Macrothink Institute™

International Journal of Social Science Research
ISSN 2327-5510
2026, Vol. 14, No. 3

An Empirically Validated Framework of AI Capabilities and Project Management Performance: The Mediating Role of Training in the UAE Public Sector

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Received: April 3, 2026 Accepted: June 10, 2026 Published: June 28, 2026

doi:10.5296/ijssr.v14i3.23865 URL: https://doi.org/10.5296/ijssr.v14i3.23865

Abstract

Artificial intelligence (AI) is increasingly transforming project management practices by improving forecasting, scheduling, decision-making, risk control, and resource allocation. However, the effectiveness of AI capabilities in enhancing project management performance depends not only on technological adoption but also on employee training. This study develops and empirically validates a framework linking AI capabilities and project management performance through the mediating role of training in the UAE public sector. Four AI capability dimensions are examined: predictive analytics, intelligent scheduling and automation, decision support systems, and risk management and resource allocation. A quantitative, cross-sectional research design was employed, and data were collected from employees involved in project-related work within UAE public sector organisations. A total of 515 valid responses were analysed using SPSS and SmartPLS. The findings show that all four AI capability dimensions have significant positive effects on project management performance and training. Training also has a significant positive effect on project management performance and emerges as the strongest direct predictor in the model. Furthermore, training partially mediates the relationships between each AI capability dimension and project management performance. These findings confirm that AI capabilities improve project outcomes both directly and indirectly through employee training. The study contributes to the literature by validating an integrated framework that combines technological and human capability perspectives. Practically, the findings highlight the need for UAE public sector organisations to align AI implementation with structured and continuous training programmes. The study concludes that AI capabilities can enhance project management performance, but their full value is realised when employees are adequately trained to apply AI tools effectively.

Keywords: Artificial intelligence, AI capabilities, project management performance, training, mediation, UAE public sector

1. Introduction

Artificial Intelligence (AI) has become a central pillar of digital transformation, fundamentally reshaping organizational processes, decision-making, and value creation across sectors (Bharadwaj et al., 2013; Mergel et al., 2019). In project management, AI capabilities such as predictive analytics, intelligent scheduling and automation, decision support systems, and risk management and resource allocation that are increasingly leveraged to enhance efficiency, improve forecasting accuracy, and support complex decision-making processes (Jarrahi, 2018; Hashfi & Raharjo, 2023; Nguyen & Tran, 2023). These capabilities are particularly relevant in dynamic and high-stakes environments, where project outcomes depend on timely, data-driven insights and effective resource coordination (APM, 2025; Project Management Institute, 2023).

In the United Arab Emirates (UAE) public sector, the adoption of AI is closely aligned with national strategies aimed at accelerating digital transformation and enhancing public service delivery (Alzarooni et al., 2024; Anshari et al., 2025). Government entities are increasingly integrating AI into project management practices to improve operational efficiency, governance, and service outcomes (Akhoirshieda et al., 2024; Dahabreh, 2023). However, despite these advancements, public sector organizations often face structural and organizational challenges that hinder the effective utilization of AI technologies, including bureaucratic rigidity, legacy systems, and capability gaps among employees (Abuzanjal & Bashir, 2024; Escobar et al., 2023).

While prior research has established the potential of AI to enhance project performance, existing studies remain limited in two important respects. First, there is insufficient empirical evidence examining how specific AI capability dimensions influence project management performance within the UAE public sector context. Second, although training is widely acknowledged as a critical factor in technology adoption and digital transformation, its role as a mediating mechanism that links AI capabilities to performance outcomes has not been adequately explored (Nguyen et al., 2022; Al-Shboul, 2024). This gap is significant because the successful implementation of AI depends not only on technological investment but also on the organization's ability to develop the human capital required to effectively utilize these tools (Noe, 2020; Faraj et al., 2018).

Training enables employees to acquire the necessary knowledge, skills, and competencies to interpret AI-generated insights, interact with intelligent systems, and integrate these tools into project workflows. Without adequate training, AI technologies may be underutilized or misapplied, limiting their effectiveness and potentially leading to suboptimal project outcomes (Dwivedi et al., 2021; Tan et al., 2024). This challenge is particularly critical in the UAE public sector, where large-scale projects require precision, accountability, and alignment with national strategic objectives (Ayyad et al., 2025).

To address these gaps, this study proposes and empirically validates a framework linking AI capabilities and project management performance through the mediating role of training. The framework conceptualizes AI capabilities as key drivers that directly influence project management performance while simultaneously enhancing training, which in turn strengthens performance outcomes. By positioning training as a central mediating mechanism, the study adopts a socio-technical perspective that emphasizes the interdependence between technological capabilities and human capital development.

