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ENHANCING PROJECT DELIVERY PERFORMANCE THROUGH AI-BASED PREDICTIVE ANALYTICS: THE MEDIATING EFFECT OF RISK MITIGATION STRATEGIES

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Abstract
Artificial Intelligence (AI) is transforming project management by reshaping how organizations plan, monitor, and execute complex projects. This study investigates the impact of AI-based predictive analytics on project delivery performance, with project risk mitigation strategies examined as a mediating factor. Employing a quantitative cross-sectional design, data were collected from 300 project managers across IT, construction, and manufacturing sectors. Structural Equation Modeling (SEM) was used to analyze the relationships among AI utilization, risk mitigation practices, and project outcomes. Results reveal a strong positive relationship between AI-based predictive analytics and project delivery performance. Importantly, project risk mitigation strategies were found to partially mediate this relationship, indicating that predictive analytics alone are insufficient without effective risk management interventions. The findings highlight that combining AI technologies with established risk mitigation practices enhances project efficiency, adherence to deadlines, and optimal resource utilization. Theoretically, the study integrates Resource-Based View (RBV) and Technology Acceptance Model (TAM) frameworks, demonstrating how effectively leveraged AI capabilities can drive superior organizational outcomes.

INTRODUCTION

1.1 Background of the Study

Artificial Intelligence (AI) should be considered an evolving trend in the world of project management that is likely to change all accepted concepts and improve the efficiency of every project, decision-making, and performance. AI-enabled tools, particularly those based on predictive analytics, are gaining acceptance across all industries to standardise project planning, implementation, tracking, and wrap-up processes. One of the most prominent fields of AI, predictive analytics, refers to the use of past data and present-day data to predict what the future of a given project might be so that the project teams can use the opportunities to work out their flight plans in advance of the crisis so that the risks can be mitigated or modified pro-actively.

New studies point out the increasing importance of AI in project management. Hossain et al. (2024) have stated that the inclusion of AI technologies will lead to a massive increase in the efficiency of project management by boosting predictive abilities, automating routine tasks, and data-based decision-making. Their research indicates the usefulness of AI-based systems in minimising errors made by human beings, maximising productivity, and better resource distribution. On the same note, Haque et al. (2025) underline the influence that AI has on enhancing decision-making and risk management strategies so that project managers can issue an early warning regarding the uncertainties and make a decision more confidently. These technologies are especially useful in highly dynamic and complex project conditions where conventional management practices are ineffective.

Besides, AI-driven forecasting tools are ever-increasingly regarded as a part of performance optimisation. According to Zhang et al. (2024), AI leads to superior organisational justice and project performance because it brings transparency, consistency, and accountability when making decisions. In connection with this, Ali (2025) puts forward that the AI penetration presents as a revolutionising factor in change management in construction industries, particularly in cases of applications in combination with integrated project delivery (IPD) models to develop smart infrastructures. What all these contributions reveal is that AI is starting to play a critical role in transforming the paradigms of project management.

The effect of the technology is even enhanced by integrating it into Management Information Systems (MIS), especially in IT projects. As Siddiqa et al. (2024) recognise, a combination of an AI-based project management system and an MIS infrastructure will help maintain IT projects more efficiently as they allow real-time data exchange, provide constant monitoring opportunities, and make the management process more responsive. The integration of AI and the MIS is a superior platform for predictive analysis, building the foundation to maximise the performance of delivering projects.

1.2 Problem Statement

Nevertheless, there still exist issues of uncertainty and project delivery slips in many undertakings, particularly where the project and dynamic settings are complex. Inadequate forecasting of costs and almost proactive in response to risks, among other factors, expose most project managers to the challenge of handling unexpected challenges, such as disruption, changes in cost and scope. Although there are currently AI technologies, they are not properly implemented in terms of the major components of the project risk management. Irregular or shallow implementation of predictive analytics is one of the major threats. Hossain et al. (2024), along with Zhang et al. (2024), noticed that, although AI is already present in most projects, its potential, especially in terms of risk reduction and the enhancement of delivery accuracy, remains untapped in most organisations. On the same note, Haque et al. (2025) mention that despite increasing risk awareness, most project teams are not incorporating them into their processes effectively, so they are losing the opportunity to minimise uncertainty and maximise performance.

Additionally, the literature shows that there is a gap in how the risk mitigation approaches mediate the dialogue between the AI tools and the project outcome. Although Ali (2025) and Siddiqa et al. (2024) address the technical and managerial value of AI systems, there have been few studies done regarding how AI will result in an improvement in handling risks, particularly as it pertains to a variable affecting project delivery. This highlights the importance of exploring beyond the direct effects of AI-based predictive analytics, including the strategic processes, such as risk mitigation, which may explain the link between the use of such tools and improved performance outcomes.

