KMAN PUBLISHING INSTITUTE

Journal of Resource Management and Decision Engineering

Volume 6, Issue 6, pp 1-15

Article history:
Received 01 February 2026
Revised 14 May 2026
Accepted 29 June 2026
Initial Publish 26 July 2026
Published online 01 November 2027

Predicting Costs and Risks in Construction Projects Using BIM and Artificial Intelligence Data Analytics

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A r t i c l e I n f o

Article type:
Original Research

How to cite this article:
Zohreh, M., (2027). Predicting Costs and Risks in Construction Projects Using BIM and Artificial Intelligence Data Analytics. *Journal of Resource Management and Decision Engineering, 6*(6), 1-15.
https://doi.org/10.61838/kman.jrmde.381

A B S T R A C T

This study aimed to predict cost overrun and project risk in construction projects using BIM-based indicators and artificial intelligence data analytics. This applied, quantitative, predictive, and analytical study was conducted on 64 construction projects in Tehran, Iran, with the participation of 148 construction professionals, including project managers, BIM specialists, cost and quantity surveying experts, planning and project control engineers, and site engineers. Data were collected using BIM-based project documentation, cost and schedule records, risk assessment forms, and expert validation checklists. The main variables included BIM maturity level, number of detected BIM clashes, design revision frequency, schedule deviation, material cost fluctuation, procurement delay, change orders, rework cost ratio, cost overrun percentage, and composite project risk score. Data were analyzed using correlation analysis and artificial intelligence-based predictive models, including multiple linear regression, decision tree, support vector regression, artificial neural network, random forest, and gradient boosting models. Inferential findings showed that cost overrun had significant positive correlations with schedule deviation, design revisions, BIM clashes, material cost fluctuation, and composite project risk score, while BIM maturity had significant negative correlations with cost overrun, schedule deviation, BIM clashes, and risk score. Gradient boosting regression produced the strongest cost prediction performance, with the lowest mean absolute error and root mean square error and the highest coefficient of determination, explaining 84% of the variance in cost overrun. For project risk classification, gradient boosting also achieved the highest performance, with accuracy of 0.89 and area under the curve of 0.93. Feature importance analysis identified schedule deviation, design revision frequency, BIM clashes, material cost fluctuation, and BIM maturity as the strongest predictors of cost and risk outcomes. The findings indicate that integrating BIM-based project information with artificial intelligence analytics provides a reliable predictive framework for early identification of cost overrun and project risk in construction projects. AI-based models, especially gradient boosting, can support proactive decision-making, improve cost control, and strengthen risk management throughout the project life cycle.

Keywords: *Building Information Modeling; Artificial Intelligence; Cost Prediction; Project Risk; Construction Management; Machine Learning; BIM Analytics*

1. Introduction

The construction industry is increasingly characterized by technical complexity, fragmented stakeholder relationships, volatile material markets, compressed project schedules, and growing expectations for cost certainty, safety, sustainability, and digital integration. In this context, cost overrun and project risk remain among the most persistent challenges in building project delivery, particularly in large urban environments where design coordination, procurement uncertainty, regulatory requirements, subcontractor interfaces, and site constraints interact throughout the project life cycle. Traditional cost estimation and risk assessment methods often depend on historical averages, expert judgment, linear assumptions, and manually updated project records; although these methods remain useful, they are frequently insufficient for capturing the dynamic, multidimensional, and nonlinear behavior of contemporary construction projects. The growing movement toward digital transformation in architecture, engineering, and construction has therefore created a need for more integrated methods capable of converting project data into predictive knowledge. Building Information Modeling (BIM), artificial intelligence (AI), digital twins, cloud computing, Internet of Things (IoT), and other Construction 4.0 technologies have emerged as core components of this transformation because they enable richer data capture, improved coordination, automated analysis, and more evidence-based decision-making across the design, construction, and operation phases (Jazzar et al., 2021; Zakaria et al., 2024; Zawada et al., 2024).

BIM has shifted from being understood merely as a three-dimensional modeling tool toward becoming an integrated information management environment for design coordination, quantity take-off, schedule simulation, cost estimation, clash detection, facility management, and multidisciplinary collaboration. This transformation is especially relevant to cost and risk management because BIM-based models can contain geometric, spatial, material, technical, temporal, and financial information that can be extracted, validated, and analyzed before errors appear in the physical construction process. Research on BIM adoption has shown that digital models can reduce information fragmentation, support more accurate project visualization, and strengthen coordination among designers, contractors, consultants, and owners, thereby reducing the probability of design inconsistencies, rework, claims, and avoidable cost escalation (Khudhair et al., 2021; Marinho et al., 2021; Tallet et al., 2021). However, the effectiveness of BIM depends on the maturity of implementation, the quality of model information, the degree of integration with project management systems, and the organizational readiness of stakeholders to use BIM as a decision-support platform rather than as a purely representational tool (Abazid et al., 2021; Li et al., 2022).

