

Artificial Intelligence Adoption and Organizational Performance: Examining the Mediating Role of Project Success

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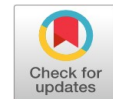
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Abstract: Artificial Intelligence (AI) has become more and more integrated in the everyday experience of project managers across quickly changing industries like information technology, telecommunications, construction, and banking. Building on the Dynamic Capabilities Theory, a model is created and tested that links AI adoption with organizational performance via project success. Data were collected in two waves, separated by a time lag, from 244 employees and project managers working in AI-enabled project-based organizations in Pakistan. Hypothesis testing was conducted using the following methods: reliability analysis, correlation analysis, and PROCESS macro Model 4 with 5,000 bootstrap resamples. The results show that the adoption of AI is positively and significantly related to project success ($\beta = .28$, $p < .001$) but there is no significant direct relationship between AI adoption and organizational performance ($\beta = .06$, $p = .080$). Project success, in turn, is significantly and positively related to organizational performance ($\beta = .43$, $p < .001$). Importantly, project success fully mediates the relationship between AI adoption and organizational performance (indirect effect = .119, Boot 95% CI [.060, .182]; direct effect = .410, Boot 95% CI [.275, .564]). The findings enrich the concept of Dynamic Capabilities Theory by showing that the value of using AI in an organization is not delivered directly but rather achieved through successful projects. Real-world applications of how AI can be used for performance improvement within an organization are considered.

Keywords: Artificial Intelligence (AI) Adoption, Project Success (PS), Organizational Performance (OP), Dynamic Capabilities Theory (DCT).

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INTRODUCTION

Artificial Intelligence (AI) has moved to the nerve-center of organizational life. Systems capable of learning, pattern recognition, natural language processing, and autonomous decision-making now enable employees to plan, monitor, and deliver work as part of their everyday tools (Dwivedi et al., 2021). AI is no longer limited to back-office automation; it is increasingly used by organizations that deliver value through discrete projects, such as financial product launches, software development, infrastructure builds, or telecommunications roll outs. AI increasingly plays a vital role in planning, risk identification, resource allocation, and progress reporting throughout the project life cycle (Fridgeirsson et al., 2023).

This has given rise to two distinct lines of research. The first examines whether and how AI use benefits the organization in terms of overall organizational performance, typically measured through productivity, profitability, agility, or competitive position (Aldossary et al., 2026; Kassa & Worku, 2025). The second focuses on communication, scheduling, and risk management within individual projects: whether AI-enabled tools make projects more likely to be completed on time, within budget, and to the satisfaction of project and program stakeholders (Lawal et al., 2024; Nikolić & Bjelica, 2025). Across both streams, the evidence is broadly encouraging but conditional: AI adoption is generally linked to better outcomes, though the effects depend on how AI is used, how well it fits organizational needs and capacity, and the degree to which employees accept it (Hamm & Klesel, 2021; Nikolić & Bjelica, 2025).

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The connection between these two streams remains largely unexplored: by what mechanism might AI help organizations become more successful in their projects? Understanding this mechanism carries real significance. Theoretically, it addresses an open question about how a technological capability translates into firm-level value. Practically, organizations across sectors are investing heavily in AI without a clear evidence base for how, or whether, that investment pays off at the organizational level — a gap that leaves managers with little guidance on where to focus their efforts. If better planning and execution of individual projects is an important value driver, project-level improvement could be one of the main mechanisms through which AI adoption creates value for organizations as a whole. Conversely, AI's distinct impact on organizational performance could be superficial or limited when its implementation is not closely tied to project success, particularly if AI tools are adopted without sufficient training (Hamm & Klesel, 2021), echoing the long-running “productivity paradox” observed with earlier technologies (Brynjolfsson et al., 2018). The present study aims to address this gap.

