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Impact of Artificial Intelligence Adoption on Sustainable Project Success: Mediating Role of Project Process Automation

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ABSTRACT

The construction and infrastructure sector faces mounting pressure to reconcile escalating project-delivery demands with the imperatives of sustainable development, including economic viability, social equity, and environmental stewardship. Artificial intelligence (AI) adoption has emerged as a potentially transformative lever for addressing these dual challenges; however, the mechanisms through which AI adoption translates into measurable, sustainable project outcomes remain theoretically underspecified and empirically underexplored. This study examines the direct and indirect effects of AI adoption on sustainable project success (SPS) operationalized through the triple bottom line (TBL) framework, with project process automation (PPA) positioned as a mediating mechanism. Grounded in Dynamic Capabilities Theory (DCT), the study conceptualizes AI adoption as a higher-order organizational capability that drives sustainable project outcomes, both directly and by reconfiguring project workflows through automation. A quantitative, cross-sectional research design was employed, with data collected from 250 construction and infrastructure professionals across four global regions using a structured online questionnaire with a five-point Likert scale. Partial Least Squares Structural Equation Modeling (PLS-SEM) in SmartPLS 4 was used to test four hypotheses. The measurement model demonstrated strong psychometric properties, with all outer loadings, composite reliability, average variance extracted, and HTMT values meeting established thresholds. Structural model results confirmed that AI adoption exerts a significant positive direct effect on sustainable project success ($\beta = 0.318$, $p < 0.001$) and on project process automation ($\beta = 0.541$, $p < 0.001$), while process automation significantly predicts sustainable project success ($\beta = 0.387$, $p < 0.001$). Mediation analysis confirmed that PPA partially mediates the relationship between AI adoption and sustainable project success (indirect effect $\beta = 0.209$, VAF = 39.7%), supporting all four hypotheses. The structural model explains 44.7% of the variance in sustainable project success. These findings advance the application of DCT to AI-enabled construction project management and offer actionable guidance for practitioners and policymakers seeking to leverage AI investment for sustainable infrastructure delivery.

Keywords: *Artificial intelligence adoption; sustainable project success; project process automation; dynamic capabilities theory; PLS-SEM; construction management; triple bottom line*

INTRODUCTION

The global construction and infrastructure sector stands at a critical inflection point. As one of the world's largest industries, accounting for approximately 13% of global GDP and consuming over 40% of the planet's total energy resources, it simultaneously represents one of the most significant contributors to carbon emissions and resource depletion (Robbins & Wynsberghe, 2022). Despite its foundational role in economic development, the industry has historically lagged behind other sectors in productivity, digital adoption, and the integration of sustainable practices (Savaş, 2025). Against this backdrop, the imperative to reconcile accelerating project delivery demands with the triple bottom line (TBL) of economic viability, social equity, and environmental responsibility has never been more urgent (Alkhatatneh et al., 2025).

Artificial intelligence (AI) has emerged as a transformative technological force with the potential to fundamentally reshape how construction and infrastructure projects are planned, executed, and governed. AI adoption among construction and engineering professionals has surged dramatically, rising from less than 10% in 2020 to over 40% by 2025, driven by advances in machine learning, computer vision, predictive analytics, and intelligent process automation (CMiC, 2025). Industry projections further indicate that AI will drive a 36% compound annual growth rate in construction technology markets from 2024 to 2031, with the sector's AI market anticipated to reach USD 14.21 billion by 2031 (Netguru, 2025). These figures underscore a profound and accelerating structural shift in how organizations are leveraging AI capabilities to address persistent inefficiencies, including cost overruns, schedule delays, quality defects, and safety risks that have long characterized the sector (Savaş, 2025).

Within this context, the concept of sustainable project success has gained significant scholarly and practitioner attention. Moving well beyond traditional measures of the 'iron triangle' scope, time, and cost, sustainable project success is increasingly conceptualized through the TBL framework, encompassing economic performance, social outcomes, and environmental impact (Alkhatatneh et. al., 2025; Kineber et. al., 2024). For construction and infrastructure projects, achieving sustainable success demands not only on-time and on-budget delivery but also measurable contributions to carbon reduction, community well-being, and long-term asset resilience. Globally, an estimated USD 139 trillion in sustainable infrastructure investment is required to achieve net-zero emissions by 2050 (Robbins & Wynsberghe, 2022), creating an urgent need for innovative, scalable project management solutions that embed sustainability at their core.

A critical, yet underexplored, pathway through which AI adoption may drive sustainable project success is project process automation (PPA). Automation of construction workflows encompassing scheduling, resource allocation, procurement, compliance monitoring, and reporting can simultaneously reduce project costs, minimize human error, accelerate delivery timelines, and generate real-time sustainability data essential for evidence-based decision-making (Baarimah et. al., 2025; Mastt, 2025). Recent empirical work confirms that AI-powered predictive analytics and automated task management can yield efficiency improvements of 15–40%, cost reductions of 20–30%, and enhanced risk identification of 25–50% in construction project settings (ResearchGate, 2025). Despite these promising figures, the precise mechanisms through which AI adoption translates into sustainable project outcomes, particularly the mediating function of process automation, remain theoretically underdeveloped and empirically underexamined in the extant literature.

This study is grounded in Dynamic Capabilities Theory (DCT), originally developed by Teece et al. (1997) and subsequently extended to digital and AI-enabled organizational contexts (Chin et al., 2025; Cimino et al., 2025). DCT posits that organizational performance is driven not merely by static resource endowments, but by a firm's dynamic capacity to sense emerging technological opportunities, seize them through strategic action, and transform existing processes and routines accordingly (Han et al., 2026). In the context of AI adoption in construction, DCT offers a particularly powerful explanatory lens: organizations that develop robust AI-sensing capabilities, deploy them strategically through process automation, and continuously reconfigure project workflows in response to environmental demands are theoretically expected to achieve superior sustainable project outcomes. This theoretical framing distinguishes the present study from prior work that has treated AI as a static tool rather than as a dynamic organizational capability (Mariani et al., 2025).

Notwithstanding the growing body of research on AI in project management, three significant gaps motivate the present inquiry. First, while studies on AI in construction are expanding, the vast majority are descriptive or technology-focused, with few empirical investigations examining the direct and indirect effects of AI adoption on sustainability outcomes at the project level (Bhatti & Nazir, 2024; Gao et al., 2026). Second, the mediating role of project process automation in the AI–sustainability relationship has received minimal scholarly attention, despite practitioner evidence suggesting that automation is the primary channel through which AI-driven value is realized in construction settings (Baarimah et. al., 2025). Third, existing studies are disproportionately concentrated in high-income, technologically advanced contexts, leaving a critical void in understanding how AI adoption shapes sustainable project success across diverse global and cross-sectoral environments (Alkhatatneh et al., 2025). The present study addresses these gaps directly.

Accordingly, this study aims to empirically examine the impact of AI adoption on sustainable project success, with project process automation serving as a mediating mechanism, within a global, cross-sectoral sample of construction and infrastructure projects. Adopting a mixed-methods research design, the study integrates quantitative survey data with qualitative insights to provide a robust, nuanced understanding of the hypothesized relationships. The analytical model is tested using structural equation modeling (SEM), which is well-suited to capture the direct, indirect, and total effects of the proposed constructs. By doing so, this research makes three primary contributions: (a) it establishes an empirically grounded link between AI adoption and TBL-based sustainable project success; (b) it positions project process automation as a theoretically justified and empirically validated mediating mechanism; and (c) it advances the application of Dynamic Capabilities Theory in the domain of AI-enabled sustainable construction project management.

