirements. This study aims to develop and test a conceptual model that integrates the Artificial Intelligence Technology Acceptance Model (AI-TAM) and Task-AI Technology Fit (TATF). The variables examined in AI-TAM include AI Output Quality, AI Output Trust, Familiarity with Scenario, Perceived Ease of Use, Perceived Usefulness, and Behavioral Intention, while TATF covers Task Characteristics, AI Technology Characteristics, and Task–Technology Fit. The model further examines the relationships of Behavioral Intention and Task–Technology Fit with AI Use, the relationship of AI Use with Project Management Performance (PMP), and the relationship of PMP with Project Success (PS). This study uses a quantitative explanatory approach with a survey method. The sampling technique is purposive sampling, with a minimum sample of approximately 155 respondents based on the inverse square root method. The variables are measured on a five-point Likert scale, and the analysis uses Partial Least Squares–Structural Equation Modeling (PLS-SEM). The results are expected to produce a framework and recommendations for AI use in construction projects in Indonesia.

Keywords - AI-TAM, Task-AI Technology Fit, AI Use, Project Management Performance, Project Success, Construction Projects

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1. INTRODUCTION

Construction projects are complex because they involve many activities, many parties, uncertainty, and interdependent relationships between work packages [1], [2]. In the Indonesian context, Damayanti et al. [3] identified structural, social, and emergent complexity in infrastructure megaprojects. On the Trans-Island Highway toll road project, costs exceeded the budget by 11% and completion was 20 months later than originally planned [3]. Furthermore, an analysis of seven Indonesian infrastructure megaprojects found four configurations of complexity conditions and leadership competencies that can lead to high megaproject

performance [4]. These findings underline the need for management that supports coordination, risk control, information processing, and decision-making [3], [4].

The development of artificial intelligence offers opportunities to support these needs [5], [6]. Pan and Zhang [5] reviewed the application of artificial intelligence to modeling, prediction, optimization, information processing, and risk management in construction management. Vo et al. [6] mapped its application practices, while Samir et al. [7] examined its opportunities and barriers in construction planning and scheduling. These applications show the potential of artificial intelligence to support project work. However, technological potential does not automatically guarantee optimal utilization, because the results obtained also depend on user readiness and on the fit of the technology with work requirements [5], [6], [7].

A survey by the Project Management Institute (PMI) [8] in 2023 reported that 21% of respondents always or often used artificial intelligence in managing projects, while 82% of senior leaders expected the technology to affect how projects are carried out within the next five years. PMI also reported that about 20% of project managers had good or extensive practical experience in using artificial intelligence, while 49% had little or no experience or understanding of the technology [8]. Separately, a survey by the Association for Project Management of 1,000 project professionals in the United Kingdom showed that the use of artificial intelligence in construction-sector organizations increased from 15% in 2023 to 75% in 2025, while another 25% planned to adopt it [9]. Meanwhile, the main barriers included limited knowledge and training (49%), data security and privacy (44%), workflow integration (42%), and inaccuracy of or low trust in outputs (41%) [9]. Although these figures reflect organizational adoption in the United Kingdom rather than individual use or Indonesian conditions, they show the importance of user readiness, trust in outputs, and the fit of the technology with task requirements [8], [9], [10], [11].

Barriers to the utilization of artificial intelligence show the importance of understanding the factors that influence user acceptance. The Artificial Intelligence Technology Acceptance Model (AI-TAM) can be used to explain user acceptance of artificial intelligence technology, including the role of output quality and trust in the technology [11]. Na et al. [12] examined the acceptance of artificial intelligence-based technologies in construction firms by integrating the Technology Acceptance Model and the Technology–Organization–Environment framework. Meanwhile, Baroni et al. [11] developed AI-TAM to examine user acceptance and collaborative intention in human-in-the-loop artificial intelligence applications. In the construction context, Regona et al. [13] examined the role of trust in the adoption and actual use of artificial intelligence. Overall, these studies show that user acceptance is related not only to the assessment of the technology, but also to output quality, trust, and the intention to use the technology at work.