Grounded in Dynamic Capabilities Theory (Teece et al., 1997; Teece, 2007), the present study develops and tests a model in which AI adoption is treated as an organizational capability with both a direct effect on organizational performance and an indirect effect transmitted through project success. Data were gathered from 244 employees and project managers of project-based organizations across the IT, telecommunications, construction, and banking sectors of Pakistan. In doing so, the study makes a unique contribution to the literature in three ways. First, it brings together two research traditions in AI: the organizational performance and the project management fields which generally have worked independently. Second, it tests project success as a mediator variable empirically. Third, it offers lessons learned from Pakistan, an area where the use of AI is gaining momentum but is still relatively overlooked in the empirical literature (Felemban et al., 2024).

Research Objective

- To examine the direct relationship between AI adoption and organizational performance.
- To examine the relationship between AI adoption and project success.
- To examine the relationship between project success and organizational performance.
- To examine whether project success mediates the relationship between AI adoption and organizational performance.

LITERATURE REVIEW

Theoretical Background: Dynamic Capabilities Theory

This study is based on Dynamic Capabilities Theory (DCT) as it is an extension of the Resource-Based View of the firm (Barney, 1991). While the RBV accounts for every aspect of what ensures a firm's competitive advantage, whether it is related to the possession of valuable, rare, inimitable and non-substitutable resources, the DCT considers how firms build, combine, and reconfigure these resources in increasingly dynamic environments (Teece et al., 1997). Teece (2007) characterizes the dynamic capabilities as three underlying processes: the sensing of opportunities and threats in the external environment, the seizing of opportunities through the allocation of resources and strategic actions, and the reconfiguration and transformation of the firm's asset base to remain competitive.

This framework aligns directly with AI adoption. Adopting AI tools is an organization acting on a technological opportunity; applying AI tools to its core processes of project management is the seizing; and reorganizing workflows, roles, and decision rights around AI-enabled processes is the new project management culture of “transforming.” This aligns with Hamm and Klesel (2021), who identify organizational readiness and the ability to integrate AI into existing processes as key factors for successful AI application. More recent work has begun to formalize this readiness challenge for project settings specifically: Armanios and Tucci (2025) propose a dialectical framework identifying organizational and project-level tensions — such as balancing centralized and distributed oversight — that must be managed for AI deployment in projects to succeed. Firms do not automatically gain performance advantages simply by acquiring technology; rather, Arifin (2015) suggests that the advantages a technology offers depend on the dynamic capabilities of the firm at the time of acquisition. This organizational-level view complements individual-level models such as the Technology Acceptance Model (Davis, 1989), which explains adoption behavior in terms of perceived usefulness and ease of use; DCT extends this logic to the organizational

level by focusing on how firms build and reconfigure capabilities around new technologies. Such readiness factors are also consistent with the Technology-Organization-Environment framework (Tornatzky & Fleischer, 1990), which similarly emphasizes organizational and environmental conditions — alongside the technology itself — as determinants of successful adoption. This conditional logic is important in interpreting the present study's finding that use of AI does not directly contribute to improving performance, but it does improve project success, from which performance gains are realized.

AI Adoption and Organizational Performance

There is a large empirical literature linking the use of AI with performance of the organization. Among small and medium-sized enterprises, Aldossary et al. (2026) found that managers' perceptions of AI's benefits were positively related to organizational performance. Similarly, Kassa and Worku (2025) found a positive relationship between AI application and organizational performance, with employee productivity acting as a partial mediator. Consistent with this pattern, Jamil et al. (2025) found that AI adoption and technological readiness improved organizational performance among Pakistani manufacturing SMEs largely through their effect on employee capacity building, again pointing to mediation rather than direct impact as the dominant mechanism. Beyond individual tasks, Murire (2024) work suggests that AI also reshapes job conventions and work processes, potentially influencing organizational culture.

The wider AI literature, however, cautions against assuming that implementing AI straightforwardly translates into improved performance. Brynjolfsson et al. (2018) describe a "productivity paradox," in which large investments in AI have not always translated into measurable productivity gains. Hamm and Klesel (2021) similarly single out organizational readiness, leadership support, and employee skills — not the technology itself — as key factors in whether AI adoption affects organizational outcomes.

H1: AI adoption is positively related to organizational performance.