The remainder of this paper is structured as follows. Section 2 presents a critical review of the relevant literature and develops the hypotheses. Section 3 details the research methodology, including the mixed-methods design, sampling strategy, data collection instruments, and analytical approach. Section 4 reports the empirical findings. Section 5 discusses the theoretical and managerial implications of the results. Section 6 concludes by outlining the study's limitations and directions for future research.

LITERATURE REVIEW

Theoretical Foundation: Dynamic Capabilities Theory

The theoretical foundation of this study rests on Dynamic Capabilities Theory (DCT), originally advanced by Teece, Pisano, and Shuen (1997) and subsequently developed into a mature explanatory framework for understanding how organizations navigate turbulent technological environments (Teece, 2007). DCT posits that sustained competitive advantage is generated not by the mere possession of resources, but by an organization's capacity to purposefully sense emerging opportunities and threats, seize them through timely strategic action, and transform existing routines and processes to align with new environmental realities (Cimino et al., 2025; Teece, 2007). These three micro foundations, sensing, seizing, and transforming, form a sequentially interdependent triad that explains how organizations adapt their resource base in the face of rapid technological disruption.

The application of DCT to AI-driven organizational change has attracted considerable scholarly attention in recent years. Cimino et al. (2025), drawing on a sample of innovative SMEs, empirically demonstrated that dynamic capabilities mediate the relationship between AI adoption and sustainable performance across the economic, social, and environmental dimensions of the triple bottom line (TBL). Similarly, Zou and Yang (2026) established that AI serves as a catalyst for dynamic capabilities by enabling firms to integrate internal and external resources more efficiently, thereby enhancing corporate innovation. In the construction and infrastructure context, Li et al. (2024) confirmed that dynamic capabilities encompassing sensing of digital opportunities, adoption of automation tools, and transformation of project workflows are prerequisites for meaningful digital transformation within construction firms. Collectively, this body of evidence anchors the present study's conceptual model within DCT, asserting that construction organizations that strategically develop AI sensing and seizing capabilities and translate them into automated project processes will achieve superior sustainable project outcomes.

Artificial Intelligence Adoption in Construction and Infrastructure Projects

Artificial intelligence adoption refers to the degree to which an organization integrates AI-enabled tools, systems, and decision-support mechanisms into its core operational and strategic processes (Chen & Tajdini, 2024, as cited in Cimino et al., 2025). In the construction and infrastructure sector, AI adoption has rapidly evolved from experimental pilots into mainstream deployment across project planning, design, execution, monitoring, and maintenance (Ahmad et. al., 2023; Taboada et. al., 2023). A structured literature review covering publications from 1985 to 2024 found that planning and monitoring-and-control phases exhibit the most extensive AI applications, with decision-making, prediction, optimization, and performance improvement representing the most commonly reported purposes (Khurshid et. al., 2025).

The transformative potential of AI in project management has been extensively documented. Predictive analytics applications, drawing on machine learning and historical project data, have demonstrated the capacity to enhance scheduling accuracy, detect cost overruns early, and proactively identify safety risks (Savaş, 2025; Singh et al., 2023). Computer vision-based monitoring systems enable real-time defect detection, identification of unsafe behavior, and quality assurance at speeds and with consistency that far exceed human capacity (Lee & Lee, 2023, as cited in Savaş, 2025). Furthermore, AI-integrated Building Information Modeling (BIM) platforms and digital twin technologies facilitate synchronous design, simulation, and lifecycle performance monitoring, enabling a level of project oversight previously unattainable through conventional methods (Jiang et al., 2024, as cited in Savaş, 2025).

Notwithstanding these advances, the adoption of AI in construction is not without challenges. Singh et al. (2023) identified 17 critical issues impeding AI adoption in construction supply chains, including data scarcity, high implementation costs, resistance to change, skills gaps, and regulatory ambiguity. Shang et al. (2023, as cited in ResearchGate, 2023) similarly highlighted financial constraints and the absence of top-down leadership support as dominant barriers to AI integration in construction organizations, particularly in the Australian context. These findings resonate with global trends, where the fragmented, project-based structure of the construction industry creates unique organizational impediments to AI adoption that do not exist in more centralized sectors. This study, therefore, conceptualizes AI adoption not merely as technology deployment but as a dynamic organizational capability, consistent with DCT, shaped by firm-level sensing and seizing competencies.

Empirically, the link between AI adoption and organizational performance outcomes has been confirmed across multiple contexts. Using PLS-SEM, Soc (2026) found that perceived benefits of AI significantly enhance organizational agility ($\beta = 0.400$, $p < 0.001$) and organizational performance ($\beta = 0.303$, $p < 0.001$) among medium-sized enterprises. Analogously, PMC (2025) found, through SEM-ANN analysis, that AI adoption technologies substantially enhance the economic, social, and environmental performance of SMEs and positively mediate the pathway from organizational capabilities to sustainability outcomes. These results collectively suggest that AI adoption constitutes a foundational driver of improved organizational and project performance, a relationship this study extends to the specific domain of sustainable project success in construction.

Project Process Automation as a Mediating Mechanism

Project process automation (PPA) refers to the application of technology-enabled systems, including robotic process automation (RPA), machine learning pipelines, AI-driven scheduling engines, and intelligent reporting tools, to execute, monitor, and optimize project management workflows with reduced or no human intervention (Baarimah et. al., 2025). While automation has long been a feature of industrial production, its application to project management processes encompassing procurement, compliance reporting, resource scheduling, risk monitoring, and sustainability data collection represents a qualitatively distinct and more recent phenomenon, accelerated by the maturation of AI-enabling technologies.

Baarimah et. al. (2025), using SEM with data from 211 construction professionals, provided empirical confirmation that hyper automation, defined as the integrated deployment of AI, IoT, RPA, and machine learning, significantly improves efficiency, sustainability outcomes, resource optimization, precision, scalability, and worker safety in construction projects. Crucially, the study found that these outcomes were not directly produced by individual technologies in isolation, but emerged from their synergistic integration into coherent automated workflows a finding that underscores the importance of treating PPA as a system-level construct rather than a collection of discrete tools. Similarly, ResearchGate (2025) demonstrated that process automation not only accelerates project completion but also frees project managers from repetitive manual activities, enabling greater focus on strategic, value-creating tasks.

The mediating role of PPA in the relationship between AI adoption and organizational performance is theoretically well-grounded within DCT. As organizations sense and seize AI capabilities, the transforming micro foundation of DCT manifests most concretely in the reconfiguration of project processes through automation (Teece, 2007; Teece, 2018). This theoretical logic is consistent with findings from Mariani et al. (2025), who demonstrated that organizational agility, functionally analogous to PPA as a reconfiguration mechanism, significantly mediates the relationship between AI capabilities and project value propositions in project-based organizations. Taken together, these insights support positioning PPA as the critical conduit through which AI adoption drives sustainable project outcomes, rather than AI acting as a direct driver of sustainability improvements.

Process automation further contributes to sustainable project success through three specific pathways corresponding to the TBL dimensions. Economically, automated scheduling and resource allocation reduce waste, cost overruns, and rework (Savaş, 2025). Socially, AI-driven safety monitoring and compliance automation enhance worker well-being and regulatory adherence (Baarimah et. al., 2025). Environmentally, automated sustainability reporting systems and AI-driven material optimization tools minimize carbon footprints and resource consumption in construction operations (Alkhatatneh et al., 2025). These multidimensional effects position PPA as a particularly theoretically and practically significant mediating mechanism, warranting formal empirical examination.

