American Journal of Smart Technology and Solutions (AJSTS)

ISSN: 2837-0295 (ONLINE)

VOLUME 5 ISSUE 1 (2026)

PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

American Journal of Smart Technology and Solutions (AJSTS)

Volume 5 Issue 1, Year 2026
ISSN: 2837-0295 (Online)
DOI: https://doi.org/10.54536/ajsts.v5i1.6989
https://journals.e-palli.com/home/index.php/ajsts

AI-Augmented Project and Program Management: Predictive Analytics for Risk, Cost and Schedule Control

Manfred Obinwanne Igwenagu[1*], Ododoade Idowu Adewuyi[2], Bella Isen[2], Fope Opeola[3]

Article Information

Received: August 02, 2025

Accepted: February 09, 2026

Published: March 31, 2026

Keywords

Artificial Intelligence, Cost Estimation, Hybrid Human–AI Systems, Predictive Analytics, Project and Program Management, Risk Management, Schedule Control

ABSTRACT

The increasing complexity and inherent uncertainty of modern projects have necessitated sophisticated analytical tools to support the consolidation of project and program management decision-making. This paper shows a systematic literature review that analyses the use of artificial intelligence (AI) -enhanced predictive analytics in improving risk, cost, and schedule control in construction, information technology, and healthcare project management. The systematic review identifies the gaps in the current state of knowledge through three research questions: (i) the current application of AI and machine-learning methods to project risk analysis, cost estimation and schedule forecasting; (ii) the success of AI-based tools to enhance project performance outcomes, and (iii) the data, organisational, trust, and ethical issues in the context of AI integration, especially hybrid human-AI models. Results have shown that highly developed AI models, such as neural networks, ensemble learning algorithms, probabilistic and Bayesian models, and natural-language processing, are significantly more accurate in prediction compared to traditional deterministic models. The AI-enhanced tools help to detect cost overruns, schedule slippage, and emergent risks earlier and provoke more proactive and informed managerial interventions. Nevertheless, the review also shows that the advantages of AI are very dependent on the quality of data, the interpretability of the model, and organisational preparedness. Experience always suggests that hybrid models that integrate AI-based insights together with expert judgment and conventional methods of assessing risk, including Monte Carlo simulation, are the most efficient and reliable ones. The paper concludes that AI is mostly a decision-supporting and diagnostic accelerant, but not a substitute for project managers. This review can help academia and practice by synthesising the latest empirical and theoretical literature to discuss how AI-enhanced predictive analytics can provide sustainable changes in project performance and governance under which conditions exist.

INTRODUCTION

The increasing scope, uncertainty, and interdependence of modern projects across sectors, including construction, information technology, healthcare, and major infrastructure, place increasing pressure on traditional project and program management methods. Traditional approaches, which are mostly based on deterministic planning tools, expert judgment, and non-dynamic forecasting structures, tend to fail in dealing with unstable environments, non-linear risk interdependence, and speedily changing stakeholder and resource limits. With increasingly data-intensive and dynamically coupled projects, relying on manual evaluation and previous experience has not been adequate to anticipate risks on time, predict costs effectively, and maintain strong schedule control (Salleh & Aziz, 2022; Battula, 2025; Sinha & Ahmed, 2025). Artificial Intelligence (AI) and Machine Learning (ML), in turn, have enabled transformative changes in project and program management through predictive analytics, extending the analytical scope of traditional management models (Sheikh *et al.,* 2025).

AI-based project and program management has become a new paradigm of the shift toward active decision-making based on data-driven predictions, rather than active control. Project data, whether in large quantities of unstructured, historical, and real-time data, can be analysed by AI to predict the likelihood of deviations in cost, schedule, and risk profiles in their early stages, creating the opportunity to take earlier and more effective action (Ajibade, 2025; Haque *et al.,* 2025; Qureshi, 2025; Poudel & Maharjan, 2025). In contrast to the classical methods of forecasting, which presuppose the linearity and stability of the relationship between project variables, AI models can learn some complex and non-linear associations between them, thus reflecting the emergent patterns that develop during the project lifecycle (Akinboboye *et al.,* 2022; Szwarcfiter *et al.,* 2023; Adejumo *et al.,* 2025). This capability is especially essential in multi-project and program contexts, where deviations that propagate, resource contention, and strategic mismatch can cause minor deviations and turn them into system failures (Viacheslav, 2022; Job, 2025).

The very essence of AI-enhanced predictive analytics is based on advanced computational algorithms, such as artificial neural networks, ensemble learning algorithms, such as Random Forests and Gradient Boosting Machines,

[1] Natural Resources and Environmental Sciences, Prairie View A & M University, United States
[2] College of Professional Studies, Northeastern University, Portland, Maine, United States
[3] National Oceanography Center, United Kingdom
[*] Corresponding author's e-mail: manfredobinwanneigwenagu@gmail.com

probabilistic algorithms, such as Bayesian networks, reinforcement learning, and Natural Language Processing (NLP) models (Hriday & Rehman, 2025; Tickoo & Kannan, 2025; Koszykowski & Orzeszko, 2025). By using these methodologies, cost estimation is performed with more accuracy, the schedule forecasting is dynamic, and risk monitoring is ongoing by utilising both structured data (schedules, budgets, performance measures) and unstructured data (such as progress reports, emails, issue logs, and stakeholder communications). Empirical research indicates that deep learning and hybrid machine-learning models are always more efficient in forecasting cost overruns and schedule slippage, especially in complex and uncertain project settings (Manchana, 2022; Mali *et al.,* 2025; Savas, 2025). In addition, NLP-based systems have demonstrated significant capacity to identify hidden indicators of risk in text, enabling earlier detection than traditional quantitative metrics (Greg, 2025; Ongbali *et al.,* 2025; Chinonye & Onah, 2025).