AI Adoption and Project Success

Project management is one of the organizational functions where the influence of artificial intelligence is most evident. AI tools are now available to assist with scheduling, resource allocation, budget forecasting, and risk identification (Fridgeirsson et al., 2023). Project professionals in the study by Fridgeirsson et al. (2023) considered such tools especially useful for cost estimation, schedule execution, and early risk identification, suggesting one pathway through which AI adoption can improve project outcomes.

Direct empirical evidence linking AI adoption to project success remains limited, but what exists is positive. Lawal et al. (2024), in a mixed-methods study, found a positive relationship between the use of AI tools and project success. Nikolić and Bjelica (2025) describe AI in projects as having a "dual role": it can improve outcomes when well integrated with organizational processes and project teams, but can hamper outcomes when applied rigidly or poorly. Adopting AI can be viewed as a sensing-and-seizing activity whose benefits are realized primarily at the project level (Teece, 2007).

H2: AI adoption is positively related to project success.

Project Success and Organizational Performance

Project success has long been recognized as encompassing much more than narrow technical objectives. Pinto and Slevin (1988) presented an influential multidimensional perspective on project success, encompassing technical validity, organizational validity, and organizational effectiveness. Project success, however, must also be measured in terms of customer impact, business success, and organizational readiness for future opportunities (Shenhar et al., 2001) – explicitly connecting project-level results with organizational-level performance. Müller and Jugdev (2012) similarly conclude that project success is increasingly conceptualized as strategic success, reflecting its contribution to longer-term business goals. In this view, successful projects should translate into better organizational performance by building reputation, retaining clients, optimizing resources, and achieving strategic milestones (Venkatraman & Ramanujam, 1986).

H3: Project success is positively related to organizational performance.

Project Success as a Mediator

The preceding sections suggest two distinct pathways by which AI adoption may relate to organizational performance: a direct pathway (*H1*) and an indirect pathway through project success (*H2* and *H3*). Kassa and Worku (2025) found that employee productivity partially mediated the AI–performance relationship; Aldossary et al. (2026) similarly found that organizational agility mediated this relationship. Project success represents a closely related but distinct mechanism: it captures whether the discrete units of work through which organizational value is delivered are completed successfully. From the standpoint of DCT, the performance benefits of a dynamic capability are realized through the firm’s capacity to seize opportunities and reconfigure resources — activities enacted at the project level in project-based organizations (Teece, 2007). If AI adoption improves project success (*H2*) and project success in turn drives organizational performance (*H3*), then project success should account for a meaningful portion of the AI adoption–performance relationship.

H4: Project success mediates the relationship between AI adoption and organizational performance.

THEORETICAL FRAMEWORK

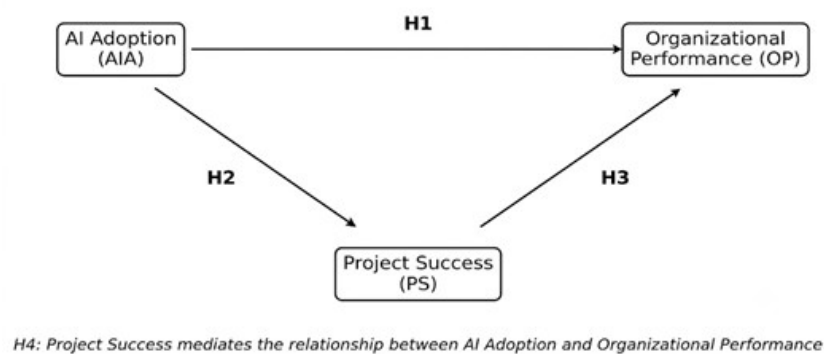


Figure 1: Theoretical model of the study

METHODOLOGY

Participants and Procedure

The target population comprised employees and project managers in Pakistani project-based organizations — spanning the IT and telecommunications, construction, and banking sectors — that have implemented AI-powered project management tools. Convenience sampling, a form of non-probability sampling, was used because it reduces the time and expense associated with other sampling approaches and is well suited to exploratory organizational research (Stratton, 2021).