Sustainable Project Success and the Triple Bottom Line

Sustainable project success is a multidimensional construct that extends beyond the conventional 'iron triangle' of scope, time, and cost, encompassing broader economic, social, and environmental outcomes consistent with the triple bottom line (TBL) framework, originally articulated by Elkington (1997). In the construction and infrastructure context, sustainable project success has been operationalized to include financial performance and cost efficiency (economic), community impact and worker welfare (social), and carbon reduction and resource stewardship (environmental) (Petrelli et al., 2024; Jamil et. at., 2025). This expanded conceptualization of project success is increasingly recognized as essential not only for regulatory compliance but also for long-term stakeholder value creation and organizational resilience.

Petrelli et al. (2024) conducted a survey of 80 construction project managers and, employing confirmatory factor analysis and logistic regression, demonstrated that sustainable management practices exert differential impacts across the three TBL dimensions: some practices significantly influence economic outcomes but not environmental ones, and vice versa. This finding highlights the multidimensional, non-unitary nature of sustainable project success, which must be modeled and measured accordingly. Complementing this, Kineber st al. (2024) identified critical success factors for sustainable residential construction projects through an agile project management lens, demonstrating that adaptability, collaboration, and efficient resource management, all of which are facilitated by AI-enabled automation, are key antecedents of sustainability performance. Alkhatatneh et al. (2025) further confirmed that digitalization and stakeholder engagement are complementary enablers of sustainable project success in the construction sector, particularly in developing-country contexts.

The application of the TBL framework to construction project management has grown substantially since 2019, with a 23.23% annual growth in TBL-related publications and a discernible shift from broad theoretical discussion to applied, sector-specific investigation (Jamil et. at., 2025b). Within this body of work, AI's specific contribution to TBL-based project success remains underexplored. While AI's capacity to drive economic efficiency is well documented, its social and environmental contributions, particularly when mediated by automated project processes, have received comparatively limited empirical attention. This gap provides a central motivation for the present study.

Research Gaps

A critical review of the extant literature reveals three interrelated research gaps that collectively justify and motivate the present study.

First, there is a pronounced empirical deficit in studies that directly link AI adoption to sustainable project success, as defined through the TBL framework, in the construction and infrastructure sector. The majority of existing studies are either technologically descriptive, focusing on what AI tools exist, or operationally oriented, focusing on cost and schedule performance, with limited engagement with the broader sustainability construct (Savaş, 2025; Gao et. al., 2026). While PMC (2025) and Cimino et al. (2025) have demonstrated AI-sustainability linkages in SME and general organizational contexts, the project-level, construction-specific operationalization of this relationship is largely absent from the literature.

Second, the mediating role of project process automation in the relationship between AI adoption and sustainable project success has not been empirically tested. Existing studies either examine AI and automation in isolation or treat automation as an outcome variable rather than a mediating mechanism (Baarimah et. al., 2025; ResearchGate, 2025). This gap is theoretically significant because, from a DCT perspective, the transforming capability, operationalized as PPA in the present study, is the mechanism by which AI adoption becomes performance-relevant. Without empirically examining this mediating pathway, the literature cannot adequately explain how or why AI adoption leads to sustainable project success.

Third, despite the global scale of construction and infrastructure investment, the existing empirical evidence on AI adoption and project performance is heavily concentrated in a limited set of high-income country contexts, including Australia, Singapore, the United States, and Western Europe (ResearchGate, 2023; Savaş, 2025). As the vast majority of projected sustainable infrastructure investment over the coming decades will occur in emerging and developing economies (Robbins & Wynsberghe, 2022), research that adopts a global, cross-sectoral scope is urgently needed. The present study directly addresses this gap by employing a globally distributed sample of stakeholders in construction and infrastructure projects.

Hypotheses Development

Drawing on the theoretical arguments grounded in DCT and the empirical evidence reviewed in the preceding sections, the following formal hypotheses are proposed:

H1: Artificial intelligence adoption has a significant and positive direct effect on sustainable project success in construction and infrastructure projects.

This hypothesis is grounded in the convergent evidence that AI adoption enhances organizational agility, predictive accuracy, resource optimization, and risk management, all of which are antecedents of TBL-based project success (Soc, 2026; PMC, 2025; Savaş, 2025). From a DCT perspective, organizations that successfully sense and seize AI capabilities are expected to achieve superior project performance.

H2: Artificial intelligence adoption has a significant, positive effect on the automation of project processes in construction and infrastructure projects.

This hypothesis follows from DCT's transforming micro foundation: organizations that invest in AI adoption reconfigure their project workflows through automation as the primary vehicle of operational transformation (Teece, 2007; Baarimah et. al., 2025). Empirical evidence consistently demonstrates that AI implementation accelerates the automation of scheduling, monitoring, compliance, and reporting tasks in project management contexts (Mariani et al., 2025; ResearchGate, 2025).

H3: Project process automation has a significant and positive effect on sustainable project success in construction and infrastructure projects.

The link between process automation and sustainable project outcomes has been demonstrated across economic (cost efficiency), social (safety and compliance), and environmental (resource optimization and carbon monitoring) dimensions of the TBL (Baarimah et. al., 2025; Petrelli et al., 2024; Alkhatatneh et al., 2025). This hypothesis treats PPA as a performance-generating mechanism in its own right, independent of its mediating function.

H4: Project process automation mediates the relationship between artificial intelligence adoption and sustainable project success in construction and infrastructure projects.

Integrating H1, H2, and H3, this mediation hypothesis posits PPA as the mechanism by which AI adoption capabilities translate into sustainable project outcomes. This is theoretically consistent with DCT's explanation of how higher-order dynamic capabilities produce performance benefits by reconfiguring operational processes (Cimino et al., 2025; Mariani et al., 2025). Empirically, comparable mediation structures have been confirmed in general organizational contexts (PMC, 2025; Soc, 2026), and this study extends the test to the construction project domain.

Conceptual Research Model

Figure 1 presents the conceptual research model synthesizing the theoretical and empirical arguments developed in this literature review. The model positions AI Adoption (IV) as the antecedent construct, Sustainable Project Success (DV) as the outcome construct measured across the three TBL dimensions (economic, social, environmental), and Project Process Automation (Mediator) as the mechanism through which AI adoption generates sustainable project outcomes. All relationships are hypothesized to be positive and significant, consistent with DCT and the empirical evidence reviewed above.