Although user acceptance is important, willingness to use a technology is not sufficient to explain whether the technology truly fits work requirements. The fit between task characteristics and technology is another aspect that needs attention. Jeyaraj [14], through a meta-regression of 104 findings from 100 studies, showed that the relationships between Task–Technology Fit and various outcome variables can differ according to the research context and how technology fit is measured. This finding underlines the importance of considering task characteristics and the context of use when examining the fit between technology and work [14]. In the context of artificial intelligence, Boulitama et al. [10] developed the Task-AI Technology Fit (TATF) approach to examine the relationships of task characteristics and artificial intelligence technology characteristics with task–technology fit. This approach provides a basis for understanding that the utilization of artificial intelligence depends not only on user acceptance, but also on its fit with work requirements [10], [14].

In addition to acceptance and technology fit, the actual use of artificial intelligence also needs to be examined in relation to project management performance. Boulitama et al. [10] discussed the benefits of using artificial intelligence for strategic decision-making performance, while Samir et al. [7] examined its application in construction planning and scheduling. Alayed [15] studied project management performance in the manufacturing sector in Saudi Arabia. Although these studies describe the potential benefits of artificial intelligence, differences in context and performance measures indicate the need for further testing of the relationship between the actual use of artificial intelligence and project management performance in construction projects in Indonesia [7], [10], [15]. Furthermore, project management performance needs to be

distinguished from project success. Project management performance concerns the performance of project management functions, while project success concerns the achievement of project outcomes. Mir and Pinnington [16] found a positive relationship between PMP and PS in project-based organizations in the United Arab Emirates. In a more specific context, Al-Balawneh and Tarabieh [17] tested the relationship between these two variables in construction projects in Jordan. Based on 165 analyzed responses from project managers, the study showed that PMP has a positive and significant effect on project success [17]. The study also used a measurement instrument comprising five items for PMP and seven items for PS, adapted from previous studies [17]. These findings provide empirical support for testing the relationship between project management performance and project success in the construction context [16], [17].

Based on this discussion, previous studies have examined the acceptance of artificial intelligence, the fit of technology with task requirements, actual use, and the benefits of technology for various aspects of performance [7], [10], [11], [12], [13], [14], [15]. The relationship between Project Management Performance and Project Success has also been studied, including in the context of construction projects [16], [17]. However, these aspects still need to be examined in a single model, particularly in construction projects in Indonesia. This study aims to develop and test a conceptual model that integrates the Artificial Intelligence Technology Acceptance Model (AI-TAM) and Task-AI Technology Fit (TATF). The variables examined in AI-TAM include AI Output Quality, AI Output Trust, Familiarity with Scenario, Perceived Ease of Use, Perceived Usefulness, and Behavioral Intention, while TATF covers Task Characteristics, AI Technology Characteristics, and Task–Technology Fit. The model further examines the relationships of Behavioral Intention and Task–Technology Fit with AI Use, the relationship of AI Use with PMP, and the relationship of PMP with PS.

2. LITERATURE REVIEW

2.1 Artificial Intelligence in Construction Project Management

The utilization of AI has been examined in various activities in construction and project management. These applications include support for project processes [5], [6], decision-making [18], risk management [19], and planning and scheduling [7]. Studies at this level generally show improvements in accuracy and speed in specific functions, for example in project decision-making [18], while also noting constraints such as data quality, limited skills, and connectivity. Beyond individual-level factors, the construction literature also discusses drivers, barriers, strategies, and readiness for AI adoption covering technological, organizational, resource, and environmental factors [7], [20], [21]. Most of these studies are descriptive or exploratory, for example through factor grouping with PCA [20] and priority weighting of barriers with AHP [21], so they do not yet explain how adoption readiness continues into realized AI use.

2.2 AI Technology Acceptance Model

The Technology Acceptance Model (TAM) was introduced by Davis (1989) as a development of the Theory of Reasoned Action (TRA) proposed by Fishbein and Ajzen. The model was designed to explain the factors that influence the acceptance and use of information technology in organizational contexts [22]. TAM states that an individual's intention to use a system is determined by two main cognitive beliefs, namely Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) [22]. Venkatesh and Bala (2008) later extended TAM2 into TAM3, which specifically expanded the determinants of Perceived Ease of Use [23]. The Artificial Intelligence Technology Acceptance Model (AI-TAM) was developed by Baroni et al. [11] to explain user acceptance of AI systems. AI-TAM retains the main TAM constructs, namely PU, Ease of Use (EOU), and BI, and adds constructs more specific to AI characteristics, namely Perceived Quality of AI Results, Trust in AI Results, Familiarity, and Collaborative Intention. In the initial structure of AI-TAM, AI output quality is related to EOU and to trust in AI outputs. This trust is in turn related to PU. Familiarity is also placed as a factor related to PU. The basic TAM relationships are retained through the relationships of EOU with PU and BI and the relationship of PU with BI. Love et al. [24] conceptually emphasized that the explainability of AI outputs is a prerequisite for the development of such trust in construction organizations.

