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AN ARTIFICIAL INTELLIGENCE DRIVEN FRAMEWORK FOR PREDICTING PROJECT DELIVERY RISKS USING ENTERPRISE RESOURCE PLANNING DATA IN LARGE MULTINATIONAL PROJECTS

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ABSTRACT

The effectiveness of contractor selection and tender bid evaluation significantly influences the success of large multinational projects, where procurement decisions directly impact cost efficiency, schedule performance, and overall project delivery outcomes. Traditional procurement evaluation methods typically rely on additive weighted scoring models and expert judgment, which often fail to capture complex relationships among operational variables and lack the ability to incorporate real-time enterprise data. This study proposes a machine learning–driven framework for tender bid evaluation and contractor selection using operational data extracted from enterprise resource planning (ERP) systems. The framework integrates financial, procurement, workforce, and operational datasets to construct predictive models capable of evaluating contractor performance and estimating delivery risk. A quantitative predictive modeling approach is implemented using multiple machine learning algorithms, including Random Forest, Support Vector Machine, Gradient Boosting, and Deep Neural Networks. Mathematical formulations are developed to transform ERP-derived variables into predictive contractor evaluation scores, enabling a shift from static scoring methods to dynamic, data-driven decision-making. The proposed framework is evaluated through a comparative analysis against traditional procurement scoring models, demonstrating improved predictive accuracy and enhanced capability in identifying high-risk contractor selections. The findings highlight the importance of integrating enterprise data analytics with artificial intelligence techniques to improve transparency, reduce subjectivity, and enhance efficiency in procurement decision processes. The study contributes to the advancement of intelligent procurement systems by providing a scalable and analytically rigorous approach to contractor selection in complex multinational project environments.

KEYWORDS: Machine Learning, Tender Bid Evaluation, Contractor Selection, Enterprise Resource Planning (ERP), Predictive Procurement Analytics.

1. INTRODUCTION

1.1 Background and Context

Large multinational infrastructure, engineering, and information technology projects operate within highly complex environments characterized by distributed teams, multi-layered supply chains, and dynamic resource allocation. These projects frequently encounter delivery challenges such as schedule delays, cost overruns, and operational inefficiencies due to the interaction of financial, logistical, and human resource constraints across geographically dispersed locations. The increasing scale and complexity of such projects have made traditional project monitoring and contractor selection approaches insufficient for ensuring optimal delivery performance (Enyejo et al., 2024; Nwokocha et al., 2021a).

Enterprise Resource Planning (ERP) systems have emerged as critical digital infrastructures for managing and integrating organizational operations in these environments. ERP platforms consolidate data from procurement systems, financial accounting modules, human resource management, and project execution systems into unified databases. These systems generate high-resolution operational datasets that capture procurement cycles, contractor performance records, resource utilization metrics, financial transactions, and supply chain activities. Such datasets provide valuable insights into contractor efficiency, bid performance, and project execution outcomes, making them highly relevant for data-driven tender evaluation and contractor selection processes (Nwokocha et al., 2021b; Nwokocha et al., 2022).

In recent years, artificial intelligence and machine learning techniques have gained significant attention in project analytics and procurement decision-making. Machine learning algorithms are capable of analyzing large-scale enterprise datasets to identify hidden patterns, evaluate contractor performance, and predict project delivery outcomes. These capabilities enable organizations to move beyond traditional scoring systems toward predictive and data-driven contractor selection frameworks. By leveraging ERP data streams, AI models can assess contractor reliability, cost efficiency, delivery timelines, and operational performance, thereby improving the accuracy and objectivity of tender bid evaluation processes (Amebleh et al., 2021; Frimpong et al., 2023).

Furthermore, the integration of machine learning with procurement analytics enables organizations to develop intelligent decision-support systems that enhance transparency and reduce bias in contractor selection. Traditional procurement methods often rely on weighted scoring models that may not fully capture the complexity of contractor performance across multiple operational dimensions. In contrast, AI-driven models can evaluate nonlinear relationships between procurement variables and project outcomes, providing a more comprehensive assessment of contractor suitability. This transformation is particularly important in multinational projects where procurement decisions significantly influence project delivery performance and organizational risk exposure (Onwuzurike & Kpogli, 2022; Idika et al., 2021).

1.2 Problem Statement

Despite the growing availability of enterprise operational data and advancements in artificial intelligence, contractor selection and tender evaluation processes in many organizations continue to rely on traditional scoring methods. These methods typically involve additive weighted scoring models, expert judgment, and manual evaluation processes that are applied during the procurement phase. While such approaches provide a structured framework for comparing bids, they are inherently limited in their ability to capture real-time operational signals and dynamic performance indicators derived from enterprise systems. As a result, procurement decisions may not fully reflect the actual performance capabilities and risk profiles of contractors (Enyejo et al., 2024; Nwokocha et al., 2021a).

Traditional procurement scoring systems often depend on static evaluation criteria such as cost estimates, technical qualifications, and past experience. These criteria are typically assessed independently and combined using predefined weights, which may introduce subjectivity and fail to account for complex interactions between variables. Moreover, such models do not incorporate continuous feedback from project execution data, making it difficult to update contractor performance assessments based on real-time operational conditions. This limitation reduces the effectiveness of procurement decisions and increases the likelihood of selecting contractors who may not perform optimally under actual project conditions (Amebleh et al., 2021; Onwuzurike & Kpogli, 2022).

Another critical limitation is the lack of integration between predictive analytics models and ERP operational datasets in contractor evaluation frameworks. Although ERP systems generate extensive data on procurement activities, financial transactions, workforce performance, and project execution outcomes, these datasets are often underutilized in procurement decision-making processes. Existing predictive models for contractor selection frequently rely on simplified datasets or historical summaries rather than leveraging real-time enterprise data streams. This disconnects between enterprise data systems and predictive analytics limits the ability of organizations to develop accurate and dynamic contractor evaluation models (Frimpong et al., 2023; Nwokocha et al., 2022). Existing predictive models for contractor selection frequently rely on simplified datasets or historical summaries rather than leveraging real-time enterprise data streams. This limitation has been widely identified in AI-driven enterprise systems, where insufficient integration of operational data reduces the effectiveness of predictive decision models and limits real-time adaptability (Onwuzurike & Kpogli, 2022).

In addition, the increasing complexity of multinational procurement environments introduces further challenges for traditional evaluation methods. Projects involving multiple contractors, suppliers, and stakeholders across different regions require decision-making frameworks that can process large volumes of data and account for diverse operational conditions. Manual evaluation processes are often unable to handle such complexity efficiently, leading to delays in procurement decisions and increased risk of suboptimal contractor selection. Machine learning techniques offer the capability to analyze multidimensional datasets and generate predictive insights that improve the accuracy and efficiency of tender evaluation processes (Idika et al., 2021; Amebleh et al., 2021).

Given these limitations, there is a clear need for an integrated machine learning–based framework that leverages ERP operational data for contractor selection and tender bid evaluation. Such a framework should be capable of analyzing enterprise datasets, capturing dynamic performance indicators, and generating predictive insights that enhance procurement decision-making. By comparing machine learning–based evaluation methods with traditional scoring approaches, this study aims to demonstrate the advantages of AI-driven procurement analytics in improving contractor selection accuracy and reducing project delivery risks.

1.3 Research Objectives

The increasing complexity of procurement processes in multinational project environments necessitates the development of intelligent, data-driven frameworks capable of improving contractor selection and tender bid evaluation. This study is therefore structured around three core research objectives that integrate artificial intelligence, enterprise resource planning data, and quantitative modeling techniques.

The first objective is to develop a machine learning–driven framework for tender bid evaluation and contractor selection using ERP-derived operational datasets. The framework is designed to integrate procurement records, financial performance indicators, workforce metrics, and historical contractor performance data into a unified analytical system. By leveraging machine learning algorithms, the framework aims to identify patterns that distinguish high-performing contractors from those associated with elevated project delivery risks.

The second objective is to construct mathematical scoring functions that transform ERP operational variables into quantitative contractor evaluation metrics. Unlike traditional additive scoring methods, which rely on static weights and independent criteria, the proposed model captures nonlinear interactions among variables such as cost efficiency, delivery reliability, and operational performance. The contractor evaluation score can be expressed as a predictive function:

$$S_i = f(X_i)$$

Where S_i represents the predicted performance score of contractor i, and X_i is the feature vector derived from ERP datasets:

$$X_i = (x_1, x_2, x_3, \ldots, x_n)$$

In this formulation, $x_1, x_2, \ldots, x_n$ represent operational indicators such as bid cost deviation, procurement reliability, workforce productivity, and past project delivery performance. The function $f(\cdot)$ is learned using machine learning algorithms, enabling dynamic and data-driven evaluation of contractor suitability.

The third objective is to conduct a comparative analysis between machine learning–based contractor evaluation models and traditional procurement scoring methods. Traditional scoring systems are typically represented as linear weighted models:

$$S_i^{trad} = \sum_{j=1}^{n} w_j x_j$$

Where w_j represents predefined weights assigned to evaluation criteria. This study compares the predictive accuracy, robustness, and decision-support capability of the proposed AI-based framework against such conventional models to demonstrate the advantages of data-driven procurement analytics.

Through these objectives, the study aims to advance procurement decision-making by introducing predictive, scalable, and analytically rigorous contractor evaluation methodologies.

1.4 Research Contributions

This research contributes to the advancement of procurement analytics and intelligent project management systems by introducing a novel machine learning–based framework for contractor selection and tender bid evaluation. The proposed framework represents a shift from traditional rule-based evaluation methods toward predictive, data-driven decision-making systems that leverage enterprise operational datasets.

A primary contribution of this study is the development of an AI-driven ERP-integrated contractor evaluation architecture. This architecture combines data extraction from ERP procurement, financial, and operational modules with feature engineering processes and machine learning prediction models. The integration of these components enables continuous evaluation of contractor performance using real-time and historical enterprise data, thereby improving the accuracy and responsiveness of procurement decisions.