The integration of BIM with AI provides an advanced pathway for improving cost and risk prediction because AI methods can process large, heterogeneous, and high-dimensional datasets and identify patterns that may not be visible through conventional analytical techniques. Machine learning, deep learning, optimization algorithms, neural networks, support vector machines, ensemble models, and intelligent rule-based systems have been increasingly applied in the AEC sector to address problems related to cost estimation, scheduling, design optimization, quality control, safety monitoring, code compliance, project forecasting, and resource allocation (Bassir et al., 2023; Wang et al., 2020; Zhang et al., 2022). The value of AI in BIM-based construction management lies in its ability to learn from structured and semi-structured project data, including model attributes, quantities, detected clashes, design changes, schedule deviations, procurement records, cost records, and risk events. This ability is particularly important in construction projects because cost overrun and risk exposure are rarely produced by a single factor; rather, they emerge from interactions among design complexity, coordination quality, market conditions, managerial decisions, resource constraints, and construction-site performance. AI-supported BIM environments can therefore move project management from retrospective reporting toward predictive and preventive control (Adeel et al., 2023; Demiss & Elsaigh, 2026).

One of the most important applications of BIM-AI integration is the prediction of project cost deviation. Cost estimation in construction has traditionally relied on bills of quantities, unit rates, historical benchmarks, and expert-based adjustments. Although these methods provide a necessary basis for budgeting, they are vulnerable to design revisions, inaccurate quantities, uncertain productivity assumptions, inflationary pressures, procurement delays, subcontractor performance problems, and unforeseen site conditions. BIM-based cost estimation improves this process by linking model elements with quantities and cost databases, while AI can further improve prediction by identifying relationships between project features and final cost outcomes. Recent studies have emphasized the use of

BIM-based 5D modeling, genetic algorithms, and intelligent optimization models to link time and cost dimensions and to improve decision-making under constraints (Alzara et al., 2023). Similarly, AI-augmented estimation frameworks have been proposed as hybrid systems that combine BIM data, cost records, time information, and risk indicators to improve the prediction of cost, time, and uncertainty in construction projects (Demiss & Elsaigh, 2026). These developments suggest that cost prediction should no longer be treated as a static calculation performed only at the early budgeting stage, but as a dynamic process updated through continuously enriched project information.

Risk prediction is equally important because construction risks are multidimensional and often interdependent. Technical risks may arise from design conflicts, incomplete model information, constructability problems, and coordination failures; financial risks may result from material price volatility, cash-flow limitations, and cost escalation; managerial risks may emerge from weak planning, poor communication, delayed decisions, and inadequate control systems; and contractual risks may appear through claims, disputes, change orders, and unclear responsibility allocation. BIM can support risk identification by revealing model inconsistencies, spatial conflicts, quantity discrepancies, and construction sequence problems, while AI can classify or predict risk levels based on historical and real-time project data. Digital twins further extend this capability by linking digital models with continuously updated data streams, enabling more dynamic monitoring of asset performance, schedule progress, and operational risk (Afzal et al., 2023; Kor et al., 2022; Sun & Liu, 2022). The use of digital twins and BIM-based intelligent platforms has also been discussed in relation to infrastructure management, tunnel construction, transportation systems, and large-span structures, showing the broader potential of integrated digital technologies beyond conventional building modeling (Salzgeber et al., 2024; Taheri & Sobanjo, 2024; Xing, 2024).

The broader literature on intelligent construction indicates that BIM-AI integration is part of a wider transition toward smart construction ecosystems. In these ecosystems, BIM can be combined with IoT, AI of Things, cloud computing, automation, robotics, digital twins, and intelligent dispatching systems to create a more connected and data-responsive project environment. For example, cloud-based AI applications can support collaborative data processing and scalable analytics across project stakeholders, while IoT-enabled systems can generate site-level data for monitoring progress, productivity, safety, and environmental conditions (Chashyn et al., 2024; Wang et al., 2024). Intelligent construction techniques have also been increasingly explored in rapidly developing construction markets, where digital technologies are used to improve productivity, standardization, and project control (Guo, 2024). These developments demonstrate that BIM-AI systems are not isolated technological tools but part of a broader digital transformation that changes how construction projects are designed, planned, monitored, and evaluated.

Scheduling is another domain where BIM and AI have direct implications for cost and risk control. Delays are among the strongest contributors to construction cost overrun because they can generate additional labor costs, extended equipment use, contractual penalties, financing costs, productivity losses, and cascading disruptions among subcontractors. BIM-based 4D scheduling enables project teams to visualize construction sequences and detect temporal-spatial conflicts, while AI and machine learning can generate, optimize, and adjust schedules based on project constraints and resource availability. Studies on automated and BIM-based construction scheduling have shown that digitally supported approaches can reduce manual planning limitations and improve schedule generation, comparison, and simulation (Doukari et al., 2022). Recent research has also proposed autonomous resource-loaded scheduling systems and machine-learning-based construction scheduling blueprints that integrate BIM with intelligent planning logic (Al-Sinan et al., 2024a, 2024b). These developments are highly relevant for cost and risk prediction because schedule deviation is not only a time-management outcome but also a major predictor of financial deviation and project uncertainty.