A two-wave, time-lagged data collection strategy was used to reduce common method bias (Podsakoff et al., 2003). Respondents completed the AI adoption scale along with demographic items at Time 1. After a 4–6 week interval, the same respondents — identified by their email address — completed the project success and organizational performance scales. Participants who did not complete the second wave were excluded from the sample.

A link to the online survey was distributed to participants in the target sectors. A final sample of 244 respondents was retained. Of these, 198 (81.1%) were male and 46 (18.9%) were female. Regarding educational qualifications, 83 (34.0%) respondents held a bachelor’s degree, 116 (47.5%) a master’s degree, 38 (15.6%) a doctoral degree, 1 (0.4%) an MPhil, and 6 (2.5%) another qualification.

Measures

Each construct was measured via multi-item scales with a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

AI Adoption (AIA): AI adoption was measured using a seven-item scale adapted from Wijayati et al. (2022). The items reflect the extent to which AI-based tools are implemented, accepted, and integrated into an organization's project-related processes (Cronbach's $\alpha = .909$).

Project Success (PS): Project success was measured using a seven-item scale adapted from Bhatti et al. (2021), covering schedule and budget performance, technical quality, and stakeholder and organizational benefit (Cronbach's $\alpha = .908$).

Organizational Performance (OP): A 10-item scale adapted from Wong et al. (2012), covering the dimensions of quality, cost, flexibility, and delivery, was used to measure organizational performance (Cronbach's $\alpha = .807$).

Data Analysis

Prior to hypothesis testing, descriptive statistics were used to summarize the demographic characteristics of the sample. The measurement model was validated using Confirmatory Factor Analysis (CFA) in AMOS, following the fit-index thresholds recommended by Kline (2023): CMIN/DF < 3, CFI, TLI, and IFI > 0.90 (> 0.95 indicating very good fit), and RMSEA < 0.08 (< 0.05 indicating very good fit). Internal consistency reliability was assessed using Cronbach's alpha, and convergent and discriminant validity using Average Variance Extracted (AVE) and Composite Reliability (CR) following Fornell and Larcker (1981). A Pearson correlation analysis examined the bivariate relationships among study variables. Direct and indirect (mediated) relationships were tested using PROCESS MACRO Model 4 (Hayes, 2017) with 5,000 bootstrap resamples to generate 95% bias-corrected confidence intervals.

RESULTS

Demographic Profile of Respondents

The final sample comprised 244 respondents drawn from project-based organizations in Pakistan's IT, telecommunications, construction, and banking sectors. Table 1 summarizes the demographic profile of the sample.

Table 1: Demographic Profile of Respondents (N = 244)

Demographic Variable	Category	Frequency (%)
Gender	Male	198 (81.1%)
	Female	46 (18.9%)
Educational Qualification	Bachelor's degree	83 (34.0%)
	Master's degree	116 (47.5%)
	Doctoral degree	38 (15.6%)
	MPhil	1 (0.4%)
	Other	6 (2.5%)
Total		244 (100%)

As shown in Table 1, the sample was predominantly male (81.1%), consistent with the male-dominated nature of project management and technical roles in Pakistan's IT, construction, and telecommunications sectors. In terms of educational attainment, the most frequent category was a master's degree (47.5%), followed by a bachelor's degree (34.0%) and a doctorate (15.6%). This educational profile signaled a well-qualified sample with the necessary contextual knowledge to make meaningful evaluations of AI uptake and organizational performance in their respective organizations.

Reliability Analysis

Internal consistency reliability was assessed for each scale using Cronbach's α . Based on the acceptance guidelines proposed by Nunnally (1978), all three constructs had alpha values $\geq .70$, indicating acceptable reliability. The reliability statistics are shown in Table 2.

Table 2: Reliability Analysis

Variable	Cronbach's Alpha α	No. of Items
AI Adoption (AIA)	.909	7
Project Success (PS)	.908	7
Organizational Performance (OP)	.807	10

Cronbach's alpha values for all three constructs were well above .70. The alpha values of AI Adoption ($\alpha = .909$) and Project Success ($\alpha = .908$) were within the excellent range ($> .90$), reflecting very high internal consistency. A good level of internal consistency was achieved for Organizational Performance ($\alpha = .807$). All three scales were found to be reliable instruments for measuring their respective constructs in this sample.