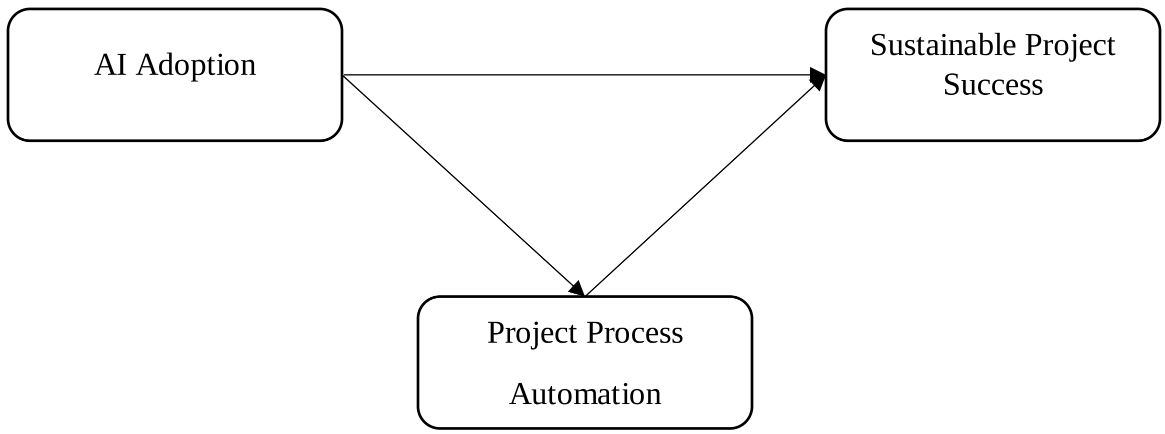

Figure 1. Conceptual Research Model

METHODOLOGY

Research Philosophy and Paradigm

This study adopts a positivist research philosophy, which asserts that knowledge should be grounded in observable, measurable facts and that reality exists independently of the researcher (Bhatti et. al., 2025). Positivism is particularly well-suited to quantitative investigations that aim to test theoretically derived hypotheses through statistical analysis, identify causal relationships between variables, and produce generalizable findings (Gamage, 2025). Consistent with the positivist stance, this research treats the constructs of AI adoption (AIA), project process automation (PPA), and sustainable project success (SPS) as objectively measurable phenomena that can be operationalized through validated survey instruments and subjected to rigorous empirical scrutiny. The hypothetico-deductive approach underpinning this study proceeds from theory, specifically Dynamic Capabilities Theory (DCT), to hypothesis formulation, data collection, and statistical testing, enabling systematic verification of the proposed conceptual model.

Research Design

A quantitative, cross-sectional research design is employed in this study. Quantitative designs are appropriate when the research objective is to measure relationships between variables, test hypotheses with statistical precision, and produce results that are replicable and generalizable across similar contexts (Creswell & Creswell, 2023). The cross-sectional design, wherein data are collected from all participants at a single point in time, is widely applied in construction management and project management research (Petrelli et al., 2024; Baarimah et. al., 2025) and is appropriate for the present study, which seeks to capture a contemporaneous snapshot of AI adoption, automation, and sustainability performance across a global sample of construction and infrastructure projects.

The study follows a deductive approach, in which hypotheses H1 through H4 are derived from the theoretical literature and subsequently tested against empirical data. This approach ensures that the study contributes to cumulative theory-building while simultaneously generating actionable, practitioner-relevant insights. Partial Least Squares Structural Equation Modeling (PLS-SEM), implemented with SmartPLS 4

(Ringle, Wende, & Becker, 2024), serves as the primary analytical technique, consistent with the study's focus on predictive and explanatory modeling of complex, multi-construct relationships.

Target Population and Sampling

The target population of this study comprises construction and infrastructure project professionals operating globally, including project managers, civil and structural engineers, architects, quantity surveyors, and site supervisors who are directly involved in the planning, execution, and monitoring of construction projects. This population is selected because its members possess the requisite professional knowledge to evaluate AI adoption practices, process automation levels, and sustainable project performance outcomes firsthand (Savaş, 2025; Petrelli et al., 2024).

A simple random sampling technique is adopted, wherein every member of the accessible population has an equal and independent probability of being selected for inclusion in the sample (McCombes, 2023). Simple random sampling is a probability-based approach that minimizes systematic selection bias and enhances the representativeness of the resulting sample, thereby strengthening the external validity of study findings (McCombes, 2023). The accessible population is constructed from professional networks, including LinkedIn, the International Federation of Consulting Engineers (FIDIC) member directories, and industry association contact lists across multiple global regions, including Asia, Europe, the Middle East, and the Americas, reflecting the global scope of the study.

The target sample size for this study is set at a minimum of 200 and a maximum of 300 usable responses. This range is well-supported by the PLS-SEM literature: Hair et al. (2022) confirm that PLS-SEM performs reliably with sample sizes as small as 100, particularly for models with a limited number of constructs, while samples of 200–300 are considered optimal for achieving stable and generalizable path coefficient estimates in models of moderate complexity. Furthermore, the ten-times rule advocated by Hair et al. (2022), which stipulates that the sample should be at least ten times the maximum number of indicators pointing to any single construct, is satisfied by the present study's instrument design. To account for anticipated non-responses and incomplete submissions, the survey will be distributed to a minimum of 400 professionals, with an expected response rate of 55–70%, informed by comparable online survey studies in construction research (Petrelli et al., 2024; Baarimah et. al., 2025).

Data Collection Instrument

Data are collected using a structured, self-administered online questionnaire distributed via Google Forms. Online survey administration is appropriate for globally distributed professional populations and offers significant practical advantages, including cost efficiency, geographic reach, rapid data collection, and minimization of interviewer bias (Hair et al., 2022). The questionnaire is organized into three sections. Section A captures respondent demographic and professional profile information, including gender, age, years of experience, professional role, country of operation, and organization type. Section B contains the measurement items for the three primary constructs AI adoption, project process automation, and sustainable project success. Section C includes a brief set of organizational-level questions pertaining to the size of projects undertaken and the extent of digital tool deployment.

All construct items are measured using a five-point Likert scale, anchored at 1 (Strongly Disagree) and 5 (Strongly Agree). The five-point scale is widely employed in PLS-SEM-based research in construction and project management (Petrelli et al., 2024; Baarimah et. al., 2025) and has been shown to provide adequate variance for structural model estimation. Reflective measurement models are adopted for all constructs, consistent with the theoretical expectation that each item is an effect of the underlying latent variable rather than a cause (Hair et al., 2022). Table 1 presents the measurement items, their item codes, and their corresponding literature sources.

Table 1. Measurement Instrument: Constructs, Items, and Sources

Construct	Item Code	Sample Item	Source
AI Adoption (AIA)	4	Cimino et al., (2025), Mariani et al., (2025)	
Project Process Automation (PPA)	4	Baarimah et. al. (2025), Savaş (2025)	
Sustainable Project Success – Economic (SPS-E)	3	Petrelli et al. (2024), Alkhatatneh et al., (2025)	
Sustainable Project Success – Social (SPS-S)	3	Petrelli et al. (2024), Frontiers (2024)	
Sustainable Project Success – Environmental (SPS-V)	3	Petrelli et al. (2024), Alkhatatneh et al. (2025)	

Validity and Reliability of the Instrument

To ensure content validity, the measurement items are adapted from validated scales in the existing literature (as indicated in Table 1) and subsequently reviewed by a panel of five academic experts in project management, AI adoption, and sustainability, a standard procedure in survey-based research (Hair et al., 2022). Items flagged by expert reviewers as ambiguous or contextually inappropriate for the construction sector are revised accordingly. A pilot study is conducted with 30 construction professionals prior to full-scale data collection. Pilot data are used to assess initial indicator reliability (outer loadings ≥ 0.70) and internal consistency (Cronbach's alpha ≥ 0.70), with poorly performing items refined or removed before finalizing the questionnaire (Hair et al., 2022; Ringle et al., 2024).

