BUSINESS, TECHNOLOGY & INNOVATION STUDIES JOURNAL (BTISJ)
ISSN 3110-9411

Volume 2, Issue 3, July–September 2026

Volume 2	Issue 3	Jul – Sep 2026
Received	Accepted	Published
19 June 2026	02 September 2026	07 September 2026

Artificial intelligence capability and project performance: integrating dynamic capabilities theory and the knowledge-based view

DOI: 10.66578/btis.v2i3.38

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ABSTRACT

Artificial intelligence (AI) is transforming project management by enhancing organizational decision-making and operational efficiency. However, the organizational mechanisms through which AI capability improves project performance remain insufficiently understood. Drawing upon dynamic capabilities theory and the knowledge-based view, this study examines the direct effect of AI capability on project performance and investigates the mediating roles of knowledge integration and project agility. Data were collected from 267 project-based organizations operating in Turkey using a two-wave survey with a four-month interval between data collection waves. Confirmatory factor analysis (CFA) was employed to assess the reliability and validity of the measurement model. The proposed hypotheses were tested using hierarchical regression analysis, bootstrapping procedures, structural equation modeling (SEM) for robustness analysis, and two-stage least squares (2SLS) estimation to address potential endogeneity. The findings indicate that AI capability positively influences knowledge integration, project agility, and project performance. Knowledge integration significantly enhances both project agility and project performance, while project agility has the strongest direct effect on project performance. The bootstrapping analysis further demonstrates that knowledge integration and project agility partially mediate the relationship between AI capability and project performance. Moreover, the sequential mediation results reveal that AI capability improves project performance by strengthening knowledge integration, which subsequently enhances project agility. This study contributes to the project management and AI literature by integrating dynamic capabilities theory and the knowledge-based view within a unified framework to explain how AI capability is transformed into superior project performance. By identifying knowledge integration and project agility as complementary organizational mechanisms, the study offers a more comprehensive explanation of AI-enabled

BUSINESS, TECHNOLOGY & INNOVATION STUDIES JOURNAL (BTISJ)
ISSN 3110-9411

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project success and provides valuable theoretical and managerial insights for organizations seeking to improve project outcomes through AI capability.
Keywords: Artificial intelligence capability; Knowledge integration; Project agility; Project performance; Dynamic Capabilities Theory; Knowledge-Based View.

1. INTRODUCTION

Project-based organizations are operating in increasingly complex and uncertain environments where rapid technological change, shorter product life cycles, and evolving stakeholder expectations continuously reshape project requirements (BenMahmoud-Jouini & Charue-Duboc, 2022). Delivering projects on time, within budget, and at the expected quality level has therefore become considerably more challenging than in the past (Oshilalu, 2024). At the same time, organizations are expected to remain innovative, flexible, and responsive while managing growing volumes of information and increasingly interconnected project activities (Chen et al., 2019). Under these conditions, project performance has become a critical indicator of organizational competitiveness because successful projects directly contribute to strategic objectives, operational excellence, and long-term organizational growth (Lin et al., 2019). Traditional project management approaches, however, often struggle to cope with the speed and complexity of modern project environments, creating a need for new organizational capabilities that support better decision-making and adaptive project execution (Giezen et al., 2015; Mews, 2025).
Artificial intelligence (AI) refers to computational systems that perform tasks commonly associated with human intelligence, including learning from data, recognizing patterns, generating predictions, interpreting language, and supporting decisions. In this study, AI capability is defined as an organization's ability to combine AI-related technological infrastructure, data resources, employee expertise, managerial commitment, and organizational routines to deploy AI effectively in project-management activities. Accordingly, AI capability is not treated as the simple possession or adoption of AI tools; rather, it reflects the organizational capacity to embed AI-enabled insights into planning, coordination, risk management, resource allocation, and decision-making processes. AI applications in project management may include conventional AI, such as machine learning, predictive analytics, optimization algorithms, and intelligent decision-support systems, as well as generative AI applications that can create text, code, reports, designs, or recommendations.
Although conventional and generative AI differ in their technical functions, this study does not examine them separately. Instead, it focuses on the broader organizational capability to use AI-enabled tools and insights effectively for project-related purposes. This capability-oriented approach is appropriate because the proposed model examines how organizations transform AI-related resources and insights into knowledge integration, project agility, and ultimately project performance. Through these applications, AI can automate routine tasks, improve forecasting accuracy, optimize resource allocation, and identify project risks at earlier stages (Wagner & Wagner, 2023). Consequently, AI is increasingly viewed not simply as a technological innovation but as an organizational capability that enhances information processing, managerial decision-making, and operational effectiveness (Mariani & Mancini, 2025). Organizations with stronger AI capability are therefore better positioned to anticipate project challenges, coordinate project activities, and respond to environmental changes efficiently. Nevertheless, despite growing

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ISSN 3110-9411

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investment in AI technologies, many organizations experience inconsistent performance improvements, suggesting that technology alone does not guarantee successful project outcomes (Mariani & Mancini, 2025; Wamba-Taguimdje et al., 2020).

Existing research presents mixed evidence regarding the relationship between AI capability and organizational performance (Shin, 2026). While numerous studies report that AI enhances innovation, operational efficiency, and organizational adaptability by improving information processing and analytical capability, other studies argue that the performance benefits of AI frequently depend on complementary organizational resources and managerial capabilities rather than technology adoption itself (Baharmand et al., 2021; Wagner & Wagner, 2023). Organizations often invest substantial financial and technological resources in AI initiatives without achieving proportional improvements in project outcomes because AI-generated information is not effectively translated into organizational knowledge or coordinated project actions (Bechtel et al., 2023; Mafakheri et al., 2008). These inconsistent findings indicate that the relationship between AI capability and project performance is more complex than previously assumed and highlight the need to examine the organizational mechanisms through which AI capability creates value in project-based environments (Baharmand et al., 2021).

To address this gap, this study integrates dynamic capabilities theory and the Knowledge-Based View (KBV) to explain how AI capability contributes to project performance. dynamic capabilities theory suggests that organizations achieve superior performance by continuously sensing opportunities, seizing emerging technologies, and reconfiguring organizational resources to adapt to changing environments (Teece, 2019; Teece et al., 1997). Complementing this perspective, the knowledge-based view emphasizes that organizational knowledge represents the most strategically important resource and that competitive advantage depends on an organization's ability to integrate and apply knowledge effectively (Grant, 1996; Sahibzada & Mumtaz, 2023). Building upon these complementary perspectives, this study proposes that AI capability enhances project performance by strengthening knowledge integration and project agility, while knowledge integration further improves project agility, creating a sequential capability-building process that ultimately leads to superior project outcomes (Lin et al., 2019; Mafakheri et al., 2008).

Accordingly, the objective of this study is to examine how AI capability influences project performance in project-based organizations and to investigate the mechanisms through which this relationship occurs. Drawing on dynamic capabilities theory and the knowledge-based view, the study proposes that AI capability improves project performance directly and indirectly by strengthening knowledge integration and project agility. More specifically, it examines whether knowledge integration and project agility operate as parallel mediators and whether AI capability enhances project performance through a sequential process in which improved knowledge integration leads to greater project agility.

To address this objective, the study is guided by the following research questions: **RQ1:** How does AI capability affect project performance? **RQ2:** Does AI capability enhance knowledge integration and project agility in project-based organizations? **RQ3:** Do knowledge integration and project agility mediate the relationship between AI capability and project performance, individually and sequentially? By addressing these questions, the study extends the AI management literature beyond the direct performance effects of AI and provides an integrated explanation of how AI-

ISSN 3110-9411

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related organizational capability is translated into superior project outcomes (Mahmood et al., 2024; Oshilalu, 2024; Wagner & Wagner, 2023).

