Journal of Business Insight and Innovation
Volume 5 Issue 9, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

# HOW AI-ASSISTED PROJECT DECISION-MAKING SHAPES PROJECT SUCCESS: THE MEDIATING ROLE OF TEAM LEARNING AGILITY AND THE MODERATING ROLE OF PROJECT COMPLEXITY

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**DOI:** https://doi.org/10.63544/jbii.v5i9.216

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**Article History:**
Received: 24.07.2026
Accepted: 29.08.2026
Published: 17.09.2026

**Abstract**

*The increasing adoption of artificial intelligence (AI) has transformed project management by enhancing decision-making, collaboration, and operational efficiency. This study investigates the influence of AI-assisted project decision-making and cross-functional knowledge integration on project success while examining the mediating role of team learning agility and the moderating role of project complexity. A quantitative, explanatory, and cross-sectional research design was adopted using a structured questionnaire administered to professionals working in project-based organizations, with 270 valid responses retained for the final analysis. Data was analysed using SPSS 27 and Hayes' PROCESS Macro to examine direct, mediating, and moderating relationships. The findings revealed that AI-assisted project decision-making and cross-functional knowledge integration significantly and positively influence project success. Team learning agility partially mediated both relationships, indicating that adaptive learning capabilities strengthen the effectiveness of AI-enabled decision-making and collaborative knowledge integration. However, project complexity did not significantly moderate the relationship between team learning agility and project success. The study contributes to AI-enabled project management literature by integrating technological, organizational, and behavioural perspectives into a unified framework and offers practical guidance for organizations seeking to improve project outcomes through AI adoption, collaborative knowledge sharing, and continuous team learning.*

**Keywords:** Artificial Intelligence, AI-Assisted Project Decision-Making, Cross-Functional Knowledge Integration, Team Learning Agility, Project Success

## 1. Introduction

### *1.1 Background of the Study*

The rapid advancement of artificial intelligence (AI) has transformed project management by enabling organizations to make faster, more accurate, and evidence-based decisions in increasingly dynamic business environments. AI-assisted decision support systems utilize machine learning, predictive analytics, and intelligent algorithms to enhance planning, optimize resource allocation, identify project risks, and improve overall project performance (Ahmed et al., 2024; Ronak, 2024). Rather than replacing managerial judgment,

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AI complements human expertise by providing real-time analytical insights that strengthen decision quality and organizational responsiveness (Abositta et al., 2024; Almalki, 2025; Wang et al., 2026; Liu & Liu, 2026). Recent studies have demonstrated that AI positively influences project planning, governance, collaboration, innovation, and project outcomes across technology-driven organizations (Iqbal et al., 2026; Asghar & Burria, 2025; Doria et al., 2026; Gahlawat & Ganatra, 2026).

However, technological capabilities alone are insufficient to ensure project success. Organizations must also develop complementary human and organizational capabilities that enable project teams to effectively interpret and apply AI-generated insights (Dawarka et al., 2026; Khan et al., 2025). Among these capabilities, team learning agility plays a crucial role by enabling teams to acquire new knowledge, adapt to changing project conditions, and continuously improve performance (Han & Zhang, 2024; Han et al., 2024). Likewise, cross-functional knowledge integration enhances collaboration and informed decision-making by combining expertise across organizational boundaries (Jahangir et al., 2025; Hussain et al., 2026). Nevertheless, the effectiveness of these relationships may vary depending on project complexity, which increases uncertainty, coordination requirements, and decision-making challenges (Ali & Yushi, 2024; Mata et al., 2023; Razzaq et al., 2025). Accordingly, this study investigates the effects of AI-assisted project decision-making and cross-functional knowledge integration on project success by examining the mediating role of team learning agility and the moderating role of project complexity, thereby contributing to the growing literature on AI-enabled project management.

Despite the growing body of research on artificial intelligence in project management, existing studies have primarily examined isolated technological, organizational, or knowledge management perspectives, leaving limited understanding of how these capabilities collectively influence project success in AI-enabled environments (Alshawish et al., 2026; Ashraf et al., 2025). Moreover, empirical evidence regarding the integration of cross-functional knowledge, adaptive learning capabilities, and project contextual factors remains fragmented across different organizational settings (Baig et al., 2021; Jintian et al., 2022). Addressing these gaps provides a more comprehensive understanding of AI-supported project management and offers valuable insights for both theory and practice.

### *1.2 Problem Statement*

The increasing adoption of artificial intelligence (AI) has transformed project management by enabling intelligent decision support for planning, scheduling, risk assessment, and resource allocation. Despite these advancements, many organizations continue to face project delays, budget overruns, and coordination challenges. Existing research has largely emphasized the direct benefits of AI while providing limited understanding of the organizational mechanisms through which AI-assisted decision-making enhances project success (Abositta et al., 2024; Almalki, 2025). In particular, the role of team learning agility in enabling project teams to interpret and effectively utilize AI-generated insights remains underexplored. Similarly, the contribution of cross-functional knowledge integration to AI-enabled project success has received limited empirical attention. Furthermore, although project complexity has been widely studied, its moderating role within AI-assisted decision-making frameworks remains insufficiently understood (Ali & Yushi, 2024; Mata et al., 2023). Therefore, this study addresses these gaps by examining the direct effects of AI-assisted project decision-making and cross-functional knowledge integration on project success, the mediating role of team learning agility, and the moderating role of project complexity within an integrated conceptual framework.

### *1.3 Research Objectives*

The primary objective of this study is to examine how AI-assisted project decision-making contributes to project success by investigating the mediating role of team learning agility and the moderating role of project complexity. In addition, the study seeks to explore the influence of cross-functional knowledge integration on project success within AI-enabled project environments. To accomplish this objective, the following specific objectives are established:

1. To examine the effect of AI-assisted project decision-making on project success.
2. To examine the effect of cross-functional knowledge integration on project success.

3. To investigate the mediating role of team learning agility in the relationship between AI-assisted project decision-making and project success.
4. To investigate the mediating role of team learning agility in the relationship between cross-functional knowledge integration and project success.
5. To examine the moderating role of project complexity in the relationship between team learning agility and project success.

### *1.4 Research Questions*

Based on the research objectives and the identified gaps in the literature, the study addresses the following research questions:

1. How does AI-assisted project decision-making influence project success?
2. How does cross-functional knowledge integration influence project success?
3. Does team learning agility mediate the relationship between AI-assisted project decision-making and project success?
4. Does team learning agility mediate the relationship between cross-functional knowledge integration and project success?
5. Does project complexity moderate the relationship between team learning agility and project success?

### *1.5 Significance of the Study*

The growing adoption of artificial intelligence has transformed project management by introducing intelligent systems capable of improving decision quality, optimizing resources, and supporting strategic planning. However, organizations increasingly recognize that technological advancement alone cannot guarantee successful project delivery. The ability to combine AI capabilities with organizational learning, knowledge integration, and adaptive project management practices has become equally important. Consequently, this study contributes meaningful insights to both academic research and professional practice by examining the mechanisms through which AI-assisted project decision-making influences project success.

