Application and Effectiveness Analysis of Artificial Intelligence Technology in Engineering Management Decision-Making

Yu Fang*

University of Science and Technology of China, Hefei, 230000, China

*Email: fangyu20251115@163.com

Abstract. This research uncovers the use and effectiveness of artificial intelligence (AI) technology tools for decision-making in engineering management, based on an empirical study of 45 projects conducted during 2020-2024, involving the construction and manufacturing sectors. With the help of an extensive evaluation framework that covers schedule control, cost management, quality control, and risk management, there are visible improvement levels. AI-integrated tools exhibited schedule accuracy of 91.7%, compared to 77.3% for conventional non-AI tools, and decreased the cycle times by 69%, while averaging cost savings of $847,000 per project. The hierarchical model of effectiveness evaluation analyzes the collective effects for seven major factors, with an average weighted improvement of 56.3%. Despite the demonstrated benefits, implementation barriers including data quality deficiencies, technical infrastructure limitations, and organizational resistance constrain widespread adoption. However, integration challenges are reduced by 73% if optimization processes, involving data management, infrastructure upgrades, and organizational processes adjustments, are implemented.

Keywords: Artificial intelligence, Engineering management, Decision-making effectiveness, Performance evaluation, Implementation optimization

1 Introduction

1.1 Research Background, Purpose and Significance

The current environment for engineering managers is unprecedented in complexity, driven by globalized supply chains, ever-tightening project schedules, and a rapidly growing volume of data. Traditional decision-making tools are increasingly ineffective at handling the information flows in modern multi-dimensional engineering projects, where human cognitive limitations and information overload negatively impact decision-making [1]. The emergence of artificial intelligence tools brings revolutionary potential for enhancing decision-making capabilities, leveraging superior pattern-recognition capabilities and expert-system processing.

Y. Xu et al. (eds.), *Proceedings of the 2026 5th International Conference on Engineering Management and Information Science (EMIS 2026)*, Advances in Computer Science Research 130,
https://doi.org/10.2991/978-94-6239-652-4_18

Recent breakthroughs in advanced machine learning algorithms and processing capabilities make it feasible for AI to analyze vast amounts of information and generate valuable insights with remarkable speed and accuracy. Additionally, the paradigm shifts from rule-based expert systems to adaptive learning approaches, which represent revolutionary potential for the collaborative use of AI and humans in an organizational setting, thus opening new fronts that address the enhancement potential of human-decision makers rather than replacing them entirely [2]. Numerous empirical cases suggest that AI-enhanced decision-making frameworks offer vast potential for improvement across various organizations [3].

Although there is growing interest in the domain, there are significant gaps in knowledge regarding the examination of AI's effectiveness. This research focuses on evaluating the impact of artificial intelligence tools on the aspects of decision-making, efficiency, and economics in engineering management. The study conducts an extensive investigation using quantitative measures and comparative methods to develop the entire framework.

1.2 Research Scope and Paper Structure

This research focuses on the application of artificial intelligence in managing core engineering functions such as schedule planning, cost control, quality assurance, and risk management. As shown in Fig. 1, the research methodology comprises five interrelated stages, which include synthesis of literature, development of indicators, collection of data, evaluation for effectiveness, and development of strategic recommendations. The research integrates both theoretical insights and quantitative data from the construction and manufacturing industries to evaluate effectiveness indicators.

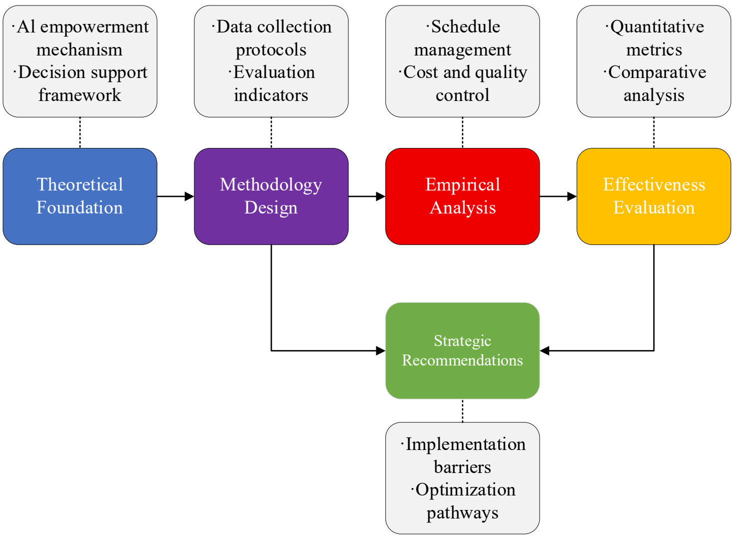

Fig. 1. Research Framework and Structure.