2. THEORETICAL BACKGROUND AND HYPOTHESES DEVELOPMENT

2.1 Theoretical Foundation

Artificial intelligence capability has become an important organizational capability because it enables firms to process information, improve decision-making, and respond more effectively to dynamic business environments (Shin, 2026). However, the value of AI capability extends beyond technological resources alone (Bechtel et al., 2023). Organizations differ considerably in their ability to integrate AI into project management processes, transform AI-generated insights into organizational knowledge, and convert those insights into superior project outcomes (Oshilalu, 2024). Explaining these differences requires a theoretical perspective that captures both organizational adaptability and knowledge utilization (Wagner & Wagner, 2023). Accordingly, this study adopts Dynamic Capabilities Theory (DCT) as the primary theoretical foundation and the knowledge-based view as a complementary perspective to explain how AI capability improves project performance (Teece et al., 1997).

Dynamic capabilities theory explains how organizations sustain effectiveness in changing environments by sensing emerging opportunities and threats, seizing those opportunities through timely decisions and investments, and reconfiguring resources and operational processes accordingly (Teece, 2019; Teece et al., 1997). In project-based settings, AI capability supports these dynamic processes by enabling organizations to detect changes in project conditions, customer requirements, resource availability, and potential risks through faster data processing and predictive insights. Organizations can then seize these insights by making more informed decisions and reallocating resources, while reconfiguring project routines, workflows, and coordination mechanisms in response to evolving conditions. Therefore, AI capability contributes to project agility not merely because it provides technology, but because it strengthens the organization's capacity to sense, seize, and reconfigure in dynamic project environments.

The knowledge-based view complements this explanation by clarifying the knowledge mechanism through which AI-enabled insights become valuable organizational action. AI systems can generate large volumes of information, but such information does not automatically improve project outcomes unless it is interpreted, shared, and integrated with the dispersed expertise of project members and functional units (Grant, 1996; Sahibzada & Mumtaz, 2023). Knowledge integration transforms AI-generated insights into a shared understanding that supports coordinated decisions and effective action. In this way, dynamic capabilities theory explains the adaptive process through which organizations respond to change, whereas the knowledge-based view explains how the knowledge required for that response is combined and applied. Together, the two perspectives suggest a sequential capability-building logic: AI capability helps organizations generate and process relevant information; knowledge integration converts this information into coordinated organizational knowledge; and project agility enables the organization to reconfigure project activities and respond effectively to change.

2.2 Artificial Intelligence Capability and Knowledge Integration

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Artificial intelligence capability enables organizations to collect, process, and analyze large volumes of structured and unstructured data, thereby generating valuable insights for organizational decision-making (Wamba-Taguimdje et al., 2020). However, AI-generated information creates value only when it is effectively integrated with existing organizational knowledge and shared across project teams (Wagner & Wagner, 2023). Knowledge integration refers to an organization's ability to combine dispersed expertise, experiences, and information from different individuals and functional units to support coordinated action and problem-solving (Grant, 1996). From the perspective of dynamic capabilities theory, organizations possessing strong AI capability are better able to continuously acquire new information and reconfigure their knowledge resources in response to changing project requirements (Bernroider et al., 2014; Teece, 2019). Similarly, the knowledge-based view argues that sustainable competitive advantage depends not only on knowledge acquisition but also on an organization's ability to integrate and apply knowledge effectively across organizational boundaries (Sahibzada & Mumtaz, 2023; Wang et al., 2026).
Recent empirical studies increasingly recognize AI as an important enabler of organizational learning and knowledge management (Fouad et al., 2025; Wamba-Taguimdje et al., 2020). AI-supported systems facilitate knowledge discovery, improve information accessibility, and strengthen collaboration among project participants, enabling organizations to transform dispersed information into actionable organizational knowledge (Mahmood et al., 2024; Wagner & Wagner, 2023). AI technologies also improve communication, reduce information silos, and support real-time knowledge sharing, thereby enhancing collective decision-making and organizational learning (Wamba-Taguimdje et al., 2020). Consequently, organizations with stronger AI capability are expected to develop higher levels of knowledge integration because they possess superior capabilities to capture, combine, and exploit knowledge generated from multiple internal and external sources (Lin et al., 2019). Therefore, the following hypothesis is proposed:
H1. Artificial intelligence capability positively influences knowledge integration.

2.3 Artificial Intelligence Capability and Project Agility

Project agility refers to an organization's ability to respond rapidly and effectively to changing project conditions, customer requirements, and environmental uncertainties while maintaining project objectives (Enberg, 2012; Mahmood et al., 2024). Agile project execution requires timely information, rapid decision-making, flexible resource allocation, and effective coordination among project participants (Kyriakopoulos et al., 2025; Oshilalu, 2024). As projects become increasingly complex and dynamic, organizations must continuously monitor project environments and adjust strategies to minimize delays and performance disruptions (Arias-Pérez et al., 2026). From the perspective of dynamic capabilities theory, project agility reflects an organization's ability to reconfigure resources and operational processes in response to environmental change (Teece, 2019; Teece et al., 1997). AI capability strengthens this adaptive capacity by enabling organizations to generate timely insights, anticipate emerging risks, and support faster and more informed project decisions (Shatila, 2025).
Recent studies suggest that AI technologies enhance organizational agility by improving data visibility, accelerating information processing, and supporting predictive decision-making (Mariani & Mancini, 2025; Wagner & Wagner, 2023). AI-enabled analytics help project managers

detect deviations from project plans, forecast potential bottlenecks, optimize resource utilization, and respond proactively to changing project requirements (Shin, 2026). These capabilities reduce response time and enable organizations to implement corrective actions before project performance is adversely affected (Ali & Jiang, 2026). Consequently, organizations with stronger AI capability are expected to develop greater project agility because they possess superior capabilities to sense environmental changes and rapidly adapt project activities. Accordingly, AI capability should serve as an important organizational antecedent of project agility.
H2. Artificial intelligence capability positively influences project agility.

2.4 Artificial Intelligence Capability and Project Performance

Project performance reflects the extent to which projects achieve their intended objectives in terms of time, cost, quality, stakeholder satisfaction, and overall strategic value (Giezen et al., 2015). Improving project performance has become a strategic priority as organizations increasingly manage complex projects under conditions of uncertainty and rapid technological change (Huang & Newell, 2003; Mews, 2025). Artificial intelligence capability provides organizations with advanced analytical and decision-support capabilities that improve project planning, risk identification, resource allocation, and performance monitoring (Shin, 2026). By transforming large volumes of project data into timely and actionable insights, AI enables project managers to make more informed decisions and respond proactively to emerging challenges (Mariani & Mancini, 2025). From the perspective of dynamic capabilities theory, organizations possessing stronger AI capability are better able to continuously adapt project processes, reconfigure resources, and improve project execution, thereby achieving superior project outcomes (Mikalef et al., 2019; Teece, 2019).

Empirical evidence increasingly supports the positive role of AI capability in improving organizational and operational performance (Fouad et al., 2025). AI enhances decision quality, increases forecasting accuracy, optimizes resource utilization, and strengthens organizational responsiveness, all of which contribute to better project outcomes (Mariani & Mancini, 2025; Wagner & Wagner, 2023). Nevertheless, the benefits of AI extend beyond operational efficiency because AI capability enables organizations to make faster, evidence-based decisions throughout the project lifecycle (Oshilalu, 2024). Organizations that effectively embed AI into project management practices are therefore more likely to complete projects successfully while improving quality, reducing delays, and increasing stakeholder satisfaction (Mahmood et al., 2024). Accordingly, organizations with stronger AI capability are expected to achieve higher levels of project performance than those with weaker AI capability. Therefore, the following hypothesis is proposed:
H3. Artificial intelligence capability positively influences project performance.

2.5 Knowledge Integration and Project Agility

Knowledge integration refers to an organization's ability to combine, share, and apply knowledge originating from different individuals, functional departments, and external stakeholders to support coordinated decision-making and problem-solving (Grant, 1996; Lee et al., 2021). In project-based organizations, knowledge is often dispersed across multiple teams, making effective integration essential for responding to changing project requirements (Wagner & Wagner, 2023). The knowledge-based view suggests that organizations create value not merely by possessing knowledge but by effectively integrating and utilizing it to improve organizational performance (Sahibzada & Mumtaz, 2023). When project teams successfully combine technical expertise, customer insights, and organizational experience, they develop a more comprehensive understanding of project conditions and become better equipped to identify emerging challenges and opportunities (Edmondson & Nembhard, 2009). This shared understanding provides the foundation for faster and more coordinated responses to project changes (Bechtel et al., 2023; Oliva et al., 2019).

