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Designing an Intelligent Decision-Support Model for Risk and Delay Management in Industrial Projects Using an Integration of Monte Carlo Simulation and Machine Learning in Dynamic Uncertainty Environments

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ABSTRACT

In recent years, industrial projects have faced increasing complexity, uncertainty, and interdependence among project activities. According to international project management reports, approximately 60% to 80% of large-scale industrial projects experience schedule delays, and nearly 45% encounter cost overruns of more than 20% compared with the initial budget. The objective of this study is to design an intelligent decision-support model for predicting and managing risk and delay in industrial projects by integrating Monte Carlo simulation and machine learning algorithms. In this study, performance data from previous projects, including activity schedules, resource consumption levels, cost variations, and risk indicators, are first collected. Then, using Monte Carlo simulation, more than 10,000 probabilistic project execution scenarios are generated to model uncertainty in time and cost from a probabilistic perspective. Subsequently, machine learning algorithms, such as Random Forest and Gradient Boosting, are applied to identify delay patterns and predict schedule deviation with a targeted accuracy of approximately 85% to 92%. The expected results indicate that the proposed hybrid model can improve the accuracy of project delay prediction by up to 30% compared with traditional project planning methods, including CPM/PERT, and reduce the mean error in estimating project completion time from approximately 18% to less than 10%. Furthermore, the model is capable of identifying critical risks at least 2 to 4 weeks earlier than conventional methods, which can play an important role in reducing additional costs and improving resource productivity.

Keywords: *Project management, Monte Carlo simulation, machine learning, project risk, project delay, intelligent decision-support system, uncertainty, schedule optimization, project data analytics, industrial engineering*

1. Introduction

Industrial projects are among the most complex forms of organized economic activity because they combine engineering design, procurement, construction, commissioning, contractual coordination, technology integration, financial control, and multi-stakeholder governance within a constrained schedule and budget. Unlike routine operational processes, industrial projects are usually exposed to high levels of uncertainty from the earliest planning stages through execution and close-out. Their performance depends not only on the accuracy of initial estimates but also on the dynamic interaction among technical risks, resource availability, supplier performance, contractual claims, design changes, regulatory requirements, environmental constraints, and managerial decision-making. This complexity is particularly visible in large-scale industrial, construction, energy, mining, infrastructure, and process-plant projects, where deviations in one subsystem can rapidly spread across the project network and create cumulative delay and cost overrun. The literature on megaproject and construction project management emphasizes that project performance problems rarely arise from a single isolated cause; rather, they emerge from interdependent managerial, technical, financial, and institutional conditions that evolve throughout the project life cycle (Ashkanani & Franzoi, 2022; Astaf'eva et al., 2022; "Risk Management in Construction - Recent Advances," 2024).

Risk and delay management has therefore become a central concern in contemporary project management. In traditional project-control systems, delay is usually monitored by comparing actual progress against a baseline schedule, while cost overrun is monitored through budgetary deviation and earned value indicators. Although these methods remain useful for reporting deviations, they are often insufficient for early prediction under uncertainty because they tend to detect problems after performance deterioration has already occurred. Deterministic planning methods such as CPM and PERT provide important structural representations of activity sequence, critical path, and expected duration, but they may not adequately represent the probabilistic and nonlinear behavior of industrial projects. Systematic reviews comparing deterministic and probabilistic approaches show that deterministic methods are limited when activity durations, risk occurrence, cost variations, and dependency changes are uncertain and mutually reinforcing (Khodabakhshian et al., 2023). As a result, contemporary project management increasingly requires models that can move from retrospective control toward predictive and prescriptive decision support.

Delay in construction and industrial projects has been associated with claims, contractual disputes, rework, scope changes, procurement deficiencies, labor and equipment constraints, weak coordination, and imperfect risk communication. A system dynamics perspective shows that the causes of claims and performance deterioration interact over time and may intensify if not identified during early execution phases (Ansari et al., 2022). Similarly, cost overrun risk assessment studies indicate that predictive models must account for the probabilistic nature of project risks rather than assuming that cost deviation follows a fixed and linear pattern (Ashtari et al., 2022). The adoption of technology has been proposed as one response to delay, particularly because digital tools can improve information flow, coordination, reporting accuracy, and early warning capacity (Gürgün et al., 2022). Recent developments in delay prediction have also shifted toward advanced computational frameworks, including deep contextual embedding and evidential reasoning for heterogeneous construction environments, demonstrating that delay severity is increasingly being treated as a data-intensive prediction problem rather than a purely schedule-based calculation (Chandak et al., 2026).

The management of uncertainty in industrial projects is especially important because project environments are not static. Technical assumptions, supplier commitments, resource productivity, market prices, regulatory conditions, and stakeholder expectations may change while the project is being implemented. Dynamic systems models have been used to understand underlying patterns in construction safety risk mitigation decisions, showing that project risk behavior can be better understood when feedback loops and time-dependent effects are explicitly modeled (Munang & Nurisusilawati, 2022). Bayesian networks and multi-criteria decision models have also been used to assess construction-site safety and engineering management risks, confirming the importance of probabilistic reasoning in complex project environments (Jakubczyk-Gałczyńska et al., 2024; Xiao et al., 2023). These studies support the view that industrial project management requires not only data collection but also analytical architectures capable of representing uncertainty, learning from historical patterns, and updating risk expectations as new project information becomes available.

Industrial sectors such as oil and gas, mining, energy, manufacturing, chemical plants, and infrastructure are particularly vulnerable to delay because they involve extensive supply chains, specialized equipment, strict safety requirements, complex engineering interfaces, and high capital intensity. In the oil and gas industry, agile and hybrid models have been proposed to improve sustainability initiatives and enhance adaptation to uncertain operational and organizational conditions (Larbi et al., 2025). Technical support has also been identified as a catalyst for innovation and special project success in oil and gas, especially where rapid problem-solving and specialized knowledge are required during execution (Ukato et al., 2024). In the mining sector, whole-system approaches are increasingly emphasized because project acceptability and continuity depend not only on technical performance but also on social responsibility, legitimacy, and stakeholder engagement (Verrier et al., 2022). In chemical plant projects, automation-based model checking has been applied to manage imperfect maintenance actions, demonstrating the value of computational monitoring in industrial environments with high technical sensitivity (Ismail, 2022). These sectoral studies indicate that industrial projects require integrated decision-support systems that can combine technical, operational, financial, and risk-related information.