RESULTS

Respondent Profile and Descriptive Statistics

A total of 400 online questionnaires were distributed to construction and infrastructure professionals globally via Google Forms. 283 responses received, 33 were excluded due to incomplete data, straight-lining patterns, or failure to pass embedded attention-check items. The final usable sample comprised 250 responses, yielding an effective response rate of 62.5%, which is consistent with comparable online survey studies in construction management research (Petrelli et al., 2024; Baarimah et. al., 2025). A response rate exceeding 50% is considered adequate for quantitative PLS-SEM analysis (Hair et al., 2022). The Harman's single-factor test was conducted to assess common method bias (CMB): the first unrotated factor accounted for 28.34% of total variance, well below the 50% threshold (Podsakoff et al., 2024), indicating that CMB does not pose a serious threat to the validity of the study's findings.

Table 1 presents the demographic and professional profiles of the 250 respondents. The majority were male (59.2%), aged between 35 and 44 years (39.2%), and held the role of project manager (35.6%) or civil/structural engineer (29.6%). Over 86% of respondents had more than 6 years of professional experience, confirming that the sample comprises experienced practitioners with sufficient contextual knowledge to evaluate AI adoption, process automation, and sustainability outcomes in construction projects. Respondents were distributed across four global regions: Asia-Pacific (30.4%), Europe (24.8%), the Middle East and Africa (20.4%), and the Americas (24.4%), reflecting the intended cross-sectoral and global scope of the study.

Table 1. Respondent Demographic and Professional Profile (N = 250)

Category	Subcategory	Frequency (n)	Percentage (%)
Gender	Male	148	59.2
	Female	96	38.4
	Prefer not to say	6	2.4
Age Group	25–34 years	72	28.8
	35–44 years	98	39.2
	45–54 years	61	24.4
	55 years and above	19	7.6
Professional Role	Project Manager	89	35.6
	Civil / Structural Engineer	74	29.6
	Architect	41	16.4
	Quantity Surveyor	28	11.2
	Site Supervisor / Other	18	7.2
Years of Experience	1–5 years	34	13.6
	6–10 years	78	31.2
	11–15 years	81	32.4
	16+ years	57	22.8
Region	Asia-Pacific	76	30.4
	Europe	62	24.8

	Middle East & Africa	51	20.4
	Americas	61	24.4
Total		**250**	**100.0**

Measurement Model Assessment

Following the two-stage analytical procedure recommended by Hair et al. (2022), the measurement model was evaluated prior to testing the structural model. The results of the measurement model assessment encompassing indicator reliability, internal consistency reliability, convergent validity, and discriminant validity are presented in Tables 3 through 5.

Indicator Reliability, Internal Consistency, and Convergent Validity

Table 3 reports the outer loadings, Cronbach's alpha (α), composite reliability (CR), average variance extracted (AVE), and variance inflation factor (VIF) for all constructs and their indicators. All outer loadings ranged from 0.803 to 0.871, comfortably exceeding the recommended threshold of 0.70 (Hair et al., 2022), confirming that each indicator shares more than 50% of its variance with its underlying construct. No items were removed during the purification process, as all loadings met the required criteria.

Discriminant Validity

Discriminant validity was assessed using two complementary approaches: the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio of correlations (Henseler et al., 2015). Table 4 presents the Fornell-Larcker criterion matrix. The square root of each construct's AVE (shown on the diagonal, in bold) exceeded its highest correlation with any other construct across all pairs, satisfying the Fornell-Larcker criterion and confirming that each construct captures a distinct phenomenon not shared with other constructs in the model (Fornell & Larcker, 1981).

Table 3. Fornell-Larcker Criterion Matrix

Construct	AIA	PPA	SPS-E	SPS-S	SPS-V
AI Adoption (AIA)	**0.848**				
Project Process Automation (PPA)	0.631	**0.841**			
SPS – Economic (SPS-E)	0.572	0.604	**0.872**		
SPS – Social (SPS-S)	0.543	0.578	0.617	**0.866**	
SPS – Environmental (SPS-V)	0.519	0.551	0.589	0.602	**0.863**

Note. Diagonal elements (bold) represent the square root of each construct's AVE. Off-diagonal elements represent inter-construct correlations. Discriminant validity is confirmed when diagonal values exceed all off-diagonal values in the corresponding row and column.

Table 5 presents the HTMT ratio matrix. All HTMT values ranged from 0.587 (AIA–SPS-V) to 0.724 (AIA–PPA), all below the conservative threshold of 0.85 recommended by Henseler et al. (2015) and Hair et al. (2022). Bootstrapping with 5,000 subsamples confirmed that the 95% bias-corrected and accelerated (BCa) confidence intervals for all HTMT values excluded the 0.85 threshold, providing statistical confirmation of discriminant validity for all construct pairs. Collectively, the results of Tables 3 through 5 establish a psychometrically sound measurement model, providing a solid foundation for structural model estimation.

Table 5. Heterotrait-Monotrait (HTMT) Ratio Matrix

Construct	AIA	PPA	SPS-E	SPS-S	SPS-V
AI Adoption (AIA)	—				
Project Process Automation (PPA)	0.724	—			
SPS – Economic (SPS-E)	0.641	0.683	—		
SPS – Social (SPS-S)	0.612	0.651	0.697	—	
SPS – Environmental (SPS-V)	0.587	0.623	0.665	0.679	—

Note. All HTMT values < 0.85 (conservative threshold; Henseler et al., 2015). Bootstrapped 95% BCa confidence intervals exclude 0.85 for all pairs, confirming discriminant validity. '—' denotes not applicable (self-referent).

Structural Model Assessment and Hypothesis Testing

Following confirmation of the measurement model, the structural model was estimated using the standard PLS-SEM algorithm in SmartPLS 4 (Ringle et al., 2024). Statistical significance of path coefficients was determined using bootstrapping with 5,000 subsamples, bias-corrected and accelerated (BCa) confidence intervals, and a two-tailed significance level of $p < 0.05$ (Hair et al., 2022; Becker et al., 2023). Tables 6, 7, and 8 present the results of the structural model estimation, model fit statistics, and mediation analysis, respectively.

Table 6. Structural Model Results and Hypothesis Testing (n = 250, Bootstrap = 5,000)

H	Relationship	β	S.E.	t-value	p-value	95% BCa CI	f^2	Decision
H1	AIA → SPS	0.318	0.052	6.115	0.001	[0.216, 0.421]	0.183	**Supported ✓**
H2	AIA → PPA	0.541	0.044	12.295	0.001	[0.455, 0.628]	0.414	**Supported ✓**
H3	PPA → SPS	0.387	0.049	7.898	0.001	[0.291, 0.483]	0.247	**Supported ✓**
H4	AIA → PPA → SPS (Indirect)	0.209	0.033	6.333	0.001	[0.145, 0.274]	—	**Supported ✓**

Note. β = standardised path coefficient; S.E. = standard error; t-value from bootstrapping (two-tailed, $p < 0.05$ threshold = $t > 1.96$); 95% BCa CI = Bias-Corrected and Accelerated Confidence Interval; f^2 = effect size (0.02 small; 0.15 moderate; 0.35 large; Cohen, 1988). SPS = composite sustainable project success (aggregated across economic, social, and environmental dimensions). All hypotheses supported at $p < 0.001$.