This research employs a quantitative, cross-sectional design to collect data from employees involved in project-related activities within UAE public sector organizations. By focusing on this context, the study contributes to the literature by providing empirical evidence from a region that has received limited attention in AI and project management research. Furthermore, it offers practical implications for policymakers and project managers by highlighting the importance of integrating AI implementation with structured and continuous training initiatives.

Overall, this study advances the understanding of AI-enabled project management by demonstrating how training functions as a critical mechanism linking AI capabilities to improved project management performance. The findings are expected to support more effective AI adoption strategies in the UAE public sector and similar organizational contexts, ensuring that digital transformation initiatives translate into sustainable and measurable performance improvements.

2. Literature Review

2.1 Artificial Intelligence in Project Management

Artificial Intelligence (AI) has evolved from rule-based systems to advanced data-driven and generative models capable of supporting complex organizational processes (Russell & Norvig, 2021; Kelvin et al., 2025). In project management, AI is increasingly recognized as a transformative enabler of digital transformation, improving efficiency, decision-making, and predictive capabilities (Marnewick & Marnewick, 2020; Project Management Institute, 2024). AI technologies such as machine learning, natural language processing, and intelligent automation allow project managers to analyze large datasets, forecast outcomes, and optimize project workflows (Jarrahi, 2018; Hashfi & Raharjo, 2023).

Within the public sector, AI adoption is gaining momentum as governments seek to enhance service delivery and operational effectiveness (Mergel et al., 2019; Anshari et al., 2025). In the UAE, AI integration is aligned with national digital transformation strategies and has been increasingly applied to improve governance, decision-making, and project execution (Akhoirshieda et al., 2024; Alzarooni et al., 2024). However, despite its potential, the implementation of AI in project management remains complex due to organizational, technical, and human-related challenges (Dacre & Kockum, 2022; Escobar et al., 2023).

2.2 AI Capabilities and Project Management Performance

AI capabilities refer to the organization’s ability to deploy and utilize AI technologies to support decision-making and operational processes (Nguyen & Tran, 2023). In the context of project management, four key AI capabilities are widely emphasized: predictive analytics, intelligent scheduling and automation, decision support systems, and risk management and resource allocation.

Predictive analytics enables organizations to forecast project outcomes, identify potential delays, and improve planning accuracy (Hashfi & Raharjo, 2023). Intelligent scheduling and automation enhance efficiency by optimizing task allocation and reducing manual intervention (Alqahtani et al., 2021). Decision support systems provide data-driven insights that improve managerial decision-making in complex project environments (Smith & Lee, 2023; Waqar, 2024). Additionally, AI-driven risk management and resource allocation capabilities support proactive identification of risks and optimal distribution of resources (Nabeel, 2024).

These capabilities collectively contribute to improved project management performance, which includes efficiency, timeliness, cost control, and overall project success (APM, 2025). Empirical studies suggest that organizations leveraging AI capabilities achieve better project outcomes due to enhanced data utilization and decision accuracy (Nguyen & Tran, 2023). However, the effectiveness of these capabilities depends on how well they are integrated into organizational processes and utilized by employees.

2.3 Training as a Critical Enabler of AI Utilization

Training plays a fundamental role in enabling organizations to effectively adopt and utilize new technologies. From a human capital perspective, training enhances employees' knowledge, skills, and competencies, thereby improving organizational performance (Noe, 2020; Fugar et al., 2013). In the context of AI adoption, training is particularly important due to the complexity of AI systems and the need for employees to interpret and apply AI-generated insights (Faraj et al., 2018).

Previous studies highlight that training significantly influences employees' ability to adopt and use AI technologies effectively (Nguyen et al., 2022). Without adequate training, employees may resist new technologies or fail to utilize them to their full potential, leading to suboptimal outcomes (Dwivedi et al., 2021). In public sector organizations, training is even more critical due to existing structural constraints and slower adaptation to technological change (Al-Shboul, 2024).

In the UAE context, bridging competency gaps through training has been identified as a key priority for successful digital transformation initiatives (Ayyad et al., 2025). Training not only improves technical proficiency but also enhances employees' confidence and readiness to engage with AI-driven systems, thereby facilitating more effective implementation.

2.4 Training and Project Management Performance

Training has been widely recognized as a key determinant of organizational and project performance. By improving employees' skills and competencies, training enhances productivity, efficiency, and the quality of decision-making (Noe, 2020). In project management, trained personnel are better equipped to manage project complexities, respond to uncertainties, and achieve project objectives (APM, 2025).

Empirical research indicates that training positively influences project performance by improving team coordination, communication, and problem-solving capabilities (Tan et al., 2024). In environments where advanced technologies such as AI are used, training becomes even more critical, as it enables employees to effectively integrate technological tools into project workflows. Consequently, organizations that invest in continuous training are more likely to achieve higher levels of project success.