The evidence of the performance advantage of AI-enhanced project management is quickly building up. According to studies in the context of construction, software engineering, and enterprise program management, there is concrete improvement in schedule and cost control and resource utilisation after the use of predictive analytics and AI-based decision-support systems (Abaneme *et al.,* 2025; Hasan & Islam, 2025; Almalki, 2025; Sheihk *et al.,* 2025). The mentioned improvements involve the decrease in budgetary overruns, an increase in delivery accuracy, and responsiveness to risk conditions through ongoing forecasting and adaptive control systems (Bibi *et al.,* 2024; Alam *et al.,* 2025). Predictive scheduling and real-time analytics have also been used in agile and large-scale agile settings to further benefit precise sprint planning, backlog prioritisation, and capacity forecasting, thus allowing more resilient and quicker delivery cycles (Afhayma & Youssef, 2025; Das, 2025; Mohamed, 2025).

Regardless of these innovations, there are still serious technical, organisational, and ethical issues connected with the implementation of AI in project and program management. Partial information, low data quality, less interoperability of project information systems, and situational variability continue to affect the reliability and generalisability of predictive models (Rusum & Anasuri, 2024; Thota, 2024). The issues of model transparency, explainability, and trust are also important when AI-generated recommendations affect high-stakes managerial choices pertaining to the cost commitments, schedule trade-offs, and risk acceptance (Mayer *et al.,* 2024; Sauer & Burggraf, 2025). Such issues are also enhanced by the organisational opposition to algorithmic decision-support tools, the ambiguities of accountability, bias, and ethical governance during AI-enabled project control (Lutz *et al.,* 2025; Taj, 2025; Poudel & Maharjan, 2025).

Therefore, recent research predicts more and more the development of hybrid intelligence, i.e. the conscious combination of human knowledge and AI capabilities, as an option to the use of AI in project management, both pragmatic and ethically justified (Dellermann *et al.,* 2021; Molenaar, 2022; Sauer & Burggraf, 2025). Hybrid expert-AI models aim to work into equilibrium between AI computational capabilities and human contextual knowledge, judgment and responsibility and thus can ensure that predictive information is readable, implementable, and organizationally strategic. Such practical applications include AI-enhanced Monte Carlo simulations that follow expert-weighted assumptions, reinforcement learning models constrained by managerial policies, and decision-support systems that make explainable, rather than autonomous, recommendations (Ed-Driouch *et al.,* 2022; Erten *et al.,* 2025; Semenov *et al.,* 2025). These methods are becoming viewed as a key to achieving sustainable value based on AI-enhanced predictive analytics in complex project settings.

It is in this context that the present study will synthesise the current research on AI-enabled predictive analytics to control risks, costs and schedule in project and program management. Based on three overarching research questions, namely, (1) Which AI and machine-learned methods are used today to predict risk, cost, and schedule control; (2) How effective are AI-enhanced methods in improving project and project management performance outcomes; and (3) What are the main implementation, data quality, trust, and ethical issues that affect their adoption, and how do hybrid human-AI models help overcome these issues, this review will present an integrated and critical view of the new role of AI in project management. The research will help to improve theoretical knowledge and practical recommendations on the utilisation of predictive AI as one of the foundations of the next-generation project and program management practice by combining existing and trustworthy academic materials.

MATERIALS AND METHODS

Study Design

This study adopts a systematic literature review (SLR) methodology to synthesise empirical and theoretical evidence on AI-augmented predictive analytics for risk, cost, and schedule control in project and program management. An SLR is particularly appropriate for this research domain due to the rapid expansion, methodological heterogeneity, and interdisciplinary dispersion of AI applications across project management, engineering, information systems, and operations research. Unlike traditional narrative reviews, an SLR provides a transparent, replicable, and bias-reducing approach to knowledge consolidation, thereby enhancing analytical rigour and credibility.

The review process follows established SLR guidelines widely adopted in software engineering, management, and information systems research, notably the protocols proposed by Kitchenham *et al.* and the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. These guidelines informed the formulation of research questions, database selection, search strategy, screening procedures, and synthesis approach, ensuring methodological consistency and traceability throughout the review process.

Search Strategy and Data Sources

An intensive and multi-faceted search was done in prominent scholarly data sources that have been known to publish high-quality studies in the field of project management, engineering and information systems. The databases searched were Scopus, Web of Science, IEEE Xplore, ScienceDirect, SpringerLink and MDPI, and additional queries were made in Google Scholar to identify recent publications, early-access publications, or interdisciplinary work that was not yet fully indexed. This multi-database approach minimised the publication bias and represented the coverage of both methodological and sectoral settings.

The search strings were formulated based on the combinations of keywords and Boolean operators with respect to artificial intelligence and project management, such as, but not limited to, artificial intelligence, machine learning, predictive analytics, project management, program management, risk analysis, cost estimation, and schedule control. Where necessary, truncation and synonym variations were used to make the retrieval as sensitive as possible. To be relevant and up to date, the reviewed studies mainly included those published after 2019, and thus captured the recent developments in the field of AI-based predictive analytics and hybrid intelligence systems.

Inclusion and Exclusion Criteria

Both inclusion and exclusion criteria were followed to ensure analytical consistency and firm quality management. The studies were considered included when they:

(1) expressly covered the use of AI or ML in the context of project or program management;

(2) discussed predictive analytics associated with risk management, cost estimation, or schedule control;

(3) were released in peer-reviewed publications or serious conference papers;

(4) reported empirical findings, approved models, systematic reviews, or conceptualised conceptual structures well.