Confirmatory Factor Analysis (CFA)

To assess the validity of the three latent factors — AI Adoption, Project Success, and Organizational Performance — confirmatory factor analysis (CFA) was conducted in AMOS. To strengthen evidence against common method bias (CMB), the hypothesized three-factor model was compared with a one-factor model using the same data, following Kline (2023). Fit indices for both models are shown in Table 3.

Table 3: Confirmatory Factor Analysis – Model Fit Indices

Model	CMIN	DF	CFI	TLI	IFI	RMSEA
Hypothesized three-factor model	1812.35	1155	0.933	0.928	0.934	0.047
One-factor model	3981.53	469	0.212	0.162	0.252	0.188

Convergent and Discriminant Validity

Criteria for convergent validity are: $AVE > 0.50$ and $CR > .70$ (Fornell & Larcker, 1981; Igbaria et al., 1995). For each construct, the square root of AVE (shown in bold along the diagonal) exceeded the corresponding off-diagonal correlations, supporting discriminant validity. The AVE, CR and inter construct correlations are shown in Table 4.

Table 4: Convergent and Discriminant Validity

Variable	1	2	3	AVE	CR
1. AI Adoption (AIA)	1			0.91	0.51
2. Project Success (PS)	.289**	1		0.92	0.65
3. Organizational Performance (OP)	.270**	.650**	1	0.85	0.67

Descriptive Statistics

Table 5: Descriptive Statistics (N = 244)

Variable	N	Min	Max	Mean	SD
AI Adoption (AIA)	244	1.00	5.00	2.63	0.92
Project Success (PS)	244	1.00	5.00	2.94	0.89
Organizational Performance (OP)	244	1.00	5.00	3.18	0.61

The mean scores for the three constructs, as shown in Table 5, are in the moderate range of the Likert scale. AI Adoption had the lowest mean ($M = 2.63$, $SD = 0.92$), indicating that, on average, respondents perceived their organizations to be at an early-to-intermediate stage of AI adoption rather than a comprehensive one. Project Success ($M = 2.94$, $SD = 0.89$) was also moderate, reflecting mixed perceptions of project outcomes. Organizational Performance received the highest mean score ($M = 3.18$, $SD = 0.61$) and displayed a notably smaller standard deviation, suggesting greater agreement among respondents on this construct.

Hypothesis Testing

Direct Effects: PROCESS MACRO Model 4 was used (Hayes, 2018) for the estimation of direct effects. Paths were considered statistically significant when $p < .05$ or when the 95% confidence interval (LLCI to ULCI) did not

include zero. Results of the three direct-effect hypotheses are shown in Table 6.

Table 6: Direct Effects – Hypothesis Testing

Path	B	SE	t	p	LLCI	ULCI
H1: AIA → OP	.059	.034	1.757	.080	-.007	.125
H2: AIA → PS	.280	.060	4.705	.000	.163	.397
H3: PS → OP	.425	.035	12.270	.000	.357	.493

Hypothesis 1 proposed that AI adoption is positively related to organizational performance. The direct path from AI Adoption to Organizational Performance was positive ($B = .059$) but not at the level of conventional statistical significance ($t = 1.757$, $p = .080$; 95% CI $[-.007, .125]$). Because the confidence interval includes zero and p exceeds .05, H1 is not supported. This finding indicates that, once project success is taken into account as a mediator, there is no significant direct relationship between AI utilization and organizational performance.

Hypothesis 2 proposed that AI adoption is positively related to project success. This path was positive and highly significant ($B = .280$, $SE = .060$, $t = 4.705$, $p < .001$; 95% CI $[.163, .397]$). Since the confidence interval excludes zero, H2 is supported. AI adoption explains approximately 8.4% of the variance in project success ($R^2 = .084$, $F(1, 242) = 22.133$, $p < .001$).

Hypothesis 3 proposed that project success is positively related to organizational performance. This path was positive and highly significant ($B = .425$, $SE = .035$, $t = 12.270$, $p < .001$; 95% CI $[.357, .493]$). H3 is strongly supported. Together, AI Adoption and Project Success explain 42.9% of the variance in Organizational Performance ($R^2 = .429$, $F(2, 241) = 90.657$, $p < .001$).