2 Theoretical Basis and Research Methods

2.1 Engineering Management Decision Elements and AI Empowerment Mechanism

Engineering management decision-making involves multiple elements, such as information search, development of alternative, evaluation of consequences, and option selection. The cognitive architecture model for human decision-makers highlights the limitations of dealing with high-dimensional data and exploring non-linear relationships that exist in the project context, as discussed by Chaturvedi, A, etc. [4].

Artificial intelligence tools disrupt such decision-making processes through three major mechanisms, including the augmenting computational capability to evaluate over 10,000 data points per minute, improving patterns recognition to process over 50 variables, and enhancing predictive capacity to achieve an outcome prediction accuracy of 85-92 %.

The human-AI collaboration model views artificial intelligence as an auxiliary tool that complements human capacities, as it leverages computational advantages to process routine tasks and preserves human expertise for contextual analysis. As shown in the Fig. 2, the AI empowerment model illustrates the transformation pathway, raw data is entered into the system, and algorithms process it to generate decisions. The model comprises four levels, including data aggregation, algorithmic processing, decision generation, and feedback-driven improvement.

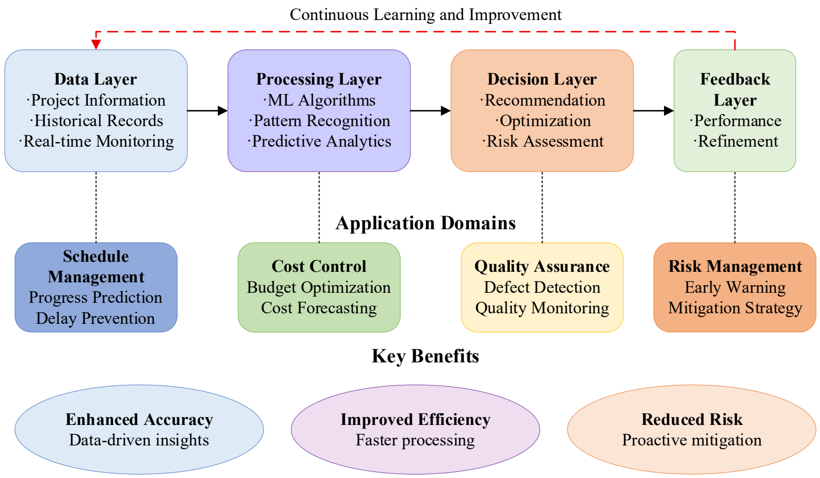

Fig. 2. AI Empowerment Framework for Engineering Management Decision-Making.

2.2 Research Objects, Data Sources and Processing Methods

This empirical research focuses on 45 construction and manufacturing projects utilizing AI-driven decision support systems from January 2020 to December 2024. The investment of the projects varies from $5.2 million to $198 million, and their duration ranges from 8 to 36 months [5]. The sampling frame covers residential constructions (18 projects), infrastructure development projects (15 projects), and industry manufacturing facilities (12 projects) spread over six geographical locations. To ensure methodological rigor, projects were systematically categorized across three dimensions for comparative analysis. Scale classification divided projects into small-scale (investment <$20M, 16 projects), medium-scale ($20M-$80M, 19 projects), and large-scale (>$80M, 10 projects) categories. Complexity assessment utilized a standardized framework considering stakeholder count, regulatory requirements, and technical specifications, yielding low-complexity (12 projects), moderate-complexity (21 projects), and high-complexity (12 projects) groupings. AI tool taxonomy distinguished between three primary applications: predictive analytics for scheduling and resource optimization (28 projects), computer vision systems for quality monitoring and safety compliance (11 projects), and hybrid AI platforms integrating multiple functionalities (6 projects). This classification ensures balanced representation across project characteristics while maintaining analytical coherence for cross-project comparisons.