Study was excluded when it:

(1) was comprised of non-peer-reviewed opinion, editorial, or practitioner blogging;

(2) was not transparent enough in terms of methodology;

(3) was concentrated on AI use beyond project management scenarios; or

(4) did not provide a clear connection between AI methods and the outcomes of predictive project control.

The standards were used to make sure that the final corpus was made up of methodologically sound and substantively relevant contributions.

Study Selection and Screening Process

The process of selecting the study was based on a stepwise screening approach in accordance with the PRISMA. At first, all records that had been retrieved were added to a reference management system, where all duplicates were found and removed. Then the title and abstract screening was conducted to filter out studies that were obviously irrelevant. Lastly, full-text screening measured methodological rigour, appropriateness to questions posed in the research, and the conciseness of AI usage and validation.

During the screening process, specific attention was paid to the fact that the studies of various project spheres were to be included, that is, construction, information technology, healthcare, infrastructure and enterprise program management to provide the cross-sectoral representativeness. The collected corpus of chosen studies has included an equal amount of quantitative modelling studies, qualitative case studies, hybrid frameworks, and systematic or scoping reviews, thus simplifying the analytical synthesis.

Data Extraction and Synthesis Approach

To extract the most important features of every chosen study, a data extraction template was developed. Outsourced information included the year of publication, the area of research and industry, the AI or ML methodology used (such as neural networks, ensemble models, Bayesian methods, reinforcement learning, natural language processing), the area of focus of the application (risk, cost, schedule), validation, the performance results of the study, and the challenges of implementation reported. The synthesis was thematic in nature, as findings were organised according to the three research questions as opposed to statistical aggregation. Such a method is especially suitable, as the models of AI, as well as datasets, evaluation metrics, and project contexts, are heterogeneous across research. Analysis of similarities was used in order to determine prevailing trends in methodology, an overlapping of evidence on effectiveness, new hybrid forms of human- AI, and research gaps.

RESULTS AND DISCUSSION

Overview of Included Studies

The evidence aimed at controlling risk, cost, and schedule in project and program management was synthesised in the systematic literature review of a heterogeneous corpus of peer-reviewed journal articles, conference papers, doctoral dissertations, and high-quality review studies investigating AI-augmented predictive analytics. The selected literature sources represent various industries, schools of thought, and analytical goals, thereby capturing the interdisciplinary nature and dynamism of AI implementation in project management.

Disciplinary Distribution

The majority of the studies included in it were published within the years 2019 to 2025, with the growth of the number of publications growing significantly since 2022, which indicates the rapid rise of scholarly and practical interest in AI-driven project management solutions. Previously, the research focused mostly on feasibility and conceptual frameworks of AI integration, but more recent studies are more likely to predict empirical validation, hybrid intelligence models, and real-time decision-support systems (Salleh & Aziz, 2022; Battula, 2025; Qureshi, 2025).

Disciplinary-wise, the literature relies on project management, construction engineering, information systems, operations research, and software engineering, which highlights the inter-sectoral applicability of predictive analytics. This variety advances the generalisability of results and, at the same time, displays sector-specific implementation patterns

Sectoral Coverage of the Reviewed Studies

The papers that were considered in the review focus on construction and infrastructure projects that comprise the biggest percentage of empirical modelling studies. Such studies periodically assess artificial intelligence usage to estimate costs, predict the schedule, and reduce risks with reference to historical project data and simulation validation (Hriday & Rehman, 2025; Mali *et al.,* 2025; Savas, 2025). The complex nature, capital intensity, and availability of data of construction projects make them especially worthy of being testbeds of predictive AI methods.

The information technology and software development projects have also been explored in a considerable amount of literature, particularly in agile and large-scale agile settings. These studies focus on predictive scheduling, forecasting sprint performance, and optimisation of resources using machine-learning models that are trained on delivery pipelines and metrics of operation (Almalki, 2025; Das, 2025; Yakkanti, 2025).

Besides, more and more research is conducted on healthcare, public-sector, and enterprise programme-management situations, where AI-based predictive analytics assists in regulatory compliance, stakeholder coordination, and decision-making at the portfolio level (Alemde, 2025; Viacheslav, 2022; Qureshi, 2025). Not as numerous as they should be, however, these studies do offer essential information about the challenges of ethics, governance, and trust.

Methodological Characteristics

There is a high level of heterogeneity in the reviewed studies methodologically. A significant percentage makes use of quantitative predictive modelling, in which they base their forecast to evaluate the accuracy of their forecast and better performance (Manchana, 2022; Akinboboye *et al.,* 2022). Such studies are usually based on past project information and compare the outputs of AI with traditional methods of estimation.

The other subgroup follows qualitative or mixed-methodology, such as case studies, interviews with experts and design science studies. The research committee investigates implementation procedures, human organisational preparedness and human-AI interface and gives an explanatory richness, which is in contrast to predictive accuracy indicators (Mayer *et al.,* 2024; Taj, 2025). The corpus also comprises systematic and scoping reviews that help further contextualise the trends, gaps in the research, and methodological development (Koszykowski & Orzeszko, 2025; Pashazanous, 2025).

Focus on AI Techniques and Application Domains

In the literature analysed, cost estimation and schedule control are the most commonly studied areas of application, with risk identification and prioritisation coming in the second place. Numerical prediction problems are dominated by deep learning and ANN-based models, and the uncertainty modelling and dynamic risk assessment problems are usually addressed by Bayesian networks, Monte Carlo simulations and reinforcement learning (Sinha & Ahmed, 2025; Tickoo & Kannan, 2025).