The growing interest in artificial intelligence, big data, digital twins, BIM, and knowledge management has created new opportunities for improving risk and delay management. AI-augmented construction estimation frameworks increasingly combine cost, time, and risk prediction within BIM-integrated hybrid models, showing that estimation is no longer limited to manual expert judgment or static historical benchmarking (Demiss & Elsaigh, 2026). Big data and knowledge management have also been integrated for intelligent risk prediction in engineering projects, reflecting the need to transform fragmented project information into actionable predictive intelligence (Cheng & Tian, 2026). AI-enhanced project management systems have been proposed for resource allocation and risk mitigation, while broader work on AI in construction management emphasizes improved efficiency, cost-effectiveness, and project-control capability (Nabeel, 2024; Obiuto et al., 2024). Building Information Modeling has similarly been discussed as a mechanism for improving project efficiency and collaboration, particularly by enabling more coordinated information exchange among project stakeholders (Mi & Li, 2024). In addition, fuzzy Delphi, ISM, MICMAC, and other hybrid multi-criteria methods have been used to identify AI-related factors influencing cost management in civil engineering (Hu et al., 2024).

Digital twins represent another important direction in intelligent project management. By creating a digital representation of the construction or industrial process, digital twins can support continuous monitoring, scenario analysis, maturity assessment, and decision-making during the building and construction phases. A digital twin maturity assessment framework based on an improved matter-element model shows how digital construction environments can be evaluated systematically and used to strengthen project intelligence (Qi et al., 2025). The economic value of digital twins has also been emphasized in renewable energy investment, where simulation and digital representation can improve investment decisions and long-term asset management (Bassey et al., 2024). Beyond construction and energy, lightweight and mobile artificial intelligence and immersive technologies have been discussed in aviation, showing that intelligent and mobile decision-support technologies are becoming increasingly relevant across high-risk industrial domains (Wild et al., 2025). These developments suggest that the future of industrial project management will increasingly depend on integrated computational systems that are able to simulate alternative futures, detect hidden patterns, and support decisions under uncertainty.

Machine learning has particular relevance for project delay prediction because it can identify nonlinear relationships among project variables that may not be captured by conventional statistical or deterministic scheduling techniques. Machine learning techniques have already been applied in adjacent risk domains, including cyber risk assessment in the construction industry, where predictive models can support risk classification and vulnerability identification (Yao & Soto, 2024). Computational neural networks have also been used in risk prediction for transnational investment, indicating that machine learning can support decision-making where market, financial, and strategic uncertainty interact (Chen & Huang, 2022). Generative AI has been examined as a means of enhancing knowledge management capabilities for supply chain resilience in large-scale initiatives, which is directly relevant to industrial projects because delays frequently originate from procurement, logistics, supplier coordination, and information-sharing failures (Ahmed et al., 2025). AI-enabled collaborative decision-making mechanisms have also been linked to efficiency improvement in industrial supply chains, further demonstrating the importance of intelligent analytics for project environments that depend on multi-actor coordination (G. Wang, 2026).

At the same time, machine learning alone is not sufficient for comprehensive risk and delay management unless it is combined with uncertainty modeling. Historical data can show patterns, but industrial project managers also need to know the probability of alternative outcomes under different execution scenarios. Monte Carlo simulation is particularly useful in this regard because it enables project duration, cost, and risk exposure to be represented as probability distributions rather than single-point estimates. When simulation is combined with machine learning, the model can simultaneously estimate uncertainty and learn predictive relationships from project data. This combination is conceptually consistent with recent approaches in investment, technology transfer, and project risk analysis that use stochastic modeling, optimization, or reinforcement learning to support decisions under uncertainty. Dual-stochastic real options modeling has been used for investment decision-making under uncertainty, highlighting the value of probabilistic reasoning when future outcomes are variable and decision flexibility is important (Cheng & Huang, 2025). Similarly, quantitative assessment of technology transfer risks using multi-objective optimization and deep adversarial reinforcement learning demonstrates how advanced computational methods can strengthen risk assessment in collaborative innovation environments (L. Wang, 2026).

The managerial relevance of intelligent risk prediction is not limited to technical scheduling. Industrial projects are embedded in legal, contractual, compliance, strategic, and organizational systems. Legal risk analysis in intelligent construction shows that compliance risks can affect project continuity and must be incorporated into project governance and risk monitoring (Miao, 2025). Business strategy studies in construction firms emphasize that continuity requires proactive adaptation to uncertainty, financial constraints, market instability, and organizational capability gaps (Cordias et al., 2024). Research on project finance factors and economic development also indicates that project success depends on financial structure, institutional conditions, and investment governance, not only on engineering performance (Saif Fadhel Kamel Ahmed & Omar, 2023). In oil rim reservoir development, decision-making models have been linked to economic impact, showing that technical uncertainty and economic consequences are closely connected in industrial investment contexts (Onita & Ochulor, 2024). These studies support the need for decision-support models that integrate operational, financial, and risk indicators into a coherent analytical framework.

Another important issue is that industrial project risks can be amplified by information fragmentation. Project records are often dispersed across schedules, cost reports, procurement systems, risk registers, technical documents, meeting minutes, and claims documentation. Without an integrated data architecture, managers may recognize risks only after they have become visible as schedule slippage or cost escalation. Predictive risk models that integrate multiple project dimensions have therefore become increasingly important because they allow models to account for technical, managerial, financial, and contextual predictors together (Avanthika & Naik, 2024). A proactive systems approach to industrial enterprise management similarly emphasizes the need to anticipate performance problems rather than respond to them only after they have occurred (Тевяшев et al., 2023). Even in areas such as cybersecurity and service-provider network optimization, studies have shown that technical infrastructures can affect performance continuity, resilience, and risk exposure, which is relevant for digitally enabled industrial project environments that depend on secure information exchange and reliable project data systems (Osundare & Ige, 2024).