Another key contribution is the formulation of mathematical models for contractor evaluation and risk prediction. The study introduces predictive scoring functions that capture complex relationships between operational variables and contractor performance outcomes. Unlike traditional linear scoring models, the proposed approach incorporates nonlinear interactions and dynamic weighting mechanisms learned from data. This mathematical formulation enhances the interpretability and analytical rigor of contractor evaluation processes.

The research also provides a comparative performance analysis of machine learning models and traditional procurement scoring methods. By evaluating multiple algorithms within a unified analytical framework, the study identifies the strengths and limitations of different approaches in predicting contractor performance and project delivery outcomes. This comparative analysis offers practical insights for organizations seeking to adopt AI-driven procurement systems.

Furthermore, the study contributes to the broader field of enterprise analytics by demonstrating how ERP datasets can be leveraged for predictive decision-making in procurement processes. The integration of enterprise data with machine learning techniques provides a scalable approach for improving transparency, reducing bias, and enhancing efficiency in contractor selection within multinational project environments.

1.5 Structure of the Paper

The remainder of this paper is organized into five sections, each addressing a critical component of the proposed research framework.

Section 2 presents a comprehensive review of the literature on project delivery risk, enterprise resource planning systems, and artificial intelligence applications in procurement and project analytics. This section establishes the theoretical foundation for the study and identifies key gaps in existing contractor evaluation methodologies.

Section 3 describes the research methodology, including the design of the AI-driven predictive framework, data extraction processes from ERP systems, feature engineering techniques, and the machine learning algorithms used for contractor evaluation. The section also details the mathematical formulations underlying the predictive scoring models and outlines the model training and validation procedures.

Section 4 presents the results and discussion, including descriptive analysis of ERP datasets, comparative evaluation of machine learning models, and interpretation of predictive contractor performance indicators. The section also examines the effectiveness of the proposed framework in improving contractor selection outcomes compared to traditional procurement scoring methods.

Finally, Section 5 provides the conclusion and recommendations. This section summarizes the key findings of the study, highlights its theoretical and practical contributions, discusses limitations, and outlines future research directions, including the integration of real-time analytics and explainable artificial intelligence techniques for enhanced procurement decision support.

2. LITERATURE REVIEW

2.1 Project Delivery Risk in Large-Scale Multinational Projects

Large-scale multinational projects are characterized by complex operational structures, distributed stakeholder networks, and high levels of financial and logistical uncertainty. These projects typically involve multiple contractors, cross-border supply chains, and diverse regulatory environments, all of which contribute to increased exposure to delivery risks. Project delivery risk refers to the likelihood that a project will fail to meet its intended schedule, budget, or performance objectives due to uncertainties arising during planning and execution phases. The management of such risks has become a critical concern in infrastructure development, global engineering projects, and multinational information technology initiatives.

One of the primary sources of project delivery risk in multinational environments is organizational and coordination complexity. Large projects often involve numerous stakeholders, including government agencies, international contractors, suppliers, and project management teams operating across different geographic locations. Communication gaps, cultural differences, and misaligned organizational priorities can create coordination challenges that disrupt project workflows. In multinational project environments, these coordination challenges are often amplified by differences in regulatory requirements, legal frameworks, and project governance structures across countries, which may introduce additional uncertainty into project execution processes (Flyvbjerg, 2014; Kerzner, 2018).

Cost escalation is another major source of delivery risk in large-scale projects. Cost overruns frequently occur when initial budget estimates fail to accurately account for uncertainties related to material prices, labor costs, currency fluctuations, or changes in project scope. Studies on global infrastructure projects have shown that large projects often experience significant budget deviations due to inaccurate cost forecasting and unforeseen operational disruptions. These deviations can arise from poor financial planning, inefficient procurement processes, or unexpected economic conditions that affect project expenditures. Cost escalation not only threatens project financial viability but may also trigger delays, contract renegotiations, and funding challenges that further compromise project delivery performance (Cantarelli et al., 2012; Love et al., 2015).

Supply chain disruption represents another critical factor affecting project delivery outcomes in multinational environments. Global projects rely heavily on international procurement networks for materials, equipment, and specialized technical components. Disruptions within these supply chains such as transportation delays, geopolitical tensions, trade restrictions, or supplier failures can interrupt project schedules and delay construction or implementation activities. The increasing globalization of project supply chains has made project delivery more vulnerable to external disruptions beyond the direct control of project managers. Consequently, effective risk monitoring mechanisms must account for supply chain volatility and logistical uncertainties that can significantly affect project timelines and operational continuity (Ivanov et al., 2017; Tang, 2006).

Resource constraints also play a significant role in influencing project delivery risk. Large multinational projects require coordinated deployment of skilled personnel, specialized equipment, and financial resources across multiple project sites. Resource shortages or inefficient allocation can result in productivity losses, operational bottlenecks, and scheduling conflicts that ultimately delay project completion. Workforce availability is particularly critical in multinational projects where specialized expertise may be required in multiple locations simultaneously. Inadequate workforce planning or delays in mobilizing technical experts can disrupt project schedules and increase operational costs. Similarly, equipment shortages and logistical constraints may limit the ability of project teams to execute planned activities within scheduled timeframes (Zwikael & Ahn, 2011; Pinto, 2019).

In addition to operational factors, project governance and decision-making processes also influence the level of delivery risk in multinational projects. Ineffective risk governance structures, poor communication between stakeholders, and delayed decision-making processes can exacerbate operational uncertainties. Large projects often require rapid responses to emerging challenges, and delays in managerial decisions may amplify the impact of operational disruptions (Ononiwu, et al., 2024). Effective project governance therefore plays an essential role in ensuring that risk signals are identified early and addressed through timely corrective actions. Without strong governance frameworks, project teams may struggle to coordinate mitigation strategies across distributed project environments (PMI, 2021; Ward & Chapman, 2003).

Overall, the literature indicates that project delivery risk in large-scale multinational projects arises from a combination of financial, operational, organizational, and supply chain factors. Cost escalation, resource constraints, supply chain disruptions, and governance inefficiencies interact dynamically throughout the project lifecycle, creating complex risk environments that challenge traditional monitoring approaches (Onyekaonwu, et al., 2022). Understanding these interconnected risk sources is therefore essential for developing advanced predictive frameworks capable of improving project delivery performance in multinational project environments.

2.2 Enterprise Resource Planning Systems in Project Monitoring

Enterprise Resource Planning (ERP) systems have become a central technological infrastructure for integrating organizational processes and supporting data-driven decision-making in modern enterprises. ERP platforms consolidate data from multiple functional areas into a unified digital environment, enabling organizations to manage financial operations, procurement activities, human resources, logistics, and project workflows within a single information system. In the context of large-scale projects, ERP systems provide an integrated data repository that allows project managers to monitor operational performance, track resource utilization, and evaluate financial activities in real time (Ononiwu, et al., 2023). This capability significantly improves organizational visibility and supports effective project governance by providing structured datasets that can be analyzed for performance monitoring and risk detection.

One of the most critical ERP modules relevant to project monitoring is financial accounting. The financial accounting component captures transactional data related to budgeting, cost allocation, expenditure tracking, and financial reporting. Within project environments, financial accounting systems allow project managers to monitor cost performance by comparing planned budgets with actual expenditures across different project phases (Sanmori, 2024). Continuous tracking of financial data enables organizations to detect cost variances, identify potential budget overruns, and implement corrective financial strategies. By integrating financial records with project scheduling and operational activities, ERP systems provide a transparent mechanism for monitoring financial performance and ensuring accountability in complex project environments.

Procurement management is another essential ERP module that contributes significantly to project monitoring. Large-scale projects typically rely on extensive procurement processes involving suppliers, contractors, and logistics providers. ERP procurement modules track purchase orders, supplier contracts, inventory levels, and delivery schedules, allowing project managers to coordinate procurement activities efficiently. Monitoring procurement performance is particularly important because delays in material delivery or supplier disruptions can directly affect project schedules and operational continuity (Kwarteng, et al., 2021). By maintaining real-time visibility over procurement transactions and supplier performance, ERP systems enable organizations to identify potential supply disruptions and manage procurement risks more effectively.

Human resource management modules within ERP systems also play an important role in supporting project monitoring. Projects require the coordinated deployment of skilled personnel, technical experts, and support staff across different project phases. ERP-based HR systems store information related to workforce allocation, employee competencies, work schedules, and labor costs (Akindote, et al., 2024). These systems allow project managers to monitor workforce productivity, evaluate staffing requirements, and ensure that project teams are appropriately resourced. In multinational projects where personnel may be distributed across multiple geographic locations, ERP-based human resource monitoring becomes particularly valuable for coordinating workforce activities and ensuring efficient utilization of human capital (Azonuche, & Enyejo, 2024).

Supply chain management modules further extend the capabilities of ERP systems by enabling integrated monitoring of logistics operations and material flows. These modules track inventory levels, warehouse operations, transportation activities, and supplier networks, providing comprehensive visibility across the supply chain (Armah, et al., 2024). In project environments that depend on complex supply chains, ERP-based supply chain systems allow project managers to monitor material availability, track shipment progress, and coordinate logistics operations with project schedules. Real-time supply chain monitoring is essential for ensuring that materials and equipment are delivered at the appropriate time and location to support project execution activities.

The integration of these ERP modules creates a comprehensive enterprise data environment that supports advanced project monitoring capabilities. Financial accounting provides insight into cost performance, procurement modules ensure the timely acquisition of materials and services, human resource systems coordinate workforce deployment, and supply chain modules manage logistics and material flows (Anokwuru, 2024). When these modules operate within an integrated ERP architecture, they generate large volumes of structured operational data that can be analyzed to evaluate project performance and detect operational anomalies.

In recent years, the role of ERP systems in project monitoring has expanded beyond traditional reporting functions to include advanced analytics and decision-support capabilities. Organizations increasingly leverage ERP data for predictive analysis, performance forecasting, and risk assessment in complex projects (Ihimoyan, et al., 2024). By integrating ERP data with analytical tools and machine learning algorithms, organizations can transform operational datasets into predictive insights that improve project planning and execution (Akello, et al., 2025). This evolution highlights the growing importance of ERP systems as foundational platforms for intelligent project monitoring and enterprise-wide project analytics.