**1.5.1 Theoretical Significance.** This study makes several important contributions to the literature on artificial intelligence and project management. First, it extends research on AI-assisted project decision-making by moving beyond the direct relationship between AI adoption and project success to examine the organizational mechanisms through which AI creates value. Specifically, by identifying team learning agility as a mediating capability, the study explains how AI-generated insights are translated into improved project outcomes (Abositta et al., 2024; Almalki, 2025). Second, grounded in Dynamic Capabilities Theory, the study integrates technological, organizational, and adaptive capabilities into a unified conceptual framework encompassing AI-assisted project decision-making, cross-functional knowledge integration, team learning agility, project complexity, and project success. This integrated perspective addresses the fragmented treatment of these constructs in previous research and enriches the literature on AI-enabled project management, organizational learning, and digital transformation. Third, the study advances project management theory by examining project complexity as a contextual boundary condition influencing the effectiveness of learning agility, thereby extending understanding of AI-supported project environments (Ali & Yushi, 2024; Mata et al., 2023). Finally, the findings reinforce the Dynamic Capabilities perspective by demonstrating that sustainable project success depends not only on AI technologies but also on organizations' ability to integrate knowledge, foster learning agility, and continuously adapt to changing project conditions.

**1.5.2 Practical Significance.** The findings of this study offer several practical implications for project managers, organizational leaders, technology developers, and policymakers responsible for implementing AI-enabled project management systems.

For project managers, the study provides evidence regarding the importance of integrating AI-assisted decision support with continuous learning and collaborative knowledge-sharing practices. Rather than relying exclusively on AI-generated recommendations, project managers should cultivate environments where project teams actively interpret, discuss, and apply intelligent insights to project execution. Such practices can improve decision quality, enhance team adaptability, and increase the likelihood of successful project completion.

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ISSN-p: 3006-2284, ISSN-e: 3006-0982
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For organizational leaders, the findings highlight that investments in AI technologies should be accompanied by investments in organizational capabilities such as team learning agility and cross-functional collaboration. Organizations that successfully combine technological innovation with adaptive learning cultures are more likely to achieve improved project performance, greater operational efficiency, and sustainable competitive advantage. The study therefore provides strategic guidance for organizations undertaking digital transformation initiatives across project-based industries.

The research is also relevant for developers of AI-enabled project management systems. The findings emphasize that AI technologies should be designed to support collaborative decision-making rather than simply automate managerial tasks. User-friendly interfaces, explainable AI models, and decision-support features that facilitate knowledge sharing and organizational learning can increase user acceptance and maximize the practical value of AI applications.

Finally, the study provides useful insights for policymakers and professional bodies involved in promoting digital transformation and AI adoption within project-intensive sectors. The findings suggest that successful implementation of AI requires complementary investments in workforce development, digital competencies, organizational learning, and change management initiatives. Such evidence can inform future policies aimed at improving organizational readiness for AI-enabled project management.

## 2. Literature Review

This study is primarily grounded in Dynamic Capabilities Theory (DCT), which posits that organizations achieve sustainable competitive advantage by continuously integrating, building, and reconfiguring their technological, organizational, and human capabilities to respond effectively to dynamic and uncertain environments (Teece et al., 1997; Teece, 2007). In AI-enabled project management, organizations increasingly rely on artificial intelligence to enhance decision quality, optimize resources, and improve project performance; however, technological resources alone are insufficient to guarantee project success (Abositta et al., 2024; Almalki, 2025; Wang et al., 2026). Dynamic Capabilities Theory suggests that organizations must complement technological capabilities with adaptive organizational capabilities to transform available resources into superior performance (Teece, 2007). Within the context of the present study, AI-assisted project decision-making represents a technological capability, while cross-functional knowledge integration reflects the organization's ability to integrate specialized knowledge across functional boundaries. Team learning agility embodies an adaptive capability that enables project teams to acquire, assimilate, and apply new knowledge in rapidly changing project environments (Han & Zhang, 2024; Dawarka et al., 2026). Furthermore, project complexity represents the contextual conditions under which these capabilities operate and interact to influence project outcomes (Ali & Yushi, 2024; Mata et al., 2023). Accordingly, Dynamic Capabilities Theory provides a comprehensive theoretical lens for explaining how AI-assisted project decision-making and cross-functional knowledge integration contribute to project success directly and indirectly through team learning agility while accounting for variations in project environments.

### *2.1 Artificial Intelligence in Project Management*

Artificial intelligence (AI) has become a transformative force in project management by enabling organizations to improve planning, scheduling, risk assessment, and resource allocation through intelligent decision support systems. Using machine learning, predictive analytics, and automation, AI assists project managers in processing complex information, forecasting project outcomes, and making timely, evidence-based decisions, thereby enhancing efficiency and organizational competitiveness (Ahmed et al., 2024; Ronak, 2024). AI technologies also support project execution by monitoring progress, optimizing resource utilization, and facilitating proactive risk management, allowing managers to focus on strategic leadership rather than routine administrative tasks (Almalki, 2025; Gahlawat & Ganatra, 2026; Shafik, 2024; Wang et al., 2026). Empirical evidence further shows that AI improves project coordination, decision quality, and organizational performance (Asghar & Burria, 2025).

Beyond operational improvements, successful AI implementation depends on complementary organizational capabilities. AI enhances managerial decision-making and knowledge sharing, but its effectiveness relies on employees' ability to interpret and apply AI-generated insights (Graca, 2025; Sun, 2026). Moreover, responsible AI governance, transparency, and accountability have become increasingly important for ensuring effective project outcomes (Dória et al., 2026; Alshawish & Tuncali Yaman, 2026). Despite these advancements, technological capability alone cannot guarantee project success, highlighting the importance of organizational learning, collaboration, and adaptive capabilities (Khan et al., 2025; Dawarka et al., 2026). Therefore, this study extends prior research by examining AI-assisted project decision-making alongside team learning agility and project complexity as key determinants of project success.

### *2.2 AI-Assisted Project Decision-Making*

AI-assisted project decision-making has become a critical capability in modern project management as organizations increasingly rely on intelligent systems to support planning, scheduling, resource allocation, and risk management. Unlike traditional decision-making, which depends largely on managerial experience, AI-assisted decision-making combines human judgment with machine learning, predictive analytics, and data-driven insights to improve the quality and speed of project decisions (Abositta et al., 2024). Rather than replacing managers, AI augments their analytical capabilities by processing large volumes of project information, evaluating multiple scenarios, and providing evidence-based recommendations that support more informed and timely decision-making (Wang et al., 2026).