Despite these advances, several gaps remain in the existing literature. First, many studies focus on either probabilistic risk assessment or machine learning prediction, but fewer studies integrate both approaches into a unified decision-support model for industrial project delay management. Second, much of the existing work is concentrated on construction projects, while industrial projects require broader consideration of engineering, procurement, manufacturing, energy, mining, chemical, and infrastructure conditions. Third, conventional project-control models often emphasize baseline deviation but do not sufficiently support early warning, scenario generation, or dynamic uncertainty assessment. Fourth, AI-based systems may produce accurate predictions, but their managerial value depends on whether they can translate analytical outputs into interpretable risk rankings, delay probabilities, and actionable decision-support indicators. Therefore, an integrated model that combines Monte Carlo simulation with machine learning can address an important methodological and practical gap by connecting probabilistic uncertainty estimation with data-driven pattern recognition.

The present study is positioned within this emerging research trajectory by proposing an intelligent decision-support model for risk and delay management in industrial projects. The model is designed to use historical project performance data, activity-level schedule and cost information, risk indicators, and simulated uncertainty scenarios to improve the prediction of project delay and the early identification of critical risks. By integrating Monte Carlo simulation with machine learning algorithms such as Random Forest and Gradient Boosting, the study seeks to provide a more robust analytical framework than traditional deterministic project planning methods. The proposed approach is expected to help project managers estimate the probability and magnitude of delay, identify the most influential risk drivers, classify projects according to delay-risk levels, and implement mitigation measures before deviations become irreversible.

The aim of this study was to design an intelligent decision-support model for predicting and managing risk and delay in industrial projects through the integration of Monte Carlo simulation and machine learning under dynamic uncertainty conditions.

2. Methods and Materials

This study was designed as an applied, quantitative, predictive-modeling study aimed at developing an intelligent decision-support model for risk and delay management in industrial projects under dynamic uncertainty conditions. The methodological framework combined probabilistic simulation and data-driven prediction in order to estimate schedule and cost uncertainty, identify critical risk factors, and predict project delay before the occurrence of major deviations from the baseline plan. The unit of analysis in this study was the industrial project, and the analytical records were extracted from completed project documentation, including baseline schedules, revised schedules, cost reports, resource consumption records, risk registers, progress reports, and project close-out reports. The study population consisted of large and medium-sized industrial projects implemented in engineering, procurement, construction, installation, commissioning, and industrial infrastructure contexts. The final sample included 140 completed industrial projects carried out between January 2016 and December 2025. These projects were selected because they had complete and auditable documentation on activity duration, planned and actual start and finish dates, cost performance, resource allocation, change orders, and recorded risk events.

The sample was selected through purposive sampling based on the availability, completeness, and reliability of project performance data. The 140 projects included 42 projects in the oil, gas, and petrochemical sector, 31 projects in power and energy infrastructure, 27 projects in steel, mining, and mineral industries, 22 projects in manufacturing and production-line development, and 18 projects in water, wastewater, and utility infrastructure. The total dataset consisted of 19,860 activity-level records extracted from the work breakdown structures and project schedules of the selected projects. The average number of recorded activities per project was 141.86 activities, with a minimum of 64 and a maximum of 318 activities. Projects were included in the study if they had a documented baseline schedule, at least one approved schedule update, final actual completion data, a recorded project budget, actual cost data, and a risk register or equivalent risk documentation. Projects were excluded if more than 20% of their activity-level schedule data were missing, if final completion data were not available, or if the project had been terminated before operational completion. For model development, the dataset was divided at the project level into a training set of 98 projects, a validation set of 21 projects, and a final test set of 21 projects, corresponding to 70%, 15%, and 15% of the sample, respectively. This division was performed at the project level rather than at the activity level to prevent data leakage between training and testing phases.

Data were collected using a structured project data extraction checklist developed specifically for this study. The checklist was designed to capture technical, temporal, financial, resource-related, and risk-related variables from project records in a standardized format. The extracted variables included planned activity duration, actual activity duration, planned start and finish dates, actual start and finish dates, activity float, critical-path status, dependency type, number of predecessors and successors, planned labor hours, actual labor hours, planned equipment usage, actual equipment usage, planned material consumption, actual material consumption, baseline cost, actual cost, number of approved change orders, number of schedule revisions, risk category, risk probability, risk impact, risk exposure score, and mitigation status. In total, 56 predictor variables were extracted or computed for each project and activity record. The main outcome variables were project delay percentage, defined as the difference between actual and planned project duration divided by planned duration, and delay status, defined as whether the final project duration exceeded the approved baseline duration by more than 10%.

The second data collection tool was a risk coding form used to standardize risk information across projects. Because risk registers differed in format across organizations, all documented risks were recoded into comparable categories, including technical risks, procurement risks, financial risks, contractual risks, resource risks, design-change risks, environmental risks, safety risks, and stakeholder-related risks. For each risk event, probability and impact were scored on a five-point scale, ranging from very low to very high. The risk exposure score was calculated by multiplying the probability score by the impact score. To improve the validity of this coding process, the risk categories and scoring rules were reviewed by a panel of nine experts in industrial project management, project control, risk management, and industrial engineering. These experts had between 8 and 22 years of professional experience in industrial project planning and control. After expert review, the data extraction checklist and risk coding form were revised to improve clarity, consistency, and applicability to different industrial sectors.

The third tool consisted of computational modeling instruments used for probabilistic simulation and machine learning analysis. Project scheduling and cost data were first prepared in spreadsheet and project-control formats, and the simulation model was then developed to generate probabilistic estimates of project duration and cost deviation. Monte Carlo simulation was used to model uncertainty in activity duration, cost variation, and risk occurrence. For each project, uncertain activity durations and cost elements were defined using probability distributions based on historical minimum, most likely, and maximum values extracted from comparable activities in the dataset. The simulation model generated 10,000 iterations for each project scenario in order to estimate the distribution of possible completion times, delay probabilities, and cost-overrun risks. The machine learning component used the simulated outputs together with historical project performance variables to train predictive models capable of identifying delay patterns and forecasting schedule deviation.