2.3 Artificial Intelligence Applications in Project Risk Prediction

Artificial intelligence (AI) has increasingly become an essential tool in modern project management, particularly in the domain of project risk prediction and performance forecasting. Large-scale projects generate extensive operational datasets involving financial transactions, scheduling updates, procurement activities, and resource allocation patterns. Traditional analytical methods often struggle to process these complex datasets effectively, especially when the relationships between project variables are nonlinear and dynamic. Artificial intelligence techniques, particularly machine learning algorithms, provide advanced analytical capabilities that allow organizations to identify hidden patterns, forecast project risks, and support proactive decision-making (Azonuche, & Enyejo, 2025). By leveraging historical project datasets and operational indicators, machine learning models can predict the likelihood of schedule delays, cost overruns, and operational disruptions with greater accuracy than conventional statistical approaches.

Among the various machine learning techniques used in project analytics, Random Forest models have gained significant attention due to their robustness and ability to handle complex datasets. Random Forest is an ensemble learning method that constructs multiple decision trees and aggregates their predictions to improve model accuracy and stability. This approach is particularly effective in project risk prediction because it can manage high-dimensional datasets and capture nonlinear relationships between project variables such as cost performance indicators, resource utilization metrics, and schedule progress measures (Ononiwu, et al., 2025). The ensemble nature of Random Forest models also helps reduce overfitting, making them suitable for predicting project delivery risks in environments characterized by uncertainty and incomplete information.

Gradient Boosting algorithms represent another widely used technique in predictive project analytics. Gradient Boosting methods operate by sequentially building decision trees where each new tree attempts to correct the prediction errors of the previous ones. This iterative learning process enables the model to capture subtle patterns in complex datasets and significantly improve predictive performance (Anokwuru, et al., 2024). In project management contexts, Gradient Boosting models have demonstrated strong performance in forecasting schedule deviations, identifying cost escalation patterns, and predicting project failure probabilities. Their ability to combine weak predictive models into a strong overall model makes them particularly useful for analyzing heterogeneous datasets generated by large organizational information systems.

Neural networks have also been widely applied in project risk prediction due to their capability to model highly nonlinear relationships among variables. Artificial neural networks are computational models inspired by the structure of biological neural systems, consisting of interconnected processing nodes that transform input variables into predictive outputs through layered transformations. In project analytics, neural networks can analyze complex interactions between multiple operational variables such as procurement lead times, workforce productivity, financial expenditure trends, and scheduling performance indicators. These models are particularly useful when project datasets are large and contain intricate relationships that traditional statistical methods cannot easily capture. Advances in deep learning architectures have further enhanced the predictive capabilities of neural networks in project management applications.

Bayesian models represent another important category of artificial intelligence techniques used in project risk analysis. Bayesian approaches are based on probabilistic reasoning and allow analysts to incorporate prior knowledge into predictive models while updating risk probabilities as new information becomes available. In project management environments characterized by uncertainty and incomplete information, Bayesian models provide a flexible framework for continuously updating risk assessments as project conditions evolve. Bayesian networks can represent complex causal relationships among project variables and estimate the probability of different project outcomes based on observed evidence. This probabilistic reasoning capability makes Bayesian approaches particularly valuable for decision support systems where uncertainty must be explicitly considered.

The integration of these machine learning techniques into project management systems has significantly improved the ability of organizations to predict and mitigate project delivery risks. Random Forest and Gradient Boosting models provide strong predictive performance through ensemble learning mechanisms, neural networks offer powerful tools for modeling nonlinear relationships in large datasets, and Bayesian models enable probabilistic reasoning under uncertainty. When combined with enterprise operational datasets such as those generated by enterprise resource planning systems, these artificial intelligence techniques can transform traditional project monitoring processes into intelligent predictive systems capable of supporting proactive project risk management.

2.4 Mathematical Modeling of Project Risk Indicators

Quantitative risk modeling plays a critical role in transforming operational project data into measurable indicators that support predictive analytics and decision-making. In large multinational projects, operational information generated through enterprise resource planning systems provides a valuable source of structured variables that reflect the real-time state of project performance. Financial transactions, procurement timelines, workforce utilization levels, and scheduling performance metrics collectively represent operational signals that can be mathematically modeled to estimate the probability of delivery disruptions. Mathematical modeling enables project managers to convert these operational signals into standardized indicators that can be analyzed using statistical and machine learning techniques for predictive risk monitoring (Kerzner, 2018; Zhang & Wang, 2020).

To quantify delivery risk in complex project environments, a composite **Project Delivery Risk Index (PDRI)** can be formulated by aggregating key operational indicators derived from ERP modules. The index integrates multiple risk dimensions associated with financial performance, schedule adherence, resource utilization, and procurement efficiency. The proposed mathematical representation of the Project Delivery Risk Index is expressed as:

$$PDRI = \alpha_1 C_v + \alpha_2 S_d + \alpha_3 R_u + \alpha_4 P_l$$

Where:

C_v represents cost variance obtained from the ERP financial accounting module, reflecting deviations between planned and actual project expenditures.

S_d denotes the schedule delay ratio derived from project scheduling data, representing the proportion of delayed tasks relative to planned activities.

R_u represents resource utilization imbalance, capturing discrepancies between planned workforce allocation and actual resource deployment.

P_l indicates procurement lead time variability, reflecting fluctuations in supplier delivery timelines recorded within procurement management systems.

The coefficients $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ represent weighting parameters that quantify the relative importance of each risk component in influencing overall project delivery performance. These coefficients can be estimated using regression analysis, optimization algorithms, or machine learning techniques that analyze historical project datasets to determine the contribution of each variable to delivery risk outcomes.

The development of composite indices such as the PDRI enables organizations to consolidate multiple operational indicators into a single analytical metric that can be continuously monitored throughout the project lifecycle. Such indices facilitate the comparison of risk levels across project phases and support the development of predictive models capable of identifying early warning signals of project disruption (Anokwuru, et al., 2022). Mathematical risk indices also improve interpretability by providing structured representations of complex operational relationships, enabling project managers to quantify the relative influence of financial, scheduling, resource, and procurement variables on project performance (Ward & Chapman, 2003; Love et al., 2015).

Furthermore, the integration of mathematical risk indicators with predictive analytics frameworks allows project monitoring systems to evolve from descriptive reporting toward predictive risk forecasting. Once operational variables are standardized and integrated into composite indices such as the PDRI, machine learning algorithms can analyze temporal changes in these indicators to predict future delivery risks (Okoh, et al., 2024). This mathematical foundation therefore serves as a bridge between enterprise operational data and artificial intelligence–based risk prediction models, enabling more systematic and data-driven project monitoring approaches (Bento et al., 2022; Taboada et al., 2023).

2.5 Research Gap

Despite significant progress in project risk management research, several limitations remain in the existing literature regarding predictive risk analytics in multinational project environments. Traditional project risk management frameworks are largely based on qualitative evaluation methods such as expert judgment, risk matrices, and manual monitoring processes. Although these methods provide structured approaches for identifying potential project risks, they often lack the capability to incorporate large-scale operational datasets generated during project execution. As projects become increasingly complex and data-rich, conventional monitoring techniques struggle to capture the dynamic interactions between financial, operational, and logistical variables that influence project outcomes (Zwikael & Ahn, 2011; Kerzner, 2018).

Another limitation in the literature concerns the fragmented use of enterprise operational data in predictive risk modeling. Many studies focusing on project risk prediction rely on survey data, historical case studies, or simplified datasets rather than real-time enterprise information systems. However, modern organizations operate sophisticated ERP infrastructures that continuously generate high-volume operational datasets describing financial transactions, procurement activities, workforce deployment, and supply chain dynamics. The potential of these datasets for predictive risk analytics remains insufficiently explored in existing research (Aloini et al., 2007; Davenport, 1998).

Furthermore, although artificial intelligence and machine learning techniques have been increasingly applied in project analytics, the integration of these technologies with enterprise resource planning data remains limited. Existing AI-based models often operate independently of enterprise operational systems, reducing their ability to capture real-time project performance indicators. Without direct integration with ERP datasets, predictive models may fail to reflect the operational realities of complex project environments. This lack of integration reduces the effectiveness of predictive risk monitoring systems and limits their practical applicability in multinational project contexts (Fridgeirsson et al., 2021; Niederman, 2021).

Consequently, there is a clear research need for integrated analytical frameworks that combine ERP operational data with artificial intelligence–based predictive modeling techniques. Such frameworks should incorporate mathematical risk indicators derived from enterprise datasets and apply machine learning algorithms to forecast delivery risks in real time. Developing such an integrated approach would significantly enhance project monitoring capabilities and provide organizations with proactive decision-support tools for mitigating delivery risks in large multinational projects.

3. METHODOLOGY

3.1 Research Design

This study adopts a quantitative research design based on predictive modeling techniques to analyze project delivery risks in large multinational projects. Quantitative research approaches are widely used in project analytics because they enable the systematic examination of relationships between operational variables and project performance outcomes. By applying statistical and machine learning techniques to structured datasets, quantitative predictive modeling frameworks allow researchers to identify patterns, estimate risk probabilities, and evaluate the predictive accuracy of analytical models. In complex project environments where operational variables interact dynamically, quantitative models provide a rigorous analytical foundation for transforming enterprise data into predictive insights that support project decision-making (Hair et al., 2019; Kerzner, 2018).

The research framework focuses on the development of a predictive analytics model capable of forecasting project delivery risks using operational data generated from enterprise resource planning systems. ERP platforms serve as centralized information systems that integrate data across multiple organizational functions, including financial management, procurement operations, human resource management, and supply chain coordination. These systems continuously record operational activities related to project execution, thereby providing a comprehensive data environment suitable for predictive analysis. By extracting structured datasets from ERP modules associated with project operations, the research design enables the identification of operational indicators that influence project delivery outcomes (Davenport, 1998; Monk & Wagner, 2013).