AI-TAM by Baroni et al. [11] was developed for human-in-the-loop AI applications and also includes Collaborative Intention. In addition, AI Functioning was treated as an experimental condition or control rather

than an acceptance construct. The structure used in this study is derived from the initial theoretical model of AI-TAM and is therefore not intended to replicate the entire final empirical model of Baroni et al. Collaborative Intention is not used because this study focuses on the acceptance and use of AI in project work, while AI Functioning is not used because it is not a user behavior construct. The relevant relationships are retested in the context of construction projects.

2.3 Task–AI Technology Fit

The concept of Task–Technology Fit (TTF) was developed by Goodhue and Thompson [25] within the Technology-to-Performance Chain. TTF explains the degree of fit between technology capabilities and users' task requirements. Technology can provide benefits when its functions match the tasks to be completed. Within this framework, task characteristics and technology characteristics form the basis of fit, while TTF is in turn related to use and performance. In the context of AI, Boulitama et al. [10] developed this concept into Task-AI Technology Fit (TATF), namely the degree of fit between AI capabilities and the demands of managerial tasks. In their model, Managerial Task Characteristics and AI Technology Characteristics are placed as the factors that shape TATF. TATF is then linked to AI Technology Use and Strategic Decision Performance Benefits, while AI use is also linked to decision-making performance. The model was tested on 360 managers in Morocco [10]. Jeyaraj [14], through a meta-regression of 104 findings from 100 TTF studies, showed that TTF effects are less often significant for usage behavior than for user perceptions, and are more consistent when TTF is measured directly. Jeyaraj's findings support the decision to measure TTF directly and to model task characteristics and AI technology characteristics explicitly.

2.4 Project Management Performance and Project Success

Project Management Performance (PMP) is a concept used to assess the performance of project management. PMP differs from Project Success (PS), because PMP focuses on the performance of project management, while PS concerns project success as a broader outcome [16]. Shenhar et al. [26], through the Diamond Model of Project Success, emphasized that project success is multidimensional and cannot be measured only at project completion, with four main dimensions, namely Project Efficiency, Impact on Customer, Business Impact, and Preparing for the Future. Zheng and Zwikael [27] discussed project management success in relation to broader project outcomes. In the context of construction projects, Al-Balawneh and Tarabieh [17] examined PMP as a variable linking management practices with project success. The study involved 165 respondents from first-class construction contracting companies in Jordan and showed that PMP has a positive and significant effect on PS. Based on Al-Balawneh and Tarabieh [17], PMP in this study is measured through five items, namely project team collaboration, project team competence, project progress management strategy, monitoring through the project management life cycle, and monitoring of project key performance indicators. Project success is measured through seven items, namely time performance, budget performance, scope achievement, quality achievement, stakeholder expectations, safety and environmental conditions, and overall project success.

2.5 Conceptual Framework

AI Output Quality (AOQ) is used to explain AI Output Trust (AOTR) and Perceived Ease of Use (PEOU). Furthermore, AOTR, Familiarity with the Scenario (FS), and PEOU are used to explain Perceived Usefulness (PU). PEOU and PU are used to explain Behavioral Intention (BI), and BI is then used to explain AI Use (AIU). In the TATF part, Task Characteristics (TAC) and AI Technology Characteristics (AITC) are used to explain Task–Technology Fit (TTF), and TTF is then used to explain AIU. In the next stage, AIU is used to explain Project Management Performance (PMP), and PMP is then used to explain Project Success (PS). Thus, the exogenous latent variables that are not influenced by other constructs in the model are AOQ, FS, TAC, and AITC. Meanwhile, AOTR, PEOU, PU, BI, TTF, AIU, PMP, and PS are endogenous latent variables because they are influenced by other constructs in the model. The conceptual research model is shown in Fig. 1.