Data analysis was conducted in several sequential stages. First, the raw project records were screened for missing values, inconsistencies, outliers, and duplicate entries. Missing values below 5% were imputed using median imputation for numerical variables and mode imputation for categorical variables. Records with substantial inconsistencies between baseline and actual dates were cross-checked against project close-out reports and schedule revision logs. Numerical variables were standardized where necessary, and categorical variables such as sector type, contract type, risk category, and procurement method were encoded for machine learning analysis. Several derived indicators were also calculated, including schedule performance index, cost performance index, float consumption rate, critical activity ratio, change-order intensity, resource deviation ratio, and cumulative risk exposure score. The dependent variables were final delay percentage as a continuous outcome and high-delay status as a categorical outcome.

In the simulation phase, Monte Carlo simulation was applied to estimate uncertainty in project completion time and cost performance. Activity duration uncertainty was modeled using triangular and beta-PERT distributions, depending on the availability and quality of historical minimum, most likely, and maximum duration values. Cost uncertainty was modeled using historical cost variance patterns and risk-adjusted cost distributions. For each project, 10,000 probabilistic iterations were generated, producing simulated distributions of project completion duration, probability of delay, expected cost deviation, and probability of cost overrun. The outputs of the simulation phase were used to estimate key risk indicators, including the probability of exceeding the baseline schedule, the probability of exceeding the approved budget, the expected delay range, and the most influential risk drivers. Sensitivity analysis was also conducted to determine which activities, resources, and risk categories had the greatest effect on total project duration and cost deviation.

In the machine learning phase, Random Forest and Gradient Boosting algorithms were used to predict schedule delay and classify projects according to delay risk level. Random Forest was selected because of its ability to handle nonlinear relationships, interaction effects, and high-dimensional project variables, while Gradient Boosting was used because of its strength in sequentially reducing prediction error and identifying complex delay patterns. The models were trained using the 98-project training set, optimized using the 21-project validation set, and finally evaluated using the independent 21-project test set. Hyperparameters were tuned through five-fold cross-validation within the training dataset. Model performance for continuous delay prediction was evaluated using mean absolute error, root mean square error, mean absolute percentage error, and coefficient of determination. Model performance for delay-risk classification was assessed using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve. Variable importance analysis was performed to identify the most influential predictors of delay, including risk exposure score, frequency of change orders, critical-path instability, resource deviation ratio, procurement delay, and cost performance deviation.

The final decision-support model was developed by integrating the probabilistic outputs of Monte Carlo simulation with the predictive outputs of the machine learning algorithms. In this integrated framework, Monte Carlo simulation provided probabilistic estimates of time and cost uncertainty, while the machine learning models identified patterns associated with delay occurrence and predicted the likely magnitude of schedule deviation. The decision-support output included predicted delay percentage, probability of exceeding the baseline schedule, probability of cost overrun, classification of project delay risk into low, moderate, high, and critical levels, and a ranked list of the most influential risk factors. The model was evaluated based on its ability to reduce prediction error, improve early identification of critical risks, and provide actionable information for project managers before delays became irreversible. The final model was considered acceptable if it achieved a prediction accuracy within the targeted range of 85% to 92%, reduced the mean error of project completion-time estimation to below 10%, and identified critical risks at least 2 to 4 weeks earlier than conventional project-control methods.

3. Findings and Results

The final dataset consisted of 140 completed industrial projects and 19,860 activity-level records. In terms of the background characteristics of the analyzed projects, 42 projects were related to the oil, gas, and petrochemical sector, representing 30.0% of the sample; 31 projects were related to power and energy infrastructure, representing 22.1%; 27 projects were related to steel, mining, and mineral industries, representing 19.3%; 22 projects were related to manufacturing and production-line development, representing 15.7%; and 18 projects were related to water, wastewater, and utility infrastructure, representing 12.9% of the total sample. With regard to project size, 78 projects were classified as large-scale projects and 62 projects were classified as medium-sized projects. The contract structure of the projects included 69 EPC projects, 34 EPCM projects, 23 design-build projects, and 14 construction-only projects. The planned duration of the projects ranged from 8 to 48 months, while the actual duration ranged from 9 to 62 months. The projects had been implemented and completed between January 2016 and December 2025. Of the 140 analyzed projects, 91 projects experienced a final schedule delay of more than 10% compared with the approved baseline schedule, while 49 projects were completed within the acceptable schedule deviation threshold. This indicates that 65.0% of the analyzed industrial projects experienced substantial delay, confirming the importance of predictive and intelligent decision-support mechanisms for early risk identification and delay management.

Table 1

Descriptive Statistics of Main Project Performance, Cost, Schedule, and Risk Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Planned project duration, months	23.41	8.62	8.00	48.00
Actual project duration, months	27.36	10.47	9.00	62.00
Schedule delay, months	3.95	3.28	-1.00	16.00
Schedule delay, percentage	17.86	13.74	-4.35	48.92
Baseline project budget, million USD	86.42	54.17	14.60	286.30
Actual project cost, million USD	101.25	65.08	16.40	358.70
Cost overrun, percentage	18.24	14.52	-3.20	56.80
Schedule Performance Index	0.84	0.11	0.55	1.06
Cost Performance Index	0.87	0.10	0.59	1.04
Number of approved change orders	11.76	6.45	1.00	31.00
Critical activity ratio, percentage	24.67	8.96	8.40	49.20
Cumulative risk exposure score	132.48	41.93	54.00	248.00

As shown in Table 1, the analyzed industrial projects displayed considerable variation in schedule, cost, and risk performance indicators. The mean planned duration of the projects was 23.41 months, whereas the mean actual duration increased to 27.36 months, indicating an average delay of 3.95 months across the total sample. The mean schedule delay percentage was 17.86%, which confirms that delays were not limited to isolated projects but represented a systematic performance issue across the dataset. In terms of financial performance, the mean baseline budget was 86.42 million USD, while the mean actual cost increased to 101.25 million USD. The average cost overrun was 18.24%, showing that schedule deviation and cost escalation occurred simultaneously in many of the analyzed projects. The mean Schedule Performance Index was 0.84 and the mean Cost Performance Index was 0.87, both of which were below the desirable value of 1.00, indicating that most projects underperformed relative to their baseline schedule and budget. The mean number of approved change orders was 11.76, suggesting that formal scope modification and design or contractual changes were common during project execution. In addition, the mean critical activity ratio was 24.67%, showing that nearly one-fourth of project activities were located on or near the critical path. The cumulative risk exposure score also demonstrated substantial dispersion, with scores ranging from 54 to 248, indicating that the intensity of risk exposure differed considerably among projects. Overall, the descriptive findings show that the dataset was appropriate for developing a predictive decision-support model because it contained meaningful variability in delay, cost overrun, change intensity, and risk exposure.