From the perspective of dynamic capabilities theory, organizations that effectively integrate knowledge are better positioned to reconfigure resources and adapt project activities as environmental conditions evolve (Bechtel et al., 2023; Teece et al., 1997). Knowledge integration enhances communication among project participants, improves collaboration across functional boundaries, and reduces delays associated with fragmented information (Huang & Newell, 2003). As a result, project teams can make timely decisions, adjust project plans, and implement corrective actions more efficiently when unexpected issues arise (Baharmand et al., 2021). Recent studies have similarly emphasized that effective knowledge integration strengthens organizational flexibility, accelerates decision-making, and enhances agile project execution in dynamic environments (Mahmood et al., 2024; Wagner & Wagner, 2023). Therefore, organizations with higher levels of knowledge integration are expected to demonstrate greater project agility.

H4. Knowledge integration positively influences project agility.

2.6 Knowledge Integration and Project Performance

Knowledge integration enables organizations to combine dispersed expertise, experiences, and information into a shared knowledge base that supports effective project execution (Enberg, 2012; Hong et al., 2008). In project-based environments, project success often depends on the ability of individuals from different functional areas to exchange knowledge, coordinate decisions, and solve complex problems collaboratively (Wamba-Taguimdje et al., 2020). The knowledge-based view argues that knowledge is the most valuable strategic resource and that organizational performance depends on an organization's ability to integrate and apply knowledge effectively rather than merely possessing it (Grant, 1996). When project teams successfully integrate technical, operational, and managerial knowledge, they improve decision quality, reduce communication barriers, minimize duplication of effort, and strengthen coordination throughout the project lifecycle (Lin et al., 2019; Mafakheri et al., 2008). These capabilities enable organizations to manage project complexity more effectively and enhance overall project performance (Chen et al., 2019).

From the perspective of dynamic capabilities theory, knowledge integration also facilitates the continuous reconfiguration of organizational resources in response to changing project conditions (Teece, 2019; Zada et al., 2024). Organizations that effectively integrate knowledge are better able to identify emerging risks, capitalize on new opportunities, and implement timely adjustments during project execution (Mews, 2025). Previous studies have consistently shown that effective knowledge integration improves project efficiency, innovation, and organizational performance by strengthening collaboration, accelerating learning, and supporting better managerial decision-making (Acharya et al., 2022; Guo et al., 2023). Consequently, organizations with higher levels of

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knowledge integration are expected to deliver projects more successfully and achieve superior project performance (Huang & Newell, 2003).
H5. Knowledge integration positively influences project performance.

2.7 Project Agility and Project Performance

Project agility reflects an organization's ability to respond rapidly and effectively to changing project requirements, emerging risks, and unexpected environmental conditions while maintaining project objectives (de Oliveira et al., 2021; Mafakheri et al., 2008; Schuh et al., 2018). Unlike traditional project management approaches that often rely on rigid planning and sequential execution, agile project management emphasizes flexibility, continuous learning, rapid decision-making, and iterative adaptation (Oshilalu, 2024). From the perspective of dynamic capabilities theory, project agility represents an important organizational capability that enables firms to continuously reconfigure resources and modify project activities in response to environmental change (Conforto et al., 2016; Teece et al., 1997). Organizations possessing higher levels of project agility are therefore better equipped to cope with uncertainty, reduce project delays, and maintain alignment between project execution and evolving stakeholder expectations (Giezen et al., 2015; Mariani et al., 2025).
The positive relationship between project agility and project performance has received increasing empirical support in project management research (Bernroider et al., 2014). Agile project teams can identify and address problems earlier, allocate resources more effectively, and respond more quickly to customer feedback and changing project priorities (Enberg, 2012; Zou & Zhang, 2009). These capabilities improve collaboration, accelerate decision-making, reduce rework, and enhance overall project efficiency, ultimately contributing to better project outcomes (Aurélio de Oliveira et al., 2012). Moreover, agile organizations are more capable of maintaining project quality and stakeholder satisfaction despite operating in uncertain and dynamic environments. Consequently, project agility should enable organizations to deliver projects more efficiently while achieving superior performance in terms of time, cost, quality, and strategic objectives (Aurélio de Oliveira et al., 2012). Therefore, the following hypothesis is proposed:
H6. Project agility positively influences project performance.

2.8 The Mediating Roles of Knowledge Integration and Project Agility

Although artificial intelligence capability provides organizations with advanced analytical and decision-support capabilities, its influence on project performance is unlikely to occur through technology alone (Shin, 2026; Sousa, 2013). AI-generated insights create value only when they are effectively integrated into organizational knowledge and translated into coordinated project actions (Cegarra-Navarro et al., 2016; Huang & Newell, 2003). Consistent with the knowledge-based view, organizations derive greater value from AI when they successfully integrate knowledge across project teams, improving collaboration, decision-making, and project execution (Grant, 1996; Sahibzada & Mumtaz, 2023). Likewise, dynamic capabilities theory suggests that AI capability strengthens an organization's ability to adapt to changing project environments by enhancing project agility (Bernroider et al., 2014; Teece et al., 1997). Therefore, knowledge integration and project agility are each expected to mediate the relationship between AI capability and project performance (Lin et al., 2019).

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Furthermore, knowledge integration and project agility are expected to operate as complementary organizational capabilities rather than independent mechanisms (Enberg, 2012; Mata et al., 2024). AI capability first enhances the integration of knowledge from multiple sources, enabling project teams to develop a shared understanding of project requirements and make better-informed decisions (Enberg, 2012). This integrated knowledge subsequently strengthens project agility by improving coordination, accelerating responses to change, and facilitating adaptive project execution (Sousa, 2013). As agile project teams implement timely adjustments and allocate resources more effectively, project performance improves (Huang & Newell, 2003; Lin et al., 2019). This sequential process reflects the complementary roles of the knowledge-based view, which explains how organizations create value through knowledge integration, and dynamic capabilities theory, which explains how integrated knowledge is transformed into adaptive organizational actions (Bechtel et al., 2023). Accordingly, AI capability is expected to improve project performance through the sequential mediating effects of knowledge integration and project agility (Mahmood et al., 2024; Wagner & Wagner, 2023).
H7. Knowledge integration mediates the relationship between artificial intelligence capability and project performance.
H8. Project agility mediates the relationship between artificial intelligence capability and project performance.
H9. Knowledge integration and project agility sequentially mediate the relationship between artificial intelligence capability and project performance.
The research model summarizing the hypothesized relationships is presented in Figure 1.

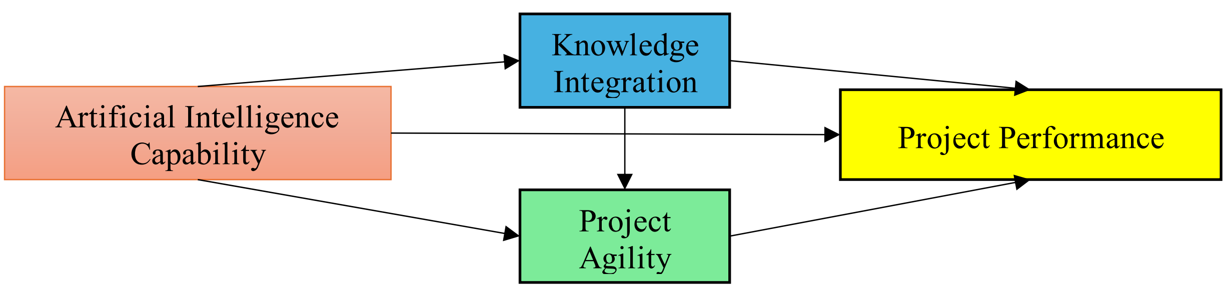

Figure 1. Proposed Research Model

Notes: Solid arrows represent hypothesized direct relationships (H1–H6). The model also proposes the mediating effects of knowledge integration (H7), project agility (H8), and the sequential mediation of knowledge integration and project agility (H9).
Source: Developed by the author.