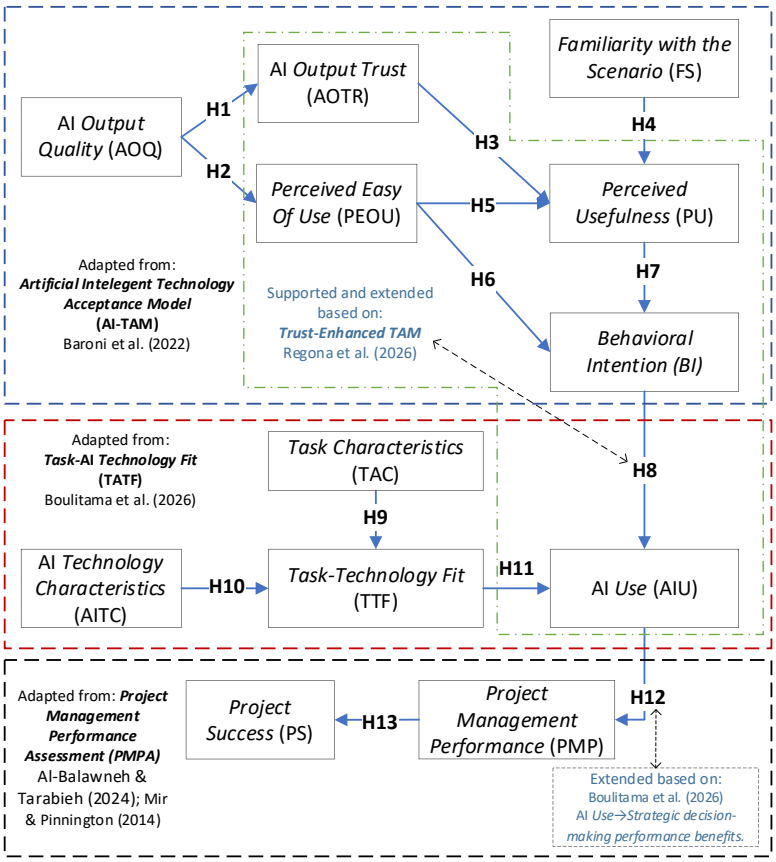

Fig. 1 Conceptual research model

2.6 Hypotheses Development

AI output quality (AOQ). According to Baroni et al. [11], AOQ is one of the constructs in AI-TAM related to users' trust in AI outputs. AI outputs that are predictable and reliable can increase users' confidence in the results provided by AI. AOQ is also related to Perceived Ease of Use (PEOU). AI outputs that are clear and easy to understand can reduce users' effort in understanding the results provided by the system. Baroni et al. [11] placed these relationships in the initial AI-TAM model. Based on these studies, the first and second hypotheses are formulated as follows:

H1: AI output quality has a positive effect on AI output trust in the use of AI in construction projects.

H2: AI output quality has a positive effect on perceived ease of use in the use of AI in construction projects.

AI output trust (AOTR). AOTR indicates the level of users' trust in AI outputs. In AI-TAM, trust in AI outputs is related to users' assessment of the usefulness of the technology [11]. The more users trust AI outputs, the more likely AI is to be seen as useful in supporting project work. Based on this study, the third hypothesis is formulated as follows:

H3: AI output trust has a positive effect on perceived usefulness in the use of AI in construction projects.

Familiarity with scenario (FS). FS describes users' level of experience with and understanding of the situations or work contexts supported by AI. Baroni et al. [11] placed FS as a factor that can influence Perceived Usefulness (PU). Based on this study, the fourth hypothesis is formulated as follows:

H4: Familiarity with the scenario has a positive effect on perceived usefulness in the use of AI in construction projects.

Perceived ease of use (PEOU) and perceived usefulness (PU). PEOU is a main construct in the Technology Acceptance Model (TAM). According to Davis [22], technology that is easier to use tends to be judged more useful by users. The relationship between PEOU and PU is also present in the development of AI-TAM [11]. In addition to influencing perceived usefulness, ease of use is also related to users' intention to use technology. In AI-TAM, PEOU is placed as one of the factors that influence Behavioral Intention (BI) [11]. PU describes the

extent to which users judge that using a technology can benefit their work. PU is one of the factors related to the formation of the intention to use technology [11], [12]. Based on these studies, the fifth, sixth, and seventh hypotheses are formulated as follows:

H5: Perceived ease of use has a positive effect on perceived usefulness in the use of AI in construction projects.

H6: Perceived ease of use has a positive effect on behavioral intention in the use of AI in construction projects.

H7: Perceived usefulness has a positive effect on behavioral intention in the use of AI in construction projects.