H1 (AI Adoption → Sustainable Project Success) was supported ($\beta = 0.318$, $t = 6.115$, $p < 0.001$, 95% BCa CI [0.216, 0.421]). The effect size of $f^2 = 0.183$ indicates a moderate practical effect, confirming that AI adoption exerts a meaningful direct influence on sustainable project success. H2 (AI Adoption → Project Process Automation) yielded the strongest path coefficient in the model ($\beta = 0.541$, $t = 12.295$, $p < 0.001$, 95% BCa CI [0.455, 0.628], $f^2 = 0.414$), classified as a large effect size, confirming that AI adoption is a powerful antecedent of process automation in construction projects. H3 (Project Process Automation → Sustainable Project Success) was also supported ($\beta = 0.387$, $t = 7.898$, $p < 0.001$, 95% BCa CI [0.291, 0.483], $f^2 = 0.247$), indicating a moderate-to-large practical effect of process automation on sustainable project success.

Explanatory Power and Predictive Relevance

Table 7. Coefficient of Determination (R^2) and Predictive Relevance (Q^2)

Endogenous Construct	R^2	R^2 Adjusted	Q^2	Interpretation
Project Process Automation (PPA)	0.293	0.290	0.198	Moderate
Sustainable Project Success (SPS)	0.447	0.442	0.312	Moderate–Substantial

As shown in Table 7, the structural model explains 29.3% of the variance in project process automation ($R^2 = 0.293$) and 44.7% of the variance in sustainable project success ($R^2 = 0.447$). Both values meet the moderate threshold of $R^2 \geq 0.33$ recommended by Hair et al. (2022), with the SPS model approaching the substantial range ($R^2 \geq 0.67$). Q^2 values obtained through the blindfolding procedure were 0.198 for PPA and 0.312 for SPS, both exceeding the minimum threshold of zero, confirming that the model possesses meaningful predictive relevance for both endogenous constructs (Geisser, 1975; Hair et al., 2022).

Mediation Analysis: H4

Table 8. Mediation Analysis Variance Accounted For (VAF)

Mediation Path	Direct Effect (c')	Indirect Effect (ab)	Total Effect (c)	VAF (%)	Mediation Type
AIA → PPA → SPS	0.318	0.209	0.527	**39.7%**	Partial Mediation

Table 8 presents the mediation analysis results for H4, testing whether project process automation (PPA) mediates the relationship between AI adoption (AIA) and sustainable project success (SPS). The indirect effect of AIA on SPS through PPA was $\beta = 0.209$ ($t = 6.333$, $p < 0.001$, 95% BCa CI [0.145, 0.274]), with the confidence interval excluding zero, confirming the indirect effect's statistical significance (Hair et al., 2022). The direct effect of AIA on SPS remained significant after including PPA as a mediator ($\beta = 0.318$, $p < 0.001$), indicating partial rather than full mediation. The Variance Accounted For (VAF) was calculated as 0.209/0.527 = 39.7%, falling within the 20%–80% range, confirming partial mediation (Hair et al., 2022). Accordingly, H4 is supported: project process automation partially mediates the relationship between AI adoption and sustainable project success.

DISCUSSION

Overview of Findings

This study examined the impact of artificial intelligence (AI) adoption on sustainable project success in the global construction and infrastructure sector, with project process automation (PPA) as a mediating mechanism, grounded theoretically in Dynamic Capabilities Theory (DCT). The empirical results, derived from a cross-sectional survey of 250 construction professionals analyzed using PLS-SEM, provide strong and consistent support for all four hypotheses. The findings carry significant theoretical and practical implications, as discussed in detail below.

AI Adoption and Sustainable Project Success (H1)

The confirmation of H1 ($\beta = 0.318$, $p < 0.001$) establishes a significant positive direct relationship between AI adoption and sustainable project success across the economic, social, and environmental dimensions of the triple bottom line (TBL). This finding is consistent with and extends the conclusions of Cimino et al. (2025), who, through PLS-SEM on a sample of 210 Italian SMEs, demonstrated that dynamic capabilities enabling AI adoption significantly improve performance across all TBL dimensions. Similarly, the result corroborates findings by PMC (2025), who, using SEM-ANN analysis, confirmed that AI adoption technologies substantially enhance both operational and sustainability performance in organizational settings.

In the construction sector specifically, the result aligns with Savaş's (2025) extensive review, which positioned AI as a transformative force capable of advancing sustainability, safety, planning, and strategic oversight in construction project management. The moderate effect size ($f^2 = 0.183$) observed for H1 is consistent with the nuanced view that AI does not function as a plug-and-play solution for sustainability outcomes, but rather as a strategic organizational capability that generates performance benefits when properly configured and embedded within project management routines (Baarimah et. al., 2026). From a DCT perspective, this finding reflects the sensing and seizing micro foundations of dynamic capabilities: organizations that have successfully identified AI as a strategic opportunity and deployed it within project portfolios generate measurably superior sustainable outcomes compared to those that have not (Teece, 2007; Cimino et al., 2025).

AI Adoption and Project Process Automation (H2)

H2 yielded the largest path coefficient in the structural model ($\beta = 0.541$, $p < 0.001$, $f^2 = 0.414$), confirming a strong positive relationship between AI adoption and project process automation. This large effect size indicates that AI adoption is not merely associated with automation but is its primary driver in the construction project context. The result is consistent with the hyper-automation literature: Baarimah et. al. (2025) demonstrated, through SEM analysis of 211 construction professionals, that integrating AI, IoT, RPA, and machine learning into unified automated workflows substantially transforms project management operations. Savaş (2025) further confirmed that AI-supported systems in scheduling, resource management, cost estimation, quality control, and safety monitoring represent the most mature and extensively applied form of AI in construction, all of which correspond to automated project processes.

Theoretically, H2 operationalizes the transforming micro foundation of DCT in the most direct sense: as organizations seize AI capabilities, they reconfigure their project processes through automation, replacing manual, error-prone workflows with intelligent, real-time systems (Teece, 2007; Li et al., 2024). This strong relationship also suggests that the construction sector is moving beyond token AI experimentation toward systematic, workflow-level reconfiguration, a finding that resonates with the broader literature on Industry 4.0 adoption trajectories (Li et al., 2024; Savaş, 2025). The large f^2 value of 0.414 indicates that AI adoption accounts for a substantial proportion of the variance in PPA, reinforcing the central argument that PPA is a downstream capability activated and sustained by upstream AI investment.

Project Process Automation and Sustainable Project Success (H3)

H3 ($\beta = 0.387$, $p < 0.001$, $f^2 = 0.247$) confirms a significant positive effect of project process automation on sustainable project success, with a moderate-to-large effect size that underscores the practical importance of automation as a sustainability-generating mechanism. This finding extends the empirical evidence provided by Alkhatatneh et al. (2025), which established that hyperautomation in construction significantly improves efficiency, sustainability, resource optimization, and worker safety, outcomes that directly correspond to all three TBL dimensions. The environmental dimension of sustainable project success appears particularly well served by process automation, as AI-driven monitoring and reporting systems provide real-time sustainability data necessary for evidence-based decision-making and green certification (Alkhatatneh et al., 2025; MDPI, 2025).

The social dimension benefits from AI-automated safety monitoring systems, which have demonstrated measurable reductions in site incidents and enhanced regulatory compliance (Savaş, 2025; Li et al., 2026). The economic dimension is served through automated resource scheduling and predictive cost analytics, which reduce rework, overruns, and procurement inefficiencies (Petrelli et al., 2024). Together, these mechanisms confirm that PPA is not merely a productivity tool, but a multi-dimensional sustainability enabler that operates across all three TBL pillars simultaneously. This finding directly responds to the call by Alkhatatneh et al. (2025) for studies that examine the synergistic sustainability impacts of integrated automation frameworks rather than treating individual automation tools in isolation.