3. METHOD

3.1 Sampling and data collection

The unit of analysis in this study is the project-based organization. Each participating organization was represented by one knowledgeable respondent, who assessed the organization's AI capability and knowledge-integration practices, as well as its typical ability to execute projects with agility

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and achieve favorable project-performance outcomes. Accordingly, AI capability and knowledge integration are conceptualized as organizational-level capabilities, whereas project agility and project performance reflect the organization's overall effectiveness in managing its project portfolio rather than the outcomes of a single individual project. This alignment ensures that all constructs are measured at a consistent organizational level.

Project-based organizations provide an appropriate context for examining the relationship between artificial intelligence capability and project performance because they routinely operate in environments characterized by uncertainty, complex coordination requirements, and time-sensitive decision-making. In such settings, organizations increasingly rely on AI technologies to support project planning, resource allocation, risk identification, and real-time decision-making, making project-based firms particularly suitable for investigating how AI capability is translated into superior project outcomes. Turkey represents an appropriate empirical setting because it is recognized as one of the world's leading AI ecosystems, supported by substantial public and private investments in AI research, advanced digital infrastructure, and widespread organizational adoption of AI across knowledge-intensive industries. Turkish organizations have increasingly incorporated AI-enabled tools into project-management practices in sectors such as information technology, engineering, construction, manufacturing, consulting, and professional services, where project success depends heavily on effective knowledge integration, organizational adaptability, and cross-functional collaboration. Consequently, the Turkish project environment provides an appropriate setting for examining the capability-building processes proposed in this study.

The sampling frame therefore consisted of project-based organizations operating across Turkey in the information technology, engineering, construction, manufacturing, consulting, and professional services sectors. These industries were selected because they are among the most active adopters of AI-enabled project management practices while relying extensively on temporary project teams to deliver complex products and services. A list of potential participants was compiled using professional project management associations, publicly available business directories, and industry databases. Using a random sampling approach, 680 organizations were invited to participate, of which 352 agreed to take part in the study.

Consistent with previous organizational research, data were collected using a two-wave survey separated by a four-month interval to reduce common method bias and strengthen causal inference. The first survey, conducted between February and April 2025, measured AI capability, knowledge integration, and organizational characteristics, whereas the second survey, conducted between June and August 2025, collected data on project agility and project performance. Of the 680 organizations invited, 352 agreed to participate. The first survey generated 311 usable responses. Following the second survey conducted four months later, 267 matched questionnaires were obtained and retained for the final analysis. This represents a panel retention rate of 75.9% among participating organizations and an overall usable response rate of 39.3% relative to the original sampling frame. The final sample comprised 267 project-based organizations, with one key informant representing each organization. Respondents were project managers, senior project engineers, PMO managers, project directors, program managers, and operations managers with at least three years of project-management experience. They were selected because of their direct involvement in AI-enabled project activities and their familiarity with the organization's AI use,

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knowledge-sharing practices, project agility, and project-performance outcomes. These positions provided respondents with the cross-functional and project-level knowledge necessary to provide informed assessments of the study constructs. Table 1 summarizes the demographic characteristics of the participating organizations and respondents. Table 1 summarizes the demographic characteristics of the participating organizations and respondents, demonstrating a diverse sample across industries, organizational sizes, managerial positions, professional experience, and levels of AI adoption.

Table 1. Profile of the Responding Organizations and Respondents (N = 267)

Characteristic	Category	Frequency	Percentage (%)
Industry	Information Technology	61	22.8
	Construction	58	21.7
	Engineering	46	17.2
	Manufacturing	39	14.6
	Consulting	35	13.1
	Professional Services	28	10.5
	Total	267	100.0
Organization Size (Employees)	Less than 50	41	15.4
	50–249	96	36.0
	250–999	79	29.6
	1,000 or more	51	19.1
	Total	267	100.0
Respondent Position	Project Manager	94	35.2
	Senior Project Engineer	53	19.9
	PMO Manager	42	15.7
	Project Director	37	13.9
	Program Manager	24	9.0
	Operations Manager	17	6.4
	Total	267	100.0
Project Management Experience	3–5 years	54	20.2
	6–10 years	97	36.3
	11–15 years	68	25.5
	More than 15 years	48	18.0
	Total	267	100.0
AI Adoption in Project Management	Less than 1 year	29	10.9
	1–3 years	102	38.2
	4–6 years	91	34.1
	More than 6 years	45	16.9
	Total	267	100.0

Source: Author's survey data.

3.2 Measures

All measurement scales used in this study were adapted from well-established instruments that have demonstrated satisfactory reliability and validity in previous research. As the questionnaire was originally developed in English and the survey was conducted among Turkish organizations, no translation procedure was required. As the questionnaire was originally developed in English

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and the survey was administered in Turkey, a translation and back-translation procedure was followed. The questionnaire was translated from English into Turkish by a bilingual researcher and independently back-translated into English by another bilingual researcher. Minor discrepancies were discussed and resolved to ensure conceptual equivalence. Before the main data collection, the questionnaire was evaluated by three academics with expertise in project management, artificial intelligence, and organizational capability, as well as five experienced project managers from different industries. Their feedback resulted in several minor revisions to improve wording clarity and contextual relevance without altering the original meaning of the measurement items. All constructs were measured using a seven-point Likert scale ranging from 1 ("strongly disagree") to 7 ("strongly agree"). The measurement items, standardized factor loadings, and reliability statistics are presented in Table 2.

Artificial intelligence capability was measured using five items adapted from the organizational AI capability and digital capability literature (Mariani & Mancini, 2025; Wagner & Wagner, 2023). The scale captures an organization's ability to deploy AI technologies, integrate AI into project management activities, leverage AI-generated insights for decision-making, and continuously develop AI-related resources and competencies to support project execution. Knowledge integration was measured using five items adapted from previous studies on knowledge management and organizational learning (Grant, 1996; Tiwana & McLean, 2005). These items assess the extent to which organizations effectively combine, share, and apply knowledge from different project teams, functional departments, and external stakeholders to improve project decision-making and execution.

Project agility was assessed using five items adapted from prior research on organizational agility and project management (Mafakheri et al., 2008; Oshilalu, 2024). The scale evaluates the organization's overall ability to respond rapidly to changing project requirements, adjust project plans, reallocate resources efficiently, and maintain flexibility when managing its projects. Project performance was measured using five items adapted from established project management literature (Giezen et al., 2015; Guo et al., 2023). The scale captures the organization's overall success in delivering projects in terms of schedule, budget, quality, stakeholder satisfaction, and the achievement of intended project objectives.

3.3 Non-response bias and common method bias

To assess the potential for non-response bias, independent-samples *t*-tests were conducted to compare early and late respondents following the procedure recommended by Armstrong and Overton (1977). The analysis revealed no statistically significant differences ($p > 0.05$) across the demographic characteristics or any of the study constructs, indicating that non-response bias was unlikely to influence the results. Because the study relied on survey data collected from organizational respondents, several procedural and statistical remedies were implemented to minimize the potential impact of common method bias (CMB). Procedurally, respondents were assured that their responses would remain anonymous and confidential, participation was voluntary, and there were no right or wrong answers. Furthermore, predictor and criterion variables were collected in two separate survey waves with a four-month interval, reducing respondents' ability to infer the proposed relationships among the study variables.