2.5 The Mediating Role of Training

While AI capabilities have the potential to improve project management performance, their impact is not always direct. Instead, training acts as a mediating mechanism that translates technological capabilities into tangible performance outcomes. Mediation theory suggests that an independent variable influences a dependent variable through an intervening variable, which explains the underlying process (Hayes, 2018, 2022).

In the context of AI adoption, training enhances employees' ability to understand and utilize AI tools, thereby strengthening the relationship between AI capabilities and performance (Nguyen et al., 2022). Without adequate training, the benefits of AI may not be fully realized, as employees may lack the necessary skills to leverage these technologies effectively.

Despite its importance, the mediating role of training in the relationship between AI capabilities and project management performance remains underexplored, particularly in the UAE public sector. Existing studies often examine training as a direct predictor of performance but do not consider its role as a linking mechanism between technology and outcomes (Al-Shboul, 2024). This study addresses this gap by empirically testing training as a mediator, providing a more comprehensive understanding of how AI capabilities influence project performance.

2.6 Research Gap and Conceptual Framework

Although prior research has highlighted the potential of artificial intelligence (AI) in enhancing project management and emphasized the importance of training in technology adoption, there remains a lack of integrated frameworks that systematically examine the relationships among AI capabilities, training, and project management performance within a unified model. Existing studies tend to focus either on the direct impact of AI on organizational outcomes or on training as an independent predictor of performance, without adequately capturing the mechanism through which AI capabilities translate into improved project outcomes (Nguyen & Tran, 2023; Hashfi & Raharjo, 2023). This gap is particularly evident in the UAE public sector, where contextual factors such as organizational structure, governance complexity, and workforce readiness significantly influence the adoption and effective utilization of emerging technologies (Abuzanjal & Bashir, 2024; Sarker et al., 2023; Alzarooni et al., 2024).

Furthermore, limited empirical research has examined the mediating role of training in the relationship between AI capabilities and project management performance. While training is widely recognized as a critical enabler of digital transformation and employee capability development, its role as a linking mechanism that enhances the effectiveness of AI implementation remains underexplored (Nguyen et al., 2022; Al-Shboul, 2024; Noe, 2020). As a result, organizations may invest in AI technologies without fully understanding how to maximize their impact through structured training and human capital development.

To address these gaps, the present study develops a conceptual framework, as shown in Figure 1, that links AI capabilities, namely predictive analytics, intelligent scheduling and automation, decision support systems, and risk management and resource allocation, to project management performance through the mediating role of training. The framework is grounded in a socio-technical perspective, which emphasizes the interdependence between technological capabilities and human factors in organizational performance (Faraj et al., 2018), as well as human capital theory, which highlights the role of training in enhancing employee competencies and productivity (Fugar et al., 2013; Noe, 2020).

Building on this theoretical foundation, the proposed framework conceptualizes AI capabilities as key drivers that influence both training and project management performance, while positioning training as a central mediating mechanism that strengthens the relationship between AI capabilities and performance outcomes. This integrated approach provides a more comprehensive understanding of how organizations can effectively leverage AI in project management, particularly in complex public sector environments.

The framework is subsequently empirically validated using partial least squares structural equation modeling through SmartPLS software, which is widely used for analyzing complex models involving multiple constructs and mediation effects (Hair et al., 2022; Ringle et al., 2023). This empirical validation enhances the robustness of the proposed model and supports its applicability within the UAE public sector context.