A key advantage of AI-assisted decision-making is its ability to enhance project forecasting and proactive management. By analyzing historical and real-time project data, AI systems can predict resource requirements, estimate project completion, identify potential risks, and recommend corrective actions before project performance deteriorates, thereby improving project control and increasing the likelihood of successful project completion (Almalki, 2025; Gahlawat & Ganatra, 2026). Empirical studies further demonstrate that AI-assisted decision-making strengthens engineering management, leadership effectiveness, collaboration, and overall project success (Abositta et al., 2024; Iqbal et al., 2026; Liu & Liu, 2026). Moreover, explainable AI enhances managers' trust in AI-generated recommendations by increasing transparency and facilitating effective human-AI collaboration (Wang et al., 2026). Nevertheless, AI-generated insights alone cannot ensure project success, emphasizing the importance of complementary organizational capabilities such as cross-functional knowledge integration and team learning agility for translating intelligent recommendations into effective project outcomes.

### *2.3 Cross-Functional Knowledge Integration*

Cross-functional knowledge integration refers to the process through which individuals from different functional areas combine their expertise, skills, and information to achieve shared project objectives. In project-based organizations, effective collaboration among engineering, IT, finance, operations, procurement, and other departments is essential because no single function possesses all the knowledge required to manage complex projects successfully. Kahn (1996) argued that organizational performance improves when departments coordinate activities, exchange information, and participate collaboratively in decision-making, thereby enhancing communication, reducing duplication of effort, and improving organizational responsiveness.

The growing adoption of artificial intelligence has further increased the importance of cross-functional knowledge integration. Although AI generates valuable analytical insights, these recommendations often require interpretation from multiple functional perspectives before being translated into effective managerial actions. Agile project environments further reinforce this need by promoting continuous communication, collaborative problem-solving, and rapid adaptation supported by AI-enabled information sharing (Shafik, 2024; Azeroual, 2026). Empirical studies consistently show that knowledge integration enhances organizational agility, innovation, and project performance by strengthening collaboration and organizational learning (Jahangir et al., 2025; Hussain et al., 2026). Similarly, research demonstrates that knowledge integration facilitates the effective utilization of AI-generated insights (Rehmat et al., 2025). Building on these findings, this study proposes that cross-functional knowledge integration enhances project success by strengthening team learning agility and enabling project teams to effectively utilize AI-generated insights.

### *2.4 Team Learning Agility*

Team learning agility refers to a team's collective ability to acquire new knowledge, adapt to changing circumstances, and continuously improve performance through shared learning and experience. In AI-enabled project environments, this capability has become increasingly important because the value of AI-generated insights depends on project teams' ability to interpret, evaluate, and apply them effectively. Rather than relying solely on established routines, learning-agile teams embrace change, experiment with new approaches, and integrate lessons learned to improve project execution, making them more effective in dynamic and technology-driven environments (Han & Zhang, 2024).

The integration of AI has further strengthened the importance of team learning agility by providing project teams with real-time information, predictive analytics, and intelligent recommendations. However, these insights contribute to project success only when teams possess the capability to transform information into practical actions. Learning-agile teams critically evaluate AI-generated recommendations, combine them with collective expertise, and adapt project strategies to evolving conditions, thereby complementing rather than replacing technological capabilities (Dawarka et al., 2026). Empirical evidence demonstrates that organizational learning and agility significantly improve project success, innovation, and adaptability (Han et al., 2024; Mata et al., 2026; Hussain et al., 2026). Moreover, learning agility strengthens cross-functional collaboration by encouraging knowledge sharing and collaborative problem-solving across project teams. Despite its growing importance, limited research has examined team learning agility as the mechanism through which AI-assisted decision-making and cross-functional knowledge integration improve project success. Therefore, this study positions team learning agility as the key mediating capability linking AI-supported decision-making, collaborative knowledge integration, and successful project outcomes.

### *2.5 Project Complexity*

Project complexity refers to the multidimensional challenges arising from technological sophistication, organizational interdependencies, stakeholder diversity, and environmental uncertainty that influence project planning and execution. Rather than being determined solely by project size or duration, complexity encompasses technical, organizational, and environmental dimensions that collectively affect coordination, communication, and managerial decision-making. The Technical, Organizational, and Environmental (TOE) framework proposed by Bosch-Rekveldt et al. (2011) conceptualizes project complexity as the interaction of these interconnected dimensions, making it one of the most widely accepted perspectives in project management research.

The increasing adoption of artificial intelligence has improved organizations' ability to manage complex projects through predictive analytics, intelligent resource allocation, and evidence-based decision support. However, highly complex projects continue to require human judgment, collaborative problem-solving, and adaptive learning beyond AI capabilities alone. Consequently, project complexity may influence how effectively project teams apply AI-generated recommendations to achieve successful outcomes. Empirical studies support this view by showing that project complexity strengthens the importance of organizational capabilities such as strategic agility, teamwork, and adaptive project management practices (Mata et al., 2023; Ali & Yushi, 2024; Razzaq et al., 2025). Building on this evidence, the present study conceptualizes project complexity as a moderating variable influencing the relationship between team learning agility and project success. It is proposed that learning-agile teams are better able to manage uncertainty and adapt to changing project conditions, although the strength of this relationship may vary depending on the level of project complexity. This perspective provides a more comprehensive understanding of project success within AI-assisted project management environments.

### *2.6 Project Success*

Project success is widely recognized as the ultimate objective of project management and extends beyond the traditional "iron triangle" of time, cost, and quality. While meeting schedule, budget, and quality targets remains essential, contemporary perspectives emphasize broader outcomes such as stakeholder satisfaction, strategic value creation, organizational learning, innovation, and long-term organizational performance. Pinto and Slevin (1988) argued that project success should be viewed as a multidimensional construct that incorporates both project management efficiency and organizational outcomes, encouraging organizations to evaluate success from multiple stakeholder perspectives.

The increasing integration of artificial intelligence has further expanded the determinants of project success. AI-assisted project management enhances planning, resource utilization, risk identification, communication, and evidence-based decision-making, enabling organizations to improve efficiency and respond more effectively to uncertainty (Ahmed et al., 2024; Almalki, 2025). Empirical studies also demonstrate that AI contributes to project success by strengthening team performance, collaboration, and managerial decision-making (Asghar & Burria, 2025; Iqbal et al., 2026). However, technology alone cannot ensure successful project outcomes. Effective leadership, cross-functional collaboration, adaptive learning, and organizational agility remain essential for translating AI-generated insights into practical project actions. Accordingly, the present study conceptualizes project success as the successful achievement of project objectives through the combined influence of AI-assisted decision-making, cross-functional knowledge integration, team learning agility, and effective management of project complexity.

### *2.7 Hypotheses Development*

Based on the literature review and theoretical framework, the following hypotheses are proposed:

**H1:** AI-assisted project decision-making positively influences project success.

**H2:** Cross-functional knowledge integration positively influences project success.

**H3:** Team learning agility mediates the relationship between AI-assisted project decision-making and project success.

**H4:** Team learning agility mediates the relationship between cross-functional knowledge integration and project success.