Natural language processing (NLP) is becoming a more common subject of study by more recent authors to analyse unstructured project data, including progress reports and stakeholder communications, which would in turn allow earlier identification of latent risks and governance problems (Greg, 2025; Ongbali *et al.,* 2025). It is a tendency of expanding predictive analytics to a wider range of structured data.

Emergence of Hybrid Human–AI Perspectives

One of the distinct features of the provided studies is the increased focus on hybrid human AI models. Instead of supporting complete automation, a number of studies emphasise the need to incorporate AI analytics into expert-guided decision-making in order to increase interpretability, trust, and ethical responsibility (Dellermann *et al.,* 2021; Molenaar, 2022; Sauer & Burggraf, 2025). This point of view is especially popular in research on high-stakes project environments and portfolio-wide governance.

AI and Machine-Learning Techniques for Risk, Cost, and Schedule Control

The systematic review indicates a strong and consistent growth in the use of advanced artificial-intelligence and machine-learning methods of predictive risk assessment, cost estimation and schedule control in a broad array of project and program management situations, hence reflecting the increased importance of data-driven decision making in the modern context.

In line with available syntheses (Salleh & Aziz, 2022; Battula, 2025), artificial neural networks (ANNs) and deep-learning frameworks are the most commonly used methodologies of cost estimation and schedule forecasting, especially in the construction, infrastructure, and massive information-technology developments.

Studies in which multilayer perceptrons, recurrent neural networks, and hybrid deep-modelling are used invariably show better predictive accuracy than the conventional parametric models and regression-based estimation methods (Hriday & Rehman, 2025; Mali *et al.,* 2025; Manu, 2024). To a great extent, this better performance can be attributed to the ability of deep-learning models to explain nonlinearity and high-dimensional interaction between cost drivers, productivity measurements, environmental parameters, and execution uncertainties, the interaction that is often simplified in traditional techniques.

In addition to cost and schedule estimation, the review emphasises the continuing applicability of both probabilistic and Bayesian methods of risk analysis as part of AI-based risk analysis. Bayesian networks are commonly applied to describe causal relationships among project risks, which is why they allow making probabilistic inferences and updating dynamically as new information becomes available throughout the project lifecycle (Szwarcfiter *et al.,* 2023; Tickoo & Kannan, 2025). Combined with Monte Carlo simulation, they give a more detailed and lifelike account of uncertainty in cost and schedule results compared to non-probabilistic planning instruments (Sinha & Ahmed, 2025). More importantly, this integration does not imply a complete replacement of the traditional risk-management practices; instead, it is a methodological convergence where AI supplements the existing project-control tools with increased learning rate, scalability, and analytics (Salleh & Aziz, 2023).

Random forests and gradient-boosting machines are ensemble learning algorithms which are becoming increasingly popular in risk prioritisation and decision-support systems, especially those that are large and data-intensive in nature. These methods are appreciated due to their strength, ability to resist overfitting, and the ability to identify the strongest predictors out of large groups of interconnected variables (Akinboboye *et al.,* 2022; Rusum & Anasuri, 2024). They are adopted particularly in the management of enterprise programs and the decision-making at a portfolio level, where several projects compete to secure limited resources and where there are high-risk interdependencies (Ayeni, 2025; Qureshi, 2025).

One interesting new development that has been found in the review is the increased use of natural language processing (NLP) on unstructured project data. NLP-based models are increasingly being used to process progress reports, risk logs, contractual correspondence, meeting minutes and stakeholder communications to elicit latent risk signals and sentiment patterns (Greg, 2025; Ongbali *et al.,* 2025). The methods significantly expand the predictive capabilities of the analytics on the basis of numeric data and allow identifying socio-organisational threats related to stakeholder mismatch, communication failure, and governance loopholes earlier (Adamantiadou & Tsironis, 2025; Taj, 2025). These results taken together suggest that there is a movement towards hybrid AI ecosystems where a number of machine-learning methods are used alongside probabilistic modelling and subject matter expertise to tackle the complexity of project risk, cost, and schedule control.

Table 1: AI and Machine-Learning Techniques Applied in Project Risk, Cost, and Schedule Control

AI Technique	Primary Application Domain	Typical Project Sectors	Key Strengths	Key Limitations	Representative Studies
Artificial Neural Networks (ANNs)	Cost estimation, schedule forecasting	Construction, IT, infrastructure	Captures non-linear relationships; high predictive accuracy	Low interpretability; data-intensive	Hriday & Rehman (2025); Mali *et al.* (2025); Manu (2024)
Deep Learning (RNN, LSTM, CNN)	Dynamic cost and schedule prediction	Construction, engineering, IT	Learns temporal patterns; adapts to evolving project data	High computational cost; black-box behaviour	Shamim *et al.* (2025); Manchana (2022)
Bayesian Networks	Risk analysis and dependency modeling	Construction, healthcare, infrastructure	Explicit uncertainty modelling; dynamic updating	Requires expert input; model complexity	Szwarcfiter *et al.* (2023); Tickoo & Kannan (2025)
Monte Carlo Simulation (AI-enhanced)	Cost and schedule uncertainty analysis	Construction, public sector	Realistic probabilistic forecasts	Dependent on input quality	Sinha & Ahmed (2025); Salleh & Aziz (2023)
Ensemble Learning (RF, GBM)	Risk prioritisation; decision support	Infrastructure, IT, enterprise PMO	Robust to noise; feature importance	Limited causal explanation	Akinboboye *et al.* (2022); Rusum & Anasuri (2024)
Natural Language Processing (NLP)	Latent risk detection; sentiment analysis	IT, public sector, healthcare	Exploits unstructured data; early warnings	Context sensitivity; language bias	Greg (2025); Ongbali *et al.* (2025)