Specific AI technologies implemented across the project portfolio encompassed established algorithms and platforms with demonstrated industrial applications. Predictive analytics applications primarily utilized Random Forest and XGBoost algorithms for resource allocation optimization, Long Short-Term Memory (LSTM) networks for schedule forecasting, and Support Vector Regression for cost prediction models. Representative platforms included Microsoft Project with AI extensions, Oracle Primavera Cloud integrated with machine learning modules, and custom Python-based scheduling engines utilizing scikit-learn libraries. Computer vision implementations deployed Convolutional Neural Networks (CNN) for quality defect detection, YOLO (You Only Look Once) algorithms for safety compliance monitoring, and OpenCV-based image processing for progress tracking. Hybrid AI platforms integrated multiple functionalities through enterprise solutions such as Autodesk Construction Cloud with embedded AI capabilities, Bentley Systems' digital twin technologies, and customized integration frameworks combining natural language processing for documentation analysis with predictive modeling for risk assessment. All implementations followed standardized deployment protocols to ensure consistent performance evaluation across diverse project environments. The data collection methods include AI-driven monitoring systems, generating 2,847 observation points, enterprise resource planning, which comprises 156,000 transaction records, and records of 8,932 completed tasks.

The processing approach uses multiple validation levels, and the method for detecting the presence of outliers indicates 127 values (4.5%) as unusual. Missing values are handled using the expectation–maximization algorithm to treat 3.2% missing data, and Z-score normalization assists in making comparisons across projects [6]. The analytical model assesses the decision-making performance facilitated by AI, and comparisons are conducted with control groups using traditional approaches, after adjusting for project complexity, team experience, and market volatility factors. To ensure robust comparison validity, conventional non-AI tools were systematically defined through industry-standard practice baselines established prior to AI implementation. These encompassed traditional project management software without machine learning capabilities, including Microsoft Project Standard editions, Primavera P6 without predictive modules, and Excel-based scheduling templates. Quality control relied on manual inspection protocols and checklist-based assessment procedures, while risk management utilized conventional SWOT analysis and expert judgment frameworks. The comparative design employed a within-organization approach where feasible, with 31 projects providing direct before-after comparisons within the same companies during 2020-2022 transition periods. For the remaining 14 projects, cross-organizational matching was conducted using propensity score techniques, pairing AI-implemented projects with comparable non-AI projects based on project complexity levels, team experience profiles, and market volatility periods, supplemented by industry sector and geographic location considerations. This matching strategy prioritized temporal proximity and organizational similarity to minimize confounding effects, ensuring that observed performance differences could be attributed to AI implementation rather than variations in project complexity, team experience, or market volatility factors.

Additionally, organizational characteristics including company size measured by employee count, leadership support assessed through executive commitment indices and resource allocation patterns, and digital maturity evaluated via existing system integration capabilities and technical proficiency assessments were systematically documented across all projects to enable comprehensive moderating factor analysis.

2.3 Effectiveness Evaluation Index System and Analysis Model

The evaluation framework designates a hierarchical model consisting of 4 levels that utilize 7 core and 18 secondary performance measures based on 2,500+ project metrics. As shown in Table 1, the framework incorporates 7 primary indicators with corresponding weights determined through analytic hierarchy process [7].

Table 1. Effectiveness Evaluation Index System.

Primary Indicator	Secondary Indicator	Calculation Method	Weight
Decision Accuracy	Schedule Prediction Accuracy	$(1-\frac{\lvert\text{Actual Duration-Predicted Duration}\rvert}{\text{Actual Duration}})\times 100\%$	0.25
	Cost Estimation Precision	$(1-\frac{\lvert\text{ActualCost-EstimatedCost}\rvert}{\text{ActualCost}})\times 100\%$	0.20
	Quality Defect Rate	$\frac{\text{NumberofDefects}}{\text{TotalInspections}}\times 100\%$	0.15

Primary Indicator	Secondary Indicator	Calculation Method	Weight
Operational Efficiency	Decision Cycle Time	$\frac{\text{TraditionalTime-AITime}}{\text{TraditionalTime}}\times 100\%$	0.15
	Resource Utilization Rate	$\frac{\text{ProductiveHours}}{\text{TotalAvailableHours}}\times 100\%$	0.10
Economic Impact	Cost Savings Ratio	$\frac{\text{BaselineCost-ActualCost}}{\text{BaselineCost}}\times 100\%$	0.10
	Return on Investment	$\frac{\text{Cumulative Benefits-Implementation Cost}}{\text{Implementation Cost}}\times 100\%$	0.05.