Indirect Effect – Mediation Analysis: Hypothesis 4 proposed that project success mediates the relationship between AI adoption and organizational performance. The indirect effect was estimated using PROCESS MACRO Model 4 with 5,000 bootstrap resamples. Table 7 presents the indirect effect results.

Table 7: Bootstrapped Indirect Effect – Mediating Role of Project Success (N = 244)

Path	Effect	BootSE	BootLLCI	BootULCI
AIA → PS → OP	.119	.031	.060	.182

As shown in Table 7, the indirect effect of AI adoption on organizational performance through project success was positive and statistically significant (indirect effect = .119, BootSE = .031, 95% Boot CI $[.060, .182]$). Since the 95% bootstrapped confidence interval excludes zero, H4 is supported. Project success fully mediates the relationship between AI adoption and organizational performance: the direct effect of AI adoption on organizational performance was non-significant ($B = .059$, $p = .080$) while the indirect effect through project success was significant. This pattern is consistent with full mediation (Baron & Kenny, 1986; Hayes, 2018), indicating that the influence of AI adoption on organizational performance is entirely channeled through its effect on project success.

Table 8 provides a summary of all four hypotheses and their status.

Table 8: Summary of Hypothesis Testing Results

Hypothesis	Statement	Result
H1	AI adoption is positively related to organizational performance.	Not Supported
H2	AI adoption is positively related to project success.	Supported
H3	Project success is positively related to organizational performance	Supported
H4	Project success mediates the relationship between AI adoption and organizational performance.	Supported

DISCUSSION, CONCLUSION AND IMPLICATIONS

Discussion

This study set out to examine the relationship between AI adoption and organizational performance as mediated by project success. The results reveal a theoretically coherent and practically informative pattern: AI adoption has a significant effect on project success, project success in turn strongly affects organizational performance, and the overall effect of AI adoption on organizational performance is transmitted entirely through this project-level pathway. Each hypothesis is discussed in turn below.

The first hypothesis proposed that AI adoption would be positively and directly related to organizational performance. This was not supported by the direct-effect model ($B = .059$, $p = .080$): once the mediating effect of project success was included, there was no statistically significant direct effect of AI adoption on organizational performance. This finding dovetails with the broader productivity paradox described by Brynjolfsson et al. (2018): large investments in technology do not necessarily yield productivity gains, particularly when they are not accompanied by organizational change. It also resonates with the conditional view of Hamm and Klesel (2021), who argue that AI's performance impact hinges on organizational preparedness, leadership support, and staff skills — without which its direct effect on performance can be negligible. A non-significant direct effect does not mean that the link between AI adoption and organizational performance is unimportant. Instead, the overall effect of AI use on performance — the non-significant direct path plus the significant indirect path through project success — is positive and significant. This suggests that AI adoption exerts an indirect, positive influence on organizational performance that operates through project success, a pattern with both theoretical and practical implications, discussed further below.

The second hypothesis proposed that AI adoption is positively related to project success. This hypothesis was supported ($B = .280$, $p < .001$, CI [.163, .397]). This aligns with the positive relationship between AI tool use and project success reported in the mixed-methods study by Lawal et al. (2024), as well as with Fridgeirsson et al.'s (2023) finding that AI tools add the most value in areas where mistakes are costliest: cost estimation, schedule projection, and risk identification. AI improves the 'sensing' and 'seizing' capacities of project teams, allowing them to spot new risks and opportunities more quickly, deploy resources more efficiently, and respond more rapidly to changes in their plans (Gull et al., 2023a). These capabilities ultimately lead to improved project results and higher rates of project success. It is worth noting that AI adoption explains a modest 8.4% of the variance in project success ($R^2 = .084$). This moderate effect size is consistent with the conditional view advanced by Nikolić and Bjelica (2025), who suggest that AI's impact on project outcomes depends on its proper integration into team processes. The substantial unexplained variance in project success suggests that other factors beyond AI use — such as team characteristics, project complexity, client relationships, and leadership effectiveness — are likely to matter as well.