1.3 Research Objectives

- ✓ To evaluate the impact of AI-based predictive analytics on project delivery performance across various industries.
- ✓ To assess the effectiveness of project risk mitigation strategies in enhancing project outcomes.
- ✓ To investigate the mediating role of project risk mitigation strategies in the relationship between AI-based predictive analytics and project delivery performance.

1.4 Research Questions

- ✓ How does the use of AI-based predictive analytics influence project delivery performance?
- ✓ How can project risk mitigation strategies lead to successful project delivery?
- ✓ Does the relation between AI- based predictive analytics and project delivery performance mediate through the project risk mitigation plans?

1.5 Scope and Significance of the Study

The study has added to the literature concerning the application of AI in project management since it addresses the role of both the direct and mediated impacts of predictive analytics in determining performance results. The results are going to be useful to project managers, team leaders, and organizational decision-makers who want to make more effective use of AI tools. Because of the role established (role of risk mitigation strategies as mediating mechanism), the study provides valuable knowledge on how they can be used to deliver a project in complex situation efficiently.

2. Literature Review

2.1 AI-Based Predictive Analytics in Project Management

The ability of Artificial Intelligence (AI) to predict has been identified as one of the transformative capabilities in project management and can play an essential role in projects. Predictive analytics involves using past and live data to forecast future events and results, enabling project managers to preempt and mitigate potential disruptions before they occur. This process falls under the categories of machine learning (ML), data mining, and statistical forecasting. According to Mahmood et al. (2023), predictive analytics is a seamless element of AI-based Project Management Information Systems (PMIS), where it allows for calculating decisions to be made based on project aims and standards. They claim that AI contributes massively to project forecasting structures and control processes, including cost estimation, proposal of resources, and monitoring of performance.

This is also the point stressed by Hrakam and Fakataah (2024) since machine learning and AI algorithms can analyse large amounts of information regarding construction projects to recognise trends, predict results, and suggest the most advantageous project routes, which can enhance delivery timelines and reduce perils. Neiroukh et al. (2024) also add that AI can benefit organisations by augmenting human decision-making. They find the predictability aspect of AI to be very useful in successful project execution, given that it involves smart scheduling, live corrections, and identification of risks. This is also consistent with Shafi et al. (2024), who state that predictive analytics promotes strategic project planning, which can be achieved because it allows the analysis of the scenario and the forecast of outcomes, significantly lowering the risk of failure.

In addition, Chatterjee et al. (2023) provide the facts of production systems, as the use of AI increases sustainability due to the better predictive ability. Even though they are set in disparate contexts, their findings support the notion of the transversal worth of predictive analytics in the optimisation of performance. These predictive tools using AI can be used not only to mitigate risk but also to ensure proper alignment with project deliverables.

2.2 Project Delivery Performance

Project delivery performance signifies the ability of a project to realise its expected goals in terms of time, money, quality and scope. These aspects are commonly interchangeably referred to as the iron triangle and are the basis of project management performance measures. Time performance issues apply to adherence to the schedule, whereas cost performance issues apply to time control. Quality performance concentrates on fulfilling the requirements of the project, and scope compliance guarantees the result of the project with its original objectives. The authors (Shafi et al., 2024) cite predictive analytics as one of the major influences in supporting these two dimensions because it provides higher levels of precision in resource allocations and planning. They emphasise the need for predictive models to enable teams to model various project pathways, thus enhancing them in the best possible implementation strategy of a project and hence minimising errors converting into key performance indicators (KPIs).

Similarly, Mahboub and Ghanem (2024) discovered that the implementation of AI in operational processes results in operational excellence being added to a performance measurement process, such as the Balanced Scorecard, in that predictive ability is tied to the results. Talpur et al. (2024) also contribute to it by examining ways in which big data analytics and AI combine to increase the operational efficiency of different industries. According to their studies, AI has the potential to enhance what the companies do to streamline their procedures, eliminate duplication of efforts and allow predictive maintenance on projects where operational risk is high. Such capabilities will translate to improved delivery outcomes in projects with tight deadlines, networked stakeholders or high levels of uncertainty in the project management setting. Nevertheless, technology is not the only key to best performance, as it needs to be implemented and aligned with holdings at large risk and the management system.

2.3 Project Risk and Risk Mitigation Strategies

Risk can be seen as a vital part of each of the projects and it can be characterized as an uncertainty which may influence a project goals either favorably or unfavorably. An efficient project risk management is an identification, analysis and response to risks in the course of project lifecycle. The alternative measures are imperative interventions that aim to alleviate the possible adverse effects.