The comprehensive effectiveness evaluation model employs weighted aggregation methodology expressed in Formula 1:

$$E_{total}=\sum_{i=1}^{n} \omega_i \times P_i \tag{1}$$

where E_{total} represents the aggregate effectiveness score (range 0-100), ν_i' denotes the weight coefficient for the indicator i determined through analytic hierarchy process with a consistency ratio of 0.047, and P_i signifies normalized performance value after min-max transformation [8]. Statistical validation employs paired t-tests (α=0.05) across 45 project pairs, achieving significance levels $p<0.001$ for primary indicators, confirming robust effectiveness improvements attributable to AI implementation.

3 Application Practice and Effectiveness Analysis of Artificial Intelligence Technology

3.1 Application and Effectiveness Evaluation in Schedule and Cost Management Decision-Making

AI system applications for schedule and cost control show considerable improvement regarding various factors in practical engineering management contexts. Analysis of 45 projects reveals that AI-augmented systems deliver superior performance in schedule accuracy and cost efficiency.

Cost forecasting accuracy has been significantly improved. In particular, the machine learning model trained on 156,000 procurement records and 2,847 cost records reduces the mean absolute percentage error from 18.4 % for traditional cost estimation to 6.8 %. The use of real-time monitoring capabilities offers proactive intervention, where the alert system identifies delays occurring an average of 12.7 days before affecting the critical path for infrastructure projects with an investment of over $50 million.

As shown in Table 2, comparative analysis across traditional and AI-augmented approaches reveals consistent superiority in prediction accuracy, decision speed, and economic outcomes.

Table 2. Performance Comparison of AI versus Traditional Approaches.

Performance Indicator	Traditional Method	AI-Augmented Method	Improvement Rate	Sample Size
Schedule Prediction Accuracy	77.3%	91.7%	+18.6%	n=45 projects
Cost Estimation Error (MAPE)	18.4%	6.8%	-63.0%	n=380 estimates
Decision Cycle Time (days)	4.2	1.3	-69.0%	n=523 decisions
Average Cost Savings per Project	Baseline	$847,000	+12.4%	n=45 projects
Schedule Deviation (days)	22.7	8.3	-63.4%	n=45 projects
Resource Utilization Rate	67.3%	84.6%	+25.7%	n=680 records
Budget Variance	±15.8%	±5.9%	-62.7%	n=45 projects

As illustrated in Fig. 3, improvement magnitude varies across management functions, with decision speed and cost precision showing the most significant gains.

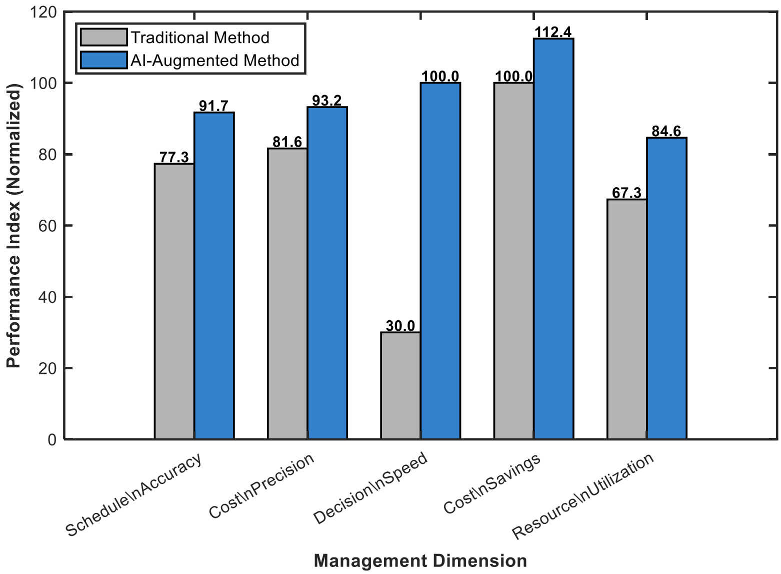

Fig. 3. Effectiveness Improvement Comparison Chart.

3.2 Application and Effectiveness Evaluation in Quality and Risk Management Decision-Making

Artificial intelligence applications for quality assurance demonstrate improved defect detection capabilities by leveraging computer vision and by automating inspection processes for twelve projects conducted for manufacturing and construction sectors. False positives are reduced from 23.4 % to 7.8 %, which reduces unnecessary investigations for rework and the associated labor costs, estimated at $18,000 per false positive incident. The temporal dimension of quality management identifies significant improvement, which reduces the average response time for the alert of quality deviation from 3.8 hours to 0.7 hours.