Behavioral intention (BI). BI describes users' intention to use AI in their work. Regona et al. [13] showed that BI is related to realized AI use among construction professionals. In this study, BI is used to explain the actual use of AI through AI Use (AIU). Based on this study, the eighth hypothesis is formulated as follows:

H8: Behavioral intention has a positive effect on AI use in construction projects.

Task characteristics (TAC) and AI technology characteristics (AITC). TAC describes the characteristics of the tasks performed by users in their work. Boulitama et al. [10] placed task characteristics as one of the factors that influence the fit between tasks and AI technology. AITC describes the characteristics and capabilities of AI technology in supporting users' work. Boulitama et al. [10] placed AI technology characteristics as one of the factors that influence the fit between technology and tasks. Based on these studies, the ninth and tenth hypotheses are formulated as follows:

H9: Task characteristics have a positive effect on task–technology fit in the use of AI in construction projects.

H10: AI technology characteristics have a positive effect on task–technology fit in the use of AI in construction projects.

Task–technology fit (TTF). TTF explains the degree of fit between technology capabilities and users' task requirements. According to Goodhue and Thompson [25], technology can provide benefits when it fits the tasks it supports. Subsequent studies have also shown a link between TTF and the use and utilization of technology [10], [28]. Thus, the more AI capabilities fit the needs of project work, the more likely AI is to be used in that work. Based on these studies, the eleventh hypothesis is formulated as follows:

H11: Task–technology fit has a positive effect on AI use in construction projects.

AI use (AIU). AIU describes the actual use of AI in project work activities. Boulitama et al. [10] showed that AI use is related to performance benefits at the decision-making level. In this study, this relationship is developed by linking AIU with Project Management Performance (PMP) to examine the relationship between AI use and project management performance. Based on this study, the twelfth hypothesis is formulated as follows:

H12: AI use has a positive effect on project management performance in construction projects.

Project management performance (PMP). PMP describes performance in managing a project. Mir and Pinnington [16] showed that PMP is related to Project Success (PS), with better project management performance supporting the achievement of project success. Based on this study, the thirteenth hypothesis is formulated as follows:

H13: Project management performance has a positive effect on project success in construction projects.

3. RESEARCH METHODOLOGY

3.1 Research Design, Population, and Sampling

This study uses a quantitative explanatory approach with a survey method. A quantitative approach is used because the research data are obtained through a questionnaire and analyzed in numerical form. An explanatory approach is used because this study aims to explain the relationships between constructs in an artificial intelligence (AI) adoption model in construction projects. The population of this study comprises individuals involved in construction project management activities in Indonesia, such as project managers, site engineers, supervisors, quantity surveyors, estimators, planners/schedulers, drafters, or other relevant technical staff. The size of the population cannot be determined precisely because of limited data access and the dynamic, project-based nature of the construction industry. The sampling technique used in this study is purposive sampling, namely sample selection based on specific criteria in line with the research objectives. The respondent criteria are: (a) involved in construction projects anywhere in Indonesia; (b) having a role or

involvement in construction project management activities; (c) having experience with or having used artificial intelligence (AI) to support project work; and (d) having used AI on a completed construction project, which serves as the reference project for assessing PMP and PS. The AI use referred to is not limited to a single application, but may include ChatGPT, Gemini, Copilot, predictive analytics, computer vision, natural language processing, or other AI applications relevant to project work.

The minimum sample size in this study refers to the inverse square root method recommended by Hair et al. [29], because the 10-times rule is considered unreliable as a basis for determining sample size in PLS-SEM. Assuming that the minimum path coefficient expected to be significant lies in the range of 0.11–0.20 at a 5% significance level, the minimum required sample is approximately 155 respondents [29]. This assumed minimum path coefficient will be confirmed using the results of the instrument pilot test. This number is used as the minimum limit. The study targets at least 155 respondents who meet the research criteria, plus a reserve to anticipate responses that are incomplete or fail the attention-check item.

3.2 Measurement Instrument

The research material used in this study is primary data obtained from respondents' answers to a questionnaire. The questionnaire was developed from the indicators of the research variables derived from the literature review and the conceptual model. The research instrument is based on the indicators of the constructs AI Output Quality (AOQ), AI Output Trust (AOTR), Familiarity with Scenario (FS), Perceived Ease of Use (PEOU), Perceived Usefulness (PU), BI, TAC, AITC, TTF, AIU, PMP, and PS. The AOQ, AOTR, FS, PEOU, PU, and BI items are adapted from Baroni et al. [11], the TAC, AITC, TTF, and AIU items are adapted from Boulitama et al. [10], and the PMP and PS items are adapted from Al-Balawneh and Tarabieh [17], as shown in Table 1. The variables are measured on a five-point Likert scale to capture respondents' level of agreement with each statement, namely 1 (strongly disagree), 2 (disagree), 3 (neutral), 4 (agree), and 5 (strongly agree).