Within this study, ERP datasets are obtained from multinational project management environments where enterprise systems are used to coordinate project activities across geographically distributed teams. The datasets include operational records related to financial transactions, procurement timelines, workforce allocation patterns, and scheduling performance indicators. These variables provide measurable signals reflecting project progress and operational efficiency. By integrating these datasets into a predictive modeling framework, the research aims to evaluate how enterprise operational indicators can be used to estimate the probability of project delivery risks. The use of ERP datasets is particularly valuable in multinational projects because such systems consolidate information from multiple project locations into a unified digital platform, allowing for comprehensive analysis of project performance across organizational units.

The predictive modeling framework developed in this study involves several analytical stages, including data extraction from ERP systems, preprocessing and feature engineering, predictive model training, and performance evaluation. Data preprocessing techniques are applied to standardize operational variables and eliminate inconsistencies within enterprise datasets. Feature engineering processes transform raw ERP variables into analytical indicators suitable for predictive modeling. Machine learning algorithms are subsequently applied to these features to identify patterns associated with project delivery risks. The predictive performance of the models is evaluated using established statistical metrics that measure the accuracy and reliability of risk predictions.

Overall, the research design integrates enterprise operational datasets with quantitative predictive analytics techniques to develop a data-driven framework for project risk prediction. By combining ERP-derived operational indicators with machine learning models, the methodology enables systematic evaluation of delivery risk signals in multinational project environments. This quantitative approach provides a structured analytical foundation for developing predictive risk monitoring systems capable of improving project governance, operational visibility, and decision-making in complex multinational projects.

3.2 Data Sources and ERP Variables

Enterprise Resource Planning (ERP) systems serve as a central source of operational data for modern project management environments. These systems integrate organizational processes across financial management, procurement, human resource planning, and operational control, thereby generating structured datasets that reflect the real-time status of project activities. In multinational project environments, ERP platforms play a critical role in consolidating operational information from multiple departments and geographic locations into a unified enterprise database. Such integrated datasets enable organizations to monitor project performance more effectively and support data-driven analytical approaches for project risk prediction (Davenport, 1998; Monk & Wagner, 2013).

The present study extracts operational variables from four key ERP modules that directly influence project delivery performance: financial management, procurement management, human resource management, and operational project control systems. Each module captures different categories of operational information that contribute to risk signals during project execution. Financial modules generate indicators related to project expenditure and budget performance, procurement systems record supplier transactions and delivery timelines, human resource modules track workforce allocation and productivity metrics, while operational systems capture project scheduling and task completion data.

The integration of these ERP modules enables the development of a comprehensive dataset for predictive modeling of project delivery risks. Cost variance and budget utilization indicators derived from financial accounting modules provide insight into financial stability and potential cost overruns. Procurement lead time variability represents supply chain uncertainty and supplier performance fluctuations that may affect project timelines. Workforce allocation metrics obtained from human resource systems indicate the efficiency of personnel deployment and potential resource constraints. Operational project control systems generate scheduling indicators such as task completion rates, which reflect the progress of project activities relative to planned schedules. Together, these variables form a multidimensional dataset suitable for analyzing operational signals associated with project delivery risks (Umble et al., 2003; Somers & Nelson, 2004).

The ERP variables collected for this study serve as input features for predictive modeling algorithms that estimate the probability of delivery risks in multinational projects. By systematically integrating operational indicators from multiple ERP modules, the dataset provides a comprehensive representation of financial, logistical, workforce, and scheduling conditions influencing project performance. This integrated data architecture enhances the ability of predictive models to identify patterns associated with emerging project risks and improves the accuracy of risk prediction systems in complex enterprise environments.

Table 1 summarizes the primary ERP modules and operational variables used in this study for predictive risk analysis. The table illustrates how different enterprise functional systems contribute distinct operational indicators relevant to project delivery risk monitoring. Financial modules generate cost performance indicators, procurement systems provide supply chain stability metrics, human resource systems capture workforce deployment efficiency, and operational modules monitor project scheduling performance. These variables collectively represent key operational signals that influence project delivery outcomes. By integrating indicators across these ERP modules, the study constructs a comprehensive dataset capable of supporting machine learning models for predictive project risk analytics.

Table 1: ERP Data Variables Used for Project Risk Prediction.

ERP Module	Data Variables	Relevance
Finance	Cost variance, budget utilization	Financial risk
Procurement	Lead time variability	Supply risk
Human Resources	Workforce allocation	Resource risk
Operations	Task completion rates	Schedule risk

3.3 AI Predictive Modeling Framework

This study develops an artificial intelligence–based predictive modeling framework designed to estimate project delivery risks using operational variables extracted from enterprise resource planning systems. The framework applies machine learning algorithms to analyze multidimensional ERP datasets and identify patterns associated with emerging project risks. Machine learning methods are particularly suitable for this purpose because they can process large datasets, capture nonlinear relationships among variables, and generate predictive insights that support proactive project monitoring and decision-making. By training predictive models on historical operational data, organizations can estimate the probability of delivery disruptions such as schedule delays, cost overruns, or resource shortages (Breiman, 2001; Goodfellow et al., 2016).

The predictive modeling framework implemented in this study evaluates four widely used machine learning algorithms: Random Forest, Support Vector Machine, Gradient Boosting, and Deep Neural Networks. Each of these models offers distinct analytical advantages when applied to complex enterprise datasets. Random Forest is an ensemble learning technique that constructs multiple decision trees and aggregates their outputs to improve prediction accuracy and reduce model overfitting. This approach is effective in handling high-dimensional data and capturing nonlinear interactions between operational variables.

Support Vector Machine (SVM) models provide another powerful method for classification and regression problems in predictive analytics. SVM algorithms identify optimal decision boundaries that separate data points belonging to different classes. In the context of project risk prediction, SVM models can distinguish between low-risk and high-risk project states by analyzing ERP-derived operational indicators. These models are particularly effective in handling datasets with complex variable relationships and limited noise.

Gradient Boosting algorithms represent an advanced ensemble learning technique in which multiple weak predictive models are sequentially combined to improve overall predictive performance. Each new model in the sequence attempts to correct the prediction errors of the previous models. This iterative learning process enables Gradient Boosting algorithms to capture subtle patterns in project datasets and significantly improve risk prediction accuracy. Because of their ability to model complex relationships between variables, Gradient Boosting models are widely used in predictive analytics applications involving large operational datasets.

Deep Neural Networks provide an additional modeling approach capable of learning highly nonlinear relationships among project variables. Neural networks consist of multiple layers of interconnected nodes that transform input variables into predictive outputs through weighted mathematical functions. When applied to ERP datasets, deep neural networks can analyze interactions among financial indicators, procurement variables, workforce allocation metrics, and scheduling performance indicators to identify patterns associated with project delivery risk. The ability of neural networks to learn hierarchical representations of data makes them particularly suitable for predictive analytics in complex enterprise environments.

The predictive modeling framework is mathematically represented through a generalized prediction function that estimates delivery risk at a given time step. The model can be expressed as:

$$R_t = f(X_t)$$

Where R_t represents the predicted project delivery risk at time t, and $f(\cdot)$ represents the predictive function learned by the machine learning model. The input vector X_t contains the operational ERP variables used for prediction and is defined as:

$$X_t = (x_1, x_2, x_3, \ldots, x_n)$$

In this formulation, $x_1, x_2, x_3, \ldots, x_n$ represent individual ERP-derived features such as cost variance indicators, procurement lead time measures, workforce allocation metrics, and project scheduling performance variables. The predictive function $f(\cdot)$ is estimated during model training by analyzing historical ERP datasets and learning the relationships between operational indicators and project delivery outcomes.

Through this framework, the predictive model transforms multidimensional ERP operational data into delivery risk predictions that can support proactive risk monitoring. By comparing the performance of different machine learning algorithms, the study identifies the most effective predictive modeling approach for forecasting project delivery risks in multinational project environments.

3.4 Feature Engineering and Risk Indicator Construction

Feature engineering plays a crucial role in the development of predictive analytics models because raw operational data obtained from enterprise systems often contains inconsistencies, scale differences, and noise that can reduce the effectiveness of machine learning algorithms. In predictive modeling for project delivery risk, ERP datasets typically contain heterogeneous variables derived from financial systems, procurement records, workforce management platforms, and project scheduling tools. These variables may differ significantly in scale and measurement units, which can influence the performance of machine learning algorithms if not properly transformed. Feature engineering therefore involves the systematic transformation of raw ERP variables into structured indicators that improve the analytical capabilities of predictive models (Goodfellow et al., 2016; Géron, 2019).

One of the most important preprocessing steps in feature engineering is feature normalization. Normalization ensures that variables with different measurement scales contribute proportionally to the predictive model rather than allowing large-scale variables to dominate the learning process. In the context of project risk analytics, ERP variables such as procurement lead times, cost variance values, workforce allocation metrics, and task completion rates may have different numerical ranges. Standardizing these variables allows machine learning algorithms to process them more effectively and ensures that each variable contributes appropriately to the prediction of delivery risks (Bishop, 2006; James et al., 2013).

In this study, standardized feature transformation is applied using a statistical normalization approach known as z-score normalization. This technique converts each input variable into a standardized value that reflects its deviation from the mean relative to the variability of the dataset. The standardized transformation is defined as:

$$Z_i = \frac{x_i - \mu}{\sigma}$$

Where Z_i represents the normalized feature value, x_i denotes the original ERP variable, μ represents the mean value of the variable across the dataset, and σ represents the standard deviation. This transformation rescales the variables so that they have a mean of zero and a standard deviation of one. As a result, each feature contributes proportionally to the predictive model regardless of its original scale.

The application of standardized feature transformation improves the stability and convergence behavior of machine learning algorithms used for risk prediction. Algorithms such as support vector machines, gradient boosting models, and neural networks rely on numerical optimization processes that are sensitive to differences in variable scales. Standardized features reduce computational instability and enhance the efficiency of model training by ensuring that all input variables are expressed on comparable numerical scales.