The synthesis of the most prevalent artificial intelligence and machine learning methods and approaches revealed in the studies reviewed in Table 1 provides clear connections between artificial intelligence and machine learning methods and particular project-management areas of control. The diversity of the methodology is attested by the table, and shows that no particular technique can be considered a universal great power to be used in all applications. Instead, deep-learning models and artificial neural networks are more closely applied to quantitative prediction, and Bayesian inference and natural-language-processing-based approaches are applied to deal with uncertainty and the qualitative aspects of risk. This empirical finding supports the conclusion of the review that the use of AI in project management is increasingly drifting towards hybrid and complementary analytical ecosystems, as opposed to the use of standalone and autonomous models.

Effectiveness of AI-Augmented Predictive Analytics on Project Performance

The methodological analysis of the available literature proves the strong and convergent evidence in favour of the opinion that AI-based predictive analytics can improve the outcomes of project performance, and the most significant impacts are observed in eliminating risks, estimating costs correctly, and meeting deadlines. In empirical studies, the adoption of AI-based forecasting models is more accurate than traditional planning tools in forecasting cost overruns and schedule slippage, especially in the unpredictable and highly complex project settings (Hasan & Islam, 2025; Savas, 2025). Deep-learning models and ensemble models reduce mistakes in estimation by adapting extensive past data and optimising the forecasts as new execution data is received (Ajibade, 2025; Mohammed & Panda, 2024). This ability allows project managers to intervene sooner in the project lifecycle so that they can transfer the control practices from reactive correction to proactive performance management.

In the field of schedule control, analytical tools developed based on AI, which are trained on a large repository of past schedules, are useful in detecting unrealistic sequencing logic, excessive constraints, and latent erosion of float factors typically related to project delays (Koszykowski & Orzeszko, 2025; Tickoo & Kannan, 2025). According to the empirical research, it is claimed that schedule realism, forecast reliability and delivery accuracy have been measurably improved after the adoption of predictive scheduling tools in construction and engineering projects, specifically (Manchana, 2022; Mali *et al.,* 2025). Machine-learning models used to forecast the speed of sprints, defect patterns, and pipeline delivery processes in similar contexts like information technology and software development are known to increase the consistency of planning and support a more stable release process (Almalki, 2025; Das, 2025; Yakkanti, 2025).

Predictive analytics based on AI is also applied to healthcare and public-sector projects, particularly within an environment with a high degree of regulatory complexity, resource shortage, and multi-stakeholder coordination. The AI-based decision-support systems enhance the situational awareness of early warning signs of compliance risk, resource bottlenecks, and schedule slippage (Alemde, 2025; Qureshi, 2025). However, there is an inconsistency in the reported performance gains as the review presents some studies that have shown slight or no improvements. This heterogeneity is often explained by underdeveloped data centres, the lack of organisational analytics maturity, and low integration of AI outputs and managerial decision-making procedures (Viacheslav, 2022; Thota, 2024). The results emphasise the importance of the fact that AI performance is socio-technical and determined not only by algorithms but also by company preparation and regulations.

Table 2: Reported Effects of AI-Augmented Predictive Analytics on Project Performance

Performance Dimension	Observed Effects	Nature of Evidence	Sectoral Emphasis	Key References
Cost Control	Reduced estimation error; earlier detection of overruns	Empirical modelling studies	Construction, engineering	Shamim *et al.* (2025); Ajibade (2025)
Schedule Adherence	Improved forecast accuracy; reduced slippage	Empirical and case-based	Construction, IT	Koszykowski & Orzeszko (2025); Mali *et al.* (2025)
Risk Mitigation	Earlier identification of high-impact risks	Case studies; probabilistic models	Infrastructure, healthcare	Hasan & Islam (2025); Qureshi (2025)
Resource Optimization	Improved allocation and utilisation	Simulation and DSS studies	Enterprise PMO, IT	Abaneme *et al.* (2025); Ayeni (2025)
Decision Responsiveness	Faster and more proactive interventions	Qualitative and mixed-method	Cross-sectoral	Haque *et al.* (2025); Viacheslav (2022)

Table 2 summarises the results of empirical studies on the effectiveness of AI-enhanced predictive analytics, thereby directly answering Research Question 2. The findings suggest a steady increase in the key areas of project performance, especially cost accuracy and schedule reliability. Nevertheless, the evidence presented is different: quantitative modelling or qualitative case study, which supports the idea that AI efficiency is situational and moderated by maturity and readiness for the data of an organisation.

Implementation Challenges and the Role of Hybrid Human–AI Models

Although the proven performance advantages, this review presents enduring and structural issues that would limit the successful application of AI-enhanced predictive analytics. The most important obstacles are identified as data quality and availability. Most organisations do not have standardised, complete, and reliable datasets of historical projects, and thus, their data landscapes are fragmented, which weakens the training of models, as well as their validation and generalizability (Rusum & Anasuri, 2024; Selvarajan, 2023). Lack of data consistency, information system silos, incomplete data governance frameworks, etc., also restrict the scalability of AI solutions across projects and portfolios (Viacheslav, 2022).