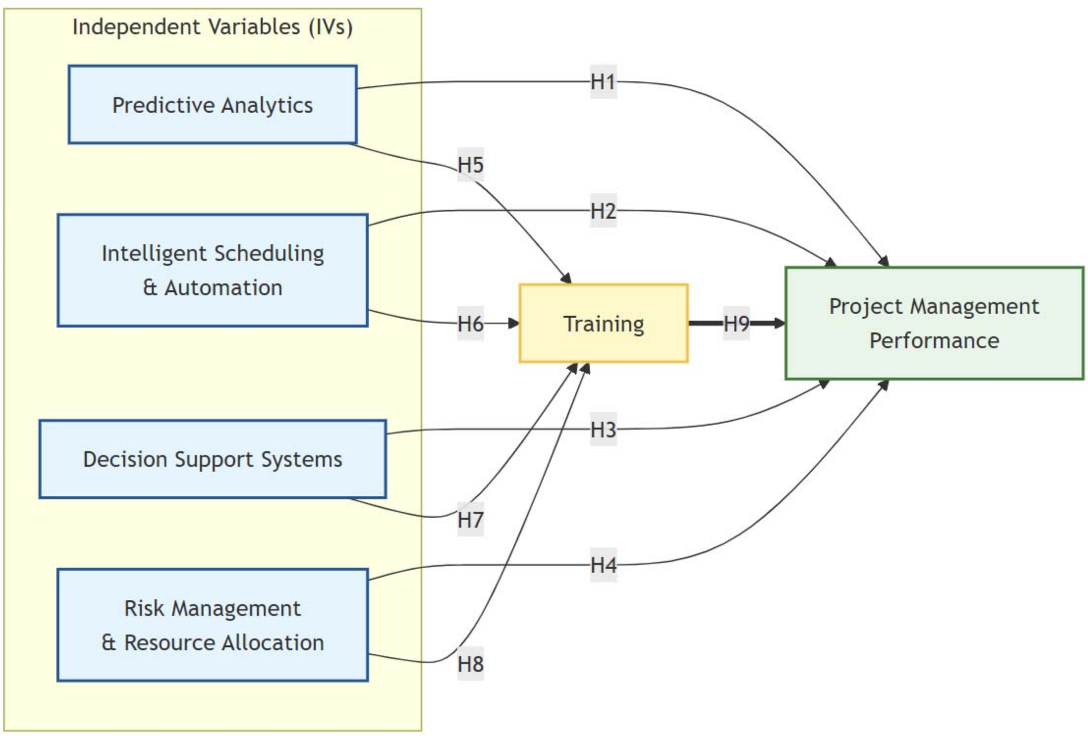

Figure 1. The conceptual framework

Based on the framework presented in Figure 1, the study hypotheses are formulated and presented in Table 1.

Table 1. Hypotheses of the framework

Hypothesis	Hypothesis Statement	Type of Effect
H1	Predictive analytics has a positive effect on project management performance.	Direct
H2	Intelligent scheduling and automation has a positive effect on project management performance.	Direct
H3	Decision support systems have a positive effect on project management performance.	Direct
H4	Risk management and resource allocation has a positive effect on project management performance.	Direct
H5	Predictive analytics has a positive effect on training.	Direct
H6	Intelligent scheduling and automation has a positive effect on training.	Direct
H7	Decision support systems have a positive effect on training.	Direct
H8	Risk management and resource allocation has a positive effect on training.	Direct
H9	Training has a positive effect on project management performance.	Direct
H10a	Training mediates the relationship between predictive analytics and project management performance.	Indirect / Mediation
H10b	Training mediates the relationship between intelligent scheduling and automation and project management performance.	Indirect / Mediation
H10c	Training mediates the relationship between decision support systems and project management performance.	Indirect / Mediation
H10d	Training mediates the relationship between risk management and resource allocation and project management performance.	Indirect / Mediation

3. Modelling of the Framework

This section presents the modelling of the proposed framework linking AI capabilities, training, and project management performance in the UAE public sector. The framework was developed based on the literature review and the hypothesised relationships among the study constructs. It positions predictive analytics, intelligent scheduling and automation, decision support systems, and risk management and resource allocation as independent variables, training as the mediating variable, and project management performance as the dependent variable.

The purpose of modelling the framework is to provide a structured representation of the direct and indirect relationships examined in the study. The direct paths assess the effects of AI capability dimensions on training and project management performance, while the indirect paths examine whether training mediates the relationship between AI capabilities and project management performance. This approach enables the study to evaluate not only whether AI capabilities influence performance, but also how training strengthens this relationship.

The framework was empirically tested using partial least squares structural equation modelling (PLS-SEM). This method is appropriate for assessing complex models involving multiple constructs, direct effects, and mediation effects. The following sections present the hypotheses of the framework, followed by the assessment of the measurement and structural models.