The PMP items deliberately do not contain the word AI so that the outcome variable is not mixed with its causal variable. The link to AI is established through the reference project, namely a completed construction project that used AI, and through testing the path from AI Use to PMP.

Table 1. Constructs, measurement items, and sources

Construct	Code	Measurement item	Source
AI output quality	AOQ1	AI outputs tend to be consistent when I use AI for similar project tasks.	[11]
	AOQ2	The outputs provided by AI are generally correct when I check them in project work.	[11]
	AOQ3	AI delivers the outputs I need quickly.	[11]
AI output trust	AOTR1	I am confident that the AI I use works well in supporting project work.	[11]
	AOTR2	I feel that I can rely on AI to obtain correct results in project work.	[11]
	AOTR3	I trust the outputs provided by AI in supporting project work.	[11]
Familiarity with scenario	FS1	I am experienced in handling project work situations similar to those in which I use AI.	[11]
	FS2	I am frequently involved in solving project problems similar to those I handle with AI support.	[11]
	FS3	I am confident that I can handle, on my own, the project work situations in which I use AI.	[11]
Perceived ease of use	PEOU1	Learning to use AI for project work is easy for me.	[11]
	PEOU2	It is easy for me to get AI to produce results that meet my needs.	[11]
	PEOU3	My interaction with AI is clear and understandable.	[11]
	PEOU4	Overall, AI is easy for me to use in project work.	[11]
	PEOU5	It is easy for me to become skillful at using AI in project work.	[11]
Perceived usefulness	PU1	Using AI helps me complete project tasks more quickly.	[11]
	PU2	Using AI improves my effectiveness in performing project tasks.	[11]

Construct	Code	Measurement item	Source
	PU3	Using AI makes it easier for me to complete project work.	[11]
Behavioral intention	BI1	I plan to continue using AI in project work in the next six months.	[11]
	BI2	I am willing to use AI when needed in project work.	[11]
	BI3	I predict that I will use AI in upcoming project tasks.	[11]
Task characteristics	TAC1	The project tasks I perform involve complex information.	[10]
	TAC2	My project tasks require the simultaneous analysis of multiple information sources.	[10]
	TAC3	The tasks I perform in projects are often characterized by uncertainty.	[10]
	TAC4	My project tasks require analytical judgment rather than merely applying existing rules or procedures.	[10]
	TAC5	The project tasks I perform have significant consequences for the project.	[10]
AI technology characteristics	AITC1	The AI I use provides accurate analyses to support project work.	[10]
	AITC2	AI is able to process large volumes of data or information.	[10]
	AITC3	AI provides outputs or recommendations that suit the context of project work.	[10]
	AITC4	The AI I use can be applied to various types of tasks in project work.	[10]
	AITC5	The outputs provided by AI are easy for me to interpret for project work.	[10]
Task–technology fit	TTF1	AI capabilities match the analytical requirements of the project tasks I perform.	[10]
	TTF2	AI effectively supports the way I complete tasks in project work.	[10]
	TTF3	AI functions are suited to the project problems I handle.	[10]
	TTF4	AI helps improve the quality of how I carry out my project tasks.	[10]
	TTF5	AI helps me understand the process of completing project tasks.	[10]
AI use	AIU1	I regularly use AI to analyze information in project work.	[10]
	AIU2	I use AI to support data or information management in project work.	[10]
	AIU3	I use AI to support planning or decision-making in project work.	[10]
	AIU4	AI has become an essential tool in my project work.	[10]
	AIU5	I use insights generated by AI when evaluating important project decisions.	[10]
Project management performance	PMP1	In the reference project, the project team was able to work together to achieve the project objectives.	[17]
	PMP2	In the reference project, the project team had competent members.	[17]
	PMP3	In the reference project, the project strategy emphasized managing project progress.	[17]
	PMP4	In the reference project, the project management life cycle was used to guide progress monitoring.	[17]
	PMP5	In the reference project, project progress was ensured to be in line with the project's key performance indicators.	[17]
Project success	PS1	The reference project was completed on time.	[17]
	PS2	The reference project was completed within budget.	[17]
	PS3	The reference project met the specified scope.	[17]
	PS4	The reference project met the specified quality.	[17]
	PS5	The reference project met stakeholders' expectations.	[17]
	PS6	The reference project met the specified safety and environmental requirements.	[17]
	PS7	Overall, the reference project was a success.	[17]