Beyond normalization, feature engineering also involves the construction of composite indicators that represent meaningful operational signals associated with project delivery risk. ERP variables such as cost variance, procurement lead time variability, workforce allocation imbalance, and schedule completion ratios can be combined into analytical indicators that capture the multidimensional nature of project performance. These indicators serve as inputs to predictive models that estimate the probability of project delivery disruptions. By transforming raw operational data into structured analytical features, the feature engineering process enhances the predictive capacity of machine learning models and improves the reliability of risk prediction frameworks in complex multinational project environments.

3.5 Model Training and Validation

Model training and validation represent critical stages in the development of predictive analytics systems for project delivery risk forecasting. During the training phase, machine learning algorithms learn the relationships between operational input variables derived from ERP systems and project delivery outcomes observed in historical datasets. These relationships are represented through mathematical functions that map multidimensional feature vectors to predicted risk outputs. The training process involves optimizing model parameters to minimize prediction error while ensuring that the resulting model generalizes effectively to unseen data. Proper model validation procedures are therefore necessary to evaluate the reliability, robustness, and predictive accuracy of the developed models (Goodfellow et al., 2016; Géron, 2019).

In this study, the model training process utilizes a supervised learning approach in which ERP-derived operational variables serve as input features and project delivery outcomes represent the target variables. Historical project datasets are divided into training and validation subsets to ensure unbiased evaluation of model performance. The training dataset is used to estimate model parameters, while the validation dataset is used to evaluate how well the trained model predicts delivery risks for previously unseen project instances. This separation of datasets helps prevent overfitting, a condition in which the model performs well on training data but fails to generalize to new observations (James et al., 2013).

The optimization of predictive models is guided by a loss function that measures the difference between predicted values and actual observed outcomes. In predictive risk modeling, minimizing this difference ensures that the model accurately estimates project delivery risk levels. The loss function applied in this research is the mean squared error (MSE), defined as:

$$L = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2$$

Where L represents the loss value, N denotes the number of observations in the dataset, y_i represents the actual project delivery outcome, and $\hat{y}_i$ represents the predicted outcome generated by the machine learning model. The mean squared error function penalizes larger prediction errors more heavily than smaller errors, thereby encouraging the model to minimize significant deviations between predicted and actual values.

Following model training, predictive performance is evaluated using several widely accepted classification metrics. Accuracy measures the proportion of correct predictions relative to the total number of observations, providing a general indicator of model performance. Precision evaluates the proportion of predicted high-risk project cases that are correctly identified, thereby reflecting the reliability of positive predictions. Recall measures the proportion of actual high-risk cases that are successfully detected by the model, which is particularly important in risk prediction scenarios where failing to identify critical risks may lead to severe project consequences.

The F1-score provides a balanced metric that combines precision and recall into a single performance measure, offering a more comprehensive assessment when datasets contain imbalanced class distributions. In addition, the receiver operating characteristic–area under the curve (ROC-AUC) metric evaluates the ability of the predictive model to distinguish between different risk categories across varying classification thresholds. A higher ROC-AUC value indicates stronger discriminative capability and better predictive performance.

The combined use of these evaluation metrics enables comprehensive validation of the predictive models used in this study. By examining multiple performance indicators, the research ensures that the selected model not only achieves high prediction accuracy but also effectively identifies high-risk project scenarios. This rigorous validation process strengthens the reliability of the proposed AI-driven predictive framework for forecasting project delivery risks in multinational project environments.

Figure 1 illustrates the end-to-end system architecture for predicting project delivery risks using ERP data and machine learning techniques. It begins with ERP data sources, including finance, procurement, human resources, and operations modules, which provide structured operational datasets. These data are processed through a data extraction layer and transformed within the feature engineering module to generate analytical inputs. The machine learning prediction engine then analyzes these features to estimate project risk levels. Finally, results are visualized through a risk scoring dashboard and integrated into a decision support system to enable proactive project management and informed decision-making.

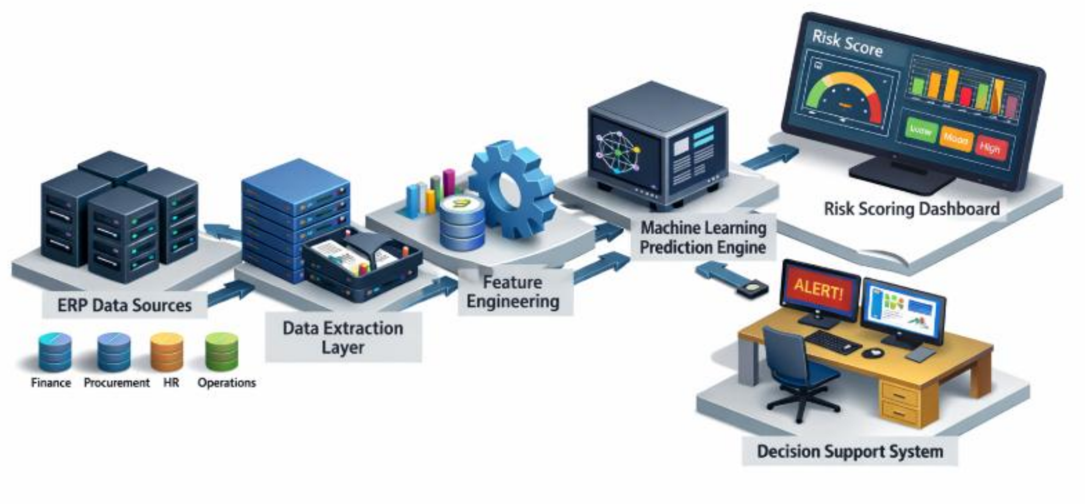

Figure 1: Architecture of the AI-Driven ERP Project Risk Prediction Framework.

4. RESULTS AND DISCUSSION

4.1 Dataset Characteristics

The dataset used in this study consists of operational records extracted from enterprise resource planning systems deployed within multinational project management environments. These datasets integrate information generated across multiple ERP modules, including financial management, procurement operations, human resource management, and project execution systems. Each dataset represents project-level observations describing operational conditions associated with project execution. The purpose of analyzing the dataset characteristics is to understand the distribution, variability, and statistical properties of ERP variables before applying predictive modeling techniques. Descriptive statistical analysis provides insight into the structure of the dataset and helps identify patterns or anomalies that may influence model training and risk prediction performance.

The ERP dataset includes key operational indicators related to financial performance, supply chain efficiency, workforce deployment, and project scheduling. Financial indicators such as cost variance measure the deviation between planned project budgets and actual expenditures recorded in ERP financial accounting modules. Procurement variables such as lead time variability represent fluctuations in supplier delivery timelines obtained from procurement management systems. Workforce allocation metrics describe the distribution of personnel resources across project activities and are derived from human resource planning modules. Task completion rates represent operational scheduling indicators obtained from project execution systems, reflecting the percentage of tasks completed within planned timeframes.

Descriptive statistical analysis is performed to evaluate the central tendency and variability of these variables across the dataset. Measures such as mean, standard deviation, and value ranges provide important insights into the operational conditions experienced across the observed projects. The mean value indicates the average performance level for each operational variable, while the standard deviation captures the degree of variation observed across projects. The range of each variable provides additional insight into the spread of values, highlighting extreme operational conditions that may contribute to elevated project delivery risk.

The analysis of dataset characteristics reveals that financial and operational indicators exhibit varying levels of variability across projects. Cost variance values demonstrate moderate dispersion, reflecting differences in budget management performance among projects. Procurement lead time variability shows wider fluctuations, indicating the influence of supply chain dynamics and vendor performance on project schedules. Workforce allocation metrics reveal variations in personnel deployment efficiency across project phases, while task completion rates illustrate differences in project execution performance. These variations highlight the importance of incorporating multiple operational indicators when developing predictive models for project delivery risk.

Understanding the statistical properties of ERP variables is essential for ensuring the reliability of predictive modeling frameworks. Descriptive statistical analysis provides a foundation for feature normalization, risk indicator construction, and model training processes. By examining the distribution and variability of operational variables, researchers can ensure that the dataset accurately represents project conditions and supports robust predictive analysis in multinational project environments.

Table 2 summarizes the descriptive statistical characteristics of the ERP operational variables used for predictive risk analysis. The results indicate moderate variability in cost variance across projects, suggesting differences in financial control efficiency among multinational project environments. Schedule delay exhibits a higher dispersion, reflecting variations in project execution performance and operational coordination. Resource utilization shows relatively high average values, indicating strong workforce deployment efficiency but with noticeable variability across projects. Procurement lead time demonstrates the widest range, highlighting the influence of supply chain uncertainty and supplier performance on project delivery outcomes.

Table 2: Descriptive Statistics of ERP Project Data Variables.

Variable	Mean	Standard Deviation	Range
Cost Variance	0.14	0.07	-0.05 – 0.32
Schedule Delay	0.18	0.09	0.00 – 0.41
Resource Utilization	0.76	0.11	0.52 – 0.95
Procurement Lead Time	12.6 days	4.3	6 – 24 days

4.2 Model Performance Comparison

This section evaluates the predictive performance of the machine learning models implemented within the proposed AI-driven ERP risk prediction framework. The models assessed include Random Forest, Support Vector Machine (SVM), Gradient Boosting, and Deep Neural Networks. These algorithms were selected because of their proven ability to capture complex nonlinear relationships between operational variables and project outcomes in high-dimensional datasets. Each model was trained using ERP-derived operational indicators including cost variance, schedule delay ratio, workforce allocation imbalance, and procurement lead time variability. The trained models were subsequently evaluated using multiple classification performance metrics in order to determine their effectiveness in predicting project delivery risk levels.

The predictive performance of the models was assessed using a validation dataset that was separated from the training data to ensure unbiased evaluation. This dataset contained previously unseen project observations, allowing the models to demonstrate their ability to generalize beyond the training samples. The evaluation process focused on key predictive performance indicators including accuracy, precision, recall, F1-score, and the receiver operating characteristic area under the curve (ROC-AUC). These metrics collectively provide a comprehensive evaluation of classification performance by measuring both overall prediction accuracy and the model's ability to correctly identify high-risk project scenarios.