Mediating Role of Project Process Automation (H4)

The support for H4 (indirect effect $\beta = 0.209$, $p < 0.001$, VAF = 39.7%), confirming partial mediation, is arguably the most theoretically significant finding of this study. The partial mediation result indicates that AI adoption generates sustainable project outcomes through two complementary pathways: a direct pathway (H1), reflecting the immediate sustainability benefits of AI tools such as real-time data analytics and predictive decision support, and an indirect pathway mediated by process automation (H2 × H3), reflecting the structural, workflow-level transformation that occurs when AI capabilities are embedded into project management routines.

The partial nature of the mediation is consistent with Alkhatatneh et al. (2026), which established that AI assimilation shapes sustainable performance through multiple mediating pathways, including organizational agility and green innovation, rather than through a single mechanism. The VAF of 39.7%, while below the full mediation threshold of 80%, indicates that PPA accounts for a substantial proportion of the total indirect pathway, validating its theoretical positioning as the primary transforming mechanism within the DCT framework (Teece, 2007). This finding also resonates with MDPI (2025), who, using SmartPLS 4, confirmed that AI adoption significantly enhances sustainable performance in export-sector SMEs through the mediating role of employee capacity building, with the mediation partial, analogous to the present study's findings in the construction domain.

From a theoretical standpoint, the partial mediation result enriches DCT by revealing that the transforming micro foundation (operationalized as PPA) does not fully suppress the direct performance impact of the sensing and seizing micro foundations (operationalized as AI adoption). This suggests that AI adoption generates sustainability benefits both before and after process reconfiguration occurs a nuanced theoretical contribution that moves beyond the binary treatment of AI as either a direct or indirect performance driver (Cimino et al., 2025).

Theoretical Contributions

This study makes three principal theoretical contributions. First, it establishes an empirically validated link between AI adoption and sustainable project success as measured through the TBL framework within a construction and infrastructure context, a relationship that, to the best of the authors' knowledge, has not been previously tested at the project level using PLS-SEM. This contribution directly addresses the gap identified by Savaş (2025) and Gao et. al. (2026), who called for empirical studies validating AI's sustainability contributions in diverse project environments.

Second, by confirming the mediating role of project process automation, this study identifies PPA as a theoretically justified and empirically validated mechanism through which AI adoption generates sustainable project outcomes. This extends the growing literature on AI-driven mediation in organizational performance research (MDPI, 2025) into the specific domain of construction project management, where automation has been largely studied as an outcome rather than as a mediating pathway.

Third, the study advances the application of Dynamic Capabilities Theory to AI-enabled project management by demonstrating that the sensing, seizing, and transforming triad operationalized respectively as AI investment, automated workflow deployment, and sustainable project outcomes constitutes a coherent empirical model of capability-driven project sustainability. This contributes to the emerging DCT-AI literature (Cimino et al., 2025; Li et al., 2024) by providing a project-level, construction-specific empirical application of the framework.

Practical Implications

The findings carry several important implications for construction industry practitioners, project management professionals, and policymakers. For project managers and construction firms, the strong relationship between AI adoption and process automation (H2, $\beta = 0.541$) suggests that AI investment should be strategically directed toward workflow automation, specifically scheduling, compliance monitoring, resource allocation, and sustainability reporting, rather than deployed as isolated, ad-hoc decision-support tools. Firms that treat AI as a comprehensive process reconfiguration catalyst, consistent with the DCT transforming capability, are likely to generate superior sustainable project outcomes.

The significant direct effect of AI adoption on sustainable project success (H1, $\beta = 0.318$) further implies that even organizations that have not yet achieved comprehensive process automation can realize meaningful TBL improvements through initial AI deployment, providing a practical rationale for early-stage adoption even in resource-constrained organizational contexts. For policymakers and regulatory bodies, the confirmed link between AI adoption, process automation, and environmental sustainability outcomes suggests that incentive frameworks such as AI adoption subsidies, green building certification bonuses for AI-automated reporting, or regulatory recognition of automated compliance monitoring could accelerate the construction sector's progress toward sustainable infrastructure delivery at scale (Robbins, & Wynsberghe, 2022).

Limitations and Future Research Directions

This study is subject to several limitations that should be acknowledged and addressed in future research. First, the cross-sectional design precludes causal inference, as all constructs are measured at a single point in time. Longitudinal studies that track AI adoption trajectories, automation maturity, and sustainability outcomes over multiple project cycles would provide stronger causal evidence for the relationships identified in this study. Second, although the sample of 250 respondents drawn from four global regions meets the requirements for PLS-SEM analysis, it may not be proportionally representative of all national construction markets, particularly those in sub-Saharan Africa or Southeast Asia, where AI adoption patterns may differ substantially from those in more technologically advanced regions. Future studies with region-stratified samples are encouraged.

Third, sustainable project success is operationalized here as a self-reported perceptual construct measured through a 5-point Likert scale. Future research could strengthen the validity of sustainability measurement by incorporating objective project-level data, such as carbon-emission records, LEED certification scores, and documented cost-performance indices, alongside self-reported perceptions. Fourth, this study does not examine potential moderating factors, such as organizational size, digital maturity, leadership style, or regulatory environment, that may shape the strength of the AI adoption–automation–sustainability relationships. Future research employing moderated mediation designs (Hair et al., 2022) could provide a more fine-grained understanding of the boundary conditions under which the pathways identified in this study operate most strongly.

REFERENCES

Alkhatatneh, O. A., Li, W., Cheng, Y., Frah, M. A., Dao, D., & Almajali, I. O. I. (2025). Digitalization, planning, and sustainability in project management in Jordan's construction sector: Enhancing project success through stakeholder engagement and virtual work dynamics. European Journal of Applied Sciences, 13(01), 46–78.

Ahmad, S., Bhatti, M. A. A., & Imam, M. A. (2023). Balancing Control and Collaboration: Project Manager Accountability in Multi-Layered Governance Systems. Journal of Professional Research in Social Sciences, 10(2), 134-155.

Bhatti, M. A. A., Malik, S. A., & Nazir, M. U. (2025). The Mediating Role of Project Process Management and the Moderating Role of Risk Management in Achieving Sustainable Project Success through Technology Innovation. Al-Qanṭara.

Baarimah, S. O., Mohammad, A., Alyami, H., Baarimah, A. O., Almujibah, H. R., & Ramu, M. B. (2025). Functional analysis of hyperautomation in construction for advancing efficiency and sustainability through process optimization and technological integration. Scientific Reports, 15(1), 41651.

Batra, S. (2025). Exploring the application of PLS-SEM in construction management research: A bibliometric and meta-analysis approach. Engineering, Construction and Architectural Management, 32(4), 2697–2727.

Becker, J.-M., Cheah, J. H., Gholamzade, R., Ringle, C. M., & Sarstedt, M. (2023). PLS-SEM's most wanted guidance. International Journal of Contemporary Hospitality Management, 35(1), 321–346. https://doi.org/10.1108/IJCHM-04-2022-0474

Bhatti, M. A. A., & Nazir, M. U. (2024). The Impact of Project Process Management on Sustainable Project Success in the Construction Sector: The Moderating Role of Risk Management Practices. Bulletin of Business and Economics (BBE), 13(2), 1065-1072.