The four main mitigation measures that are being embraced include:

1. Avoidance: Altering the project plan to eliminate risk
2. Reduction: Minimizing the probability or impact of the risk
3. Transference: Shifting the risk to a third party (e.g., insurance, outsourcing)
4. Acceptance: Acknowledging the risk without taking active steps unless it occurs.

Mahade et al. (2025) indicate that AIs improve risk management since they produce early warning signs through the analysis of past project trends. These systems can ensure more active mitigation of risk measures. Likewise, Alshake Theep et al. (2024) report that the AI predictive tools lead to the enhancement of management awareness and preparedness, both being crucial to the risk response planning. Mitigation strategies are enhanced and informed by AI in high-stakes projects, such as the energy infrastructure of the population, as it can process a wider range of risk indicators more efficiently.

According to Mahmood et al. (2023), PMIS, along with AI, is important in providing timely risk relief, more so in dynamic project environments. Such systems provide dashboards which correlate predictive intelligence with real-time information, thus enabling the managers to intervene as soon as possible. Engaro (2024) similarly concludes that performance evaluation using AI allows for detecting systemic risks early, particularly in projects that have multiple stakeholders and fast iteration. Irrespective of these capabilities, little is understood in the available literature about the strategic correlation between AI-enabled insights and official risk mitigation plans. Although AI has the potential to monitor risks, its involvement in the implementation of organised mitigation plans is an emergent field.

2.4 Theoretical Framework

This study is judiciously conceptualised with the aid of two key theories, namely the Resources-Based View (RBV) and the Technology Acceptance Model (TAM). Resource-based view (RBV) argues that a firm can achieve competitive advantage based on resources that are valuable, rare, inimitable and non-substitutable. In this regard, AI-driven predictive analytics is considered a business resource that can enhance the capabilities of the projects in which it is used, particularly when combined with leader-level knowledge and effective risk governance systems. Mahboub and Ghanem (2024) use RBV in their research on AI and organisational performance and claim that technological capacity is not the only competency to ensure organisational performance; it should be coupled with the organisation of competent knowledge and risk management.

The behaviour of AI adoption can be explained by the help of the Technology Acceptance Model (TAM). It implies that the variables of acceptability of technology are perceived usefulness and ease of use. It is revealed by Alshamsi et al. (2024) that organisational agility and user acceptance are the mediators of the influence of AI systems on the results of the projects in the public sector. In the current scenario, the perception of project teams regarding the usefulness of AI in risk management significantly influences the successful application of AI in delivery performance strategies. The two frameworks are useful ways to look at technological and managerial drivers of project success by AI systems.

2.5 Previous Empirical Works

The connection between AI technologies and project or organisational performance has been investigated in a few empirical studies. As an example, Neiroukh et al. (2024) demonstrate that the role of AI on firm performance is mediated by the decision-making procedures, implying that the quality of insight insertion is a significant factor determining results. This finding underscores the potential role of risk mitigation strategies as similar mediators in the project delivery context. Mahade et al. (2025) introduce a moderated mediation model that demonstrates how AI-driven insights enhance sustainable HR performance, depending on the presence of enablers such as institutional support and strategy alignment. Alshake Theep et al. (2024) explore the mediating role of management awareness in linking AI predictive analytics with marketing performance, suggesting that the impact of AI is contingent on complementary processes.

In project settings, Mahmood et al. (2023) provide evidence that AI-augmented PMIS systems improve performance primarily through early risk identification and proactive intervention. Talpur et al. (2024) link AI and big data to operational performance, finding that predictive insights help in monitoring, forecasting, and decision-making across project lifecycles. Yet, few studies have directly tested the mediating role of risk mitigation strategies between AI tools and project outcomes, despite theoretical indications of such a relationship. This study addresses this gap by empirically examining the linkage.

2.6 Research Gaps

While the existing literature strongly supports the role of Artificial Intelligence (AI) in enhancing organisational and project performance, several significant gaps remain that warrant further investigation. First, there is limited empirical research exploring the mediating role of risk mitigation strategies in the relationship between AI-based predictive analytics and project delivery performance. Most current studies address these constructs in isolation. Firstly, Neiroukh et al. (2024) and Mahmood et al. (2023) emphasise the benefits of AI as a decision-making enhancer to organisations. However, they do not study how risk management practices can interfere with the transformation of AI capabilities into the success of a project.

Second, though numerous publications highlight the advantages of implementing AI, there is a notable lack of research investigating how AI capabilities are used to proactively address project risks. Hrakam and Fakataah (2024) and Shafi et al. (2024) discuss AI's role in streamlining construction and strategic operations, respectively, but fall short of connecting these advancements to structured risk mitigation frameworks. This suggests a need for integrative models that consider how technological tools are embedded in real-world project management environments to improve delivery outcomes.