Among the evaluated models, ensemble learning approaches demonstrated strong predictive capabilities due to their ability to combine multiple decision structures into a single predictive system. Random Forest models performed effectively in identifying complex interactions between financial and operational indicators, particularly in cases where nonlinear relationships existed between ERP variables and project outcomes. Gradient Boosting models also demonstrated strong predictive performance due to their sequential error correction mechanism, which improves model accuracy by focusing on misclassified observations during training iterations.

Support Vector Machine models exhibited stable classification performance and were particularly effective in identifying optimal decision boundaries within multidimensional feature spaces. However, their performance was somewhat sensitive to parameter tuning and kernel selection. Deep Neural Networks demonstrated the ability to capture highly nonlinear relationships among ERP operational variables, especially in datasets containing large numbers of observations. Their multilayer structure allowed the model to learn hierarchical representations of operational risk signals derived from ERP data.

Overall, the comparative analysis indicates that ensemble learning models such as Random Forest and Gradient Boosting generally provide the highest predictive accuracy for ERP-driven project risk prediction tasks. These models effectively capture complex interactions between financial, scheduling, procurement, and resource variables, thereby improving the detection of early delivery risk signals. Deep neural networks also show strong predictive potential when sufficient training data is available, while Support Vector Machines offer stable performance in moderate-sized datasets.

The results of this comparison highlight the importance of selecting appropriate machine learning algorithms for predictive project analytics. Different algorithms exhibit varying strengths depending on dataset size, feature complexity, and model interpretability requirements. Consequently, the selection of predictive models should consider both predictive performance and practical implementation factors within enterprise project monitoring systems.

Table 3 presents the comparative predictive performance of the machine learning models evaluated in this study. The results show that Gradient Boosting achieved the highest overall accuracy and ROC-AUC score, indicating strong capability in identifying high-risk project delivery scenarios from ERP operational data. Random Forest also demonstrated strong performance due to its ensemble learning structure that captures nonlinear interactions between financial, scheduling, and procurement variables. The Neural Network model produced competitive results, reflecting its ability to model complex relationships among ERP indicators. The Support Vector Machine model achieved slightly lower predictive performance but still maintained reliable classification capability for moderate-sized datasets.

Table 3: Comparative Performance of AI Models for Risk Prediction.

Model	Accuracy	Precision	Recall	AUC
Random Forest	0.91	0.89	0.90	0.94
Gradient Boosting	0.93	0.91	0.92	0.96
SVM	0.88	0.86	0.87	0.91
Neural Network	0.92	0.90	0.91	0.95

Figure 2 presents a comparative visualization of four machine learning models; Random Forest, Gradient Boosting, Support Vector Machine (SVM), and Neural Network evaluated across key performance metrics. The grouped 3D bar chart illustrates Accuracy, Precision, Recall, and AUC values for each model, enabling direct comparison of predictive effectiveness. Gradient Boosting demonstrates the highest overall performance, particularly in AUC and accuracy, indicating superior capability in risk classification. Random Forest and Neural Network also exhibit strong and consistent performance across all metrics, reflecting their robustness in handling ERP-derived datasets. In contrast, SVM shows comparatively lower values, suggesting reduced effectiveness in capturing complex nonlinear relationships in project risk prediction.

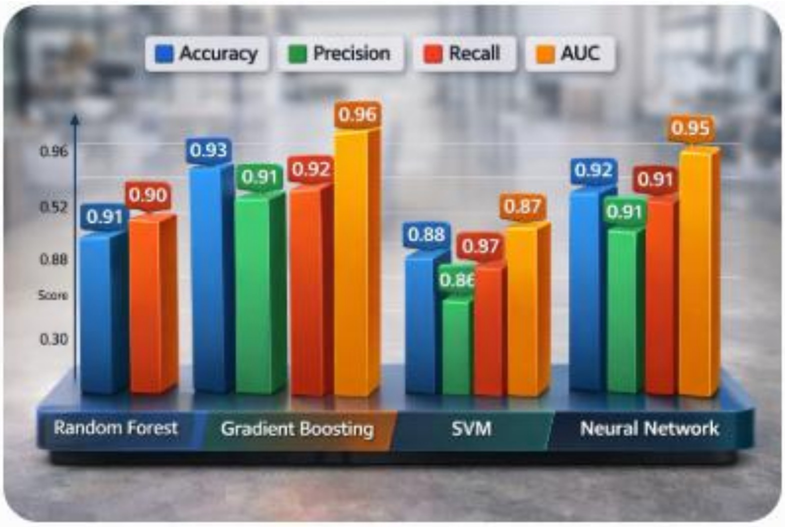

Figure 1: A Comparative Visualization of Four Machine Learning Models Across Key Performance Metrics.

4.3 Predictive Risk Indicator Analysis

This subsection interprets the predictive risk indicators generated by the AI-driven framework and examines how ERP-derived operational variables influence the probability of project delivery disruptions across different project phases. By integrating financial, procurement, workforce, and scheduling indicators into a predictive model, the framework enables the estimation of delivery risk levels at various stages of project execution. The predictive analysis provides insight into how operational conditions recorded within ERP systems contribute to emerging project risks and helps identify the most influential variables affecting delivery performance.

The probability of project delivery risk is estimated using a logistic regression–based predictive model that converts ERP operational indicators into a probabilistic risk score. The model estimates the likelihood that a project will experience delivery disruptions based on observed operational conditions. The risk probability model is expressed as:

$$P(Risk) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)}}$$

Where $P(Risk)$ represents the probability that a project will experience delivery disruption. The parameter β_0 represents the intercept term, while $\beta_1, \beta_2, \ldots, \beta_n$ represent regression coefficients associated with ERP-derived operational indicators. The variables $x_1, x_2, \ldots, x_n$ correspond to normalized ERP features such as cost variance, schedule delay ratio, procurement lead time variability, workforce allocation imbalance, and task completion performance. The logistic transformation ensures that predicted risk values are constrained between zero and one, allowing the model to interpret risk as a probability.

The predictive analysis reveals that financial indicators derived from ERP accounting modules demonstrate strong correlation with project delivery delays. Projects exhibiting high cost variance values frequently correspond to elevated delivery risk probabilities, suggesting that financial instability during execution phases often signals underlying operational inefficiencies or scope deviations. This finding highlights the importance of continuous financial monitoring in large multinational projects, where budget deviations may cascade into broader project disruptions.

Procurement lead time variability also emerges as a significant predictor of delivery risk. ERP procurement datasets indicate that fluctuations in supplier delivery schedules frequently contribute to schedule uncertainty during project execution. When procurement lead times increase beyond expected thresholds, project teams experience delays in obtaining materials and equipment necessary for scheduled activities. This supply chain instability directly affects project scheduling performance and increases the probability of delivery delays.

Resource allocation imbalance represents another influential risk indicator identified through the predictive model. ERP human resource management systems record workforce allocation across project activities, enabling analysis of personnel deployment efficiency. Projects exhibiting significant deviations between planned and actual workforce allocation frequently experience reduced execution efficiency. Such imbalances create operational bottlenecks, reduce productivity, and increase the likelihood of delayed project completion.

Overall, the predictive risk indicator analysis demonstrates that ERP-derived operational variables provide valuable signals for identifying emerging delivery risks in multinational projects. Financial deviations, procurement delays, and workforce allocation inefficiencies interact dynamically throughout the project lifecycle and significantly influence delivery outcomes. The logistic risk prediction model successfully integrates these indicators into a probabilistic framework that enables project managers to monitor evolving risk conditions and implement proactive mitigation strategies before operational disruptions escalate into major project delays.

4.4 Implications for Multinational Project Governance

The results obtained from the predictive modeling framework have important implications for governance structures in large multinational projects. Modern multinational projects often involve geographically distributed teams, complex supply chains, and diverse regulatory environments. These conditions create operational uncertainty that can significantly affect project delivery performance. The integration of artificial intelligence with enterprise resource planning datasets enables organizations to strengthen project governance mechanisms by providing real-time insights into operational conditions and emerging risk signals. By leveraging predictive analytics, governance frameworks can transition from reactive risk management approaches toward proactive monitoring systems that anticipate project disruptions before they escalate.

One of the most significant implications of the proposed framework is the early detection of project delivery risk signals. Traditional project governance mechanisms often rely on periodic reporting cycles and manual monitoring processes that may fail to detect emerging operational problems in a timely manner. In contrast, the AI-driven predictive framework continuously analyzes ERP-generated operational data such as financial expenditures, procurement timelines, workforce deployment patterns, and task completion rates. By monitoring these indicators in real time, the system can identify deviations from expected operational patterns that signal potential delivery risks. Early detection enables project leaders to intervene before operational disruptions affect project schedules, budgets, or resource allocation strategies.

Another important governance implication involves improved decision support for project managers and executive stakeholders. Predictive analytics systems transform raw operational datasets into structured risk insights that can inform strategic decision-making. Instead of relying solely on subjective judgment or historical experience, project managers can use predictive risk indicators derived from ERP datasets to evaluate the likelihood of delivery disruptions. These insights support evidence-based decision-making processes by enabling project leaders to prioritize risk mitigation actions, allocate resources more efficiently, and adjust project schedules when early warning signals emerge. Such decision-support capabilities enhance organizational agility and improve the ability of multinational project teams to respond effectively to operational challenges.

The development of ERP-driven risk monitoring dashboards represents an additional governance benefit of the proposed framework. Visualization tools integrated with ERP analytics platforms can display predictive risk indicators, operational performance metrics, and anomaly detection alerts in real time. These dashboards provide project managers and organizational leaders with a comprehensive overview of project performance across multiple operational dimensions. Financial indicators, procurement metrics, workforce utilization data, and scheduling performance measures can be visualized simultaneously, allowing decision-makers to quickly identify areas of concern and implement corrective actions.