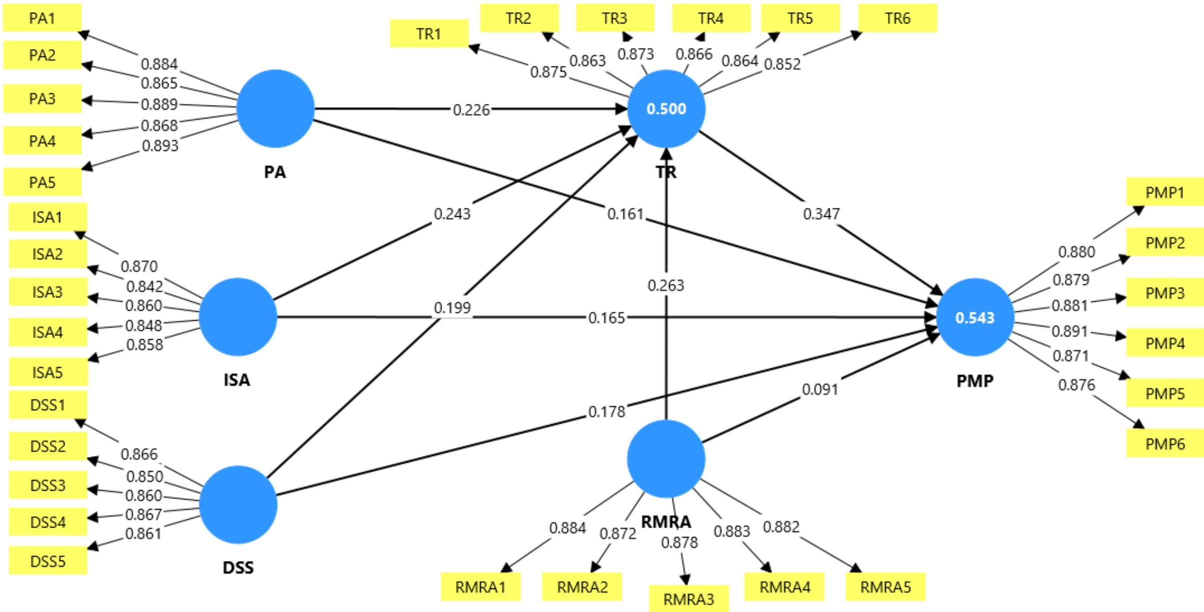

Figure 2. Model after PLS Algorithm procedure

3.1 Measurement Model Assessment

The measurement model was assessed to evaluate the reliability and validity of the constructs using partial least squares structural equation modelling (PLS-SEM). Specifically, the assessment focused on internal consistency reliability, convergent validity, and discriminant validity (Hair et al., 2022). Establishing these properties ensures that the constructs are measured accurately before proceeding to structural model analysis.

3.1.1 Internal Consistency Reliability and Convergent Validity

Internal consistency reliability was first evaluated using Cronbach's alpha and composite reliability. Composite reliability is preferred in PLS-SEM because it accounts for varying indicator loadings (Hair et al., 2022), with values above 0.70 indicating acceptable reliability. As presented in Table 2, Cronbach's alpha values range from 0.909 to 0.941, while composite reliability values range from 0.932 to 0.954. These results indicate satisfactory internal consistency across all constructs. Building on this, convergent validity was assessed using the average variance extracted (AVE). An AVE value above 0.50 indicates that a construct explains more than half of the variance in its indicators (Fornell & Larcker, 1981; Hair et al., 2022). All constructs report AVE values between 0.733 and 0.774, confirming adequate convergent validity.

Table 2. Internal consistency reliability and convergent validity

Construct	Code	Cronbach's Alpha	Composite Reliability	AVE
Predictive Analytics	PA	0.927	0.945	0.774
Intelligent Scheduling and Automation	ONE	0.909	0.932	0.733
Decision Support Systems	DSS	0.913	0.935	0.741
Risk Management and Resource Allocation	RMRA	0.927	0.945	0.774
Training	TR	0.933	0.947	0.749
Project Management Performance	PMP	0.941	0.954	0.774

3.1.2 Discriminant Validity

Following the establishment of reliability and convergent validity, discriminant validity was assessed to determine whether the constructs are empirically distinct. This is particularly important given the conceptual relatedness among the AI capability dimensions, as well as the expected association between training and project management performance. In line with recommended PLS-SEM procedures, discriminant validity was evaluated using both the Fornell-Larcker criterion and the Heterotrait-Monotrait ratio (HTMT) (Hair et al., 2022; Henseler et al., 2015).

3.1.2.1 Fornell-Larcker Criterion

The Fornell-Larcker criterion assesses whether each construct shares more variance with its own indicators than with other constructs. This requires the square root of the AVE for each construct to exceed its correlations with other constructs (Fornell & Larcker, 1981). As shown in Table 3, all diagonal values are greater than the corresponding inter-construct correlations, indicating that this condition is satisfied.

Table 3. Fornell-Larcker criterion

Construct	PA	ONE	DSS	RMRA	TR	PMP
PA	**0.880**					
ONE	0.475	**0.856**				
DSS	0.384	0.376	**0.861**			
RMRA	0.449	0.465	0.425	**0.880**		
TR	0.535	0.547	0.487	0.562	**0.865**	
PMP	0.535	0.539	0.508	0.511	0.662	**0.880**

3.1.2.2 Heterotrait-Monotrait Ratio (HTMT)

To complement the Fornell-Larcker assessment, discriminant validity was further examined using the heterotrait-monotrait ratio (HTMT), which provides a more stringent evaluation (Henseler et al., 2015). As presented in Table 4, all HTMT values are below 0.85, with the highest value being 0.706 between training and project management performance. These results confirm that discriminant validity is established.