AI has also been applied to architectural design, sustainable architecture, automated code compliance, healthy built environments, and digitally enabled design management, all of which indirectly affect project cost and risk. AI-supported design tools can assist in generating alternatives, analyzing design performance, improving sustainability decisions, and identifying design problems earlier in the project life cycle (Amer, 2023; Krausková & Pifko, 2021; Rane et al., 2023). Automated recognition of BIM objects and their visible properties can support code compliance checking and reduce the probability of regulatory or technical errors that later cause redesign, delay, or cost escalation (Kim, 2022). At the same time, AI and digital modeling can contribute to healthier, more sustainable, and more equitable places by supporting evidence-based design evaluation and performance-oriented decision-making (Bernstein et al., 2022). From a project management perspective, these capabilities show that the predictive value of BIM-AI integration is not limited to cost records alone; it also depends on the quality of design information, the ability to detect errors early, and the extent to which digital workflows support coordinated decision-making.

Despite the growing potential of BIM-AI integration, implementation challenges remain significant. Construction projects are often fragmented across multiple organizations, and data are frequently dispersed among designers, contractors, consultants, suppliers, and owners. Many project teams still face difficulties related to data interoperability, inconsistent modeling standards, limited BIM maturity, insufficient digital skills, resistance to innovation, and weak integration between design models and project control systems. Bibliometric and systematic studies of BIM and AI research show that the field is expanding rapidly, but also that there are gaps in standardization, practical implementation, integrated platforms, and empirical validation across different project contexts (Bassir et al., 2023; Özturk & Tunca, 2020; Wang et al., 2024). The adoption of BIM and AI also depends on organizational learning, managerial attitudes, and the ability of engineering project teams to balance control-based project management with exploratory digital learning (Yang et al., 2020). Therefore, successful implementation requires not only technological capability but also managerial commitment, data governance, skilled personnel, and a culture of evidence-based decision-making.

In construction cost and risk prediction, one key limitation of existing approaches is that many studies examine BIM, AI, scheduling, cost optimization, or digital twins separately, while fewer empirical studies integrate BIM-derived variables, cost indicators, schedule deviations, and risk factors within a unified predictive model. Some studies have addressed BIM and AI applications at the conceptual or review level, while others have focused on specific technical applications such as 5D optimization, automated scheduling, object recognition, or digital twin development (Afzal et al., 2023; Alzara et al., 2023; Kim, 2022; Zhang et al., 2022). However, project managers need applied models that can identify which variables most strongly predict cost overrun and risk exposure in real construction projects. This is especially important in metropolitan construction markets such as Tehran, where projects are affected by dense urban conditions, market fluctuations, regulatory complexity, coordination challenges, and high stakeholder interdependence. In such environments, the ability to predict cost and risk based on BIM-derived and project management variables can improve early warning systems, support resource allocation, prioritize risk mitigation, and strengthen decision-making before deviations become severe.

The current study is grounded in the assumption that BIM-based project data become more valuable when transformed into predictive intelligence through AI analytics. This assumption is consistent with recent developments in smart construction management, AI-supported BIM applications, emerging technology integration, and digital transformation in AEC industries (Adeel et al., 2023; Zakaria et al., 2024; Zawada et al., 2024). It also reflects the need to move from descriptive project documentation toward predictive and prescriptive management systems. By combining BIM indicators such as model maturity, detected clashes, design revision frequency, quantity information, and coordination issues with project management variables such as schedule deviation, material cost fluctuation, procurement delay, change orders, rework costs, and subcontractor performance, it becomes possible to evaluate how digital and managerial factors jointly influence cost and risk outcomes. Such an approach can contribute to the development of practical BIM-AI frameworks that support construction managers, cost engineers, planners, BIM specialists, and decision-makers in controlling uncertainty and improving project performance.

Therefore, the aim of this study was to predict cost overrun and project risk in construction projects in Tehran using BIM-based indicators and artificial intelligence data analytics.

2. Methods and Materials

This study was designed as an applied, quantitative, predictive, and analytical study aimed at developing and evaluating a data-driven framework for predicting cost deviations and risk levels in construction projects using Building Information Modeling and artificial intelligence-based data analytics. The research was conducted in Tehran, Iran, because of the high concentration of medium- and large-scale building projects, the increasing adoption of BIM-based project management systems, and the availability of project documentation suitable for digital analysis. The statistical population consisted of construction projects implemented by private and semi-public contractors in Tehran, as well as project managers, cost engineers, BIM specialists, planning and control experts, and site engineers involved in these projects. The final sample included 64 construction projects and 148 professional participants selected through purposive sampling based on their direct involvement in BIM-based project planning, cost control, scheduling, risk assessment, or construction supervision. The inclusion criteria for projects were the availability of architectural, structural, and mechanical BIM models, access to cost and schedule documentation, completion of at least 40% of the construction phase, and the existence of recorded project risks or change events. Projects with incomplete documentation, non-standard cost records, or insufficient BIM model development were excluded from the study. The professional participants included 37 project managers, 29 BIM specialists, 31 cost and quantity surveying experts, 24 planning and project control engineers, and 27 site engineers. All participants were active in construction projects located in different districts of Tehran and had at least five years of professional experience in building project delivery. The purpose of including professional participants was to verify the accuracy of extracted project data, identify relevant risk indicators, and validate the practical relevance of the predictive variables used in the artificial intelligence models.