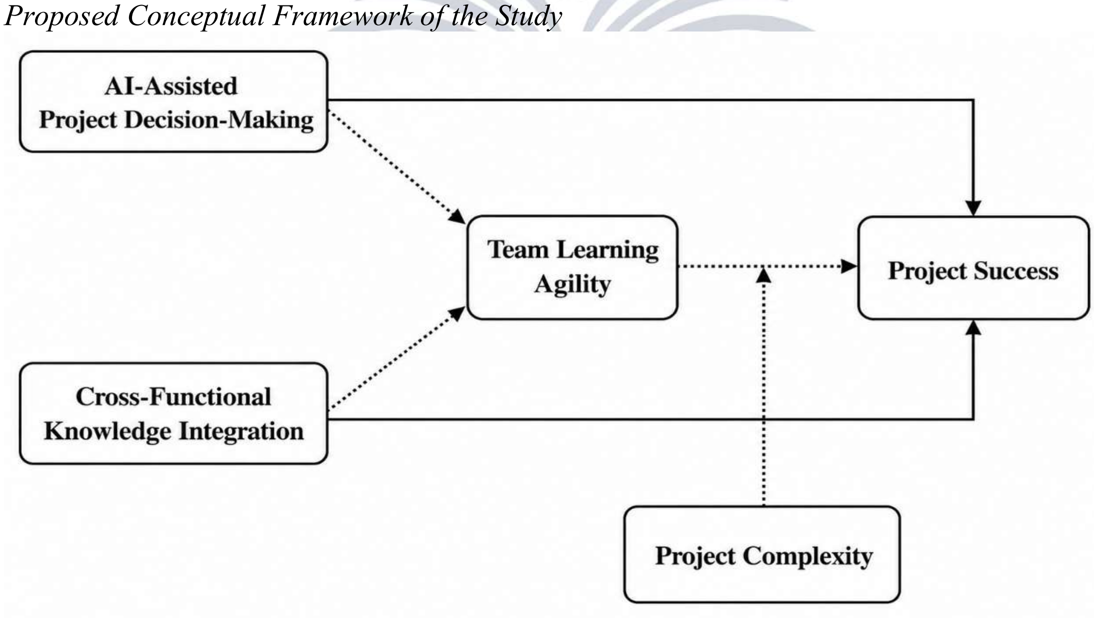
**H5:** Project complexity positively moderates the relationship between team learning agility and project success such that the positive relationship is stronger when project complexity is high.

### *2.8 Conceptual Framework*

Figure 1 presents the proposed conceptual framework of the study, illustrating the relationships among AI-assisted project decision-making, cross-functional knowledge integration, team learning agility, project complexity, and project success.

**Figure 1**

*Proposed Conceptual Framework of the Study*




*Note.* Solid arrows represent direct effects; dashed arrows represent mediating and moderating relationships.

## 3. Research Methodology

### *3.1 Research Philosophy*

This study adopted the positivist research philosophy, which assumes that relationships among variables can be objectively measured and empirically tested using quantitative methods (Bougie & Sekaran, 2025). Positivism was considered appropriate because the study examined the relationships among AI-assisted project decision-making, cross-functional knowledge integration, team learning agility, project complexity, and project success through hypothesis testing and statistical analysis. The philosophy emphasizes objectivity, reliability, validity, and generalizability while minimizing researcher bias. Given the increasing application of quantitative approaches in AI-enabled project management research, the positivist paradigm provides a suitable foundation for examining organizational phenomena (Ahmed et al., 2024; Khan et al., 2025).

### *3.2 Research Approach*

The study employed a deductive research approach, whereby hypotheses were derived from established theories and empirical literature before being tested using quantitative data (Bougie & Sekaran, 2025). The proposed conceptual framework was developed from prior studies on artificial intelligence, organizational learning, and project management (Almalki, 2025; Wang et al., 2026). The deductive approach was appropriate because the objective was to validate theoretical relationships rather than generate new theory.

### *3.3 Research Design*

A quantitative, explanatory, and cross-sectional research design was adopted. The quantitative design enabled objective measurement of the study constructs using numerical data collected through structured questionnaires. The explanatory design was appropriate because the study investigated direct, mediating, and moderating relationships among the variables. A cross-sectional survey was employed as data was collected from respondents at a single point in time, a design widely used in organizational and project management research (Bougie & Sekaran, 2025; Asghar & Burria, 2025).

### *3.4 Population and Sampling*

The target population comprised professionals working in project-based organizations, including project managers, engineers, software developers, consultants, team leaders, and other employees involved in project planning and decision-making across the information technology, construction, manufacturing, and telecommunication sectors. Purposive sampling was adopted because only respondents possessing relevant project management experience and familiarity with AI-assisted decision-making could provide meaningful information. Approximately 300 questionnaires were distributed, and after screening for completeness and consistency, 270 valid responses were retained for analysis.

### *3.5 Measurement Instrument*

Primary data were collected through a structured self-administered questionnaire. All measurement items were adapted from established and validated scales, with only minor wording modifications to improve clarity while preserving their conceptual meaning. Responses were measured using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree).

**Table 1**
*Measurement of Study Variables*

| Construct | No. of Items | Source |
|---|---|---|
| AI-Assisted Project Decision-Making | 6 | Buschmeyer et al. (2023) |
| Cross-Functional Knowledge Integration | 6 | Kahn (1996) |
| Team Learning Agility | 5 | DeRue et al. (2012) |
| Project Complexity | 4 | Bosch-Rekveldt et al. (2011) |
| Project Success | 4 | Pinto and Slevin (1988) |

### *3.6 Data Collection Procedure*

Questionnaires were distributed through professional networks, organizational contacts, LinkedIn, and email. Participation was voluntary, and respondents were informed about the purpose of the research before

Journal of Business Insight and Innovation
Volume 5 Issue 9, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

completing the survey. Confidentiality and anonymity were assured, and participants could withdraw at any stage without consequence. After data collection, questionnaires were screened for missing values and inconsistent responses before being coded and entered into IBM SPSS Statistics Version 27 for analysis.

### *3.7 Data Analysis Strategy*

Data analysis was conducted using IBM SPSS Statistics Version 27. Descriptive statistics summarized respondents' demographic characteristics. Internal consistency was assessed using Cronbach's alpha, where values exceeding 0.70 indicate satisfactory reliability (Peterson, 1994). Construct validity was evaluated through Exploratory Factor Analysis (EFA) using the Kaiser-Meyer-Olkin (KMO) measure and Bartlett's Test of Sphericity. Pearson correlation analysis examined associations among the study variables. Hypotheses were tested using Hayes' (2018) PROCESS Macro, with Model 4 assessing the mediating role of team learning agility and Model 1 examining the moderating role of project complexity. Indirect effects were estimated using 5,000 bootstrap resamples with 95% bias-corrected confidence intervals, a robust procedure for mediation and moderation analysis (Hayes, 2018; Mata et al., 2023).

### *3.8 Ethical Considerations*

The study complied with accepted ethical research standards. Informed consent was obtained from all respondents before participation, and all responses were treated confidentially and analyzed only in aggregate form. No personally identifiable information was collected, and organizational identities remained anonymous. The collected data were used solely for academic purposes, and all theoretical foundations, measurement scales, and supporting literature were appropriately acknowledged to maintain academic integrity and transparency (Bougie & Sekaran, 2025).