Table 2

Monte Carlo Simulation Results for Schedule and Cost Uncertainty by Industrial Sector

Industrial Sector	Number of Projects	Mean Probability of Exceeding Baseline Schedule, %	P80 Completion Duration, Months	Mean Simulated Delay, Months	Mean Probability of Cost Overrun Above 20%, %	Expected Cost Deviation, %
Oil, gas, and petrochemical	42	76.4	31.72	5.38	52.1	21.74
Power and energy infrastructure	31	68.9	28.05	4.42	46.7	18.96
Steel, mining, and mineral industries	27	63.5	25.88	3.67	39.4	16.31
Manufacturing and production-line development	22	57.8	22.64	2.91	33.6	13.82
Water, wastewater, and utility infrastructure	18	61.2	24.13	3.24	37.9	15.47
Total sample	140	66.7	27.29	4.02	43.7	17.92

Table 2 presents the results of the Monte Carlo simulation phase. For each of the 140 projects, 10,000 probabilistic iterations were generated, resulting in a total of 1,400,000 simulated project execution scenarios. The simulation results showed that the mean probability of exceeding the baseline schedule across the total sample was 66.7%, indicating that approximately two-thirds of the projects had a high probabilistic tendency toward schedule overrun when activity duration uncertainty, cost variability, and risk occurrence were considered simultaneously. The overall P80 completion duration was 27.29 months, meaning that, under uncertainty, there was an 80% probability that the projects would be completed within this duration or less. The mean simulated delay across the total sample was 4.02 months, which was very close to the observed mean delay reported in Table 1 and confirmed the consistency of the simulation model with actual project performance records. Sector-level results indicated that oil, gas, and petrochemical projects had the highest uncertainty burden, with a 76.4% probability of exceeding the baseline schedule, a mean simulated delay of 5.38 months, and a 52.1% probability of cost overrun above 20%. Power and energy infrastructure projects also showed a high level of uncertainty, with a 68.9% probability of schedule overrun and an expected cost deviation of 18.96%. Manufacturing and production-line development projects showed the lowest uncertainty indicators, although their 57.8% probability of schedule overrun still reflected a considerable level of execution risk. These findings demonstrate that Monte Carlo simulation was able to quantify uncertainty in project duration and cost and to differentiate risk intensity across industrial sectors.

Table 3

Predictive Performance of Traditional and Machine Learning-Based Delay Prediction Models on the Independent Test Set

Model	Mean Absolute Error, Months	Root Mean Square Error, Months	Mean Absolute Percentage Error, %	R^2	Accuracy, %	Precision	Recall	F1-Score	ROC-AUC
Traditional CPM/PERT-based estimate	3.92	4.84	18.37	0.42	66.67	0.69	0.75	0.72	0.68
Random Forest	2.31	3.05	10.84	0.71	85.71	0.87	0.93	0.90	0.89
Gradient Boosting	2.08	2.76	9.71	0.76	90.48	0.93	0.93	0.93	0.94
Integrated Monte Carlo–Random Forest model	1.96	2.58	9.12	0.79	85.71	0.87	0.93	0.90	0.92
Integrated Monte Carlo–Gradient Boosting model	1.74	2.31	8.46	0.83	90.48	0.93	0.93	0.93	0.96

As reported in Table 3, the machine learning-based models showed stronger predictive performance than the traditional CPM/PERT-based estimate across all evaluation indicators. The traditional CPM/PERT-based estimate had a mean absolute error of 3.92 months and a mean absolute percentage error of 18.37%, indicating that conventional deterministic scheduling methods had limited accuracy in predicting final project delay under uncertainty. In comparison, the Random Forest model reduced the mean absolute error to 2.31 months and improved the classification accuracy to 85.71%. Gradient Boosting performed better than Random Forest, with a mean absolute error of 2.08 months, a mean absolute percentage error of 9.71%, an R^2 value of 0.76, and an accuracy of 90.48%. The integrated models further improved predictive performance by combining probabilistic uncertainty outputs from Monte Carlo simulation with machine learning-based pattern recognition. The best-performing model was the integrated Monte Carlo–Gradient Boosting model, which achieved a mean absolute error of 1.74 months, a root mean square error of 2.31 months, a mean absolute percentage error of 8.46%, and an R^2 value of 0.83. This model also achieved an accuracy of 90.48%, precision of 0.93, recall of 0.93, F1-score of 0.93, and ROC-AUC of 0.96 in classifying projects into delay-risk categories. Compared with the traditional CPM/PERT-based estimate, the integrated Monte Carlo–Gradient Boosting model reduced the mean absolute percentage error from 18.37% to 8.46% and improved classification accuracy from 66.67% to 90.48%. This indicates that the proposed intelligent decision-support approach was able to reduce prediction error to below 10% and improve delay prediction accuracy by approximately 35.7% relative to the traditional model.