Table 4. HTMT ratio of correlations

Construct	PA	ONE	DSS	RMRA	TR	PMP
PA	1.000	0.518	0.418	0.485	0.576	0.572
ONE	0.518	1.000	0.413	0.506	0.594	0.583
DSS	0.418	0.413	1.000	0.462	0.529	0.549
RMRA	0.485	0.506	0.462	1.000	0.605	0.547
TR	0.576	0.594	0.529	0.605	1.000	0.706
PMP	0.572	0.583	0.549	0.547	0.706	1.000

3.1.3 Summary of Measurement Model Assessment

Taken together, the results demonstrate that the measurement model satisfies the recommended criteria for reliability and validity. Internal consistency reliability and convergent validity are established, and discriminant validity is supported by both the Fornell-Larcker criterion and HTMT. The model is therefore suitable for subsequent structural model analysis.

3.2 Structural Model Assessment

After confirming the adequacy of the measurement model, the structural model was assessed to examine the hypothesised relationships among the constructs. Following PLS-SEM guidelines, the assessment included collinearity, coefficient of determination, effect size, predictive relevance, direct path coefficients, and mediation effects (Hair et al., 2022; Henseler et al., 2009; Sarstedt et al., 2022). The structural model comprised four AI capability dimensions as exogenous constructs, training as a mediator, and project management performance as the final endogenous construct. The analysis was conducted using 515 valid responses.

3.2.1 Collinearity Assessment

Collinearity was assessed using inner variance inflation factor values. VIF values below 5.00 indicate that collinearity is not a critical concern, while values below 3.30 provide more conservative evidence of acceptable collinearity levels (Hair et al., 2022; Kock, 2015). As shown in Table 5, all VIF values range from 1.327 to 1.992. These values are well below both recommended thresholds, indicating that collinearity does not affect the interpretation of the structural paths.

Table 5. Collinearity assessment using inner VIF values

Endogenous Construct	Predictor	VIF
Training	Predictive Analytics	1.459
Training	Intelligent Scheduling and Automation	1.474
Training	Decision Support Systems	1.327
Training	Risk Management and Resource Allocation	1.488
Project Management Performance	Predictive Analytics	1.560
Project Management Performance	Intelligent Scheduling and Automation	1.592
Project Management Performance	Decision Support Systems	1.404
Project Management Performance	Risk Management and Resource Allocation	1.627
Project Management Performance	Training	1.992

3.2.2 Coefficient of Determination

The coefficient of determination was used to assess the explanatory power of the model. In PLS-SEM, R^2 values of 0.25, 0.50, and 0.75 are generally interpreted as weak, moderate, and substantial, respectively (Hair et al., 2022).

As presented in Table 6, the model explains 50.0% of the variance in training and 54.3% of the variance in project management performance. These results indicate moderate explanatory power for both endogenous constructs.

Table 6. Coefficient of determination

Endogenous Construct	R^2	Interpretation
Training	0.500	Moderate
Project Management Performance	0.543	Moderate

3.2.3 Effect Size

Effect size was assessed using f^2 to determine the contribution of each predictor to the explained variance of the endogenous constructs. Values of 0.02, 0.15, and 0.35 indicate small, medium, and large effects, respectively (Hair et al., 2022). As shown in Table 7, most effects are small. Training has the strongest effect on project management performance, with an f^2 value of 0.134, which is close to the medium threshold. This indicates that training contributes more strongly to project management performance than the direct AI capability dimensions.

Table 7. Effect size values

Endogenous Construct	Predictor	f^2	Interpretation
Training	Predictive Analytics	0.069	Small
Training	Intelligent Scheduling and Automation	0.080	Small
Training	Decision Support Systems	0.058	Small
Training	Risk Management and Resource Allocation	0.093	Small
Project Management Performance	Predictive Analytics	0.037	Small
Project Management Performance	Intelligent Scheduling and Automation	0.036	Small
Project Management Performance	Decision Support Systems	0.048	Small
Project Management Performance	Risk Management and Resource Allocation	0.011	Very small
Project Management Performance	Training	0.134	Small, close to medium

3.2.4 Predictive Relevance

Predictive relevance was assessed using Stone-Geisser's Q^2. A Q^2 value above zero indicates that the model has predictive relevance for the endogenous construct (Hair et al., 2022; Shmueli et al., 2019). As shown in Table 8, the Q^2 values for training and project management performance are both above zero, confirming the predictive relevance of the structural model.

Table 8. Predictive relevance of the structural model

Endogenous Construct	Q^2	Interpretation
Training	0.487	Predictive relevance established
Project Management Performance	0.528	Predictive relevance established

3.2.5 Direct Path Coefficients

The significance of the direct relationships was assessed using bootstrapping. The results are reported using standardised beta coefficients, t values, and p values. A positive and statistically significant coefficient indicates support for the corresponding hypothesis (Hair et al., 2022). As shown in Table 9, all direct paths are positive and statistically significant. Therefore, H1 to H9 are supported. Among the predictors of project management performance, training shows the strongest direct effect ($\beta = 0.347$, $t = 8.860$, $p < 0.001$). This indicates that training plays a central role in enhancing project management performance. Figure 3 presents the bootstrapped structural model, showing the significant paths and R^2

values for the endogenous constructs.