The third hypothesis proposed that project success is positively related to organizational performance. There was strong support for this hypothesis ($B = .425$, $p < .001$, CI [.357, .493]), and project success proved to be the best predictor of organizational performance in the model. Together, AI adoption and project success accounted for 42.9% of the variance in organizational performance, indicating strong explanatory power. This finding supports the view — advanced by Pinto and Slevin (1988), Shenhar et al. (2001), and Müller and Jugdev (2012) — that project success is closely linked to organizations' strategic goals. The strong path from project success to organizational performance ($B = .425$) suggests that, in this context, the cumulative delivery of projects on time, within budget, and to stakeholders' satisfaction is a primary mechanism through which Pakistani project-based organizations achieve performance gains. This is consistent with the wider literature linking project execution excellence to organizational-level outcomes such as productivity, efficiency, and competitive positioning (Venkatraman & Ramanujam, 1986).

The fourth and central hypothesis proposed that project success mediates the relationship between AI adoption and organizational performance. This hypothesis was supported: the indirect effect was positive and significant (indirect effect = .119, 95% Boot CI [.060, .182]), and the direct effect of AI adoption on organizational performance was non-significant ($B = .059$, $p = .080$) once project success was included as a mediator. This pattern is consistent with full mediation (Hayes, 2018), whereby the effect of AI adoption on organizational performance can be traced entirely to project success. This finding makes a significant theoretical contribution. It shows that the

organizational performance benefits of AI adoption are neither automatic nor direct, but instead depend on how well an organization leverages AI to improve project performance. This is exactly what Dynamic Capabilities Theory (DCT) expects; the value of a dynamic capability is not inherent in the capability itself but rather accomplished through the seizing and transformation processes through which a capability becomes operational (Teece, 2007). In project-based organizations, the processes of seizing and transformation are embodied at the project level. It consequently adds project success as an additional project-management mechanism to a literature that has so far highlighted employee productivity (Kassa & Worku, 2025) and organizational agility (Aldossary et al., 2026) as mediators between AI adoption and performance.

Theoretical Contributions

This study makes three major theoretical contributions. First, it extends Dynamic Capabilities Theory by empirically describing the process through which a technological capability — AI adoption — is translated into organizational performance via a conditional, project-level pathway. The full mediation finding is consistent with the theoretical prediction that the performance benefits of dynamic capabilities are realized through seizing and transformation processes, rather than being intrinsic to the capability itself (Teece, 2007). This adds empirical specificity to DCT by identifying project success as one such transformation process in the context of AI adoption.

Second, the study integrates two streams of research — AI and organizational performance (Aldossary et al., 2026; Kassa & Worku, 2025), and AI and project-level outcomes (Lawal et al., 2024; Fridgeirsson et al., 2023; Nikolić & Bjelica, 2025) — that have largely developed independently. By demonstrating that project success is the mechanism through which AI adoption influences organizational performance, this study provides a theoretical bridge between these two literatures.

Third, the study contributes evidence from Pakistan, a context in which AI adoption in project-based industries is accelerating but remains under-represented in the empirical literature (Felemban et al., 2024). The findings suggest that the dynamics of AI adoption, project success, and organizational performance observed in more developed AI contexts also operate in the Pakistani context, albeit with some distinctive features, such as the moderate levels of AI adoption and the early-stage nature of AI integration in many organizations.

Practical Implications

The findings carry several important practical implications for managers and organizations. First, and most directly, the full mediation result implies that AI adoption does not independently improve organizational performance: the performance gains from AI adoption are contingent on whether AI tools actually improve project outcomes. Organizations that invest in AI without ensuring that those tools are effectively integrated into project management processes are unlikely to see performance gains at the organizational level. Senior management should therefore focus not only on acquiring AI tools but on embedding them within project planning, scheduling, risk management, and reporting processes — the domains in which AI is most likely to improve project execution (Fridgeirsson et al., 2023).