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Statistically, Harman's single-factor test was first performed. The unrotated exploratory factor analysis showed that the first factor explained 32.8% of the total variance, which is well below the recommended threshold of 50%, suggesting that common method bias was not a serious concern. In addition, a single-factor confirmatory factor analysis (CFA) was estimated to compare the fit of a one-factor model with the proposed measurement model. The single-factor model demonstrated poor fit to the data ($\chi^2 = 2{,}143.86$, df = 324, CFI = 0.531, TLI = 0.487, RMSEA = 0.146, SRMR = 0.124), substantially worse than the proposed measurement model. Following the recommendation of Kock (2015), full collinearity variance inflation factors (VIFs) were also examined to assess the possibility of common method bias. The VIF values ranged from 1.41 to 2.37, well below the recommended threshold of 3.3, providing additional evidence that common method bias was unlikely to threaten the validity of the findings. Collectively, these results indicate that neither non-response bias nor common method bias presents a significant concern in this study.

3.4 Reliability and validity

Confirmatory factor analysis was performed using AMOS to evaluate the psychometric properties of the measurement model before testing the proposed hypotheses. The four-factor measurement model demonstrated an acceptable fit to the observed data ($\chi^2 = 512.68$, df = 164, $\chi^2/df = 3.13$, CFI = 0.921, TLI = 0.908, RMSEA = 0.089, and SRMR = 0.058). Although the RMSEA approached the upper acceptable threshold, all goodness-of-fit indices met commonly recommended criteria, indicating that the measurement model adequately represented the observed data. The reliability of the measurement scales was assessed using Cronbach's alpha and composite reliability (CR). As reported in Table 2, Cronbach's alpha values ranged from 0.819 to 0.882, while CR values varied between 0.851 and 0.896, exceeding the recommended minimum value of 0.70. These findings indicate satisfactory internal consistency for all study constructs. Convergent validity was evaluated by examining standardized factor loadings and the average variance extracted (AVE). All factor loadings were statistically significant ($p < 0.001$) and ranged from 0.694 to 0.864. Furthermore, the AVE values ranged from 0.537 to 0.633, exceeding the recommended threshold of 0.50 and confirming adequate convergent validity.

Discriminant validity was assessed using the Fornell-Larcker criterion. As presented in Table 3, the square root of the average variance extracted (AVE) for each construct exceeded its corresponding inter-construct correlations, demonstrating satisfactory discriminant validity. The correlation matrix also indicates that the relationships among the study constructs are in the expected directions. Although several constructs exhibit moderate positive correlations, none exceeds the commonly accepted threshold of 0.80, suggesting that multicollinearity is unlikely to be a concern. Furthermore, the control variables displayed generally low to moderate correlations with the principal constructs, indicating that organizational characteristics may influence project outcomes but are unlikely to confound the hypothesized relationships. Collectively, these findings provide evidence that the measurement model demonstrates satisfactory reliability and construct validity and is appropriate for subsequent hypothesis testing.

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Table 2. Measurement Model Assessment

Construct	Code	Measurement Item	Loading	Cronbach's α	CR	AVE
Artificial Intelligence Capability (Mariani & Mancini, 2025; Wagner & Wagner, 2023)	AIC1	Our organization effectively utilizes artificial intelligence to support project planning and decision-making.	0.83	0.874	0.892	0.623
	AIC2	AI applications improve the quality of project-related decisions.	0.79			
	AIC3	AI enables timely analysis of project information during project execution.	0.76			
	AIC4	Our organization possesses strong AI capabilities to support project management activities.	0.71			
	AIC5	AI supports continuous monitoring and evaluation of project performance.	0.84			
Knowledge Integration (Grant, 1996; Sahibzada & Mumtaz, 2023; Tiwana & McLean, 2005)	KI1	Project teams effectively share knowledge across functional departments.	0.73	0.845	0.871	0.577
	KI2	Knowledge from different project teams is successfully integrated.	0.81			
	KI3	Employees combine their expertise to solve project problems collaboratively.	0.75			
	KI4	Project knowledge is effectively disseminated throughout the organization.	0.70			
	KI5	Lessons learned from previous projects are incorporated into future projects.	0.82			
Project Agility (Mafakheri et al., 2008; Oshilalu, 2024)	PA1	Our organization rapidly responds to changes in project requirements.	0.79	0.862	0.885	0.607
	PA2	Project teams quickly modify project plans when circumstances change.	0.72			
	PA3	Resources can be rapidly reallocated during project execution.	0.84			
	PA4	Our organization effectively adapts to unexpected project challenges.	0.76			
	PA5	Project teams make timely decisions under changing project conditions.	0.78			
Project Performance (Giezen et al., 2015; Guo et al., 2023)	PP1	Projects are completed within the planned schedule.	0.71	0.829	0.858	0.549
	PP2	Projects are completed within the allocated budget.	0.76			
	PP3	Projects consistently achieve their expected quality standards.	0.81			
	PP4	Projects satisfy stakeholder expectations.	0.69			
	PP5	Overall, our projects successfully achieve their intended objectives.	0.77			

Notes: All constructs were measured using a seven-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. Standardized factor loadings are statistically significant ($p < 0.001$). Cronbach's α = Cronbach's alpha; CR = Composite Reliability; AVE = Average Variance Extracted.
Source: Adapted from the cited studies; statistical results are based on the author's survey.

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Table 3. Means, Standard Deviations, and Correlations

Variables	1	2	3	4	5	6	7	8	9	10
Organization size	**1**									
Organization age	0.117	**1**								
Industry type	0.084	0.069	**1**							
SMEs	0.148*	0.086	0.172**	**1**						
Large organizations	0.062	0.093	0.121	0.581**	**1**					
Artificial intelligence capability	0.181**	0.129*	0.097	0.071	0.114	**0.789**				
Knowledge integration	0.153*	0.167**	0.082	0.064	0.108	0.432**	**0.760**			
Project agility	0.109	0.142*	0.075	0.051	0.083	0.371**	0.516**	**0.779**		
Project performance	0.118	0.161**	0.069	0.078	0.096	0.336**	0.418**	0.553**	**0.741**	
Project complexity	0.193**	0.208**	0.134*	0.118	0.097	0.249**	0.284**	0.321**	0.357**	**1**
Mean	2.46	8.91	3.12	0.63	0.37	4.98	5.21	4.87	5.13	4.08
SD	1.03	5.87	1.41	0.48	0.48	0.93	0.76	0.84	0.69	0.97

Notes: $p < 0.05$; $p < 0.01$; $p < 0.001$. Diagonal values in **bold** represent the square root of the average variance extracted (AVE).
Source: Author's survey data.

4. RESULT

4.1 Hypotheses testing

Hierarchical regression analysis was conducted to examine the proposed hypotheses. Models 1, 3, and 6 include only the control variables and provide the baseline estimates for knowledge integration, project agility, and project performance, respectively. Models 2, 4, 5, 7, and 8 sequentially introduce the independent and mediating variables to evaluate the proposed relationships. The regression results are presented in Table 4. Variance inflation factor (VIF) values ranged from 1.21 to 2.36, well below the recommended threshold of 5.0, indicating that multicollinearity was not a concern. Model 2 shows that artificial intelligence capability positively influences knowledge integration ($\beta = 0.394$, $p < 0.001$), supporting H1. Model 4 indicates that artificial intelligence capability also has a significant positive effect on project agility ($\beta = 0.287$, $p < 0.001$), thereby supporting H2. After knowledge integration was introduced in Model 5, the coefficient for artificial intelligence capability decreased to 0.214 ($p < 0.001$), while knowledge integration exhibited a significant positive effect on project agility ($\beta = 0.364$, $p < 0.001$), providing support for H4 and suggesting a partial mediating effect.

Regarding project performance, Model 7 demonstrates that artificial intelligence capability ($\beta = 0.127$, $p < 0.001$) and knowledge integration ($\beta = 0.241$, $p < 0.001$) both positively influence project performance, supporting H3 and H5. After project agility was incorporated into Model 8, project agility emerged as the strongest predictor of project performance ($\beta = 0.371$, $p < 0.001$), while the coefficient for artificial intelligence capability remained positive and significant (β =

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0.118, $p < 0.001$). These findings support H6 and provide preliminary evidence that both knowledge integration and project agility partially mediate the relationship between artificial intelligence capability and project performance. The specific indirect effects are examined using bootstrapping analysis in the following section.