Table 4

Relative Importance of Predictors in Project Delay Prediction

Predictor Variable	Random Forest Importance, %	Gradient Boosting Importance, %	Average Rank	Direction of Association with Delay
Cumulative risk exposure score	15.84	17.31	1	Positive
Change-order intensity	13.67	14.82	2	Positive
Critical-path instability index	12.28	13.46	3	Positive
Procurement delay ratio	10.94	12.07	4	Positive
Resource deviation ratio	9.72	8.88	5	Positive
Cost Performance Index	8.11	7.94	6	Negative
Schedule Performance Index	7.86	7.21	7	Negative
Design revision frequency	6.42	5.96	8	Positive
Float consumption rate	5.88	4.71	9	Positive
Contractual claim frequency	4.59	3.84	10	Positive
Material availability variance	2.71	2.29	11	Positive
Safety interruption frequency	1.98	1.51	12	Positive

Table 4 shows the relative importance of the main predictors used by the Random Forest and Gradient Boosting models to predict project delay. The results indicated that cumulative risk exposure score was the most influential predictor in both models, with an importance value of 15.84% in Random Forest and 17.31% in Gradient Boosting. This finding suggests that projects with higher combined probability-impact risk scores were more likely to experience considerable schedule deviation. Change-order intensity was the second most important predictor, showing that frequent changes in scope, design, contractual requirements, or execution plans had a direct positive relationship with delay. Critical-path instability index ranked third, indicating that repeated changes in critical activities and unstable sequencing of key project tasks substantially increased the likelihood of delayed completion. Procurement delay ratio and resource deviation ratio were also among the five most influential predictors, confirming that late delivery of equipment and materials, labor-hour deviation, equipment underavailability, and inefficient resource allocation were central drivers of schedule risk. Together, the five most important predictors accounted for 62.45% of total importance in the Random Forest model and 66.54% in the Gradient Boosting model. Cost Performance Index and Schedule Performance Index showed negative associations with delay, meaning that lower cost and schedule performance values were associated with higher delay risk. Design revision frequency, float consumption rate, contractual claim frequency, material availability variance, and safety interruption frequency also contributed to model prediction, although their relative importance was lower than the core risk, change, critical-path, procurement, and resource variables. Overall, the variable-importance findings show that project delay was not caused by a single isolated factor but emerged from the interaction of risk exposure, change management, critical-path instability, procurement performance, and resource deviation.

Figure 1

Observed and Predicted Project Delay Percentages Based on the Integrated Monte Carlo–Gradient Boosting Model

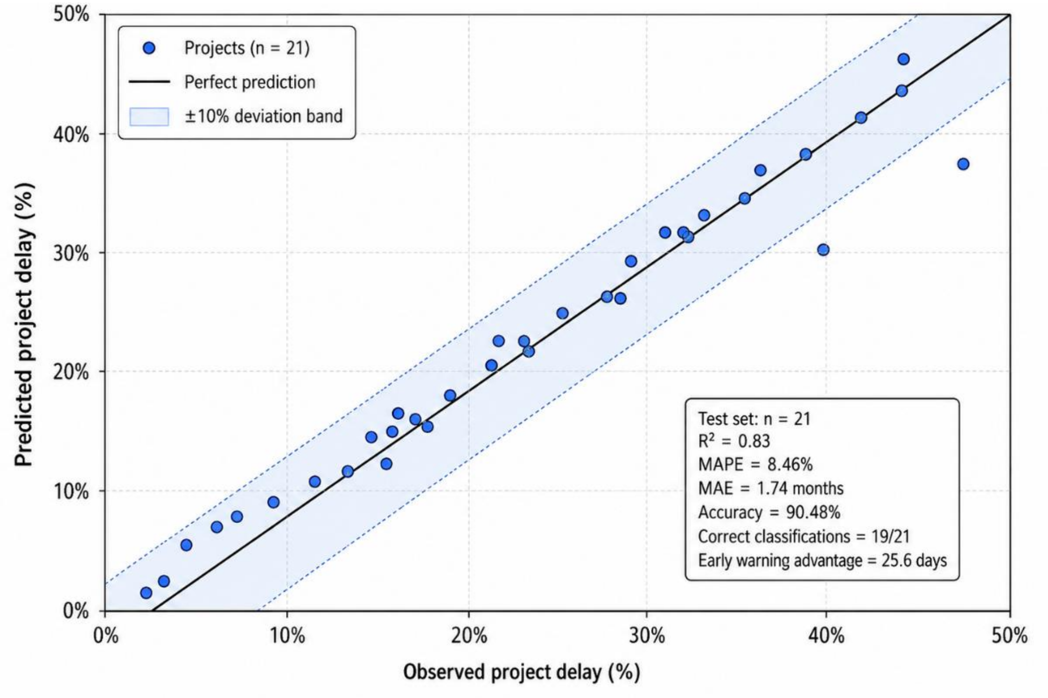

Figure 1 illustrates the alignment between observed project delay percentages and the delay percentages predicted by the integrated Monte Carlo–Gradient Boosting model in the independent test set. The visual pattern showed that predicted values were closely distributed around the observed values, indicating a strong agreement between actual project outcomes and model-generated estimates. Among the 21 test projects, 19 projects were correctly classified into their appropriate delay-risk category, while only 2 projects were misclassified. In 17 of the 21 projects, the predicted delay percentage remained within a ±10% deviation band from the observed delay percentage, confirming the practical accuracy of the model for project-control decision-making. The model showed stronger performance in identifying high-delay and critical-delay projects than low-delay projects, which is especially important from a managerial perspective because early identification of high-risk projects allows project managers to allocate mitigation resources before major deviations occur. The early-warning output of the integrated model identified critical delay risks an average of 25.6 days earlier than the conventional project-control method, with the warning advantage ranging from 14 to 31 days across the test projects. Therefore, the figure supports the quantitative results reported in Table 3 and demonstrates that the proposed intelligent decision-support model can provide reliable, timely, and actionable predictions for managing risk and delay in industrial projects under dynamic uncertainty conditions.

4. Discussion and Conclusion

The findings of this study demonstrated that delay and cost overrun were prevalent and structurally significant among the analyzed industrial projects. Of the 140 completed industrial projects included in the dataset, 91 projects, equivalent to 65.0% of the sample, experienced a final schedule delay of more than 10% compared with the approved baseline schedule. The average planned duration of the projects was 23.41 months, whereas the average actual duration increased to 27.36 months, producing a mean delay of 3.95 months and a mean delay percentage of 17.86%. The financial performance pattern was similarly unfavorable, as the mean baseline budget increased from 86.42 million USD to an actual mean cost of 101.25 million USD, with an average cost overrun of 18.24%. These findings confirm that delay and cost escalation in industrial projects are not isolated technical problems but are systemic performance issues resulting from the interaction of schedule uncertainty, resource deviation, change orders, risk exposure, and project-control limitations. This interpretation is consistent with the literature on megaproject and construction project management, which emphasizes that project underperformance often emerges from complex combinations of technical, contractual, managerial, and environmental factors rather than from a single deterministic cause (Ansari et al., 2022; Ashkanani & Franzoi, 2022; Astaf'eva et al., 2022).