3.3 Instrument Validation

Before it is used for data collection, the instrument is validated in four stages: (1) translation and back-translation of the items from English; (2) a content validity test using Claude AI; (3) a readability test (cognitive pretest) using Claude AI; and (4) a pilot test with approximately 30–50 respondents to screen items based on outer loading, composite reliability, AVE, and HTMT. If the research instrument still requires improvement, the questionnaire statements are refined. Once the instrument is declared feasible, the study proceeds to the data collection stage.

3.4 Data Collection and Analysis

The questionnaire is distributed to respondents who meet the research criteria, namely staff involved in construction projects throughout Indonesia. The questionnaire is distributed in two ways: directly to respondents at project sites, and online using Google Forms shared through professional networks such as project colleagues and construction-related communication groups. During data collection, the number of incoming respondents is monitored to ensure that it meets the target sample. The collected data are then screened to ensure complete answers and the conformity of respondents with the research criteria. This study uses descriptive analysis to provide an initial overview of respondent characteristics and patterns of artificial intelligence (AI) use in construction project work. Descriptive analysis is used as the initial stage before further analysis using Partial Least Squares–Structural Equation Modeling (PLS-SEM).

The analysis uses PLS-SEM because this method can analyze relationships among latent variables simultaneously in a complex research model. PLS-SEM is a variance-based multivariate analysis method that is nonparametric, so it does not strictly require normally distributed data [29], [30]. The questionnaire data are processed using SmartPLS version 3.0. The PLS-SEM analysis in this study is carried out in several stages, namely model specification, parameter estimation, evaluation of the measurement model, and evaluation of the structural model. The measurement model (outer model) is evaluated through indicator reliability (outer loading), internal consistency (composite reliability), convergent validity (average variance extracted), and discriminant validity (Fornell-Larcker criterion or heterotrait-monotrait ratio). The structural model (inner model) evaluation includes collinearity testing using the variance inflation factor (VIF), significance testing of relationships between constructs through bootstrapping based on t-statistics or p-values, testing of the coefficient of determination (R^2), and testing of predictive relevance through blindfolding or other predictive measures consistent with PLS-SEM guidelines.

4. IMPLICATIONS OF THE STUDY

Theoretically, this study is expected to contribute to the development of research on the adoption and use of artificial intelligence (AI) in construction project management through the integration of the Artificial Intelligence Technology Acceptance Model (AI-TAM) and Task-AI Technology Fit (TATF). This study is also expected to broaden understanding of the relationships of AI Use (AIU) with Project Management Performance (PMP) and Project Success (PS). The novelty of this study is the integration of AI-TAM and TATF to examine AI use (AI Use/AIU) in construction projects, and the empirical testing of the model in the context of construction projects in Indonesia.

Practically, this study is expected to serve as a consideration for the construction management sector, project managers, and parties involved in construction projects in the use of AI. The results are expected to produce a framework and recommendations that help identify AI acceptance factors, the fit of AI with tasks, actual AI use, and their relationship with PMP and PS in construction projects in Indonesia.

5. CONCLUSION

Taken together, the hypotheses show the flow of relationships in the AI adoption model developed in this study. The relationships in the model begin with the AI-TAM constructs, which explain user acceptance of AI, and with TATF, which explains the fit between task characteristics and AI technology characteristics. Both approaches are used to explain AIU as the actual use of AI in project work. AIU is then used to explain PMP,

and PMP is used to explain PS as the final outcome of the research model. The research model will then be tested empirically using Partial Least Squares–Structural Equation Modeling (PLS-SEM).

The boundaries of this study are as follows. This study does not develop artificial intelligence (AI) systems, AI algorithms, or new computational models. This study does not test the technical accuracy of AI outputs, such as prediction accuracy, classification accuracy, or algorithm performance. This study does not compare project characteristics across specific regions of Indonesia. Project Management Performance (PMP) and Project Success (PS) are measured based on respondents' perceptions through the questionnaire and do not use objective project data such as actual cost, actual time, or project performance documents.

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