Second, the relatively low level of AI adoption observed in the sample ($M = 2.63$ on a 1–5 scale) indicates that many organizations in Pakistan's project-based sectors remain in the early stages of AI adoption. Superficial or one-off engagement with AI tools is unlikely to generate meaningful benefits; organizations that pursue a more systematic, deeper implementation of AI across their project management practices are more likely to see improved project success and, in turn, better organizational performance. This represents a clear strategic priority for organizations operating in the IT, telecommunications, construction, and banking sectors.

Third, the results indicate that building project teams' capabilities to effectively apply AI tools is as crucial as the tools themselves. Training and change-management initiatives that help project managers and team members adopt AI tools, interpret their outputs, and incorporate them into project decision-making were likely important enablers of the AI adoption → project success relationship identified in this study (Hamm & Klesel, 2021). The project and organizational benefits highlighted here will not be achieved by organizations that treat AI adoption merely as a technical "problem" and fail to consider the human and organizational aspects of how AI is put to use in practice.

Limitations and Future Research Directions

Several limitations need to be taken into account when interpreting the results of the present study. First, although the two-wave, time-lagged design reduces common method bias (Podsakoff et al., 2003), all variables were measured using self-report instruments. A degree of shared method variance cannot be ruled out, although the CFA results (Table 3) offer some reassurance that common method bias is not a serious concern. Future research should incorporate objective performance indicators, such as project schedule and budget variance indices, alongside objective organizational-performance data such as financial records and operational metrics.

Second, because a convenience sampling approach was used, the results may not generalize to the broader population of project-based organizations. Although the sample of 244 respondents was adequate for the complexity of the model tested, it remains modest in absolute terms. Future research should employ probability sampling and larger, more representative samples — including cross-country samples where possible — to strengthen external validity (Podsakoff et al., 2012).

Third, the model tested in this study is necessarily simplified. The modest path coefficient from AI adoption to project success ($B = .280$) and the full mediation result together suggest that other relevant variables are likely at play. Future research could examine possible moderators of the AI adoption–project success relationship (e.g., team digital literacy, project complexity, organizational size, leadership style), as well as additional mediators of the project success–organizational performance relationship (e.g., client satisfaction, knowledge transfer). Other mechanisms identified in the broader AI-performance literature, such as employee productivity (Kassa & Worku, 2025; Gull et al., 2023b) and organizational agility (Aldossary et al., 2026), could also be examined alongside project success in an extended model.

Fourth, although the AI adoption measure preceded the project success and organizational performance measures, the latter two constructs were captured at the same time point, so the study remains cross-sectional with respect to the temporal relationship between project success and organizational performance. A fully longitudinal design — with three or more time points, in which project outcomes are measured prior to organizational performance — would allow stronger causal inferences to be drawn. Finally, qualitative methods, such as in-depth interviews with project managers and AI champions, could complement the variance-based approach used here, shedding light on how and why AI adoption is — or is not — translated into improved project performance.

Conclusion

This study aimed to investigate the link between AI adoption and organizational performance, considering the mediating effect of project success, using a sample of 244 employees and project managers. Drawing on Dynamic Capabilities Theory, the proposed model treated AI adoption as an organizational capability whose value is realized not directly, but through its impact on project success through which organizations create value.

The results were consistent with this model: positive and significant relationships were found between AI adoption and project success (H2 supported) and between project success and organizational performance (H3 supported). The direct path from AI adoption to organizational performance was non-significant (H1 not supported), while the indirect path from AI adoption to organizational performance through project success was positive and significant (H4 supported), indicating full mediation. These results indicate that the value of AI use within organizations is not self-generating, but instead unfolds through a project-level process that translates this capability into concrete project results and, subsequently, into organizational performance gains.

Collectively, this study shows that these two strands of AI research — organizational performance and project-level outcomes — are closely intertwined, and that the relationship between them reflects more than mere co-occurrence, though stronger longitudinal evidence would be needed to establish causality with confidence. Embedding and leveraging AI within project management practices is essential for realizing AI's potential to drive organizational performance. This underscores the need to treat AI adoption as an organization-wide capability to be developed and institutionalized, rather than as a technology that is simply deployed.

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