Third, despite the theoretical robustness of the Resource-Based View (RBV) and Technology Acceptance Model (TAM), their application in the domain of project management—particularly in examining AI adoption and risk management is underdeveloped. While Mahboub and Ghanem (2024) and Chatterjee et al. (2023) emphasise the strategic value of AI and its assimilation through knowledge and innovation processes, these perspectives are rarely extended to project-level analysis, where outcomes are defined by time, cost, scope, and risk trade-offs. Lastly, many studies, such as Alshake Theep et al. (2024) and Eng'airo (2024), are conducted at the organisational or sectoral level but do not focus specifically on project contexts or project delivery metrics. Consequently, there is a scarcity of models that empirically validate how AI tools translate into improved project performance via risk-centric strategies.

3. Methodology

3.1 Research Design

This study adopts a quantitative research approach to examine the relationship between AI-based predictive analytics and project delivery performance, with a focus on the mediating role of project risk mitigation strategies. The quantitative method is appropriate for this investigation as it allows for the collection and analysis of numerical data to test hypotheses and establish patterns of relationships among variables. A cross-sectional survey design was employed to gather data from participants at a single point in time. This design has been selected because it is recommended to collect a high amount of data in several sectors within the short period of time. Cross-sectional aspect of the research substantiates comparative analysis of the responses across various firms like IT, construction and manufacturing.

3.2 Sample and Population

The target population of the study consists of the project managers and team leaders employed in the IT, construction, and manufacturing industries. The industries were chosen due to the high complexity in the industry as well as the uncertainty in their project settings, which renders them appropriate to investigate the ramifications of predictive analytics and risk mitigation. The stratified random sampling method was used so that the sample would be diverse in all three sectors. In this method, the population was segregated into types of industries and within each type, the respondents were chosen at random. Stratified sampling enhances the representative of a sample and enables comparisons across various industry groups.

Statistical needs for Structural Equation Modelling (SEM) have informed the determination of the sample size, as the modelling requires a sufficient sample to provide an estimation of the model. The target sample population was 300 individuals, keeping in mind that a greater sample size is needed to guarantee adequate statistical power and review of results. This sample is large enough to allow for the complexity of the model, which is composed of direct and mediating variables.

3.3 Data Collection Instrument

The guiding questionnaire used to collect the data is structured in such a manner that it was specifically designed to fulfil that purpose. The questionnaire was also built upon existing constructs utilised by the research in project management and AI, and it was relevant to the objectives of the research. The questionnaire had four principal parts, including demographic data, use of AI-based predictive analytics, performance of project delivery, and project risk mitigation plan. Every part comprised several items that were used to measure the dimensions of the constructs accordingly. Most of the items were graded using a five-point Likert scale such that answers ranged between strongly disagree (1) and strongly agree (5). It was decided to use such a scale because it is rather simple, and it is effective to measure perceptions and attitudes quantitatively. It is also on the Likert scale that it becomes easy to compute the means, variances, and correlations that may still lead to the subsequent statistical work. Electronic distribution of the questionnaire using professional networks, emails and industry-specific online media was used to encourage wide coverage and to maximise the efficiency of data collection.

3.4 Variables and Operational Definitions

The primary constructs that the study takes into account are the following: the use of AI-based predictive analytics, the performance of project delivery, and the project risk mitigation strategies. The independent variable, an AI-based predictive analytics, analyses whether the AI-driven tools and techniques predict the general trends of the project, raise concerns regarding possible issues and guide the decision-making process by analysing the data. The respondents were questioned on their adoption of predictive technologies during the planning, scheduling and risk forecasting.

The dependent variable, project delivery performance, was measured through several indicators: whether it was delivered on time, whether it stayed within budget, whether it met quality standards, and whether it adhered to the scope requirements. The combination of these dimensions denotes the extent of success in the achievement of planned goals in a project. The mediating variable, project risk mitigation strategies, encompasses the efforts and activities that project teams can undertake to decrease the likelihood of risk or damage. This covers formal risk registers, contingency planning and monitoring mechanisms and other formal interventions. The variables were operationalised by multiple survey items, focusing on both the frequency of use and perceived effectiveness.