## 4. Data Analysis and Results

### *4.1 Introduction*

This chapter presents the empirical findings of the study based on data collected from professionals working in project-based organizations. The primary objective of this chapter is to examine the relationships among AI-assisted project decision-making, cross-functional knowledge integration, team learning agility, project complexity, and project success. The data were analyzed using the Statistical Package for Social Sciences (SPSS Version 27), while Hayes' PROCESS Macro was employed to test the mediating and moderating relationships proposed in the conceptual framework.

The analysis was conducted in several stages. First, respondents' demographic characteristics were examined to describe the sample profile. Second, reliability analysis was performed using Cronbach's alpha to assess the internal consistency of the measurement scales. Third, construct validity was evaluated using Exploratory Factor Analysis (EFA), including the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. Subsequently, Pearson correlation analysis was conducted to examine the relationships among the study variables. Finally, mediation and moderation analyses were performed using PROCESS Macro to test the proposed hypotheses.

A total of 270 valid responses were included in the final analysis.

### *4.2 Demographic Profile of Respondents*

The demographic analysis provides an overview of the characteristics of respondents participating in the study. The respondents represented professionals working in project-based organizations across multiple industries, ensuring diversity in project experience and organizational context.

**Table 2**

*Demographic Profile of Respondents (N = 270)*

| Variable | Category | Frequency | Percentage (%) |
|---|---|---|---|
| Gender | Male | 159 | 58.9 |
| | Female | 111 | 41.1 |
| | Total | 270 | 100.0 |
| Age | 20–29 Years | 144 | 53.3 |
| | 30–39 Years | 120 | 44.4 |
| | 40–49 Years | 6 | 2.2 |

| Variable | Category | Frequency | Percentage (%) |
|---|---|---|---|
| | Total | 270 | 100.0 |
| Project Management Experience | Less than 3 Years | 132 | 48.9 |
| | 3–5 Years | 121 | 44.8 |
| | 6–10 Years | 16 | 5.9 |
| | More than 10 Years | 1 | 0.4 |
| | Total | 270 | 100.0 |
| Industry/Sector | Information Technology | 82 | 30.4 |
| | Construction & Engineering | 102 | 37.8 |
| | Manufacturing | 66 | 24.4 |
| | Telecommunication | 20 | 7.4 |
| | Total | 270 | 100.0 |

The results indicate that the majority of respondents were male (58.9%), while females represented 41.1% of the sample. Regarding age distribution, more than half of the respondents (53.3%) belonged to the 20–29 years category, followed by respondents aged 30–39 years (44.4%). Only 2.2% of participants were between 40 and 49 years of age.

With respect to project management experience, nearly half of the respondents (48.9%) had less than three years of experience, while 44.8% had between three and five years of experience. Only 6.3% of respondents possessed more than five years of experience. This distribution indicates that the sample largely represents early- and mid-career professionals actively involved in project environments.

The respondents represented diverse industries. Construction and engineering organizations contributed the largest proportion (37.8%), followed by information technology (30.4%), manufacturing (24.4%), and telecommunication sectors (7.4%). This diversity enhances the generalizability of the findings across project-based industries.

***4.3 Reliability Analysis***

Reliability analysis was conducted to evaluate the internal consistency of the measurement scales. Cronbach's alpha coefficient was employed because it is one of the most widely accepted measures of reliability. According to Peterson (1994), values above 0.70 indicate acceptable reliability, while values exceeding 0.80 demonstrate good internal consistency.

The reliability results indicate that all constructs achieved Cronbach's alpha values above the recommended threshold. Specifically, AI-assisted decision-making achieved the highest reliability coefficient (α = .922), followed by cross-functional knowledge integration (α = .918), team learning agility (α = .906), project complexity (α = .817), and project success (α = .810). The overall reliability of the instrument comprising twenty-five items was α = .932, indicating excellent internal consistency.

**Table 3**

*Reliability Analysis and Factor Loadings*

| Variable | Item | Factor Loading | Reliability |
|---|---|---|---|
| AI-Assisted Decision Making | AIADM1 | .854 | .922 |
| | AIADM2 | .840 | |
| | AIADM3 | .842 | |
| | AIADM4 | .857 | |
| | AIADM5 | .853 | |
| | AIADM6 | .846 | |
| Cross-Functional Knowledge Integration | CFKI1 | .858 | .918 |
| | CFKI2 | .828 | |
| | CFKI3 | .856 | |
| | CFKI4 | .837 | |
| | CFKI5 | .828 | |

Journal of Business Insight and Innovation
Volume 5 Issue 9, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

| Variable | Item | Factor Loading | Reliability |
|---|---|---|---|
| | CFKI6 | .845 | |
| Team Learning Agility | TLA1 | .863 | .906 |
| | TLA2 | .852 | |
| | TLA3 | .832 | |
| | TLA4 | .853 | |
| | TLA5 | .865 | |
| Project Complexity | PC1 | .600 | .817 |
| | PC2 | .862 | |
| | PC3 | .874 | |
| | PC4 | .869 | |
| Project Success | PS1 | .625 | .810 |
| | PS2 | .840 | |
| | PS3 | .865 | |
| Total Items = 25 | | | .932 |

The factor loadings for all measurement items exceeded the minimum threshold of 0.50, ranging from 0.600 to 0.874, indicating satisfactory item reliability. The findings confirm that the measurement instrument possesses adequate internal consistency and is suitable for further statistical analysis.

### *4.4 Validity Analysis*

Construct validity was assessed using Exploratory Factor Analysis (EFA). Before extracting the factors, the suitability of the data for factor analysis was evaluated using the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy and Bartlett's Test of Sphericity. The KMO statistic determines whether the sample size is adequate for factor analysis, while Bartlett's Test examines whether the correlation matrix significantly differs from an identity matrix. Generally, KMO values greater than 0.70 indicate adequate sampling, whereas a statistically significant Bartlett's Test ($p < 0.05$) confirms the appropriateness of factor analysis.

The results presented in Table 4 demonstrate that all constructs achieved satisfactory KMO values ranging from 0.781 to 0.926, exceeding the minimum recommended threshold. Similarly, Bartlett's Test of Sphericity was statistically significant ($p = .000$) for all constructs, indicating that the correlations among the measurement items were sufficiently strong to justify factor extraction.

The results further indicate that each construct extracted only one principal component, supporting the unidimensionality of the measurement scales. The percentage of variance explained ranged from 64.47% to 72.78%, suggesting that a substantial proportion of the total variance was explained by the extracted factors. Collectively, these findings confirm that the measurement instrument possesses satisfactory construct validity and is appropriate for subsequent hypothesis testing.