Table 4. Results of Hierarchical Regression Analysis

Variables	Knowledge Integration		Project Agility			Project Performance		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Control Variables								
Organization size	0.058	0.044	0.049	0.037	0.031	0.041	0.032	0.025
Organization age	0.071	0.063	0.067	0.058	0.051	0.064	0.055	0.047
Industry type	0.026	0.018	0.029	0.022	0.017	0.021	0.015	0.010
SMEs	0.039	0.028	0.034	0.026	0.020	0.031	0.024	0.018
Large organizations	0.047	0.034	0.042	0.031	0.024	0.038	0.029	0.022
Project complexity	0.148*	0.117*	0.171**	0.139*	0.126*	0.179**	0.151**	0.128*
Independent Variables								
Artificial intelligence capability	0.394*	0.287*	0.214*	0.231*	0.127*	0.118*		
Knowledge integration	—	—	—	0.364*	—	0.241*	0.168	
Project agility	—	—	—	—	—	—	—	0.371*
R^2	0.081	0.238	0.097	0.192	0.314	0.114	0.271	0.436
ΔR^2	—	0.157	—	0.095	0.122	—	0.157	0.165
F-change	—	24.18***	—	15.67***	21.34***	—	27.51***	31.86***

Notes: $p < 0.05$; **p** < 0.01; ***p*** < 0.001.
Source: Author's survey data.

Table 5. Bootstrapping Results for the Mediation Analysis

Indirect Path	Indirect Effect (β)	Direct Effect (β)	Boot SE	95% Boot LLCI	95% Boot ULCI	Decision
AI Capability → Knowledge Integration → Project Performance	0.126	0.118*	0.034	0.061	0.192	H7 Supported (Partial Mediation)
AI Capability → Project Agility → Project Performance	0.101	0.118*	0.029	0.047	0.158	H8 Supported (Partial Mediation)
AI Capability → Knowledge Integration → Project Agility → Project Performance	0.067	0.118*	0.022	0.031	0.106	H9 Supported (Sequential Partial Mediation)

Notes: Bootstrap estimates are based on 5,000 bias-corrected resamples. An indirect effect is considered statistically significant when the 95% confidence interval does not include zero.
Source: Author’s survey data.

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4.2 Mediation analysis

The mediating effects proposed in H7–H9 were examined using a bias-corrected bootstrapping procedure based on 5,000 resamples. The results are presented in Table 5. The indirect effect of artificial intelligence capability on project performance through knowledge integration was positive and statistically significant (β = 0.126, SE = 0.034, 95% CI = [0.061, 0.192]), supporting H7. Because the direct effect of artificial intelligence capability on project performance remained statistically significant after the inclusion of the mediator (β = 0.118, $p < 0.001$), knowledge integration functions as a partial mediator. Similarly, the indirect effect of artificial intelligence capability on project performance through project agility was positive and significant (β = 0.101, SE = 0.029, 95% CI = [0.047, 0.158]), providing support for H8. The continued significance of the direct effect indicates that project agility also partially mediates the relationship between AI capability and project performance. Finally, the sequential indirect effect through knowledge integration and project agility was statistically significant (β = 0.067, SE = 0.022, 95% CI = [0.031, 0.106]), supporting H9. These findings indicate that AI capability contributes to project performance not only directly but also indirectly by strengthening knowledge integration, which subsequently enhances project agility and ultimately improves project outcomes. The significant direct effect alongside the significant indirect effects suggests complementary rather than fully substitutive mediation mechanisms.

4.3 Robustness test

To verify the robustness of the hierarchical regression results, this study estimated the proposed research model using structural equation modeling (SEM) with AMOS. SEM allows the simultaneous estimation of all hypothesized relationships while accounting for measurement error. The standardized path coefficients obtained from the SEM analysis were consistent with those reported in the hierarchical regression models. As illustrated in Figure 2, artificial intelligence capability positively influenced knowledge integration, project agility, and project performance, while both knowledge integration and project agility significantly enhanced project performance. Furthermore, knowledge integration exerted a positive effect on project agility. These findings confirm that the proposed relationships remain stable across different analytical techniques, providing additional support for the robustness of the study's conclusions.

Table 6. Results of Robustness Test

Hypothesized Path	**Standardized Coefficient (β)**	**t-value**	**Decision**
AI Capability → Knowledge Integration	0.382*	7.94	Supported
AI Capability → Project Agility	0.276*	5.81	Supported
AI Capability → Project Performance	0.116*	2.41	Supported
Knowledge Integration → Project Agility	0.359*	6.88	Supported
Knowledge Integration → Project Performance	0.234*	4.27	Supported
Project Agility → Project Performance	0.364*	6.91	Supported

Notes: $p < 0.05$; **p** < 0.01; $\boldsymbol{p} < 0.001$.
Source: Author's survey data.

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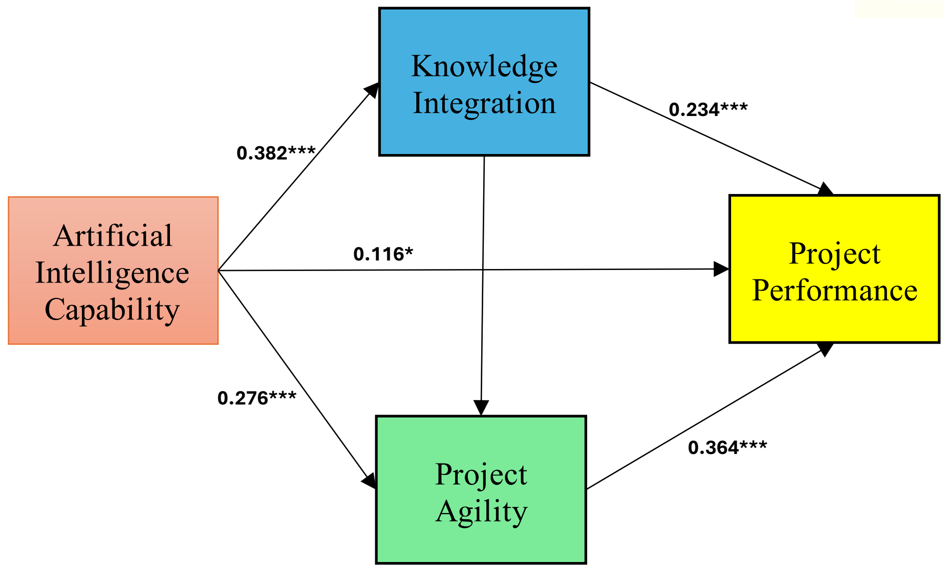

Figure 2. SEM Results

Note: Standardized path coefficients are reported. *** p < 0.001.

Source: Developed by the author.

4.4 Endogeneity test

To examine whether the estimated relationship between artificial intelligence capability and project performance was affected by endogeneity, a two-stage least squares (2SLS) estimation was conducted. Following prior organizational research, AI investment intensity was employed as an instrumental variable because organizations investing more heavily in AI are more likely to develop stronger AI capability, whereas the influence of AI investment on project performance is expected to occur primarily through the development of AI capability rather than through a direct pathway. In the first-stage regression, AI investment intensity was positively associated with AI capability ($\beta = 0.214$, $p < 0.001$), and the first-stage F-statistic (28.46) exceeded the conventional threshold of 10, confirming that the instrument was sufficiently strong.

The second-stage estimation demonstrated that AI capability remained positively associated with project performance ($\beta = 0.176$, $p < 0.001$) after accounting for potential endogeneity. Knowledge integration ($\beta = 0.182$, $p < 0.001$) and project agility ($\beta = 0.349$, $p < 0.001$) also exhibited significant positive effects on project performance. Importantly, these coefficients are consistent in both direction and magnitude with those obtained from the hierarchical regression and structural equation modeling analyses, providing additional evidence that the findings are robust and are unlikely to be driven by reverse causality or omitted-variable bias.