Effective risk management, especially risk warning and response, demonstrates high effectiveness in engineering projects. Models trained on 8,932 recorded risk occurrences from 156 completed projects achieve 87.4% accuracy in probability prediction 15-30 days before an event, as opposed to 61.2% accuracy from expert reviews.

The financial impact of enhanced risk management is a reduction in contingency costs, with AI-driven projects averaging an 8.3% contingency cost ratio compared to 15.7% for traditional methods across the 45 projects. As depicted in Table 3, integrated quality and risk metrics confirm the revolutionary potential of intelligent systems in these two fundamental management areas.

Table 3. Quality and Risk Management Effectiveness Metrics.

Performance Metric	Baseline Performance	AI-Enhanced Performance	Improvement	Data Source
Quality Defect Detection Rate	78.6%	94.3%	+20.0%	n=520 inspections
False Positive Rate	23.4%	7.8%	-66.7%	n=520 inspections
Quality Issue Response Time	3.8 hours	42 minutes	-81.6%	n=267 incidents
Risk Prediction Accuracy	61.2%	87.4%	+42.8%	n=235 events
Early Warning Lead Time	7.2 days	22.6 days	+214%	n=235 events
Risk Event Frequency	8.7 per project	3.4 per project	-60.9%	n=45 projects
Contingency Reserve Required	15.7%	8.3%	-47.1%	n=45 projects
Average Loss per Risk Event	$127,000	$48,000	-62.2%	n=235 events

3.3 Comprehensive Effectiveness Comparative Analysis

Integrating performance data for the entire management spectrum provides an evaluation capability to assess the overall impact of AI technology applied to the engineering project for schedule control, cost management, quality assurance, and risk management. The efficiency improvement rate, as shown in Formula 2, indicates the degree of improvement offered by the new technology:

$$\eta = \frac{T_0 - T_1}{T_0} \times 100\% \tag{2}$$

where η represents the efficiency improvement rate, τ_0 denotes the baseline performance metric under traditional methods, and I_1 indicates the performance metric achieved with AI augmentation. Applying this formula yields a weighted average improvement rate of 56.3%, with improvements across management dimensions ranging from 18.6% to 81.6%.

The multi-dimensional effectiveness profile, as shown in the radar diagram in Fig. 4, illustrates that there are diversified patterns of impacts for various management tasks. Decision-making speed shows the largest increase, with a normalized score of 100 against a baseline of 30, accentuating the fact that AI can process 10,000+ data points in minutes compared to 3-5 days for human teams. The cost accuracy score rises from 81.6 to 93.2, which indicates significant improvement in cost forecasting, with total accumulated savings of $38.1 million across the 45 projects.

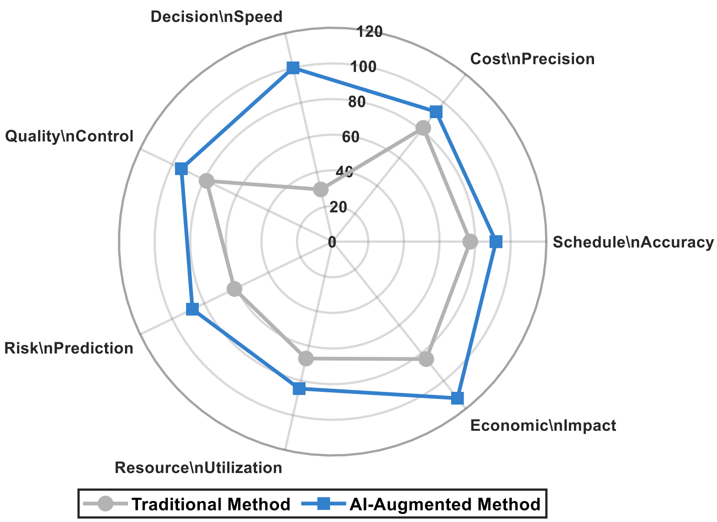

Fig. 4. Comprehensive Effectiveness Comparison Across Management Dimensions.