**Table 4**

*Validity Analysis Results*

| Construct | KMO | Bartlett's Test $\chi^2$ | Sig. | Variance Explained (%) | Components Extracted |
|---|---|---|---|---|---|
| AI-Assisted Decision Making | 0.926 | 1070.345 | .000 | 72.014 | 1 |
| Cross-Functional Knowledge Integration | 0.922 | 1027.851 | .000 | 70.904 | 1 |
| Team Learning Agility | 0.888 | 817.106 | .000 | 72.780 | 1 |
| Project Complexity | 0.784 | 437.422 | .000 | 65.599 | 1 |
| Project Success | 0.781 | 397.483 | .000 | 64.473 | 1 |

The high KMO values demonstrate that the collected sample is suitable for factor analysis, while the statistically significant Bartlett's Test confirms that meaningful relationships exist among the measurement items. Furthermore, the extraction of a single component for each construct supports the theoretical structure of the measurement model. Therefore, the validity analysis confirms that all constructs adequately represent their intended latent variables.

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Volume 5 Issue 9, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

### *4.5 Correlation Analysis*

Pearson correlation analysis was performed to examine the direction and strength of relationships among AI-assisted decision-making, cross-functional knowledge integration, team learning agility, project complexity, and project success. Correlation coefficients range from -1 to +1 where positive values indicate positive relationships and negative values indicate inverse relationships. The statistical significance of each correlation coefficient was assessed at the 0.01 significance level.

The results reveal that AI-assisted decision-making is positively and significantly associated with cross-functional knowledge integration ($r = .212, p < .01$), team learning agility ($r = .564, p < .01$), project complexity ($r = .498, p < .01$), and project success ($r = .615, p < .01$). These findings indicate that greater utilization of AI-supported decision-making is associated with improved collaboration, enhanced learning agility, and higher levels of project success.

Similarly, cross-functional knowledge integration demonstrates significant positive relationships with team learning agility ($r = .542, p < .01$) and project success ($r = .554, p < .01$). However, its relationship with project complexity is weak and statistically insignificant ($r = .092, p = .133$) suggesting that collaborative knowledge integration is not directly associated with perceived project complexity in the sampled organizations.

Among all study variables, team learning agility exhibits the strongest positive relationship with project success ($r = .727, p < .01$). This strong correlation indicates that organizations possessing agile and adaptive project teams tend to achieve superior project outcomes. Team learning agility also demonstrates significant positive relationships with AI-assisted decision-making ($r = .564$) and cross-functional knowledge integration ($r = .542$), supporting its proposed mediating role within the conceptual framework.

Project complexity shows a moderate positive relationship with AI-assisted decision-making ($r = .498, p < .01$), a relatively weak positive relationship with team learning agility ($r = .235, p < .01$), and a weak but statistically significant relationship with project success ($r = .250, p < .01$). Although project complexity is associated with project success, its relatively modest correlation suggests that other organizational capabilities play a more influential role in determining successful project outcomes.

Importantly, none of the correlation coefficients exceeded the commonly accepted threshold of 0.80, indicating that multicollinearity is unlikely to affect the regression-based analyses conducted in subsequent sections.

**Table 5**

*Correlation Analysis Results*

| Variables | AIADM | CFKI | TLA | PC | PS |
|---|---|---|---|---|---|
| AI-Assisted Decision Making (AIADM) | 1 | .212** | .564** | .498** | .615** |
| Cross-Functional Knowledge Integration (CFKI) | .212** | 1 | .542** | .092 | .554** |
| Team Learning Agility (TLA) | .564** | .542** | 1 | .235** | .727** |
| Project Complexity (PC) | .498** | .092 | .235** | 1 | .250** |
| Project Success (PS) | .615** | .554** | .727** | .250** | 1 |

*Note.* Correlation is significant at the 0.01 level (2-tailed). **

The correlation analysis provides preliminary empirical support for the proposed research model. The statistically significant positive relationships among most of the study variables indicate that higher levels of AI-assisted decision-making, cross-functional knowledge integration, and team learning agility are associated with improved project success. These findings provide a sound basis for conducting mediation and moderation analyses using Hayes' PROCESS Macro.

### *4.6 Hypotheses Testing*

To examine the proposed hypotheses, Hayes' PROCESS Macro was employed. The mediation hypotheses (H3 and H4) were tested using PROCESS Model 4, while the moderation hypothesis (H5) was examined using PROCESS Model 1. Regression-based mediation and moderation analyses were conducted using 5,000 bootstrap samples with 95% confidence intervals. A hypothesis was considered supported when the regression coefficient was statistically significant ($p < .05$) and the confidence interval did not include zero.

**4.6.1 Testing of H1 and H3.** The first mediation model examined the effect of AI-Assisted Project Decision-Making on Project Success through Team Learning Agility.

The model summary indicates that AI-assisted decision-making significantly predicts team learning agility ($R = .564$, $R^2 = .318$, $F = 125.027$, $p < .001$). This result suggests that AI-assisted decision-making explains 31.8% of the variance in team learning agility.

Similarly, the outcome model demonstrates that AI-assisted decision-making and team learning agility jointly explain 59.0% of the variance in project success ($R = .768$, $R^2 = .590$, $F = 192.029$, $p < .001$). These findings indicate that the proposed mediation model possesses strong explanatory power.

**Table 6**

*Mediation Model Summary for AIADM → TLA → PS*

| Outcome | R | R² | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|---|
| Team Learning Agility | .564 | .318 | .684 | 125.027 | 1 | 268 | .000 |
| Project Success | .768 | .590 | .413 | 192.029 | 2 | 267 | .000 |

**Table 7**

*Regression Paths for AIADM → TLA → PS*

| Path | Coefficient | SE | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| AIADM → TLA | .564 | .050 | 11.182 | .000 | .465 | .663 |
| AIADM → PS | .301 | .047 | 6.339 | .000 | .207 | .394 |
| TLA → PS | .557 | .047 | 11.737 | .000 | .464 | .651 |

**Table 8**

*Indirect Effect for AIADM → TLA → PS*

| Indirect Path | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| AIADM → TLA → PS | .314 | .041 | .237 | .398 |

The regression results indicate that AI-assisted decision-making has a significant positive effect on team learning agility ($\beta = .564$, $p < .001$). Furthermore, AI-assisted decision-making exerts a significant direct effect on project success ($\beta = .301$, $p < .001$). Team learning agility also significantly predicts project success ($\beta = .557$, $p < .001$).

The indirect effect of AI-assisted decision-making on project success through team learning agility equals 0.314, with a 95% bootstrap confidence interval ranging from 0.237 to 0.398. Because the confidence interval does not include zero, the indirect effect is statistically significant.

Moreover, the direct effect of AI-assisted decision-making on project success remains statistically significant after including the mediator ($\beta = .301$, $p < .001$). Therefore, team learning agility partially mediates the relationship between AI-assisted decision-making and project success.

Accordingly:

- H1 is supported.
- H3 is supported (Partial Mediation).

**4.6.2 Testing of H2 and H4.** The second mediation model examined the influence of Cross-Functional Knowledge Integration on Project Success through Team Learning Agility.

The mediator model indicates that cross-functional knowledge integration significantly predicts team learning agility ($R = .542$, $R^2 = .294$, $F = 111.696$, $p < .001$), explaining 29.4% of the variance in team learning agility.