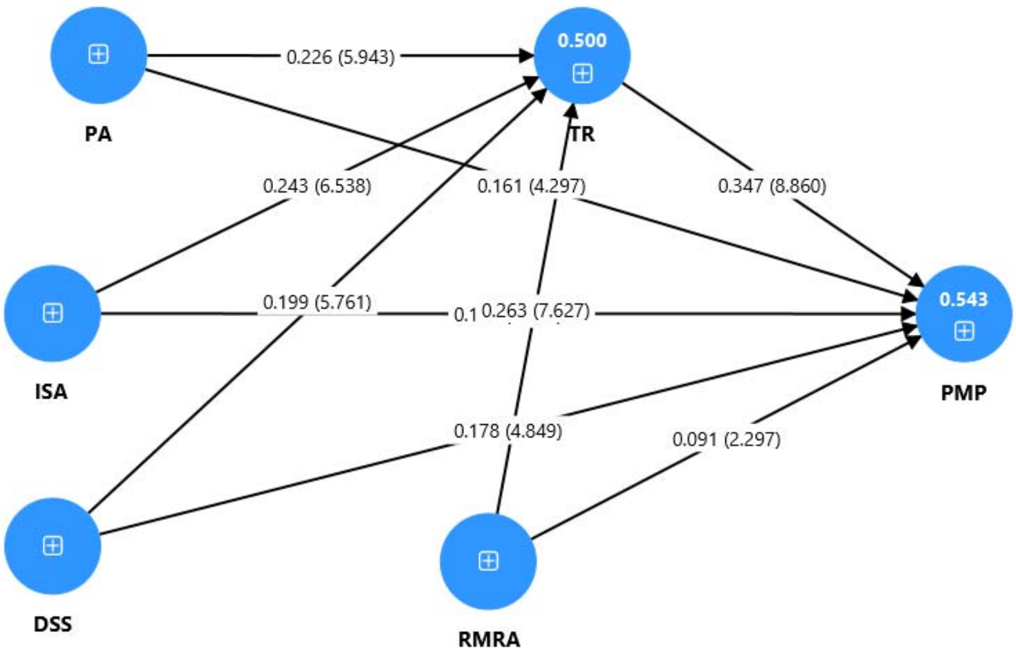

Figure 3. Structural model after bootstrapping procedure

Table 9. Path coefficients and direct hypothesis testing

Hypothesis	Direct Path	Beta	t value	p value	Decision
H1	Predictive Analytics → Project Management Performance	0.161	4.297	< 0.001	Supported
H2	Intelligent Scheduling and Automation → Project Management Performance	0.165	4.505	< 0.001	Supported
H3	Decision Support Systems → Project Management Performance	0.178	4.849	< 0.001	Supported
H4	Risk Management and Resource Allocation → Project Management Performance	0.091	2.297	0.022	Supported
H5	Predictive Analytics → Training	0.226	5.943	< 0.001	Supported
H6	Intelligent Scheduling and Automation → Training	0.243	6.538	< 0.001	Supported
H7	Decision Support Systems → Training	0.199	5.761	< 0.001	Supported
H8	Risk Management and Resource Allocation → Training	0.263	7.627	< 0.001	Supported
H9	Training → Project Management Performance	0.347	8.860	< 0.001	Supported

3.2.6 Mediation Analysis

The mediating role of training was assessed by examining the indirect effects of the four AI

International Journal of Social Science Research
ISSN 2327-5510
2026, Vol. 14, No. 3

capability dimensions on project management performance through training. An indirect effect is significant when the bootstrapped test statistic is significant or when the confidence interval does not include zero (Hair et al., 2022; Hayes, 2022). As shown in Table 10, all indirect effects are positive and significant. Therefore, H10a, H10b, H10c, and H10d are supported. These findings confirm that training mediates the relationships between AI capabilities and project management performance.

Table 10. Indirect effects and mediation analysis

Hypothesis	Indirect Path	Indirect Effect	t value	Decision
H10a	Predictive Analytics → Training → Project Management Performance	0.078	4.849	Supported
H10b	Intelligent Scheduling and Automation → Training → Project Management Performance	0.085	5.260	Supported
H10c	Decision Support Systems → Training → Project Management Performance	0.069	4.890	Supported
H10d	Risk Management and Resource Allocation → Training → Project Management Performance	0.092	5.652	Supported

To determine the mediation type, variance accounted for was calculated. VAF values between 20% and 80% indicate partial mediation (Hair et al., 2022). As shown in Table 11, all VAF values fall within this range, confirming partial mediation across all four indirect paths.