Table 7. Two-Stage Least Squares (2SLS) Results for Endogeneity Analysis

Variables	**First Stage: AI Capability (β)**	**Second Stage: Project Performance (β)**
Organization size	0.094	0.038
Organization age	0.056	0.067

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Industry type	0.049	0.029
SMEs	0.081	0.026
Large organizations	0.103	0.035
Project complexity	0.146*	0.121*
AI investment intensity (Instrument)	0.214*	—
Artificial intelligence capability	—	0.176*
Knowledge integration	—	0.182*
Project agility	—	0.349*
R^2	0.187	0.441
F-statistic	28.46*	19.14*

Notes: Standardized coefficients are reported. The first-stage regression examines the relationship between the instrumental variable (AI investment intensity) and AI capability. The first-stage F-statistic of 28.46 exceeds the conventional threshold of 10, indicating that the instrument is sufficiently strong and minimizing concerns regarding weak-instrument bias. The second-stage regression estimates the effect of AI capability on project performance after controlling for potential endogeneity. Robust standard errors were used to account for heteroskedasticity. $p < 0.05$; p < 0.01; $p < 0.001$.

5. DISCUSSION AND IMPLICATIONS

5.1 Discussion

The primary objective of this study was to examine how artificial intelligence capability contributes to project performance by integrating dynamic capabilities theory and the knowledge-based view. Specifically, this study investigated whether knowledge integration and project agility explain the mechanisms through which AI capability translates into superior project outcomes. Using data collected from Turkish project-based organizations, the findings provide strong empirical support for all proposed hypotheses. The results demonstrate that AI capability directly enhances knowledge integration, project agility, and project performance. Furthermore, knowledge integration positively influences both project agility and project performance, while project agility exerts the strongest direct effect on project performance. Finally, the mediation analyses reveal that AI capability improves project performance both independently and indirectly through knowledge integration, project agility, and their sequential interaction. Collectively, these findings provide a more comprehensive explanation of how organizations transform technological capability into tangible project success.

The results indicate that AI capability positively influences knowledge integration, project agility, and project performance. These findings reinforce the growing body of literature suggesting that AI should not be viewed merely as an operational technology but rather as an organizational capability that enables firms to sense opportunities, process information more effectively, and continuously reconfigure internal resources to improve performance. This finding is consistent with previous studies demonstrating that AI enhances organizational decision-making, knowledge utilization, and adaptive capability (Mariani & Mancini, 2025; Wagner & Wagner, 2023; Wamba-Taguimdje et al., 2020). From the perspective of dynamic capabilities theory, AI capability represents a higher-order capability that strengthens an organization's ability to integrate technological resources with managerial processes, allowing project teams to respond more

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effectively to changing project requirements. Rather than generating superior performance directly through automation alone, AI capability creates value by enabling organizations to continuously reconfigure their knowledge assets and operational routines, thereby increasing both organizational responsiveness and project effectiveness.

The findings further demonstrate that knowledge integration positively influences project agility and project performance, while project agility significantly improves project performance. These results emphasize that organizational knowledge becomes strategically valuable only when it is effectively integrated across project teams and transformed into coordinated actions. This finding supports the central argument of the knowledge-based view that competitive advantage depends less on possessing knowledge than on an organization's ability to combine and apply dispersed knowledge resources (Grant, 1996; Sahibzada & Mumtaz, 2023). When organizations successfully integrate technical expertise, project experience, and stakeholder knowledge, project teams become better equipped to respond rapidly to changing customer requirements, emerging risks, and unexpected project challenges. Consequently, improved knowledge integration strengthens project agility, enabling organizations to modify plans, reallocate resources, and make timely decisions that ultimately improve project performance. These findings are also consistent with recent research highlighting the complementary relationship between knowledge management, organizational agility, and project success (Aurélio de Oliveira et al., 2012; Oshilalu, 2024).

The mediation analyses provide additional insight into the mechanisms through which AI capability enhances project performance. Both knowledge integration and project agility partially mediate the relationship between AI capability and project performance, while the sequential mediation analysis demonstrates that AI capability first strengthens knowledge integration, which subsequently enhances project agility before improving project performance. These findings suggest that organizations do not realize the full benefits of AI investments immediately after technology adoption. Instead, AI-generated information and analytical capabilities must first be translated into organizational knowledge, which then enables more agile project execution and ultimately leads to superior project outcomes. This sequential process extends previous research by demonstrating that AI capability operates through multiple complementary organizational mechanisms rather than a single direct pathway (Mahmood et al., 2024; Wagner & Wagner, 2023). The results therefore highlight that technological capability alone is insufficient to guarantee project success unless organizations simultaneously develop the knowledge integration processes and adaptive capabilities necessary to exploit AI-generated insights.

From a theoretical perspective, the findings illustrate the complementary roles of dynamic capabilities theory and the knowledge-based view in explaining AI-enabled project performance. Dynamic capabilities theory explains how organizations develop the capacity to reconfigure internal resources and adapt to changing project environments, whereas the knowledge-based view explains how integrated organizational knowledge serves as a strategic resource that enables effective adaptation. Rather than competing explanations, the two theories jointly describe the process through which AI capability generates organizational value. AI capability enhances the organization's dynamic capability to sense, seize, and transform opportunities, while knowledge integration facilitates the creation, combination, and application of knowledge resources that support agile project execution. Consequently, project agility emerges as the operational mechanism through which these dynamic capabilities are translated into superior project outcomes.

This integrated theoretical explanation contributes to a more comprehensive understanding of AI-enabled project management and extends previous studies that have examined these theoretical perspectives independently (Grant, 1996; Teece, 2019; Wagner & Wagner, 2023).

Overall, the findings demonstrate that achieving superior project performance requires considerably more than simply investing in AI technologies. Organizations create value when AI capability is embedded within organizational processes that encourage knowledge integration and support agile project execution. These findings suggest that technological capability, knowledge management capability, and organizational agility should be viewed as mutually reinforcing organizational resources rather than isolated capabilities. Consequently, organizations seeking to improve project performance should focus not only on expanding AI adoption but also on developing the managerial practices, collaborative culture, and adaptive project processes that enable AI-generated knowledge to be effectively transformed into project success. This integrated perspective provides a more complete explanation of how organizations convert AI investments into sustainable project performance improvements in increasingly dynamic and uncertain project environments.

5.2 Theoretical Contributions

This study advances the AI management literature by conceptualizing AI capability as a higher-order organizational capability rather than as a stand-alone technological resource. A technological resource refers to the availability of AI tools, software, data infrastructure, or algorithms. In contrast, an operational capability concerns the efficient performance of established project-management activities. AI capability is higher-order because it enables the organization to purposefully mobilize, combine, and reconfigure technological resources, data, human expertise, and managerial processes in response to changing project conditions (Teece, 2019; Teece et al., 1997). It therefore does not create value merely through automation or information processing; rather, it enhances the organization's capacity to renew project routines, integrate AI-generated insights with managerial judgment, and adapt resource deployment. This distinction shifts attention from whether organizations possess AI technologies to whether they have developed the organizational capability to use those technologies strategically and continuously.

The study also addresses two important limitations in the existing literature. First, AI management research has often emphasized AI adoption, technological investment, or the direct performance consequences of AI, while offering limited explanation of the organizational mechanisms through which AI-related resources are transformed into project-level value (Wamba-Taguimdje et al., 2020; Wagner & Wagner, 2023). Second, although the knowledge-based view recognizes knowledge as a strategically important resource, it has provided less clarity regarding how organizations integrate rapidly generated, data-driven, and AI-enabled insights with the dispersed expertise of project participants in dynamic environments (Grant, 1996; Sahibzada & Mumtaz, 2023). By positioning knowledge integration and project agility as sequential mechanisms, this study responds to both limitations. It shows that AI capability generates project value when AI-derived information is converted into shared organizational knowledge and subsequently used to reconfigure project activities in response to changing conditions.

Second, this study extends the knowledge-based view by identifying knowledge integration as a central organizational mechanism through which AI capability generates project outcomes.