The issue of trust, transparency, and interpretability is also of equal importance. Complex AI models, especially deep-learning-based ones, are often viewed with distrust by project managers due to the perceived aspect of the black box and lack of explainability (Mayer *et al.,* 2024; Sauer & Burggraf, 2025). This is more heightened in high-stakes settings where responsibility in terms of cost overruns and delays, as well as risk-taking, is well-grounded on the human aspect. The presence of ethical concerns within AI usage, such as algorithmic bias, excessive dependence on automated suggestions, and privacy concerns, only makes the use of AI more complex in the area of healthcare and project setup in the public sector (Ed-Driouch *et al.,* 2022; Lutz *et al.,* 2025).

Table 3: Key Implementation Challenges in AI-Augmented Project Management

Challenge Category	Description	Impact on AI Effectiveness	Representative Sources
Data Quality and Availability	Incomplete, inconsistent, or siloed project data	Reduces model accuracy and generalizability	Rusum & Anasuri (2024); Selvarajan (2023)
Model Interpretability	Black-box nature of deep learning models	Limits trust and adoption	Mayer *et al.* (2024); Sauer & Burggräf (2025)
Organizational Readiness	Limited analytics skills; resistance to AI	Weak integration into decisions	Viacheslav (2022); Taj (2025)
Ethical and Governance Concerns	Bias, accountability, data privacy	Restricts use in regulated contexts	Ed-Driouch *et al.* (2022); Lutz *et al.* (2025)
Tool–Process Misalignment	Poor integration with PM workflows	Underutilization of insights	Thota (2024); Job (2025)

Table 3 is a response to Research Question 3 because it classifies the most common barriers to AI adoption. The table highlights that the issues of implementation are socio-technical and not simply algorithmic. The most problematic constraints are found to be data quality and interpretability, thus supporting the argument of the review that technological capability in itself does not ensure performance improvement.

As a reaction, the literature narrows down to the usefulness of hybrid human-AI models as a viable solution that is ethically acceptable. Instead of making AI a decision-maker, hybrid solutions integrate AI-enhanced ideas, like probabilistic risk ratings, cost projections, and schedule diagnostics, into formal processes of expert evaluation and management (Dellermann *et al.,* 2021; Molenaar, 2022). Empirical research indicates that AI analytics, as applied alongside expert judgment, Monte Carlo simulation, and scenario analysis, can be used to achieve a better understanding of the results, develop trust, and improve decision quality (Erten *et al.,* 2025; Semenov *et al.,* 2025). Such hybrid frameworks match the AI outputs with organisational strategy, stakeholder expectations and contextual realities, resulting in more adoption and creation of value in the long term.

Table 4: Role of Hybrid Human–AI Models in Addressing Implementation Challenges

Hybrid Model Feature	AI Contribution	Human Expert Contribution	Resulting Benefit	Key References
AI + Expert Risk Review	Probabilistic risk ranking	Contextual validation	Improved trust and accuracy	Dellermann *et al.* (2021); Molenaar (2022)
AI + Monte Carlo Simulation	High-speed computation	Assumption calibration	Robust uncertainty analysis	Salleh & Aziz (2023); Sinha & Ahmed (2025)
Explainable AI Dashboards	Pattern detection	Interpretation and decision-making	Transparency and accountability	Sauer & Burggräf (2025); Mayer *et al.* (2024)
AI-Supported PMO	Predictive insights	Strategic oversight	Portfolio-level optimisation	Qureshi (2025); Ayeni (2025)

Table 4 summarises the countermeasures of constraints noted in Table 3 by hybrid human-AI models. It has been shown that hybrid configurations increase trust and interpretability and ethical governance, making AI insights more practical. This table makes the main argument of this review practical, where AI is provided with the highest value when integrated into project governance systems that are expert-led.

Synthesis and Implications

A combination of findings of all three research questions suggests that AI-enhanced predictive analytics represent a significant breakthrough in project and program management, which has essentially transformed risk, cost, and schedule performance monitoring and management. The use of advanced AI methods significantly increases predictive accuracy and timeliness, thus allowing the deviations to be identified sooner and the managerial intervention rely on more accurate information. However, it is also evident in the evidence that AI by itself is not a sustainable value-creating autonomous technological solution.

Theoretically, the findings are in line with emerging conceptualisations of considering project control as a predictive, adaptive and learning process as opposed to a mere monitoring role that is purely statistical. The combination of AI helps in learning continuously, dynamic prediction, and making evidence-based decisions at each stage of the project lifecycle. In practice, the findings highlight the need to ensure that organisations invest in AI technologies, as well as in data governance, analytical ability, human skill, and ethical management systems.

Future studies should focus on longitudinal and comparative research that assesses AI-enabled project systems in the long-term, explore explainable AI techniques that are specific to project management situations and create maturity models of hybrid human-AI project governance. These efforts are critical to the fulfilment of the full potential of the AI-enhanced predictive analytics as the foundation of the next generation project and program management.

CONCLUSION

The current review proves that predictive analytics based on AI is changing the sphere of project and project management with specific references to risk and cost management and schedule control. Compared to traditional deterministic procedures, AI and machine-learning approach allow detecting abnormal trends earlier, increasing the accuracy of forecasting, and proactive decision making. However, the effectiveness of these methods depends on the quality of data, organisational preparedness, openness and ethical control. As empirical data always shows, the most significant gains of AI are being achieved once it becomes a part of hybrid human-AI systems that combine computational intelligence and expert judgement. Instead of replacing managerial skills, AI-enhanced analytics supplements dynamic project control and organisational learning by implementing it in a human-centered way.