Table 11. Type of mediation based on VAF

Path	Direct Effect	Indirect Effect	Total Effect	VAF	Mediation Type
Predictive Analytics → Training → Project Management Performance	0.161	0.078	0.239	32.6%	Partial mediation
Intelligent Scheduling and Automation → Training → Project Management Performance	0.165	0.085	0.250	34.0%	Partial mediation
Decision Support Systems → Training → Project Management Performance	0.178	0.069	0.247	27.9%	Partial mediation
Risk Management and Resource Allocation → Training → Project Management Performance	0.091	0.092	0.183	50.3%	Partial mediation

The mediation results indicate that AI capabilities influence project management performance both directly and indirectly through training. The strongest mediation effect is observed for risk management and resource allocation, where training accounts for 50.3% of the total effect. This suggests that training is particularly important in translating AI-supported risk and resource capabilities into improved project management performance.

3.2.7 Summary of Structural Model Assessment

The structural model results provide support for all proposed hypotheses. Collinearity was not a concern, the model demonstrated moderate explanatory power, and predictive relevance was established for both endogenous constructs. All direct paths were positive and significant, and training partially mediated the relationships between all four AI capability dimensions and project management performance. These findings validate the proposed framework and confirm the central role of training in linking AI capabilities to project management performance in the UAE public sector.

4. Discussion of the Findings

This study examined the relationship between AI capabilities, training, and project management performance in the UAE public sector. The results provide empirical support for the proposed framework, as all direct and indirect hypotheses were supported. The findings confirm that AI capabilities positively influence project management performance, both directly and indirectly through training.

First, predictive analytics, intelligent scheduling and automation, decision support systems, and risk management and resource allocation were found to have significant positive effects on project management performance. This suggests that AI capabilities contribute to improved project outcomes by enhancing forecasting, scheduling accuracy, decision quality, risk control, and resource use. These findings are consistent with previous studies highlighting the value of AI in improving project efficiency, decision-making, and operational performance (Jarrahi, 2018; Hashfi & Raharjo, 2023; Nguyen & Tran, 2023).

Second, all four AI capability dimensions significantly influenced training. This indicates that the adoption of AI capabilities creates a need for employee development and skill enhancement. As AI tools become more embedded in project management processes, employees require training to interpret AI-generated outputs, use intelligent systems effectively, and integrate these tools into daily project activities. This supports the view that training is a key enabler of AI adoption and digital transformation (Noe, 2020; Nguyen et al., 2022; Al-Shboul, 2024).

Third, training had the strongest direct effect on project management performance among all predictors. This finding highlights that technology alone is insufficient to improve project outcomes unless employees have the skills and confidence to use it effectively. Training strengthens employees' ability to apply AI capabilities in project planning, decision-making, risk management, and performance monitoring. This aligns with human capital theory, which argues that employee capability development improves organisational performance (Fugar et al., 2013; Noe, 2020).

The mediation analysis further confirms the central role of training in the framework. Training partially mediated the relationships between each AI capability dimension and project management performance. This means that AI capabilities improve project performance both directly and through training. The strongest mediation effect was observed for risk management and resource allocation, suggesting that training is particularly important in helping employees translate AI-supported risk and resource capabilities into improved project outcomes.

Overall, the findings validate the proposed framework and support the socio-technical view that successful AI-enabled project management depends on both technological capability and human capability development. In the UAE public sector, where projects are often complex, strategic, and high-impact, AI implementation should therefore be accompanied by structured and continuous training initiatives. This ensures that AI investments are not only adopted but also effectively converted into measurable project performance improvements.

5. Conclusion

This study developed and empirically validated a framework linking AI capabilities and project management performance through the mediating role of training in the UAE public sector. The results show that predictive analytics, intelligent scheduling and automation, decision support systems, and risk management and resource allocation positively influence project management performance. The findings also show that these AI capability dimensions positively influence training, and that training significantly improves project management performance.

The study further confirms that training partially mediates the relationship between AI capabilities and project management performance. This indicates that AI capabilities generate stronger project outcomes when supported by employee training. Therefore, the value of AI in project management should not be viewed as purely technological. Instead, it depends on the ability of organisations to develop employees' knowledge, skills, and readiness to use AI tools effectively.

The study contributes to the literature by providing empirical evidence from the UAE public sector and by validating a framework that integrates AI capabilities, training, and project management performance within a single model. Practically, the findings suggest that public sector organisations should align AI implementation with continuous training programmes to maximise performance benefits.

Despite its contributions, the study has some limitations. The use of a cross-sectional design limits causal interpretation, and the data were collected from UAE public sector employees only. Future studies may adopt longitudinal designs, include other sectors or countries, and examine additional factors such as leadership support, organisational culture, AI readiness, and digital maturity.

In summary, the study concludes that AI capabilities enhance project management performance in the UAE public sector, but their full value is realised when supported by effective training. Training serves as a critical mechanism that links technological capability with improved project outcomes.

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