Data were collected using a combination of BIM-based project documentation, structured project cost records, risk assessment forms, and an expert validation checklist. The BIM-based data extraction form was developed to collect model-based information from architectural, structural, and building services models, including quantities of materials, building area, number of floors, structural system, project complexity indicators, clash detection reports, design revision frequency, model development level, and the number of coordination issues identified during the design and construction phases. The BIM models were reviewed using model coordination and quantity take-off procedures, and the extracted variables were checked against project documentation to ensure consistency. The cost data collection form was used to record estimated cost, actual cost, cost variance, material cost changes, labor cost changes, subcontractor costs, equipment costs, design change costs, rework costs, and claims-related costs. These data were obtained from project financial reports, cost control documents, bills of quantities, interim payment certificates, and project management records. Cost risk was operationalized through indicators such as percentage of cost overrun, frequency of cost-related change orders, and deviation between planned and actual expenditure.

The project risk assessment instrument was developed to measure technical, financial, managerial, contractual, environmental, and execution-related risks affecting construction projects. The instrument included items related to design errors, BIM coordination problems, inaccurate quantity estimation, delay in approvals, inflation in material prices, labor shortages, subcontractor performance, safety incidents, procurement delays, contract disputes, site constraints, and changes in employer requirements. Each risk item was assessed based on probability of occurrence and impact severity using a five-point Likert scale ranging from very low to very high. A composite risk score was calculated by multiplying probability and impact values and then aggregating the results across risk categories. To improve content validity, the initial list of risk indicators was reviewed by seven experts in construction management, BIM implementation, and project risk analysis. Their comments were used to refine the wording of items, remove overlapping indicators, and ensure that the selected variables reflected the actual conditions of construction projects in Tehran.

An expert validation checklist was also used to evaluate the relevance, clarity, and completeness of the variables extracted from BIM models and project records. This checklist was completed by the professional participants after reviewing the preliminary dataset for their respective projects. The checklist focused on whether the extracted BIM variables, cost indicators, and risk factors were accurate, measurable, and suitable for use in predictive modeling. The reliability of the risk assessment instrument was examined using Cronbach’s alpha, and the internal consistency of the final instrument was found to be acceptable. In addition, data accuracy was enhanced through triangulation of BIM outputs, project financial records, schedule reports, and expert confirmation. Before analysis, all project data were anonymized, and each project was assigned a unique code to protect organizational and participant confidentiality.

Data analysis was conducted in several stages using descriptive statistics, correlation analysis, and artificial intelligence-based predictive modeling. First, the collected data were screened for missing values, outliers, inconsistencies, and duplicate records. Missing values were handled based on the type and extent of missingness; variables with excessive missing data were removed, while limited missing values were treated using appropriate imputation methods. Continuous variables such as project area, estimated cost, actual cost, duration, quantity values, number of clashes, and number of design revisions were standardized to improve comparability across projects. Categorical variables such as structural system, contract type, project delivery method, and BIM maturity level were coded for inclusion in machine learning models. Descriptive statistics, including mean, standard deviation, minimum, maximum, frequency, and percentage, were used to describe the characteristics of projects and participants. Correlation analysis was then performed to examine the relationships between BIM-derived variables, project cost indicators, and risk scores.

In the predictive phase, artificial intelligence models were developed to estimate project cost deviation and overall project risk level. The dependent variables were cost overrun percentage and composite risk score, while the independent variables included BIM model indicators, project characteristics, cost components, design change indicators, coordination issues, schedule deviations, and risk-related variables. Several machine learning algorithms were tested, including multiple linear regression as a baseline model, decision tree regression, random forest, support vector regression, gradient boosting, and artificial neural networks. The dataset was divided into training and testing subsets, with 80% of the project data used for model training and 20% used for model testing. Cross-validation was applied to reduce overfitting and to improve the generalizability of the predictive models. Model performance for cost prediction was evaluated using mean absolute error, root mean square error, and coefficient of determination. For risk prediction, model accuracy was assessed using classification accuracy, precision, recall, F1-score, and receiver operating characteristic analysis when risk scores were categorized into low, moderate, and high levels.

Feature importance analysis was conducted to identify the most influential BIM and project management variables in predicting cost and risk outcomes. This analysis made it possible to determine which factors, such as design revision frequency, number of detected clashes, project complexity, material cost fluctuation, schedule deviation, and procurement delay, had the strongest predictive contribution. The final model was selected based on predictive accuracy, interpretability, stability, and practical applicability for construction project management. The results of the artificial intelligence analysis were interpreted in relation to BIM-based decision-making and cost-risk control in construction projects. All statistical and predictive analyses were performed at a significance level of 0.05, and the findings were used to propose a BIM-AI analytical framework for early identification of cost overruns and project risks in building construction projects in Tehran.