Similarly, the outcome model demonstrates that cross-functional knowledge integration and team learning agility jointly explain 56.5% of the variance in project success ($R = .751$, $R^2 = .565$, $F = 173.051$, $p < .001$).

Journal of Business Insight and Innovation
Volume 5 Issue 9, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

**Table 9**

*Mediation Model Summary for CFKI → TLA → PS*

| Outcome | R | R² | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|---|
| Team Learning Agility | .542 | .294 | .708 | 111.696 | 1 | 268 | .000 |
| Project Success | .751 | .565 | .439 | 173.051 | 2 | 267 | .000 |

**Table 10**

*Regression Paths for CFKI → TLA → PS*

| Path | Coefficient | SE | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| CFKI → TLA | .542 | .051 | 10.569 | .000 | .441 | .643 |
| CFKI → PS | .227 | .048 | 4.720 | .000 | .132 | .322 |
| TLA → PS | .604 | .048 | 12.558 | .000 | .509 | .698 |

**Table 11**

*Indirect Effect for CFKI → TLA → PS*

| Indirect Path | Effect | BootSE | BootLLCI | BootULCI |
|---|---|---|---|---|
| CFKI → TLA → PS | .327 | .039 | .251 | .403 |

The results reveal that cross-functional knowledge integration significantly influences team learning agility ($\beta = .542$, $p < .001$) and project success ($\beta = .227$, $p < .001$). Team learning agility also exhibits a strong positive influence on project success ($\beta = .604$, $p < .001$).

The indirect effect equals 0.327, with a bootstrap confidence interval ranging from 0.251 to 0.403. Since zero does not fall within the confidence interval, the indirect effect is statistically significant.

Furthermore, the direct relationship between cross-functional knowledge integration and project success remains significant after introducing the mediator ($\beta = .227$, $p < .001$). Consequently, team learning agility partially mediates the relationship between cross-functional knowledge integration and project success.

Therefore:

- H2 is supported.
- H4 is supported (Partial Mediation).

### *4.7 Moderation Analysis*

The moderating effect of Project Complexity on the relationship between Team Learning Agility and Project Success was examined using PROCESS Model 1. The moderation model produced an overall correlation coefficient of $R = .733$ and explained 53.7% of the variance in project success ($R^2 = .537$, $F = 102.682$, $p < .001$), indicating that the model possesses substantial explanatory power.

The regression coefficients indicate that team learning agility has a significant positive effect on project success ($\beta = .706$, $t = 16.448$, $p < .001$). Similarly, project complexity independently exerts a positive influence on project success ($\beta = .087$, $t = 2.027$, $p = .044$).

However, the interaction term between team learning agility and project complexity ($\beta = .043$, $t = 1.016$, $p = .310$) is not statistically significant. In addition, the interaction contributes only 0.2% additional explained variance ($\Delta R^2 = .002$, $F = 1.033$, $p = .310$). The 95% confidence interval for the interaction effect ranges from -0.041 to 0.127, which includes zero, providing further evidence that the moderating effect is not statistically significant.

Consequently, although project complexity independently influences project success, it does not significantly strengthen or weaken the relationship between team learning agility and project success.

Therefore, H5 is not supported.

**Table 12**

*Moderation Analysis Results*

| R | R² | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|
| .733 | .537 | .469 | 102.682 | 3 | 266 | .000 |

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Volume 5 Issue 9, 2026
ISSN-p: 3006-2284, ISSN-e: 3006-0982
https://insightfuljournals.com/

**Table 13**
*Regression Coefficients for Moderation Analysis*

| Predictor | Coefficient | SE | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| Constant | -.010 | .043 | -.236 | .813 | -.094 | .074 |
| Team Learning Agility | .706 | .043 | 16.448 | .000 | .622 | .791 |
| Project Complexity | .087 | .043 | 2.027 | .044 | .003 | .172 |
| TLA × PC | .043 | .043 | 1.016 | .310 | -.041 | .127 |

### *4.8 Summary of Hypotheses Testing*

Following the direct, mediation, and moderation analyses, the proposed hypotheses were evaluated based on their statistical significance. The findings indicate that both independent variables—AI-assisted project decision-making and cross-functional knowledge integration—have significant positive effects on project success. Moreover, team learning agility significantly mediates both relationships, indicating that organizations can enhance project success by fostering adaptive learning capabilities within project teams.

In contrast, the moderating role of project complexity was not supported. Although project complexity exhibited a significant direct relationship with project success, it did not significantly influence the relationship between team learning agility and project success. Therefore, the effectiveness of team learning agility appears to remain consistent regardless of the perceived complexity of projects.

**Table 14**
*Summary of Hypotheses Testing*

| Hypothesis | Statement | Result | Decision |
|---|---|---|---|
| H1 | AI-Assisted Project Decision-Making positively influenced Project Success. | Supported | Accepted |
| H2 | Cross-functional Knowledge Integration positively influenced Project Success. | Supported | Accepted |
| H3 | Team Learning Agility mediates the relationship between AI-Assisted Project Decision-Making and Project Success. | Supported (Partial Mediation) | Accepted |
| H4 | Team Learning Agility mediates the relationship between Cross-Functional Knowledge Integration and Project Success. | Supported (Partial Mediation) | Accepted |
| H5 | Project Complexity positively moderates the relationship between Team Learning Agility and Project Success. | Not Supported | Rejected |

The hypothesis testing results provide strong empirical support for the proposed conceptual framework, with the exception of the moderating role of project complexity. Specifically, the findings highlight the importance of AI-assisted decision-making and cross-functional knowledge integration in enhancing project success, both directly and indirectly through team learning agility.

## 5. Discussion, Implications, and Conclusion

### *5.1 Discussion of Findings*

The findings provide substantial support for the proposed conceptual framework by confirming four of the five hypotheses. AI-assisted project decision-making and cross-functional knowledge integration significantly enhanced project success, while team learning agility partially mediated both relationships. However, project complexity did not significantly moderate the relationship between team learning agility and project success, indicating that learning-agile teams contribute to project performance irrespective of project complexity. These findings reinforce the growing argument that technological capabilities generate superior project outcomes only when supported by organizational learning and collaborative knowledge-sharing capabilities.

H1 was supported, as AI-assisted project decision-making positively influenced project success ($\beta$ = .301, $p < .001$). This finding suggests that AI-enabled decision-support systems improve planning, resource allocation, risk prediction, and managerial responsiveness, thereby enhancing project performance. The result is consistent with Abositta et al. (2024), Ahmed et al. (2024), Almalki (2025), Ronak (2024), Gahlawat and Ganatra (2026), Wang et al. (2026), and Liu and Liu (2026), all of whom reported that AI strengthens evidence-based decision-making, human-AI collaboration, and overall project effectiveness.

H2 was also supported, demonstrating that cross-functional knowledge integration significantly improves project success ($\beta = .227$, $p < .001$). The findings indicate that effective collaboration and knowledge sharing across organizational functions enhance communication, problem-solving, and coordinated decision-making. These results align with Kahn (1996), Asghar and Burria (2025), Rehmat et al. (2025), Jahangir et al. (2025), and Han et al. (2024), who emphasized that integrating diverse expertise strengthens organizational agility and project outcomes, particularly in AI-enabled environments.