In multinational project environments where coordination across departments and geographic regions is essential, such integrated dashboards improve transparency and communication among stakeholders. By presenting predictive risk indicators in an accessible visual format, ERP-driven monitoring systems enable project teams to share consistent information about project conditions and risk levels. This improved visibility strengthens governance processes by ensuring that project decisions are informed by accurate and timely operational data.

Overall, the integration of AI-driven predictive analytics with ERP monitoring systems significantly enhances governance capabilities in multinational project environments. Early detection of risk signals, improved decision-support mechanisms, and real-time monitoring dashboards collectively strengthen the ability of organizations to manage complex projects effectively. These capabilities enable project governance frameworks to evolve toward more intelligent, data-driven systems that support proactive risk management and improved project delivery performance.

5. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

This study developed an artificial intelligence–driven predictive framework for identifying project delivery risks using operational data extracted from enterprise resource planning systems. The results demonstrate that machine learning algorithms can effectively analyze ERP-derived operational indicators and generate predictive insights that support proactive risk monitoring in large multinational projects. By integrating financial performance indicators, procurement lead time variability, workforce allocation metrics, and project scheduling variables, the predictive models were able to estimate the probability of delivery disruptions with a high level of accuracy.

The findings indicate that the integration of multiple ERP modules significantly enhances predictive performance. Financial indicators derived from ERP accounting systems provided strong signals related to cost instability, while procurement datasets captured supply chain volatility that often affects project schedules. Workforce allocation metrics obtained from human resource systems revealed patterns of resource imbalance that influence execution efficiency. When these variables were integrated within machine learning models, the predictive framework successfully identified relationships between operational indicators and project delivery outcomes.

The comparative evaluation of machine learning models further confirmed that ensemble learning techniques and neural network architectures offer strong predictive capabilities in ERP-driven risk prediction environments. These algorithms effectively captured nonlinear relationships among operational indicators and demonstrated strong classification performance across evaluation metrics. Overall, the results confirm that artificial intelligence–based predictive analytics can significantly enhance project monitoring systems by enabling early detection of delivery risk signals within complex multinational project environments.

5.2 Key Contributions

This research contributes to the advancement of intelligent project management systems by proposing a comprehensive predictive framework that integrates enterprise operational datasets with artificial intelligence techniques. One of the primary contributions of the study is the development of an AI-driven ERP risk prediction architecture capable of transforming operational project data into predictive risk indicators. The framework integrates ERP data extraction processes, feature engineering mechanisms, machine learning prediction models, and decision-support systems into a unified analytical architecture designed for multinational project environments.

Another important contribution involves the mathematical formulation of project risk indicators derived from ERP operational variables. By constructing quantitative indicators based on financial performance, procurement variability, workforce allocation efficiency, and scheduling performance, the study provides a structured approach for transforming enterprise operational data into measurable risk indicators. These mathematical representations allow predictive models to estimate delivery risk probabilities in a transparent and systematic manner.

The research also provides a comparative evaluation of multiple machine learning algorithms for predictive project analytics. By assessing the performance of Random Forest, Support Vector Machine, Gradient Boosting, and Deep Neural Network models, the study identifies the strengths and limitations of different algorithms when applied to ERP-driven project risk prediction tasks. This comparative analysis provides valuable insights for organizations seeking to implement predictive analytics systems within enterprise project management environments.

5.3 Limitations

Despite the promising results obtained in this study, several limitations should be acknowledged. One limitation concerns the dependence of predictive models on the quality and completeness of ERP datasets. Enterprise operational data may contain inconsistencies, missing values, or measurement errors that could affect predictive model performance. Ensuring data accuracy and standardization is therefore essential for maintaining the reliability of predictive analytics systems.

Another limitation relates to the diversity of the dataset used in the analysis. Although the dataset represents operational records from multinational project environments, the sample may not fully capture the wide range of project types across different industries. Variations in project structures, supply chain configurations, and organizational governance models may influence the applicability of the predictive framework across sectors such as construction, information technology, energy, and manufacturing. Expanding the dataset across multiple industries could improve the generalizability of the predictive models.

5.4 Recommendations for Future Research

Future research should explore the integration of real-time Internet of Things (IoT) monitoring data with enterprise resource planning datasets to further enhance predictive project analytics systems. IoT-enabled sensors embedded within project environments can generate continuous streams of operational data related to equipment performance, material flows, and environmental conditions. Combining these real-time data streams with ERP datasets could improve the accuracy and responsiveness of predictive risk monitoring frameworks.

Another promising research direction involves the incorporation of explainable artificial intelligence techniques into predictive project management systems. Methods such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations) can improve transparency by identifying which operational variables contribute most strongly to predicted risk outcomes. Enhancing interpretability is particularly important in organizational environments where project managers and stakeholders require clear explanations of predictive model outputs before implementing risk mitigation strategies.

Finally, future research should focus on the development of real-time predictive dashboards designed for monitoring multinational project portfolios. Such dashboards could integrate ERP datasets, machine learning predictions, and visual analytics tools into interactive platforms that support strategic decision-making across large project networks. By enabling continuous monitoring of delivery risk indicators across multiple projects, these systems would strengthen organizational governance frameworks and improve the management of complex multinational project portfolios.

REFERENCES

1. Ajayi, J. O., Omidiora, M. T., Addo, G., & Peter-Anyebe, A. C. Prosecutability of the crime of aggression: Another declaration in a treaty or an achievable norm? International Journal of Applied Research in Social Sciences, 2019; 1(6).
2. Akello, E. F., Ijiga, O. M., Idoko, I. P., & Enyejo, L. A. Multimodal Large Language Models for Diagnostic Feedback Analytics in STEM Learning Platforms. *International Journal of Scientific Research and Modern Technology*, 2025; *4*(1): 182–210. https://doi.org/10.38124/ijsrmt.v4i1.1163
3. Akindote, O., Enyejo, J. O., Awotiwon, B. O. & Ajayi, A. A. Integrating Blockchain and Homomorphic Encryption to Enhance Security and Privacy in Project Management and Combat Counterfeit Goods in Global Supply Chain Operations. *International Journal of Innovative Science and Research Technology,* NOV. 2024; 9(11): ISSN No:-2456-2165. https://doi.org/10.38124/ijisrt/IJISRT24NOV149.
4. Akinleye, K. E., Jinadu, S. O., Onwusi, C. N., & Raphael, F. O. Utilizing enhanced artificial lift technologies to improve oil production rates in aging onshore American petroleum fields. International Journal of Scientific Research and Modern Technology, 2022; 1(6).
5. Akkermans, H., Bogerd, P., Yücesan, E., & Van Wassenhove, L. The impact of ERP on supply chain management: Exploratory findings from a European Delphi study. European Journal of Operational Research, 2003; 146(2): 284–301.
6. Aloini, D., Dulmin, R., & Mininno, V. Risk management in ERP project introduction: Review of the literature. Information & Management, 2007; 44(6): 547–567.
7. Amebleh, J., Igba, E., & Ijiga, O. M. Advanced anomaly detection systems in financial transactions using graph-based learning. International Journal of Scientific Research in Science, Engineering and Technology, 2021; 8(6).
8. Amebleh, J., Igba, E., & Ijiga, O. M. Graph-based fraud detection in open-loop gift cards: Heterogeneous GNNs, streaming feature stores, and near-zero-lag anomaly alerts. International Journal of Scientific Research in Science, Engineering and Technology, 2021; 8(6).
9. Anokwuru, E. A. Leveraging AI-Enhanced Commercial Insights for Precision Marketing in the Biopharmaceutical Industry. *International Journal of Scientific Research and Modern Technology*, 2024; *3*(9): 110–125. https://doi.org/10.38124/ijsrmt.v3i9.1204
10. Anokwuru, E. A., Omachi, A. & Enyejo, J. O. Automation-Enabled RFI/RFP Market Intelligence Platforms: Redefining Data-Driven Business Development in Global Pharmaceutical Markets *International Journal of Scientific Research in Science and Technology*, 2024; 12(3): 1016-1036. doi: https://doi.org/10.32628/IJSRST54310301
11. Anokwuru, E. A., Omachi, A. & Enyejo, L. A. Human-AI Collaboration in Pharmaceutical Strategy Formulation: Evaluating the Role of Cognitive Augmentation in Commercial Decision Systems *International Journal of Scientific Research in Computer Science, Engineering and Information Technology,* 2022; 8(2): 661-678. doi: https://doi.org/10.32628/CSEIT2541333
12. Armah, G. D., Idoko, P. I. Adeyeye, Y. I. Enyejo, L. A., & Azonuche, T. I. Quantifying The Economic Spillover Effects of Healthcare Data Breaches Using Panel Regression. *European Journal of Biomedical and Pharmaceutical Sciences,* 2024; 11(12): 631–656. https://www.ejpmr.com/home/abstract_id/14810