3. Findings and Results

The findings of the study are presented based on data collected from 64 construction projects located in Tehran and from 148 professional participants directly involved in the planning, design coordination, cost control, risk assessment, BIM implementation, and execution management of these projects. The demographic and professional characteristics of the participants showed that 112 participants were male and 36 were female. The mean age of the participants was 38.64 years with a standard deviation of 7.42 years, and their professional experience ranged from 5 to 27 years, with a mean of 11.38 years and a standard deviation of 5.61 years. In terms of educational level, 78 participants held a bachelor's degree, 61 held a master's degree, and 9 held a doctoral degree in fields related to civil engineering, architecture, construction management, project management, quantity surveying, or building services engineering. Regarding professional role, the participants included 37 project managers, 29 BIM specialists, 31 cost and quantity surveying experts, 24 planning and project control engineers, and 27 site engineers. The project-level data also showed that the studied projects included 24 residential projects, 15 commercial projects, 11 office buildings, 8 mixed-use projects, and 6 institutional or service buildings. The average gross floor area of the projects was 28,460.94 square meters, and the mean planned project duration was 24.78 months. These demographic and project characteristics indicate that the dataset represented a diverse group of construction professionals and building projects with sufficient technical, managerial, and financial variation to support predictive analysis of cost and risk outcomes.

Table 1

Descriptive Statistics of BIM, Cost, Schedule, and Risk Variables in the Studied Construction Projects

Variable	Mean	Standard Deviation	Minimum	Maximum
Gross floor area of project (m^2)	28,460.94	14,832.27	7,850.00	68,400.00
Planned project duration (months)	24.78	7.31	12.00	42.00
Actual or projected duration (months)	28.16	8.42	14.00	49.00
Estimated project cost (billion IRR)	1,426.37	718.54	386.00	3,870.00
Actual or projected final cost (billion IRR)	1,595.82	814.63	421.00	4,530.00
Cost overrun (%)	11.84	6.37	1.90	29.60
Schedule deviation (%)	13.62	8.48	2.10	38.70
BIM maturity level score	3.28	0.74	1.80	4.70
Number of detected BIM clashes	186.53	92.14	42.00	438.00
Number of major design revisions	7.41	3.26	2.00	16.00
Number of cost-related change orders	9.18	4.72	1.00	22.00
Material cost fluctuation (%)	15.76	7.39	3.80	34.50
Rework cost ratio (%)	5.63	3.11	0.90	14.80
Composite project risk score	47.68	14.25	18.00	82.00

The descriptive findings in Table 1 show that the construction projects included in the analysis varied considerably in terms of physical scale, duration, cost, BIM maturity, coordination complexity, and risk exposure. The average cost overrun among the studied projects was 11.84%, indicating that, on average, actual or projected final costs exceeded initial estimated costs by more than one-tenth of the planned budget. The average schedule deviation was also notable at 13.62%, suggesting that time-related deviations were closely connected with financial and managerial instability in the studied projects. The mean BIM maturity score was 3.28, showing that most projects had moved beyond basic three-dimensional modeling and had adopted BIM for coordination, quantity extraction, or partial project control, although full integration of BIM with cost, schedule, and risk management was not consistently observed across all projects. The relatively high mean number of detected clashes, equal to 186.53, reflects the technical complexity of the studied projects and confirms the importance of BIM-based coordination in early identification of design and execution conflicts. The mean composite project risk score was 47.68, with a wide range from 18.00 to 82.00, demonstrating that the projects differed substantially in their exposure to technical, financial, managerial, contractual, and execution-related risks. Overall, the descriptive results indicate that cost overrun and project risk were sufficiently variable across the sample, making the dataset appropriate for predictive modeling using BIM indicators and artificial intelligence data analytics.

Table 2

Correlation Matrix Between BIM-Based Indicators, Project Characteristics, Cost Overrun, and Composite Risk Score

Variable	Project Area	BIM Maturity	BIM Clashes	Design Revisions	Schedule Deviation	Material Cost Fluctuation	Cost Overrun	Risk Score
Project area	1.00	0.21	0.43**	0.32*	0.26*	0.18	0.29*	0.31*
BIM maturity	0.21	1.00	-0.36**	-0.28*	-0.33**	-0.14	-0.39**	-0.34**
BIM clashes	0.43**	-0.36**	1.00	0.52**	0.49**	0.27*	0.58**	0.61**
Design revisions	0.32*	-0.28*	0.52**	1.00	0.55**	0.31*	0.63**	0.57**
Schedule deviation	0.26*	-0.33**	0.49**	0.55**	1.00	0.35**	0.69**	0.66**
Material cost fluctuation	0.18	-0.14	0.27*	0.31*	0.35**	1.00	0.54**	0.46**
Cost overrun	0.29*	-0.39**	0.58**	0.63**	0.69**	0.54**	1.00	0.72**
Risk score	0.31*	-0.34**	0.61**	0.57**	0.66**	0.46**	0.72**	

The correlation results presented in Table 2 indicate meaningful relationships between BIM-derived variables, project management indicators, cost overrun, and overall project risk. Cost overrun had the strongest positive correlation with schedule deviation ($r = 0.69$, $p < 0.01$), followed by design revisions ($r = 0.63$, $p < 0.01$), number of