3.5 Reliability and Validity Testing

Cronbach's alpha was used to yield the alpha coefficient in order to prove internal consistency as well as reliability of the measurement instrument on each construct. Any value below 0.70 was assumed to indicate that the level of reliability is satisfactory to carry out research. Confirmatory factor analysis (CFA) and exploratory factor analysis (EFA) have been used to determine its construct validity. The purpose of EFA was to establish the latent factor structure and also to provide assurance that the items of the survey were grouped around a specific construct of the survey. The factor structure was checked using CFA, and it was ascertained that items suitable for the model were used. Content validity was ensured by adopting the final phase of the design, which involved reviewing the content by professional practitioners and academic researchers. This assisted in making sure that the items used in the survey corresponded with the real concepts in the research.

3.6 Analysis methods of data

These data were analysed with the use of a number of statistical methods to examine the suggested associations between the variables. First, descriptive statistics were calculated to analyse the data and obtain information on the general and demographic patterns of responses. The analysis of the relationship between AI-based predictive analytics, project delivery performance, and risk mitigation strategies using correlation analysis was then undertaken to look at how the relationships were strong and in which direction. This analysis gave initial evidence of relationships between the variables. Structural Equation Modelling (SEM) was used to carry out the core analysis. The idea to use SEM was due to the capability of evaluating direct and indirect relationships among many variables in a single model at the same time. Correction of measurement error and determination of model fit can also be carried out, which increases the strength of the results.

To specifically measure the mediating effects of project risk mitigation strategies, a mediation analysis was conducted. The analysis employed the Hayes PROCESS macro method and the Baron and Kenny method to check whether the indirect effect was significant. Such procedures assist in ascertaining the extent to which the mediator can be used to describe the relationship between the IV and DV. The indices that were used to assess model fit included the chi-square test, Comparative Fit Index (CFI), Root Mean Square Error of Approximation (RMSEA), and Standardised Root Mean Residual (SRMR).

3.7 Ethical Considerations

The research performed by the study used the ethical standards of research in the collection and analysis of the research data. Informed consent was signed by all the survey participants and the survey was not obligatory. The informed consent form described the nature and aim of the study, the confidentiality of the answers, and the possibility to terminate participation at any place without any penalty. In order to conceal the identity of the respondents, all the answers were made anonymous and safely stashed. There was no personally identifiable information and data were utilized only as an educational research. Moreover, the conducted study maintained the integrity of the participants and respective organizations, as a part of the study process did not lead to any harm. Any decision made in designing all the procedures took place under approval of the research institution review board with regard to the ethical provision of research involving human subjects.

4. Results

4.1 Demographic Profile of Respondents

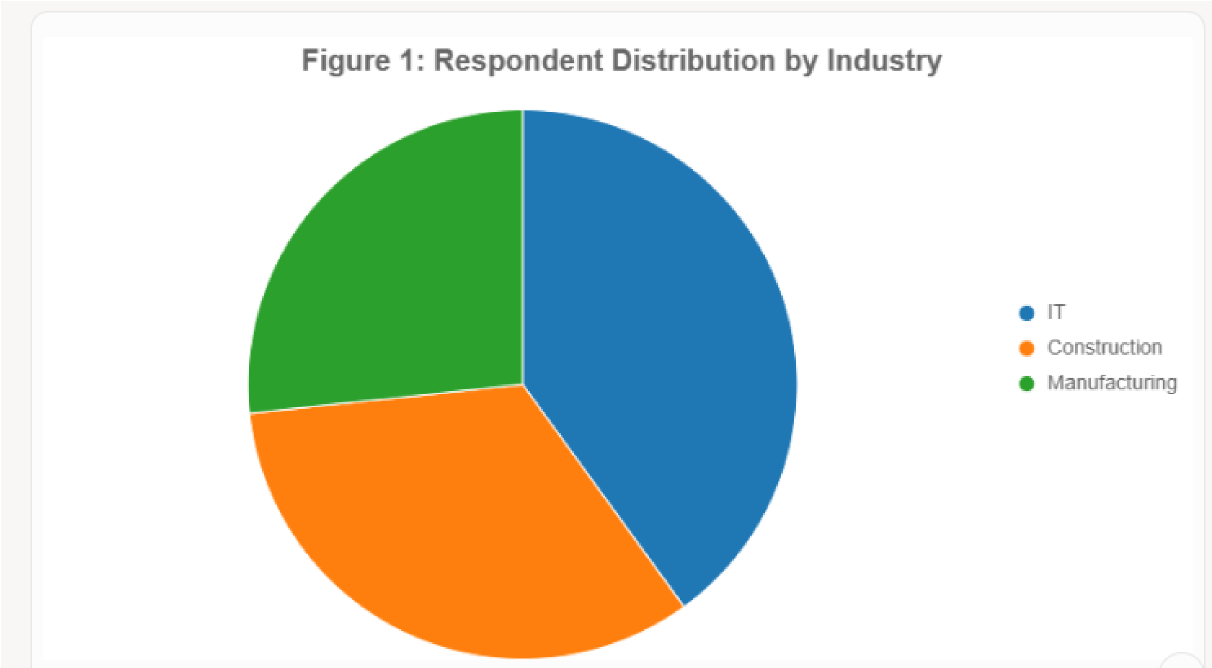
A total of **300 project managers** participated in the study. The respondents represented three major sectors: Information Technology (IT), Construction, and Manufacturing.