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Existing research has largely examined knowledge integration as an independent organizational capability or as a general knowledge management process. The present findings demonstrate that knowledge integration also serves as an important mediating mechanism linking AI capability to both project agility and project performance. This contribution enriches KBV by illustrating that organizational knowledge creates value not simply through its accumulation but through its continuous integration, sharing, and application across project teams operating in dynamic environments. Consequently, the study provides empirical evidence that effective knowledge integration transforms AI-generated information into actionable organizational knowledge capable of supporting superior project execution (Grant, 1996).

Third, this study contributes to the project management literature by introducing and empirically validating a sequential capability-building process through which AI capability enhances project performance. While previous studies have typically examined knowledge management or organizational agility as separate mediating mechanisms, the present study demonstrates that these capabilities operate sequentially. Specifically, AI capability strengthens knowledge integration, which subsequently improves project agility before ultimately enhancing project performance. This sequential mediation provides a more comprehensive explanation of how technological capabilities are translated into project success and responds to recent calls for research examining multiple complementary organizational capabilities rather than isolated mediating mechanisms (Mahmood et al., 2024; Oshilalu, 2024; Wagner & Wagner, 2023). By integrating DCT and KBV within a single theoretical framework, this study offers a more holistic explanation of AI-enabled project performance and provides a stronger foundation for future research examining organizational capability development in project-based environments.

5.3 Practical Implications

The findings of this study provide several important implications for managers responsible for improving project performance through artificial intelligence. First, the results demonstrate that simply investing in AI technologies is unlikely to generate substantial improvements in project outcomes unless organizations simultaneously develop the organizational capabilities required to exploit those technologies effectively. Many organizations continue to evaluate AI initiatives primarily in terms of technological sophistication or financial investment. However, the findings suggest that managers should instead view AI capability as a strategic organizational capability that requires complementary investments in people, processes, and organizational learning. Accordingly, executives should integrate AI initiatives into broader project management strategies by developing governance structures, training programs, and decision-support systems that encourage project teams to use AI-generated insights throughout the project lifecycle. Such an integrated approach is more likely to produce sustainable improvements in project performance than technology adoption alone (Wagner & Wagner, 2023).

Second, the significant mediating role of knowledge integration highlights the importance of strengthening knowledge-sharing practices within project-based organizations. AI systems can generate large volumes of valuable information, but this information contributes little to project success if it remains isolated within functional departments or individual project teams. Managers should therefore establish formal mechanisms that facilitate the integration of technical knowledge, project experience, customer feedback, and AI-generated recommendations across organizational

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boundaries. Cross-functional project meetings, collaborative digital platforms, AI-supported knowledge repositories, and structured post-project reviews can help organizations transform dispersed information into shared organizational knowledge. By embedding knowledge integration into everyday project activities, organizations can improve decision quality, reduce duplication of effort, and increase the effectiveness of AI-supported project management practices (Grant, 1996; Sahibzada & Mumtaz, 2023).

Third, the results indicate that project agility represents the final mechanism through which AI capability and knowledge integration generate superior project performance. Consequently, managers should focus not only on adopting AI technologies but also on developing agile project management practices that enable rapid adaptation to changing project conditions. Organizations should encourage flexible planning, continuous monitoring, rapid decision-making, iterative problem solving, and timely resource reallocation to respond effectively to uncertainty and evolving stakeholder requirements. AI technologies should support these practices by providing real-time analytics, predictive insights, and early identification of project risks rather than simply automating routine activities. When AI capability, knowledge integration, and project agility are developed simultaneously, organizations become better positioned to deliver projects on time, within budget, and at higher levels of quality and stakeholder satisfaction (Aurélio de Oliveira et al., 2012; Guo et al., 2023; Oshilalu, 2024).

Overall, the findings suggest that organizations should adopt a capability-based approach to AI implementation rather than a technology-centered approach. AI investments create the greatest organizational value when they are integrated with effective knowledge management practices and agile project execution processes. Managers who recognize these complementary relationships will be better equipped to convert AI capability into sustainable improvements in project performance while enhancing their organizations' ability to respond to increasingly dynamic and uncertain project environments.

6. CONCLUSION AND LIMITATIONS

This study investigated how artificial intelligence capability contributes to project performance by integrating dynamic capabilities theory and the knowledge-based view. Specifically, it examined the direct effects of AI capability on knowledge integration, project agility, and project performance, together with the mediating roles of knowledge integration and project agility. Based on data collected from 267 project-based organizations operating in Turkey, the findings provide empirical support for all nine proposed hypotheses. The results indicate that AI capability directly enhances knowledge integration, project agility, and project performance. Furthermore, knowledge integration positively influences both project agility and project performance, while project agility exerts the strongest direct effect on project performance. The mediation analyses further demonstrate that AI capability improves project performance not only through its direct influence but also indirectly through knowledge integration, project agility, and their sequential interaction. These findings collectively suggest that organizations create greater value from AI when technological capability is accompanied by effective knowledge integration and agile project execution.

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Beyond validating the proposed research model, this study contributes to a broader understanding of AI-enabled project management by explaining how technological capabilities are translated into superior project outcomes through complementary organizational capabilities. By integrating DCT and KBV within a single theoretical framework, the study demonstrates that AI capability should not be viewed merely as a technological resource but as a strategic organizational capability that enables firms to continuously integrate knowledge, adapt to changing project conditions, and improve project performance. The findings therefore extend existing project management and AI literature by providing empirical evidence that sustainable project success depends not only on adopting AI technologies but also on developing the organizational capabilities required to leverage those technologies effectively. This integrated perspective offers a more comprehensive explanation of how AI investments generate organizational value and provides a stronger theoretical foundation for future research on AI-enabled project management.

Despite these contributions, several limitations should be acknowledged. First, although the time-lagged research design strengthens causal inference by reducing common method bias, it does not completely eliminate the possibility of reciprocal relationships among the study variables. Future research could employ longitudinal panel studies or experimental research designs to examine how AI capability, knowledge integration, project agility, and project performance evolve over time and influence one another throughout different stages of project execution. Such research would provide deeper insights into the dynamic processes through which AI capability generates sustained project success.

Second, this study focused exclusively on project-based organizations operating in Turkey. While this context provides valuable evidence from an advanced digital economy, institutional environments, digital infrastructure, and project management practices differ considerably across countries and industries. Consequently, caution should be exercised when generalizing the findings to other contexts. Future studies should replicate the proposed model in different national settings, emerging economies, public-sector organizations, and industry sectors to determine whether the observed relationships remain consistent under varying institutional and competitive conditions.

Third, the proposed model examined knowledge integration and project agility as the primary mechanisms through which AI capability influences project performance. Although the findings confirm the importance of these complementary capabilities, other organizational processes may also contribute to the effective utilization of AI in project environments. Future studies could extend the model by examining additional mediating mechanisms such as organizational learning, absorptive capacity, digital collaboration capability, innovation capability, knowledge-sharing quality, or project resilience. Similarly, incorporating contextual moderators such as environmental uncertainty, project complexity, organizational culture, leadership style, digital maturity, or organizational learning orientation would provide a more nuanced understanding of the conditions under which AI capability creates the greatest project value. Such extensions would further enrich both dynamic capabilities theory and the knowledge-based view by identifying important boundary conditions that influence AI-enabled project success.

Fourth, the study relied on a single key informant from each project-based organization. Although respondents were selected because of their direct knowledge of AI-enabled project activities and organizational project-management practices, their assessments may still be subject to perceptual bias. Future research could collect matched responses from project managers, information-

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technology specialists, functional managers, and project team members, or combine survey data with objective project-performance indicators. Such multi-source designs would provide a more complete assessment of how AI capability, knowledge integration, and project agility influence project outcomes.

In conclusion, this study demonstrates that superior project performance is achieved not simply through AI adoption but through the effective integration of technological capability with organizational knowledge processes and agile project execution. By combining the explanatory power of dynamic capabilities theory and the knowledge-based view, this research offers a comprehensive framework for understanding how organizations convert AI capability into tangible project outcomes. As artificial intelligence becomes increasingly embedded in project environments, understanding how organizations combine technological capability with knowledge integration and project agility will be essential for achieving sustainable project performance and maintaining long-term competitive advantage.

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