BIM clashes ($r = 0.58$, $p < 0.01$), and material cost fluctuation ($r = 0.54$, $p < 0.01$). These findings suggest that projects with higher time deviation, frequent design changes, greater unresolved coordination conflicts, and stronger material price instability were more likely to experience substantial cost increases. The composite project risk score was also strongly correlated with cost overrun ($r = 0.72$, $p < 0.01$), which confirms that financial deviation and risk exposure were closely linked in the studied construction projects. The number of BIM clashes showed a significant positive relationship with both cost overrun and risk score, indicating that coordination conflicts identified in BIM models can serve as early warning indicators for later financial and operational problems. In contrast, BIM maturity had significant negative correlations with cost overrun ($r = -0.39$, $p < 0.01$), risk score ($r = -0.34$, $p < 0.01$), schedule deviation ($r = -0.33$, $p < 0.01$), and BIM clashes ($r = -0.36$, $p < 0.01$). This means that projects with higher BIM maturity tended to have fewer coordination problems, lower schedule deviation, lower cost overrun, and lower overall risk. These results support the assumption that BIM is not merely a modeling tool, but a project intelligence environment that can improve cost and risk predictability when it is implemented at a mature and integrated level.

Table 3

Performance of Artificial Intelligence Models in Predicting Project Cost Overrun

Predictive Model	Mean Absolute Error (%)	Root Mean Square Error (%)	Mean Absolute Percentage Error (%)	R^2	Model Performance Rank
Multiple linear regression	4.82	6.11	18.64	0.48	6
Decision tree regression	3.94	5.36	15.28	0.57	5
Support vector regression	3.51	4.82	13.91	0.64	4
Artificial neural network	3.08	4.36	12.17	0.71	3
Random forest regression	2.76	3.91	10.84	0.78	2
Gradient boosting regression	2.41	3.47	9.36	0.84	1

The results in Table 3 show that artificial intelligence models predicted cost overrun with higher accuracy than the traditional multiple linear regression model. Multiple linear regression explained 48% of the variance in cost overrun and produced a mean absolute error of 4.82%, which indicates that linear modeling was able to detect general relationships among the variables but was not sufficiently powerful to capture complex nonlinear interactions between BIM indicators, schedule deviation, design changes, material cost fluctuation, and project risk factors. Decision tree regression improved the prediction accuracy, but its performance remained weaker than ensemble learning and neural network models, most likely because single-tree models are more sensitive to data partitioning and may not generalize well when project conditions are heterogeneous. Support vector regression and artificial neural network models performed better than the baseline and decision tree models, showing that nonlinear methods were more suitable for modeling construction cost behavior. Among all tested models, gradient boosting regression achieved the best performance, with the lowest mean absolute error of 2.41%, the lowest root mean square error of 3.47%, the lowest mean absolute percentage error of 9.36%, and the highest coefficient of determination of 0.84. This indicates that the gradient boosting model explained 84% of the variance in project cost overrun and provided the most accurate estimation of cost deviation among the examined models. Random forest regression also performed strongly, with an R^2 value of 0.78, but it was slightly less accurate than gradient boosting. These findings demonstrate that ensemble-based artificial intelligence models are particularly effective for predicting construction cost overrun because they can process multiple interacting predictors, identify nonlinear patterns, and reduce prediction error through iterative learning from project data.

Table 4

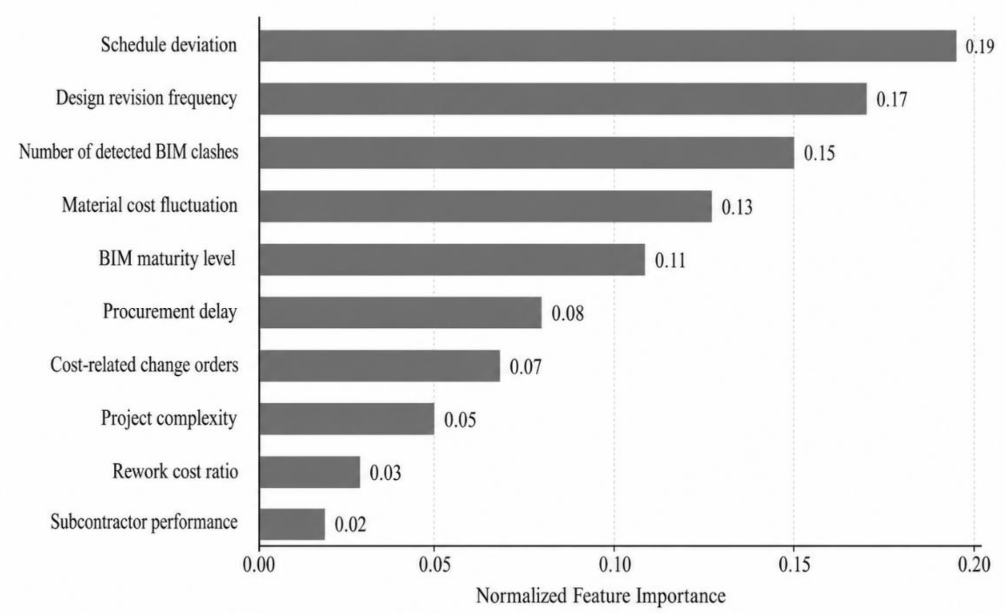
Performance of Artificial Intelligence Models in Classifying Project Risk Level