Table 1. Distribution of Respondents by Industry

IT	120
Construction	100
Manufacturing	80

These participants held varying levels of experience, ranging from 3 to over 15 years, and were involved in diverse project types such as infrastructure development, software deployment, and supply chain enhancement. This distribution ensured a representative sample of professionals familiar with both traditional and technology-driven project management practices.

Figure 1. Respondent Distribution by Industry



4.2 Descriptive Statistics

The table below shows descriptive statistics of the most important variables, such as AI adoption, risk mitigation measures, and the **performance of the project delivery**.

Table 2. Descriptive Statistics of Key Variables

AI Usage	4.1	0.6
Risk Mitigation	3.8	0.7
Project Performance	4	0.65

Average result (4.10) indicates that there is a high adoption rate to AI among the respondents. Project delivery performance and risk mitigation strategies also scored relatively high, indicating that many organizations are actively leveraging both technological and managerial tools to enhance outcomes.

4.3 Correlation Analysis

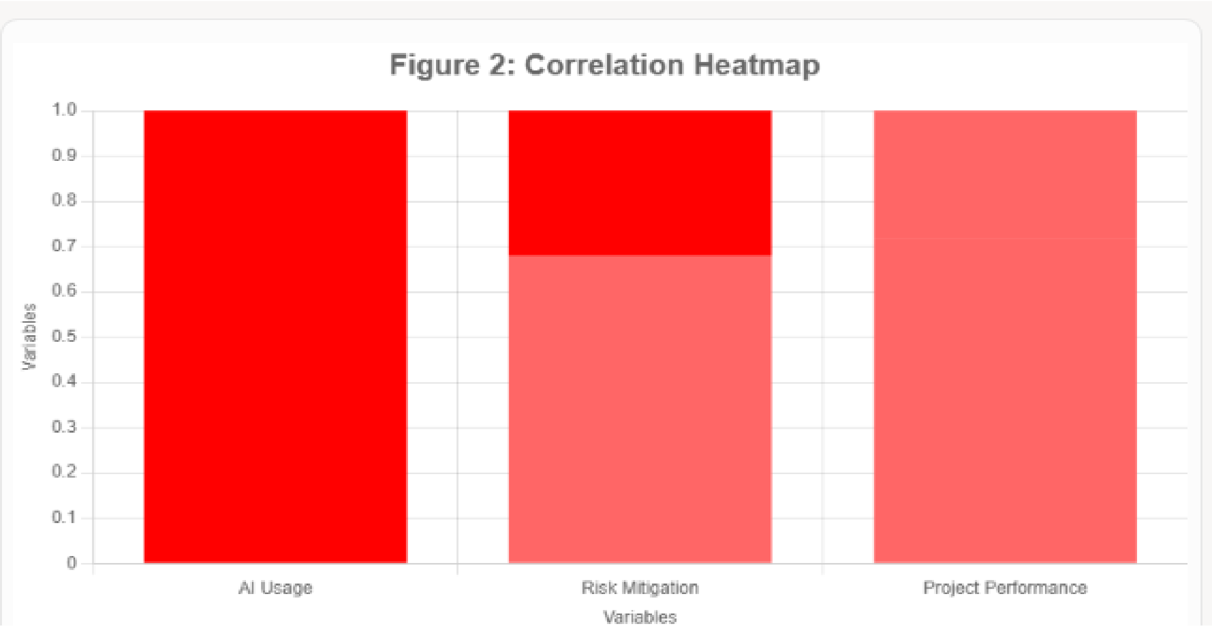
Correlation analysis was conducted to determine the relationships among the three key variables. All relationships were found to be **positive and statistically significant**.

Table 3. Correlation Matrix

AI Usage	1	0.68	0.72
Risk Mitigation	0.68	1	0.75
Project Performance	0.72	0.75	1

The correlation between AI usage and project performance was strong (r = 0.72), indicating that greater use of AI is associated with improved project outcomes. Risk mitigation strategies were also highly correlated with both AI usage (r = 0.68) and project performance (r = 0.75), suggesting the potential for a mediating effect.