Recommendations

The use of hybrid AI-human decision-making systems, not complete automation, should be prioritised by organisations, governance and standardisation of project data should be strengthened, and explainable AI models should be used to enhance trust and accountability. It is essential to develop AI literacy and analytical skills among professionals of the project. Further studies need to focus on longitudinal, industry-specific evaluations of hybrid AI systems throughout the project life cycle and focus on their long-term organisational and ethical consequences.

REFERENCES

Abaneme, O. G., Ezenwaka, C., Popoola, R., Soetan, O., Obajaja, H. A., & Umah, E. (2025). Augmented Project Management: Exploring the Role of AI Tools in Decision-making and Resource Optimisation. *Asian Journal of Advanced Research and Reports, 19*(7), 258-271.

Adamantiadou, D. S., & Tsironis, L. (2025). Leveraging artificial intelligence in project management: A systematic review of applications, challenges, and future directions. *Computers, 14*(2), 66.

Adejumo, O. A., Asemota, O. J., & Olanrewaju, S. O. (2025). R-Shiny web application development for multilayer perceptron state switching model for predicting regimes of time series returns. *American Journal of Smart Technology and Solutions, 4*(2), 70–79. https://doi.org/10.54536/ajsts.v4i2

Afhayma, S., & Youssef, M. I. (2025). The Future of Project Scheduling: Leveraging Machine Learning for Precision Planning. *International Journal of Humanities and Information Technology, 7*(03).

Ajibade, O. M. (2025). AI Enhanced Project Management: Leveraging Predictive Analytics and Intelligent Automation.

Akinboboye, I. O., Okoli, I., Frempong, D., Afrihyia, E., Omolayo, O., Appoh, M., ... & Umar, M. O. (2022). Applying predictive analytics in project planning to improve task estimation, resource allocation, and delivery accuracy. *International Journal of Multidisciplinary Research and Growth Evaluation, 3*(4), 675-689.

Alam, K. R., Barua, C., & Kabir, J. U. Z. (2025). The Future of Agile: Utilizing AI Together with Machine Study to Support Real Time Project Control and Modifying Decision Making. *Journal of Innovative Science and Research Technology, 10*(1), 1004-1007.

Alemde, V. O. (2025). Deploying strategic operational research models for AI-augmented healthcare logistics, accessibility, and cost reduction initiatives. *Int Res J Mod Eng Technol Sci, 7*(2), 2353.

Almalki, S. S. (2025). AI-Driven Decision Support Systems in Agile Software Project Management: Enhancing Risk Mitigation and Resource Allocation.

Systems, 13(3), 208.

Ayeni, O. (2025). Strategic Portfolio Optimization: Balancing Agile, Lean Six Sigma, and AI-Augmented Resource Allocation Models. *International Journal of Computer Applications Technology and Research.*

Battula, Y. (2025). The Role of Artificial Intelligence in Modern Project Management: Trends and Implications for 2025. *International Journal of Engineering, Science, 5*(4).

Bibi, S., Saaed, M. A., & Khan, M. Y. (2024). Advancing Sustainable Project Management: Interplay of Cost, Risk, and Schedule Management with AI and Knowledge Management Processes. *Global Management Sciences Review, 9*(3), 143-154.

Chinonye, A. E., & Onah, B. I. (2025). Assessing the efficacy of AI-based techniques in anomaly detection in financial institutions. *American Journal of Data Science and Artificial Intelligence, 1*(2), 11–17. https://doi.org/10.54536/ajdsai.v1i2

Das, U. (2025). Scaling Agile with AI: Enhancing Large-Scale Agile Frameworks through Predictive Analytics and Automation. *IJSAT-International Journal on Science and Technology, 16*(2).

Dellermann, D., Calma, A., Lipusch, N., Weber, T., Weigel, S., & Ebel, P. (2021). The future of human-AI collaboration: a taxonomy of design knowledge for hybrid intelligence systems. *arXiv preprint* arXiv:2105.03354.

Ed-Driouch, C., Mars, F., Gourraud, P. A., & Dumas, C. (2022). Addressing the challenges and barriers to the integration of machine learning into clinical practice: An innovative method to hybrid human–machine intelligence. *Sensors, 22*(21), 8313.

Erten, G. E., Mokdad, K., Nisenson, J., Brandao, G., & Boisvert, J. (2025). Human-AI Interaction: Machine Learning-Based Geostatistical Hybrid Models. *Applied Soft Computing*, 113580.

Greg, J. (2025). AI-augmented risk identification and mitigation in project management via natural language processing.

Haque, E., Fahad, F. M., Hasan, Z., & Islam, M. B. (2025). Artificial Intelligence in Project Management: Enhancing Decision-Making, Efficiency and Risk Management. *Strategic Data Management and Innovation, 2*(01), 62-77.

Hasan, K. M., & Islam, A. (2025). AI Augmented Project Management: Using Machine Learning to Improve Delivery Outcomes. *Pacific Journal of Business Innovation and Strategy, 2*(4), 173-182.

Hriday, M. S. H., & Rehman, A. (2025). Artificial intelligence and machine learning applications in construction project management: enhancing scheduling, cost estimation, and risk mitigation. *International Journal of Business and Economics Insights, 5*(3), 30-64.

Job, G. (2025). Evolving Role of IT Program Managers in the Age of AI and Automation. *IPHO-Journal of Advance Research in Science And Engineering, 3*(11), 39-47.

Koszykowski, M., & Orzeszko, W. (2025). Machine learning in project schedule creation: a systematic literature review. *Journal of Scheduling*, 1-18.