The mediation analysis further confirmed the importance of team learning agility. H3 revealed that team learning agility partially mediates the relationship between AI-assisted project decision-making and project success (Effect = .314, 95% CI = .237–.398), while H4 showed a significant partial mediation between cross-functional knowledge integration and project success (Effect = .327, 95% CI = .251–.403). These findings suggest that AI technologies and integrated knowledge contribute to project success by fostering adaptive learning, continuous improvement, and collaborative problem-solving. The results are consistent with Han and Zhang (2024), Han et al. (2024), Hussain et al. (2026), Azeroual (2026), Dawarka et al. (2026), Mata et al. (2023), Mata et al. (2026), and Jintian et al. (2022), who highlighted learning agility as a critical mechanism linking organizational capabilities with superior project performance.

In contrast, H5 was not supported because project complexity did not significantly moderate the relationship between team learning agility and project success ($\beta = .043$, $p = .310$). Although project complexity exhibited a modest direct effect on project success ($\beta = .087$, $p = .044$), it did not strengthen or weaken the contribution of learning agility. This finding differs from Ali and Yushi (2024), Mata et al. (2023), and Razzaq et al. (2025), who reported significant moderating effects of project complexity. A plausible explanation is that AI-enabled predictive analytics, intelligent monitoring, and decision-support systems reduce uncertainty associated with complex projects, allowing learning-agile teams to maintain consistent performance regardless of project complexity. Overall, the findings suggest that AI-supported organizational learning and knowledge integration are more influential determinants of project success than contextual project complexity.

***5.2 Theoretical Implications***

This study makes several important theoretical contributions to the literature on artificial intelligence, project management, organizational learning, and project success. First, grounded in Dynamic Capabilities Theory, it extends AI-enabled project management research by providing empirical evidence that AI-assisted project decision-making directly enhances project success, reinforcing the view that technological capabilities create value when effectively integrated with organizational capabilities (Abositta et al., 2024; Almalki, 2025; Ronak, 2024). Second, the study advances organizational learning theory by identifying team learning agility as a key mediating mechanism through which AI-assisted project decision-making and cross-functional knowledge integration improve project outcomes, thereby extending prior research on learning agility beyond leadership contexts into AI-enabled project environments (DeRue et al., 2012; Han & Zhang, 2024). Third, the findings reinforce knowledge integration theory by confirming that cross-functional knowledge integration remains a critical determinant of project success in AI-supported settings, consistent with Kahn (1996). Furthermore, the non-significant moderating effect of project complexity challenges previous findings (Ali & Yushi, 2024; Mata et al., 2023), suggesting that AI-enabled decision support may mitigate the influence of project complexity on team effectiveness. Overall, the study contributes to the human-AI collaboration literature by demonstrating that AI delivers greater organizational value when complemented by adaptive learning, collaborative knowledge integration, and dynamic organizational capabilities (Dawarka et al., 2026; Wang et al., 2026).

***5.3 Practical Implications***

The findings offer several practical implications for organizations implementing AI in project management. First, organizations should treat AI-assisted decision-making as a strategic capability rather than merely an operational tool by investing in intelligent decision-support systems, predictive analytics, and AI-enabled planning to improve project success. Second, managers should prioritize the development of team learning agility alongside AI adoption. Continuous training, knowledge-sharing initiatives, and learning-oriented cultures can help project teams effectively interpret and apply AI-generated insights, maximizing the value of AI investments.

Third, organizations should strengthen cross-functional knowledge integration by promoting collaboration among engineering, IT, finance, operations, and other functional areas. Establishing interdisciplinary teams and digital knowledge-sharing platforms can improve communication, decision quality, and project coordination. Fourth, AI should complement rather than replace managerial expertise. Project managers should critically evaluate AI-generated recommendations while incorporating professional judgment and contextual understanding into final decisions.

Finally, although project complexity did not significantly moderate the proposed relationship, organizations should continue developing adaptive learning capabilities rather than focusing solely on complexity management. Learning-agile teams appear capable of maintaining strong project performance across varying project conditions, suggesting that investments in organizational learning, collaboration, and AI capabilities together provide a more sustainable pathway to long-term project success.

### *5.4 Conclusion*

This study examined how AI-assisted project decision-making influences project success by considering the mediating role of team learning agility and the moderating role of project complexity. The empirical findings demonstrate that both AI-assisted project decision-making and cross-functional knowledge integration significantly enhance project success. Furthermore, team learning agility serves as an important mechanism through which these organizational capabilities improve project outcomes, highlighting the critical role of continuous learning and adaptability within AI-enabled project environments.

The findings further reveal that project complexity does not significantly alter the relationship between team learning agility and project success. This suggests that adaptive project teams maintain their effectiveness regardless of increasing project complexity, particularly when supported by AI-enabled decision-making capabilities.

Overall, the study emphasizes that successful project management in the era of artificial intelligence requires more than technological adoption alone. Organizations must simultaneously cultivate collaborative knowledge integration and learning-agile project teams capable of effectively utilizing AI-generated insights. By integrating technological capabilities with human adaptability and organizational learning, project-based organizations can substantially improve their ability to deliver successful projects in increasingly dynamic and competitive environments.

### *5.5 Limitations and Directions for Future Research*

This study has several limitations that provide opportunities for future research. First, the study employed a cross-sectional design, limiting the ability to establish causal relationships among the variables. Future studies should adopt longitudinal designs to examine how AI-assisted decision-making and team learning agility evolve over time. Second, data were collected through self-reported questionnaires from project professionals, which may introduce common method bias despite using validated measurement scales. Future research may incorporate multi-source data or objective project performance indicators. Third, the study focused on project-based organizations with a sample of approximately 300 respondents, which may limit the generalizability of the findings across industries and countries. Future studies should replicate the model in different organizational and cultural contexts using larger and more diverse samples. Finally, future research may examine additional mediators (e.g., trust in AI, organizational agility, digital capability) and moderators (e.g., technological readiness, leadership style, AI maturity, or organizational culture) to further explain AI-enabled project success.

**Author Contributions**

All authors participated in ideation, development, and writing the manuscript. All authors read and approved the final manuscript.

**Conflict of Interest Statement**

The authors declare that there is no conflict of interest regarding the publication of this article.

**Funding Statement**

The authors did not receive financial support from any funding agency or external organization for the research, authorship, or publication of this article.

**Informed Consent**

Informed consent was obtained from all participants prior to data collection. Participants were informed about the purpose of the study, the voluntary nature of their participation, and their right to withdraw at any time without any consequences. The confidentiality and anonymity of respondents were guaranteed throughout the research process.

**Data Availability**

The datasets generated and analysed during the current study are available from the corresponding author upon reasonable request. The authors are committed to transparency and will provide detailed methodological information and analysis protocols upon request.

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