The descriptive findings also showed that the mean Schedule Performance Index was 0.84 and the mean Cost Performance Index was 0.87, both below the desirable benchmark of 1.00. These results indicate that the analyzed projects generally progressed more slowly and consumed more financial resources than originally planned. The relatively high mean number of approved change orders, equal to 11.76 per project, further suggests that project scope, design, contractual assumptions, or execution requirements were frequently modified during implementation. This finding supports previous studies showing that claims, change orders, and contractual modifications are important drivers of project performance deterioration and can create reinforcing feedback loops that intensify delay and cost overrun over time (Ansari et al., 2022; Cordias et al., 2024). The observed relationship between schedule deviation and cost deviation is also aligned with studies on cost overrun risk prediction, which indicate that financial escalation in construction and industrial projects is strongly associated with uncertainty in duration, procurement, resources, and risk-response effectiveness (Ashtari et al., 2022; Avanthika & Naik, 2024).

The Monte Carlo simulation results provided a probabilistic understanding of project uncertainty and showed that the mean probability of exceeding the baseline schedule across the total sample was 66.7%. This result is particularly important because it demonstrates that delay risk was not only observed retrospectively but was also probabilistically embedded in the structure of project duration, activity uncertainty, cost variation, and risk occurrence. The total P80 completion duration was 27.29 months, and the mean simulated delay was 4.02 months, which closely corresponded to the observed mean delay of 3.95 months. This convergence indicates that the simulation model was able to reproduce the uncertainty pattern of actual project outcomes with practical accuracy. The value of this finding is supported by previous research emphasizing the superiority of probabilistic risk management over purely deterministic planning in uncertain construction and engineering environments (Khodabakhshian et al., 2023). It is also consistent with research on Bayesian networks, dynamic systems, and stochastic decision models, which shows that complex project outcomes should be analyzed through probability-based and scenario-oriented approaches rather than fixed-point estimates (Jakubczyk-Gałczyńska et al., 2024; Munang & Nurisusilawati, 2022; Xiao et al., 2023).

The sectoral simulation results showed that oil, gas, and petrochemical projects had the highest level of uncertainty, with a 76.4% probability of exceeding the baseline schedule, a mean simulated delay of 5.38 months, and a 52.1% probability of cost overrun above 20%. This finding may be explained by the capital-intensive nature of oil, gas, and petrochemical projects, their dependency on specialized equipment and procurement chains, their exposure to technical and safety constraints, and their reliance on coordination among multiple contractors and suppliers. Previous studies in oil and gas and industrial investment contexts have similarly emphasized that project success depends on technical support, adaptive decision-making, innovation capacity, and the management of complex economic and operational uncertainties (Larbi et al., 2025; Onita & Ochulor, 2024; Ukato et al., 2024). The relatively high uncertainty observed in power and energy infrastructure projects also aligns with studies on renewable energy investment and digital twins, where uncertainty in asset development, technology implementation, and investment performance is treated as a central managerial issue (Bassey et al., 2024; Qi et al., 2025).

The comparison between traditional and machine learning-based prediction models showed that the proposed intelligent approach substantially improved delay prediction accuracy. The traditional CPM/PERT-based estimate produced a mean absolute percentage error of 18.37%, an R^2 value of 0.42, and a classification accuracy of 66.67%. In contrast, the integrated Monte Carlo–Gradient Boosting model achieved the best performance, with a mean absolute percentage error of 8.46%, an R^2 value of 0.83, a classification accuracy of 90.48%, and a ROC-AUC of 0.96. This improvement demonstrates that deterministic scheduling approaches are insufficient when project outcomes are influenced by nonlinear interactions among risk exposure, activity dependencies, procurement uncertainty, resource deviation, and change-order intensity. The stronger performance of machine learning models is consistent with recent studies emphasizing the ability of artificial intelligence and data-driven analytics to improve construction estimation, resource optimization, cost prediction, risk classification, and project-control intelligence (Cheng & Tian, 2026; Demiss & Elsaigh, 2026; Nabeel, 2024; Obiuto et al., 2024). The results are also consistent with emerging delay prediction frameworks that use deep contextual embedding and evidential reasoning to predict delay severity under heterogeneous project conditions (Chandak et al., 2026).

The superiority of the integrated Monte Carlo–Gradient Boosting model over the standalone machine learning models suggests that the combination of probabilistic simulation and pattern-recognition algorithms provides a more complete representation of industrial project risk. Random Forest and Gradient Boosting were able to learn predictive patterns from historical project data, but their performance improved when probabilistic uncertainty indicators generated by Monte Carlo simulation were added to the prediction structure. This indicates that delay prediction benefits from both historical learning and forward-looking scenario generation. The finding is consistent with studies that emphasize the importance of combining artificial intelligence, knowledge management, big data, optimization, and stochastic modeling for intelligent decision-making under uncertainty (Ahmed et al., 2025; Cheng & Huang, 2025; G. Wang, 2026; L. Wang, 2026). It also supports the broader movement toward AI-augmented, BIM-integrated, and hybrid models for simultaneous cost, time, and risk prediction in project environments (Demiss & Elsaigh, 2026; Hu et al., 2024; Mi & Li, 2024).