Lutz, C., Newlands, G., & Jarrahi, M. H. (2025). Hybrid Intelligence. In *Handbook of Human-Centered Artificial Intelligence* (pp. 1-33). Singapore: Springer Nature Singapore.

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.

Manchana, R. (2022). Optimizing Real Estate Project Management through Machine Learning, Deep Learning, and AI. *Journal of Scientific and Engineering Research, 9*(4), 192-208.

Manu, B. A. (2024). Leveraging Artificial Intelligence for optimized project management and risk mitigation in construction industry. *World Journal of Advanced Research and Reviews, 24*(3), 2924-2940.

Mayer, V., Schüll, M., Aktürk, O., & Guggenberger, T. (2024). Designing Human-AI Hybrids: Challenges and Good Practices from a Multiple Case Study.

Mohamed, A. (2025). Revolutionizing Agile project management: The role of AI in driving innovation overcoming challenges, and enhancing benefits. In Emerging Technologies In *Sustainable Innovation, Management and Development* (pp. 469-478). Routledge.

Mohammed, A. K., & Panda, B. B. (2024). Enhancement of predictive analytics using AI models: A framework for real-time decision support systems. *International Journal of Advanced Research in Computer and Communication Engineering, 13*(11), 80-90.

Molenaar, I. (2022). Towards hybrid human-AI learning technologies. *European Journal of Education, 57*(4), 632-645.

Ongbali, S. O., Ajanaku, O., Salawu, E. Y., & Inegbenebor, A. O. (2025). Exploring the Impact of Generative AI on Enhancing Efficiency in Project Planning and Control. *Nipes Jstr Special Issue, 7*(1), 1529-1542.

Pashazanous, E. (2025). *Exploring the Evolution of Project Management: Harnessing the Potential of Artificial Intelligence for Future Success* (Doctoral dissertation, Politecnico di Torino).

Poudel, S., & Maharjan, S. (2025). Artificial intelligence and education in Nepal: A mixed-methods study on student adoption and learning outcomes. *American Journal of Data Science and Artificial Intelligence, 1*(2), 18–25. https://doi.org/10.54536/ajdsai.v1i2

Qureshi, F. M. (2025). The Algorithmic PMO: AI-Augmented Program Management for the Digital Enterprise. Available at SSRN 5712742.

Rusum, G. P., & Anasuri, S. (2024). AI-Augmented Cloud Cost Optimization: Automating FinOps with Predictive Intelligence. *International Journal of Artificial Intelligence, Data Science, and Machine Learning, 5*(2), 82-94.

Salleh, M. H., & Aziz, K. A. (2022, December). Artificial intelligence augmented project management. In

International Conference on Technology and Innovation Management (ICTIM 2022) (pp. 274-284). Atlantis Press.

Salleh, M. H., & Aziz, K. A. (2023, February). Artificial Intelligence Augmented Project. In *Proceedings of the International Conference on Technology and Innovation Management (ICTIM 2022)* (Vol. 228, p. 274). Springer Nature.

Sauer, C. R., & Burggräf, P. (2025). Hybrid intelligence–systematic approach and framework to determine the level of Human-AI collaboration for production management use cases. *Production Engineering, 19*(3), 525-541.

Savaş, S. (2025). Artificial intelligence in construction project management: Trends, challenges and future directions. *Journal of Design for Resilience in Architecture and Planning, 6*(2), 221-238.

Selvarajan, G. P. (2023). Augmenting Business Intelligence with AI: A Comprehensive Approach to Data-Driven Strategy and Predictive Analytics. *International Journal of All Research Education and Scientific Methods, 11*(10), 2121-2132.

Semenov, I., Jacyna, M., Auguściak, I., & Wasiak, M. (2025). Hybrid Human–AI Collaboration for Optimized Fuel Delivery Management. *Energies, 18*(19), 5203.

Sheikh, A., Sheikh, M. S., & Rinvee, T. M. (2025). Smart transportation systems with artificial intelligence: Enhancing efficiency, safety, and sustainability. *American Journal of Smart Technology and Solutions, 4*(2), 87–90. https://doi.org/10.54536/ajsts.v4i2

Sinha, M. K., & Ahmed, J. (2025). *Project Management Control: Planning and Role of AI*. Pen and Paper Academy.

Szwarcfiter, C., Herer, Y. T., & Shtub, A. (2023). Balancing project schedule, cost, and value under uncertainty: A reinforcement learning approach. *Algorithms, 16*(8), 395.

Taj, M. A. A. (2025). Artificial Intelligence Integration in Enterprise Project Management: Transforming Traditional Frameworks Through Automated Decision-Making and Strategic Communication. *Journal Of Engineering And Computer Sciences, 4*(9), 87-92.

Tanim, S. H., & Ahmad, M. S. (2025). AI driven strategic decision-making in IT project management: Enhancing risk assessment, cost control, and efficiency. Available at SSRN.

Thota, R. C. (2024). AI-augmented predictive analytics for proactive cloud infrastructure management. Journal of Science & Technology, 5(4), 246.

Tickoo, M. Y. S., & Kannan, M. P. (2025). AI For Project Management: Predictive Scheduling And Risk Monitoring. Artificial Intelligence and Machine Learning in Management Science: Emerging Research and Applications, 199.

Viacheslav, L. (2022). The AI-Powered PMO: Leveraging Automation and Analytics for Strategic Advantage. Universal Library of Engineering Technology, (Issue).

Yakkanti, P. R. (2025). AI-Augmented DevOps for Application Modernization: Transforming Software Development and Operations. *Journal of Computer Science and Technology Studies, 7*(2), 368-376.