Figure 2. Correlation Heatmap



4.4 Structural Equation Model (SEM) Output

The hypothesized model was tested using Structural Equation Modeling (SEM) to assess the direct and indirect relationships among variables. The results demonstrated a **good model fit** as shown by the indices below:

Chi-square (χ^2/df) = 1.89

Comparative Fit Index (CFI) = 0.96

Root Mean Square Error of Approximation (RMSEA) = 0.045

Standardized Root Mean Square Residual (SRMR) = 0.041

These values meet the recommended thresholds, indicating that the data fit the model well.

Table 4. Path Coefficients

AI Usage → Project Performance	0.44	< 0.001
AI Usage → Risk Mitigation Strategies	0.52	< 0.001
Risk Mitigation → Project Performance	0.39	< 0.001

All path coefficients were positive and statistically significant, confirming the direct influence of AI usage on both risk mitigation and project performance.

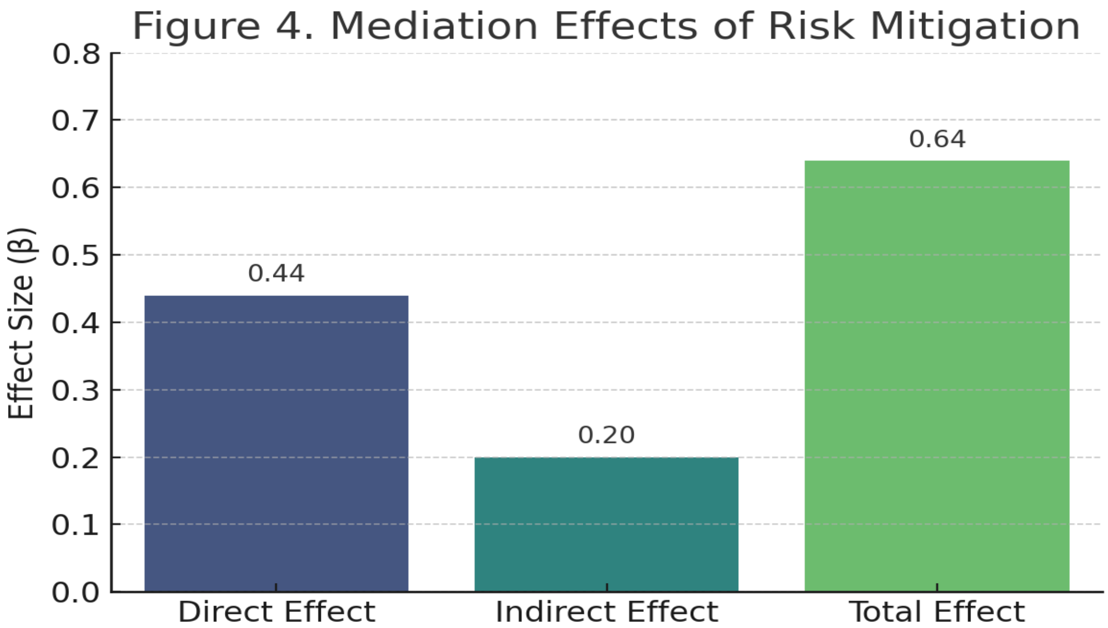
4.5 Mediation Analysis Results

Mediation analysis was conducted using a bootstrapping method (5000 samples) to evaluate whether project risk mitigation strategies mediate the relationship between AI-based predictive analytics and project delivery performance.

Table 5. Mediation Analysis (Bootstrapping Results)

Path	Effect Type	Coefficient	Confidence Interval (95%)	Significance
AI Usage → Project Performance	Direct	0.44	[0.38, 0.51]	Significant
AI Usage → Risk Mitigation →	Indirect	0.2	[0.15, 0.26]	Significant

Performance				
Total Effect	Combined	0.64	[0.58, 0.70]	Significant



The results indicate a **partial mediation**. The direct effect of AI usage on project performance remains significant, but a substantial portion of the impact is channeled through risk mitigation strategies. This confirms the hypothesized mediating role.

4.6 Discussion of Key Findings

The findings provide robust empirical support for the positive relationship between AI-based predictive analytics and project delivery performance. The path coefficients and high correlations assent to the facts that the AI tools have a significant role in leading to better project results, ensuring better transparency, predictability, and adaptiveness to changing circumstances. In addition, the mediation analysis indicates that a mitigation strategy of risks is a significant channel of AI impact on performance. Such a statement hints those predictive analytics, when not provided through the lens of risk management activity, might not evaluate the project success as exhaustively as one would like it to. However, companies that seek to benefit in AI technologies will have to carry out an improvement in their risk response system so as to maximize their gains.