Predictive Model	Accuracy	Precision	Recall	F1-Score	Area Under the Curve	Model Performance Rank
Logistic regression	0.71	0.69	0.68	0.68	0.74	6
Decision tree classifier	0.74	0.72	0.71	0.71	0.77	5
Support vector machine	0.79	0.78	0.77	0.77	0.82	4
Artificial neural network	0.82	0.81	0.80	0.80	0.86	3
Random forest classifier	0.86	0.85	0.84	0.84	0.90	2
Gradient boosting classifier	0.89	0.88	0.87	0.87	0.93	1

The classification results in Table 4 show that the artificial intelligence models were also effective in predicting the overall project risk level. For this analysis, the composite risk score was categorized into three levels: low risk, moderate risk, and high risk. Logistic regression produced the weakest classification performance, with an accuracy of 0.71 and an F1-score of 0.68, suggesting that a conventional linear classifier was limited in distinguishing risk categories when the predictors included complex BIM, financial, technical, and schedule-related variables. The decision tree classifier showed a slight improvement, but its performance was still lower than that of more advanced machine learning models. The support vector machine and artificial neural network models achieved acceptable classification results, with accuracy values of 0.79 and 0.82, respectively, indicating that nonlinear classification methods were better able to identify risk patterns in the project dataset. However, the strongest results were obtained from ensemble learning models. Random forest achieved an accuracy of 0.86, an F1-score of 0.84, and an area under the curve of 0.90, while gradient boosting achieved the highest classification performance, with an accuracy of 0.89, precision of 0.88, recall of 0.87, F1-score of 0.87, and area under the curve of 0.93. These findings show that gradient boosting was the most reliable model for classifying project risk level and was able to distinguish low-, moderate-, and high-risk projects with a high degree of accuracy. The superior performance of gradient boosting can be attributed to its ability to learn sequentially from prediction errors and to assign greater weight to complex cases that are more difficult to classify. This result confirms that artificial intelligence data analytics can transform BIM-based project information into a practical risk prediction system that supports early intervention, more accurate decision-making, and proactive risk control in construction management.

Figure 1

Relative Importance of BIM-Based and Project Management Variables in Predicting Cost Overrun and Project Risk



The feature importance analysis illustrated in Figure 1 showed that schedule deviation, design revision frequency, number of detected BIM clashes, material cost fluctuation, BIM maturity level, procurement delay, cost-related change orders, project complexity, rework cost ratio, and subcontractor performance were the most influential predictors of cost overrun and project risk. Schedule deviation had the highest predictive contribution, indicating that delay-related instability was one of the strongest signals of financial and risk escalation in construction projects. Design revision frequency was also among the most important predictors, showing that repeated changes in design documents and model information substantially increased uncertainty in cost estimation, procurement planning, site execution, and coordination between project stakeholders. The number of detected BIM clashes had a major role in the prediction models, which suggests that unresolved or frequently occurring design conflicts in architectural, structural, and building services models can be treated as measurable risk indicators before they appear as rework, claims, delays, or additional costs during construction. Material cost fluctuation also contributed strongly to cost prediction, confirming the sensitivity of construction budgets to market instability and procurement timing. BIM maturity level had an inverse predictive pattern, meaning that higher BIM maturity reduced the probability of higher cost overrun and higher project risk. This finding implies that the effectiveness of BIM depends not only on the existence of a digital model but also on the degree to which BIM is integrated with quantity take-off, clash detection, design coordination, cost control, scheduling, and project decision-making. Therefore, the feature importance results confirm that the combined use of BIM and artificial intelligence analytics can identify the most critical drivers of cost and risk and can support a preventive management approach rather than a reactive response after deviations occur.

Overall, the findings indicate that cost and risk in construction projects can be predicted with acceptable to high accuracy when BIM-derived indicators are combined with artificial intelligence data analytics. The descriptive findings showed that the studied projects experienced meaningful variation in cost overrun, schedule deviation, BIM maturity, design revision frequency, coordination conflicts, and composite risk scores. The correlation findings demonstrated that cost overrun and risk were significantly associated with schedule deviation, design revisions, BIM clashes, material cost fluctuation, and BIM maturity. The predictive modeling results further showed that artificial intelligence models, especially gradient boosting and random forest, outperformed traditional regression and single-tree models in both cost prediction and risk classification. The best-performing model for cost prediction was gradient boosting regression, which explained 84% of the variance in cost overrun, while the best-performing model for risk classification was gradient boosting classification, which achieved an accuracy of 0.89 and an area under the curve of 0.93. These findings confirm that BIM-based data, when analyzed through advanced artificial intelligence models, can provide a reliable empirical basis for forecasting cost deviations and identifying high-risk construction projects at earlier stages of project delivery.