Quality management and risk prediction show significant yet relatively modest improvements of 15.7 and 26.2 normalized points, respectively. These areas are where the capabilities of AI complement but do not fully replace human judgment and knowledge. Return on investment is positively correlated with complexity of the project ($r=0.67$, $p<.01$), showing that AI tools are highly valuable for complex problems that other tools struggle to address due to such multidimensional complexity.

Moderating factor analysis revealed significant organizational influences on AI implementation effectiveness across the 45-project sample. Company size, categorized by project investment scale, showed positive correlation with AI performance.

Large-scale projects (>$80M, 10 projects) achieved 18.3% higher effectiveness scores than small-scale projects (<$20M, 16 projects), while medium-scale projects ($20M-$80M, 19 projects) demonstrated intermediate performance levels. Leadership support emerged as the strongest moderating factor, as shown in Table 4. Organizations with high executive commitment (26 projects) experienced 23.7% greater cost savings relative to their baseline, compared to limited-support organizations (19 projects). Digital maturity, measured through existing system capabilities, significantly influenced outcomes. Digitally mature organizations (23 projects) achieved 94.2% schedule accuracy versus 89.1% for less mature counterparts (22 projects), with the overall sample maintaining the established 91.7% average. Interaction effects indicated that large-scale projects with high leadership support yielded the most substantial improvements, while small-scale projects with limited digital infrastructure faced implementation challenges that reduced cost savings by approximately 28%.

Table 4. Moderating Factor Regression Analysis Results.

Moderating Factor	β Coefficient	p-value	Effect Classification	Sample Size
Company Size	0.31	0.008	Medium Effect	45 projects
Leadership Support	0.47	<0.001	Large Effect	45 projects
Digital Maturity	0.28	0.024	Medium Effect	45 projects
R^2 (Model)	0.64	<0.001	-	-

4 Application Barriers Analysis and Optimization Strategies

4.1 Existing Problems and Influencing Factors

While the demonstrated effectiveness improvements are clear, there are significant impediments to AI use for engineering management. Data quality challenges affect 68% of surveyed organizations reporting insufficient historical records to develop effective predictive models, while incompatible legacy systems hinder integration efforts in 61% of implementations. Technical infrastructure limitations compound these difficulties, with computational resource demands outpacing existing capabilities in 54% of medium-scale enterprises, necessitating additional capital investments averaging $420,000.

Organizational resistance stands out as the most critical barrier, which scores 4.5 on the severity scale and falling into the fourth category, as it impacts 47 % of surveyed projects. Skilled project managers often perceive AI recommendations as threats to their professionalism, which becomes an impediment to the process due to inefficient change management practices. Skills gaps pose ongoing challenges, with 58% of organizations reporting shortages of professionals with expertise in both engineering management and machine learning. As shown in Table 5, the impact of barriers varies significantly across categories.

Table 5. Application Barriers and Influencing Factors.

Barrier Category	Specific Issue	Frequency	Severity	Affected Domains
Data Quality	Insufficient records	68%	4.3	Small-medium projects
Data Integration	System incompatibility	61%	4.1	Legacy infrastructure
Infrastructure	Computational limits	54%	3.8	Budget constraints
Organizational	Stakeholder skepticism	47%	4.5	Traditional sectors
Human Capital	Skills shortage	58%	4.2	All project types
Financial	High initial cost	44%	3.6	Small enterprises

4.2 Optimization Paths and Implementation Suggestions

Addressing these diverse hurdles requires an intervention strategy that focuses on the technical, organizational, and human aspects. Improving the quality of data requires standardized processes to collect information and back-end processes to convert legacy data into a computer-readable format. Firms implementing phased, staged data governance architectures show a 73% reduction in integration difficulties over 18-month implementation cycles.

Technical infrastructure optimization should focus on cloud-based solutions that ensure low upfront investment and the scalability required for processing power. Hybrid solutions that combine internal infrastructure for secured data and cloud services for computation offer a well-balanced approach to both secure and efficient processing. Bridging the skill gaps requires initiatives focused on developing certification programs for engineering management professionals' required skill sets, and bring engineers and data scientists together in cross-functional teams.