13. Azonuche, T. I., & Enyejo, J. O. Agile Transformation in Public Sector IT Projects Using Lean-Agile Change Management and Enterprise Architecture Alignment. *International Journal of Scientific Research and Modern Technology*, 2024; *3*(8): 21–39. https://doi.org/10.38124/ijsrmt.v3i8.432
14. Azonuche, T. I., & Enyejo, J. O. Adaptive Risk Management in Agile Projects Using Predictive Analytics and Real-Time Velocity Data Visualization Dashboard. International Journal of Innovative Science and Research Technology, April – 2025; 10(4). ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/25apr2002
15. Bento, S., Pereira, L., Gonçalves, R., Dias, Á., & Costa, R. Artificial intelligence in project management: A systematic literature review. International Journal of Technology Intelligence and Planning, 2022; 14(2): 143–160.
16. Bishop, C. M. Pattern recognition and machine learning. Springer, 2006.
17. Bradford, M. Modern ERP: Select, implement, and use today's advanced business systems (3rd ed.). Lulu Press, 2015.
18. Breiman, L. Random forests. Machine Learning, 2001; 45(1): 5–32.
19. Cantarelli, C., Flyvbjerg, B., Molin, E., & Van Wee, B. Cost overruns in large-scale transportation infrastructure projects. Transport Reviews, 2012; 32(5): 577–596.
20. Chen, T., & Guestrin, C. XGBoost: A scalable tree boosting system. Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016; 785–794.
21. Cortes, C., & Vapnik, V. Support-vector networks. Machine Learning, 1995; 20(3): 273–297.
22. Davenport, T. H. Putting the enterprise into the enterprise system. Harvard Business Review, 1998; 76(4): 121–131.
23. Enyejo, J. O., Fajana, O. P., Jok, I. S., Ihejirika, C. J., Awotiwon, B. O., & Olola, T. M. Digital twin technology, predictive analytics, and sustainable project management in global supply chains for risk mitigation, optimization, and carbon footprint reduction through green initiatives. International Journal of Innovative Science and Research Technology, 2024; 9(11).
24. Fridgeirsson, T. V., Ingason, H. T., Jonasson, H. I., & Jonsdottir, H. The future role of artificial intelligence in project management. Sustainability, 2021; 13(19): 11009.
25. Friedman, J. H. Greedy function approximation: A gradient boosting machine. Annals of Statistics, 2001; 29(5): 1189–1232.
26. Frimpong, G., Peter-Anyebe, A. C., & Ijiga, O. M. Artificial intelligence driven compliance automation improving audit readiness and fraud detection within healthcare revenue cycle management systems. Global Journal of Engineering, Science & Social Science Studies, 2023; 9(9).
27. Géron, A. Hands-on machine learning with Scikit-Learn, Keras, and TensorFlow (2nd ed.). O'Reilly Media, 2019.
28. Goodfellow, I., Bengio, Y., & Courville, A. Deep learning. MIT Press, 2016.
29. Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. Multivariate data analysis (8th ed.). Cengage Learning, 2019.
30. Idika, C. N., Salami, E. O., Ijiga, O. M., & Enyejo, L. A. Deep learning driven malware classification for cloud-native microservices in edge computing architectures. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 2021; 7(4).
31. Idika, C. N., Salami, E. O., Ijiga, O. M., & Enyejo, L. A. Machine learning approaches for predictive analytics in distributed systems. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 2021; 7(4).
32. Ivanov, D., Sokolov, B., & Dolgui, A. The ripple effect in supply chains: Trade-off efficiency–flexibility–resilience in disruption management. International Journal of Production Research, 2017; 52(7): 2154–2172.
33. Ihimoyan, M. K., Ibokette, A. I., Olumide, F. O., Ijiga, O. M., & Ajayi, A. A. The Role of AI-Enabled Digital Twins in Managing Financial Data Risks for Small-Scale Business Projects in the United States. *International Journal of Scientific Research and Modern Technology,* 2024; 3(6): 12–40. https://doi.org/10.5281/zenodo.14598498
34. James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning with applications in R. Springer.
35. Kerzner, H. (2018). Project management: A systems approach to planning, scheduling, and controlling (12th ed.). Wiley.
36. Klaus, H., Rosemann, M., & Gable, G. G. What is ERP? Information Systems Frontiers, 2000; 2(2): 141–162.
37. Kwarteng, R. A., Idoko, I. P. & Ijiga, O. M. DATA-DRIVEN PROJECT MANAGEMENT FRAMEWORKS FOR IMPROVING IT SERVICE DELIVERY IN DISTRIBUTED ORGANIZATIONS. Computer Science & IT Research Journal, November 2021; 2(1).
38. Love, P. E. D., Edwards, D. J., & Irani, Z. Moving beyond optimism bias and strategic misrepresentation: An explanation for social infrastructure project cost overruns. IEEE Transactions on Engineering Management, 2015; 59(4): 560–571.
39. Marnewick, C., & Marnewick, A. Artificial intelligence and machine learning for project risk management. South African Journal of Industrial Engineering, 2020; 31(3): 1–14.
40. Monk, E., & Wagner, B. (2013). Concepts in enterprise resource planning (4th ed.). Cengage Learning.
41. Niederman, F. Project management: Opening the door for disruption from artificial intelligence and advanced analytics. Information Technology & People, 2021; 34(5): 1340–1361.
42. Nwokocha, C. R., Peter-Anyebe, A. C., & Ijiga, O. M. Evaluating FHIR-driven interoperability frameworks for secure system migration and data exchange in U.S.

health information networks. International Journal of Scientific Research in Science and Technology, 2021a; 7(5).
43. Nwokocha, C. R., Peter-Anyebe, A. C., & Ijiga, O. M. Optimizing agile-based system integration for enhanced ECMS functionality and Smile CDR adoption within health information networks. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 2021b; 7(6).
44. Nwokocha, C. R., Soetan, K. T., & Peter-Anyebe, A. C. Automating ETL pipelines with SQL Server Integration Services to improve health data quality and reporting accuracy in national health systems. International Journal of Scientific Research in Science and Technology, 2022; 9(4).
45. Okoh, O. F., Ukpoju, E. A., Otakwu. A., Ayoolad, V. B. & Enyejo, L. A. (2024). CONSTRUCTION MANAGEMENT: SOME ISSUES IN THE CONSTRUCTION PROJECT. *Engineering Heritage Journal (GWK).* ISSN: 2521-0440 (Online). DOI: http://doi.org/10.26480/gwk.01.2024.42.50
46. Ononiwu, M., Azonuche, T. I., & Enyejo, J. O. Investigating Agile Portfolio Management Techniques for Prioritizing Strategic Initiatives in Large-Scale Government IT Projects *International Journal of Management & Entrepreneurship Research* Fair East Publishers, 2025; 7(6): 464-483. https://doi.org/10.51594/ijmer.v7i6.1941
47. Ononiwu, M., Azonuche, T. I., Imoh, P. O. & Enyejo, J. O. Evaluating Blockchain Content Monetization Platforms for Autism-Focused Streaming with Cybersecurity and Scalable Microservice Architectures *ICONIC RESEARCH AND ENGINEERING JOURNALS*, 2024; 8(1).
48. Ononiwu, M., Azonuche, T. I., Okoh, O. F. & Enyejo, J.O. Machine Learning Approaches for Fraud Detection and Risk Assessment in Mobile Banking Applications and Fintech Solutions *International Journal of Scientific Research in Science, Engineering and Technology*, 2023; 10(4). https://doi.org/10.32628/IJSRSET232531
49. Onwuzurike, M. A., & Kpogli, S. A. AI-driven decision-making frameworks for enterprise systems optimization. International Journal of Scientific Research and Modern Technology, 2022; 1(12).
50. Onwuzurike, M. A., & Kpogli, S. A. Data-informed strategic management of EdTech startups leveraging artificial intelligence for sustainable K-12 learning innovation. International Journal of Scientific Research and Modern Technology, 2022; 1(12).
51. Onwuzurike, M. A., & Kpogli, S. A. Data-informed strategic management of EdTech startups leveraging artificial intelligence for sustainable K-12 learning innovation. *International Journal of Scientific Research and Modern Technology,* 2022; *1*(12): 187–200.
52. Onyekaonwu, C. B., Peter-Anyebe, A. C., & Raphael, F. O. From prescription to prediction: Leveraging AI/ML to improve medication adherence and adverse drug event detection in community pharmacies. International Journal of Scientific Research in Science and Technology, 2019; 6(5).
53. Onyekaonwu, C. B., Peter-Anyebe, A. C., Ijiga, O. M., Amebleh, J., & Balogun, S. A. Securing the Digital Vault: Enterprise Data Loss Prevention (DLP) in the Age of GDPR and NDPR. *International Journal of Scientific Research and Modern Technology*, 2022; *1*(6): 14–28. https://doi.org/10.38124/ijsrmt.v1i6.1159
54. Pinto, J. K. Project management: Achieving competitive advantage (5th ed.). Pearson, 2019.
55. Powers, D. M. W. Evaluation: From precision, recall and F-measure to ROC, informedness, markedness and correlation. Journal of Machine Learning Technologies, 2011; 2(1): 37–63.
56. Project Management Institute. (2021). A guide to the project management body of knowledge (PMBOK Guide) (7th ed.).
57. Sanmori, M. T. AI-Driven Functional Independence Prediction and Assistive Technology Optimization to Reduce Medicare Expenditures Among Older Adults in the United States. International Journal of Scientific Research and Modern Technology, 2024; 3(11): 186–205. https://doi.org/10.38124/ijsrmt.v3i11.1295
58. Somers, T. M., & Nelson, K. A taxonomy of players and activities across the ERP project life cycle. Information & Management, 2004; 41(3): 257–278.
59. Taboada, I., Daneshpajouh, A., Toledo, N., & De Vass, T. Artificial intelligence enabled project management: A systematic literature review. Applied Sciences, 2023; 13(8): 5014.
60. Tang, C. S. Robust strategies for mitigating supply chain disruptions. International Journal of Logistics Research and Applications, 2006; 9(1): 33–45.
61. Umble, E. J., Haft, R. R., & Umble, M. M. Enterprise resource planning: Implementation procedures and critical success factors. European Journal of Operational Research, 2003; 146(2): 241–257.
62. Wang, E. T. G., Shih, S. P., Jiang, J. J., & Klein, G. The consistency among facilitating factors and ERP implementation success: A holistic view of fit. Journal of Systems and Software, 2008; 81(9): 1609–1621.
63. Ward, S., & Chapman, C. Transforming project risk management into project uncertainty management. International Journal of Project Management, 2003; 21(2): 97–105.
64. Zhang, L., Lee, M. K. O., Zhang, Z., & Banerjee, P. Critical success factors of enterprise resource planning systems implementation success in China. Proceedings of the 36th Hawaii International Conference on System Sciences, 2003.
65. Zhang, Y., & Wang, L. Machine learning approaches for project risk prediction. IEEE Access, 2020; 8: 193567–193577.
66. Zou, P. X., Zhang, G., & Wang, J. Understanding the key risks in construction projects in China. International Journal of Project Management, 2007; 25(6): 601–614.
67. Zwikael, O., & Ahn, M. The effectiveness of risk management: An analysis of project risk planning across industries. Risk Analysis, 2011; 31(1): 25–37.