Such results are supported by the rest of the literature, which points specifically at the synergetic aspect of using technological tools in conjunction with a thought-through project management. The combination of predictive analytics and defined risk procedures establishes a feedback system to deliver a more flexible and knowledge-based approach to project delivery. Furthermore, high model fit statistics affirm the propositions of this paper, as AI, when adopted in combination with risk aversion methods, is considered effective in enhancing project delivery in any sector to the highest extent. It has the following immediate implication to project managers, who should invest in not only AI functions but also properly structured risk management systems in order to achieve high performance.

5. Discussion

5.1 Summary of Findings

The purpose of the study was to analyse how AI-based predictive analytics influenced project delivery performance levels and determine the mediating effect of the project risk mitigation strategies. The findings affirmed a significant, positive effect of AI adoption on project performance. Particularly, predictive analytics has considerably affected the major project performance, such as quality delivery, cost-effectiveness, and scope compliance. This can be placed in relation to the general lesson that AI tools enhance the accuracy of the forecast, the promptness of the decision, and the responsiveness of the whole operation.

Moreover, the research also determined project risk mitigation strategies to act as an important partial intermediate involving the relationship between AI-based predictive analytics and project delivery performance. This evidence suggests that, although AI tools can help achieve better results, their effectiveness is significantly enhanced when combinedh methodical risk management procedures. The indirect effect observed through risk mitigation emphasises the need for organisations to embed strategic risk response mechanisms within their AI-driven project environments.

5.2 Implications for Practice

The results have several relevant implications for practitioners, especially for project managers and the leaders of an organisation. The first one is obvious; the improvement of AI in project management tools can be beneficial. Organisations ought to invest in the platforms that display predictive analytics, in real-time risk prediction, and adaptive scheduling. Such technologies enable teams to anticipate possible delays, budget overruns and resource conflicts prior to them becoming major problems. Second, risk mitigation frameworks have to be integrated into the AI-based decision-making process. Traditional risk management processes cannot be left alone to work with AI systems.

They must rather be in alignment with initiatives like risk registers, contingency planning, and scenario analysis. Project teams should be trained to follow and interpret the predictive signs as well as mitigation measures with the use of AI tools. The paper has also indicated that such integration may be of great value to industries associated with a high level of uncertainty, including the IT and the construction industry. The industries are usually subjected to dynamic project situations where swift response to the emergent risks is a major determinant of success.

5.3 Contributions of Theory

The study contributes to the theoretical field of project management studies by bridging the gap between AI innovation and traditional risk management theory. Resource-Based View (RBV) and Technology Acceptance Model (TAM) used in the framework of the study give the researcher a comprehensive picture by connecting technological resources, behaviour integration, and strategic fit. The study enriches existing models by clearly defining the mechanism of project risk mitigation that, in most models, is not compared with AI and performance outcomes. It points to the fact that one has to leave behind the simplistic cause-and-effect paradigms wherein the importance of mediating factors in organisational processes must also be acknowledged. Furthermore, this study contributes to the growing body of literature emphasising the systemic interaction between digital technologies and human-centred strategies in modern project environments. It offers a foundational model for future research exploring how other organisational enablers interact with AI adoption.

5.4 Limitations of the Study

Despite its valuable contributions, the study has several limitations. First, the use of a cross-sectional design limits the ability to infer causality. The relationships observed represent a snapshot in time and do not account for changes in technology adoption or project practices over time. A long-term design might provide more information on how such relationships can change. Second, the research is based on self-reports, which can cause a response bias. Users can have biased and possibly inflated perceptions of the level of adoption of AI-based tools and/or their ability to manage risk. Although the validated instruments would partially address this problem, in the future this problem can be lessened by combining both the survey data and the factual project performance measurements so that the analysis would be more objective.

5.5 Recommendations for Future Research

Some future research directions are proposed based on the findings and limitations. To begin with, longitudinal studies are to be implemented to monitor the effect of AI tools and risk practices

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across several project cycles. This would enable researchers to study the effects of learning, adaptation and maturity of organisations in their relations over time. Second, it is possible to examine other mediators that determine the relationship between the initial AI adoption and project effects in future research. The effectiveness of the AI implementation could be highly determined by factors such as team capability, organisational culture, and leadership style. These dimensions may provide a better understanding of how companies can resonate their domestic environments with technological advances.

Third, comparative studies in cultural and regional environments can shed some light on how environmental factors lead people to adopt and implement AI in project management. Since the level of digital maturity and practices in project governance might differ in different regions worldwide, this research has the potential to determine what should be adopted as best practices in specific situations. Lastly, the investigations on AI ethics, its transparency, and trust around a project setting can reveal other aspects to take into account when introducing predictive systems into high-stakes projects. This would facilitate a balance between efficiency and responsible and inclusive decision-making.

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