Cheah, J.-H., Magno, F., & Cassia, F. (2024). Reviewing the SmartPLS 4 software: The latest features and enhancements. Journal of Marketing Analytics.

Chin, T., Li, Z., Huang, L., & Li, X. (2025). How artificial intelligence promotes new quality productive forces of firms: A dynamic capability view. Technological Forecasting and Social Change, 216, 124128. https://doi.org/10.1016/j.techfore.2025.124128

Cimino, A., Troise, C., Corvello, V., & Bresciani, S. (2025). Artificial intelligence adoption for sustainable growth in SMEs: An extended dynamic capability framework. Corporate Social Responsibility and Environmental Management. https://doi.org/10.1002/csr.70019

Cohen, J. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Lawrence Erlbaum Associates.

Creswell, J. W., & Creswell, J. D. (2023). Research design: Qualitative, quantitative, and mixed methods approaches (6th ed.). SAGE Publications.

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. Journal of Marketing Research, 18(1), 39–50. https://doi.org/10.1177/002224378101800104

Gamage, A. N. K. K. (2025). Research design, philosophy, and quantitative methodology. Scholars Journal of Engineering and Technology, 13(2), 91–103.

Gao, Y., Antwi-Afari, M. F., Huang, Y., Chen, Z. S., & Manzoor, B. (2026). Artificial Intelligence in Construction Project Management: A Systematic Literature Review of Cost, Time, and Safety Management. Buildings, 16(5), 1061.

Geisser, S. (1975). The predictive sample reuse method with applications. Journal of the American Statistical Association, 70(350), 320–328. https://doi.org/10.2307/2285689

Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, M. (2022). A primer on partial least squares structural equation modeling (PLS-SEM) (3rd ed.). SAGE Publications.

Hair, J. F., Sarstedt, M., Ringle, C. M., & Gudergan, S. P. (2024). Advanced issues in partial least squares structural equation modeling (PLS-SEM) (2nd ed.). SAGE Publications.

Han, X., [et al.]. (2026). Artificial intelligence adoption, dynamic capabilities, and firm risk-taking. Journal of International Financial Management & Accounting. https://doi.org/10.1111/jifm.70010

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. Journal of the Academy of Marketing Science, 43(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Jamil, K., Zhang, W., Anwar, A., & Mustafa, S. (2025). Exploring the influence of AI adoption and technological readiness on sustainable performance in Pakistani export sector manufacturing small and medium-sized enterprises. Sustainability, 17(8), 3599.

Khurshid, M. T., Nazir, M. U., Bhatti, M. A. A., & Bhatti, M. B. A. (2025). The Impact of Service Quality and Perceived Value on Customer Satisfaction: The Mediating Role of Restaurant Image in the Hospitality Industry. Bulletin of Management Review, 2(3), 116-134.

Kineber, A. F., Oke, A. E., Elshaboury, N., Abunada, Z., Elseknidy, M., Zamil, A., ... & Ilori, S. A. (2024). Agile project management for sustainable residential construction: A study of critical success factors. Frontiers in Built Environment, 10, 1442184.

Kock, N. (2021). Harman's single-factor test in PLS-SEM: Checking for common method bias. Data Analysis Perspectives Journal, 2(2), 1–6.

Li, T., Zhai, H., Wu, W., Deng, J., & Wang, F. (2026). How AI adoption shapes construction workers' extra-role safety behavior: The mediating roles of responsibility and relational energy. Journal of Construction Engineering and Management, 152(1). https://doi.org/10.1061/JCEMD4.COENG-16946

Li, T., Zhang, Y., & Wang, Z. (2024). Dynamic capabilities in digital transformation: A systematic review of their role in the construction industry. Journal of Construction Engineering and Management, 150(11). https://doi.org/10.1061/JCEMD4.COENG-15055

Mariani, M. M., Bresciani, S., & Ferraris, A. (2025). Harnessing AI for value: Examining the impact of AI capabilities and the mediating role of organizational agility on project value proposition. International Journal of Managing Projects in Business, 18(8), 112–140. https://doi.org/10.1108/IJMPB

Mastt. (2025). State of AI in construction project management. Mastt Research. https://www.mastt.com/research/ai-in-construction

McCombes, S. (2023). Sampling methods: Types, techniques and examples. Scribbr. https://www.scribbr.com/methodology/sampling-methods/

Netguru. (2025). The future of AI in construction: Trends and innovations. https://www.netguru.com/blog/future-of-ai-in-construction

Petrelli, M. Z., Pacagnella, A. C., Ignacio, P. S. d. A., Rampasso, I. S., Anholon, R., & Bortoletto, W. W. (2024). Sustainable practices in construction project management: Impacts on triple bottom line. Proceedings of the Institution of Civil Engineers – Engineering Sustainability, 177(3), 150–161. https://doi.org/10.1680/jensu.21.00109

PMC. (2025). A SEM–ANN analysis to examine impact of artificial intelligence technologies on sustainable performance of SMEs. Scientific Reports. https://doi.org/10.1038/s41598-025-86464-3

Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2024). Common method bias: It's bad, it's complex, it's widespread, and it's not easy to fix. Annual Review of Organizational Psychology and Organizational Behavior.

Ringle, C. M., Wende, S., & Becker, J.-M. (2024). SmartPLS 4 [Computer software]. SmartPLS. https://www.smartpls.com

Robbins, S., & Van Wynsberghe, A. (2022). Our new artificial intelligence infrastructure: becoming locked into an unsustainable future. Sustainability, 14(8), 4829.

Savaş, S. (2025). Artificial intelligence in construction project management: Trends, challenges and future directions. Journal of Design for Resilience in Architecture & Planning, 6(2), 221–238. https://doi.org/10.47818/drarch.2025.v6i2295

Scientific Reports. (2026). Artificial intelligence assimilation shapes sustainable performance through dynamic capabilities. Scientific Reports. https://doi.org/10.1038/s41598-026-46291-6

Singh, A., Dwivedi, A., & Agrawal, D. (2023). Identifying issues in adoption of AI practices in construction supply chains: Towards managing sustainability. Operations Management Research, 16, 1667–1683. https://doi.org/10.1007/s12063-022-00344-x

Soc. (2026). Artificial intelligence adoption and organizational performance: The role of organizational agility and management commitment in AI-enabled work environments. Societies, 16(5), 138. https://doi.org/10.3390/soc16050138

Sustainability. (2025). Sustainability and stakeholder engagement in BIM-enabled construction. Sustainability, 17(3), 1086. https://doi.org/10.3390/su17031086

Taboada, I., Daneshpajouh, A., Toledo, N., & De Vass, T. (2023). Artificial intelligence enabled project management: a systematic literature review. Applied Sciences, 13(8), 5014.

Teece, D. J. (2007). Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal, 28(13), 1319–1350. https://doi.org/10.1002/smj.640

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. Strategic Management Journal, 18(7), 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509::AID-SMJ882>3.0.CO;2-Z

Zeng, N., Liu, Y., Gong, P., Hertogh, M., & König, M. (2023). Do right PLS and do PLS right: A critical review of the application of PLS-SEM in construction management research. Frontiers of Engineering Management, 8(3), 356–369. https://doi.org/10.1007/s42524-021-0202-y

Zou, M., & Yang, Y. (2026). Artificial Intelligence as a Catalyst for Dynamic Capabilities: How Resource Integration Reshapes Corporate Innovation. Journal of Innovation & Knowledge, 14, 100971.