The variable-importance findings provided further insight into the main drivers of project delay. Cumulative risk exposure score was the most influential predictor in both the Random Forest and Gradient Boosting models, followed by change-order intensity, critical-path instability, procurement delay ratio, and resource deviation ratio. Together, these five predictors accounted for 62.45% of total importance in the Random Forest model and 66.54% in the Gradient Boosting model. This result indicates that delay in industrial projects is primarily driven by the combined effect of accumulated risks, unstable scope and design conditions, disruptions in critical project sequences, delayed procurement, and inefficient resource utilization. This interpretation is supported by previous studies showing that construction delay and cost overrun are strongly associated with claims, risk accumulation, design changes, resource constraints, and weak coordination across project systems (Ansari et al., 2022; Gürgün et al., 2022; "Risk Management in Construction - Recent Advances," 2024). It also aligns with predictive risk modeling studies showing that risk models must integrate multiple technical, managerial, and contextual dimensions to explain project performance accurately (Avanthika & Naik, 2024).

The negative association of Schedule Performance Index and Cost Performance Index with delay further confirms the practical relevance of earned value indicators in intelligent project-control systems. Lower SPI and CPI values reflected weaker schedule and cost efficiency and were associated with higher delay risk. However, these indicators alone were not sufficient to explain delay; their predictive value increased when combined with risk exposure, change-order intensity, critical-path instability, procurement delay, and resource deviation. This finding suggests that conventional project-control indicators should not be abandoned but should be embedded within broader intelligent decision-support systems. Prior studies on technology adoption against construction delays and AI-based project management similarly suggest that digital tools are most effective when they enhance, rather than replace, core project-control functions (Gürgün et al., 2022; Nabeel, 2024). In this sense, the proposed model offers a complementary advancement by transforming conventional control indicators into predictive inputs for early warning and risk classification.

The finding that the integrated model identified critical delay risks an average of 25.6 days earlier than conventional project-control methods has direct managerial significance. Early identification of critical risks allows project managers to intervene before deviations become irreversible, reallocate resources, adjust procurement priorities, revise mitigation plans, and communicate risk information to stakeholders in a timely manner. This early-warning function reflects the broader shift from reactive project management to proactive and intelligent project governance. Previous research on proactive management in industrial enterprises, intelligent construction compliance, and whole-system approaches to mining and industrial responsibility supports the need for anticipatory systems that identify risks before they generate severe operational or social consequences (Miao, 2025; Verrier et al., 2022; Тевяшев et al., 2023). The relevance of early warning is also reinforced by studies on automation-based monitoring in chemical plant projects and digital decision-support technologies in aviation and other high-risk industrial domains (Ismail, 2022; Wild et al., 2025).

Overall, the results show that the proposed intelligent decision-support model can improve risk and delay management in industrial projects by integrating three analytical capacities: probabilistic scenario generation, machine learning prediction, and interpretable risk-factor ranking. The model reduced the mean error of completion-time estimation to below 10%, improved delay classification accuracy to more than 90%, and provided an early-warning advantage of approximately four weeks. These findings are aligned with the growing body of research emphasizing artificial intelligence, digitalization, knowledge management, and computational decision support as essential components of modern project management (Ahmed et al., 2025; Cheng & Tian, 2026; Osundare & Ige, 2024; Yao & Soto, 2024). Therefore, the study contributes to project management literature by demonstrating that the integration of Monte Carlo simulation and machine learning can produce a more reliable, dynamic, and actionable model for managing industrial project uncertainty than traditional deterministic scheduling methods alone.

This study had several limitations that should be considered when interpreting the findings. First, although the dataset included 140 completed industrial projects and 19,860 activity-level records, the projects were selected based on the availability and completeness of historical project documentation; therefore, the sample may not represent all types of industrial projects, particularly projects with weak documentation systems or informal project-control practices. Second, the study relied on retrospective project data, which may include inconsistencies in reporting standards, risk-register quality, schedule-update frequency, and cost documentation across organizations and sectors. Third, although the model incorporated multiple schedule, cost, resource, procurement, and risk-related variables, some contextual factors such as leadership quality, organizational culture, stakeholder conflict, political constraints, and informal decision-making processes were not fully captured in the quantitative dataset. Fourth, the model was evaluated using project-level training, validation, and test sets, but external validation on new projects from other industrial environments was not conducted. Finally, the simulation assumptions and probability distributions were based on available historical data, meaning that the quality of Monte Carlo outputs depended on the accuracy and representativeness of the underlying project records.

Future studies are recommended to validate the proposed model using larger and more diverse datasets from different countries, industrial sectors, contract types, and project delivery systems. Researchers should examine whether the predictive performance of the integrated Monte Carlo–machine learning approach remains stable in highly specialized sectors such as nuclear energy, renewable energy, transportation megaprojects, defense infrastructure, and large-scale digital transformation projects. Future research may also extend the model by incorporating real-time project-control data from BIM platforms, enterprise resource planning systems, procurement databases, sensor-based monitoring systems, and digital twin environments. In addition, future studies should compare the performance of other algorithms, such as XGBoost, LightGBM, artificial neural networks, Bayesian machine learning, reinforcement learning, and hybrid deep learning models. Qualitative studies could also be conducted to explore how project managers interpret, trust, and use intelligent decision-support outputs in actual decision-making situations. Finally, future research should investigate the ethical, organizational, and governance implications of AI-based project-control systems, particularly in relation to accountability, transparency, data quality, and human oversight.

Project managers, project-control specialists, and industrial organizations are advised to adopt predictive decision-support systems that combine probabilistic simulation with machine learning rather than relying only on deterministic baseline schedules and retrospective progress reports. Organizations should improve the quality of their project data by standardizing schedule records, risk registers, cost reports, procurement logs, change-order documentation, and resource-consumption records across projects. The most important risk indicators identified in this study, including cumulative risk exposure, change-order intensity, critical-path instability, procurement delay ratio, and resource deviation ratio, should be monitored continuously during project execution. Industrial firms should also develop early-warning dashboards that translate model outputs into practical managerial information, such as probability of delay, expected completion-time deviation, probability of cost overrun, and ranked risk drivers. Finally, intelligent decision-support tools should be used as aids to professional judgment rather than replacements for project managers; the most effective application of such systems occurs when analytical predictions are combined with expert interpretation, stakeholder communication, and timely corrective action.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

Data are available for research purposes upon reasonable request to the corresponding author.

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Declaration of Interest

The authors report no conflict of interest.

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Ethics Considerations

In this research, ethical standards including obtaining informed consent, ensuring privacy and confidentiality were considered.

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