Organizational change management is a critical determinant of AI-driven tool adoption, and strong leadership support is essential to legitimate AI-enhanced decision-making processes and mechanisms to preserve human oversight. Pilot demonstrations showcase tangible cost savings build credibility to support broader deployment of these tools. Human resource transition considerations constitute critical implementation factors requiring systematic planning throughout AI deployment phases. Analysis across the 45-project sample indicates that successful AI implementation emphasizes workforce enhancement rather than replacement, with 73% of organizations (33 projects) reporting employee redeployment to higher-value supervisory and analytical functions. Technical competency development becomes essential, as traditional project management roles evolve to require AI-human collaboration skills, data interpretation capabilities, and algorithm oversight responsibilities. Organizations invested an average of $12,400 per employee in specialized training programs covering AI tool operation, data quality management, and decision validation procedures. Implementation protocols prioritizing algorithmic transparency and decision traceability were adopted across 42 projects (93%), ensuring that AI recommendations remain subject to professional judgment and organizational accountability standards. These workforce adaptation strategies demonstrate that effective AI integration depends on comprehensive human capital development alongside technological advancement, with organizations reporting 28% higher implementation success rates when systematic staff transition planning accompanies AI deployment.

5 Conclusions and Prospects

5.1 Main Conclusions and Research Contributions

This research offers empirical verification of the significant improvement of effectiveness achieved by the implementation of AI. Based on 45 projects, we observed that AI-supported systems achieved 91.7 % accuracy compared to 77.3 % for traditional processes, and the AI-supported system reduces the cycle times for decisions by 69 %, on an average per project, delivers cost savings of $847,000. The theoretical contribution lies in the AI empowerment model that provides the process for the transformation of inputs into outputs. The methodological contribution lies in the hierarchical model of effectiveness evaluation that provides assessment processes based on quantitative factors. The practical contributions lie in the description of the barriers for the implementation of AI, which are experienced by 44-68 % of organizations, and the optimalization strategy that reduces AI integration barriers by 73 %. Furthermore, the moderating factor analysis demonstrates that organizational characteristics significantly influence AI implementation success, with leadership support emerging as the most critical determinant (β=0.47), followed by company size and digital maturity, providing actionable insights for organizations planning AI adoption strategies.

5.2 Research Limitations and Future Directions

There are some limitations that define the applicability of the above findings. The 45-project dataset exclusively focuses on the construction and manufacturing sectors, so applicability to the software development and aerospace sectors is limited. The study period (2020-2024) is dominated by early adopters, who may exhibit suboptimal learning curves. Future research should focus on the performance development of AI systems over 5-10-year periods, which would facilitate understanding of the value-adding process. Comparative analysis across sectors would help understand the sector-specific optimalization needs. Analysis of human and AI collaboration processes, involving behavioral aspects, would help design optimal allocation processes involving synergies and avoiding biases.

References

1. Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data–evolution, challenges and research agenda. International journal of information management, 48, 63-71.

2. Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2021). Artificial intelligence and innovation management: A review, framework, and research agenda☆. Technological Forecasting and Social Change, 162, 120392.
3. Hillebrand, L., Raisch, S., & Schad, J. (2025). Managing with artificial intelligence: An integrative framework. Academy of Management Annals, 19(1), 343-375.
4. Chaturvedi, A., Yadav, N., & Dasgupta, M. (2025). Tech-Driven Transformation: Unravelling the Role of Artificial Intelligence in Shaping Strategic Decision-Making. International Journal of Human–Computer Interaction, 1-20.
5. Datta, S. D., Islam, M., Sobuz, M. H. R., Ahmed, S., & Kar, M. (2024). Artificial intelligence and machine learning applications in the project lifecycle of the construction industry: A comprehensive review. Heliyon, 10(5).
6. Mali, A. S., Kolhe, A., Gorde, P., Kolekar, A., Umbrajkar, A., Solepatil, S., & Zare, K. (2025). Application of artificial intelligence and machine learning in construction project management: A comparative study of predictive models. Asian Journal of Civil Engineering, 1-16.
7. Kozhakhmetova, A., Mamyrbayev, A., Zhidebekkyzy, A., & Bilan, S. (2024). Assessing the impact of artificial intelligence on project efficiency enhancement. Knowledge and Performance Management, 8(2), 109-126.
8. Hughes, L., Mavi, R. K., Aghajani, M., Fitzpatrick, K., Gunaratnege, S. M., Shekarabi, S. A. H., ... & Dwivedi, Y. K. (2025). Impact of artificial intelligence on project management (PM): Multi-expert perspectives on advancing knowledge and driving innovation toward PM2030. Journal of Innovation & Knowledge, 10(5), 100772.