4. Discussion and Conclusion

The present study aimed to predict cost overrun and project risk in construction projects using BIM-based indicators and artificial intelligence data analytics. The findings showed that the studied construction projects in Tehran experienced meaningful variation in cost deviation, schedule deviation, BIM maturity, coordination conflicts, design revision frequency, and composite risk scores. The average cost overrun and schedule deviation indicated that financial and temporal instability were not exceptional events, but recurrent project performance problems. This result is consistent with the broader understanding that construction projects operate within uncertain, fragmented, and data-intensive environments in which cost and risk outcomes are shaped by the interaction of technical, managerial, financial, and organizational variables. The finding that cost overrun was strongly associated with schedule deviation, design revision frequency, BIM clashes, and material cost fluctuation supports the argument that construction cost performance cannot be accurately understood through isolated budgetary variables alone. Rather, cost deviation is a multidimensional outcome that reflects the quality of design coordination, the stability of project information, the reliability of procurement, and the effectiveness of planning and control systems. This interpretation is aligned with recent BIM-AI literature emphasizing that integrated digital models and intelligent analytics can connect design, cost, time, and risk information within a unified project management environment (Demiss & Elsaigh, 2026; Zakaria et al., 2024; Zhang et al., 2022).

One of the central findings of the study was the significant positive relationship between the number of detected BIM clashes and both cost overrun and composite project risk score. This result suggests that model-based coordination conflicts are not merely technical design issues, but measurable early warning indicators of later project disruption. When architectural, structural, and building services models contain unresolved clashes, the probability of rework, redesign, site delay, material waste, subcontractor conflict, and claims increases. Therefore, clash detection results can be used as predictive signals in cost and risk analytics. This finding is supported by studies that describe BIM as a coordination and information management platform capable of reducing information fragmentation and improving multidisciplinary project control (Khudhair et al., 2021; Tallet et al., 2021). It is also consistent with research on digitally enabled construction management, which argues that the value of BIM increases when model data are connected to downstream decision-making processes rather than being limited to visualization (Jazzar et al., 2021; Zawada et al., 2024). In this regard, the present findings show that clash-related BIM data can function as an empirical bridge between model coordination and project performance forecasting.

The negative association between BIM maturity and cost overrun, schedule deviation, and project risk was another important result. Projects with higher BIM maturity tended to experience fewer coordination conflicts, lower cost deviation, and lower risk exposure. This finding indicates that BIM implementation quality is more important than the mere existence of a digital model. A project may formally use BIM, but if the model is not integrated with quantity take-off, scheduling, cost control, coordination review, and risk assessment, its contribution to performance improvement remains limited. Conversely, mature BIM implementation allows project teams to extract reliable information, coordinate design decisions, compare alternatives, detect conflicts earlier, and improve communication between stakeholders. This result aligns with studies emphasizing that BIM adoption depends on organizational readiness, managerial perception, digital competence, and integration with project processes (Abazid et al., 2021; Li et al., 2022). It also supports the argument that emerging technology adoption in construction should be examined not only as a technical issue, but also as an organizational and managerial transformation (Wang et al., 2020; Yang et al., 2020).

The predictive modeling results demonstrated that artificial intelligence models outperformed traditional linear approaches in predicting project cost overrun. Although multiple linear regression provided a baseline level of explanatory power, ensemble learning models, particularly gradient boosting regression and random forest regression, achieved substantially stronger prediction performance. The superior performance of these models can be explained by their ability to capture nonlinear relationships, variable interactions, threshold effects, and complex patterns within project data. Construction cost overrun is rarely produced through a simple linear relationship between one cause and one outcome; instead, it emerges from the cumulative and interacting effects of design changes, schedule delays, market fluctuations, coordination problems, procurement constraints, and managerial decisions. Therefore, the stronger performance of gradient boosting and random forest models is theoretically expected and empirically meaningful. This finding is consistent with reviews showing that AI and machine learning methods are increasingly suitable for BIM-based prediction, optimization, classification, and decision support in construction management (Adeel et al., 2023; Bassir et al., 2023). It also supports the use of AI-augmented BIM frameworks for hybrid cost, time, and risk prediction in complex project environments (Demiss & Elsaigh, 2026).

The finding that gradient boosting regression explained a high proportion of variance in cost overrun indicates that BIM-derived and project management variables contain substantial predictive information. This confirms that cost overrun can be forecast more accurately when models incorporate technical indicators such as BIM clashes and design revisions together with managerial and financial indicators such as schedule deviation, material cost fluctuation, procurement delay, change orders, and rework costs. The result aligns with studies on 5D BIM and optimization-based cost management, which demonstrate that time and cost dimensions should be integrated to support more accurate project control (Alzara et al., 2023). It is also consistent with research on automated and BIM-based scheduling, which shows that digitally supported planning approaches can improve the analysis of construction sequences and resource constraints (Doukari et al., 2022). The present study extends these ideas by showing that cost prediction becomes stronger when scheduling, coordination, cost, and risk variables are analyzed together through AI models.

The classification results also showed that artificial intelligence models were effective in distinguishing low-, moderate-, and high-risk projects. Gradient boosting classification achieved the highest accuracy, precision, recall, F1-score, and area under the curve, followed by random forest classification. This finding suggests that project risk level can be predicted with a high degree of accuracy when BIM and project management data are combined in an intelligent analytical framework. Traditional risk assessment often relies on expert judgment and probability-impact scoring, which are useful but may be affected by subjective bias, incomplete information, and delayed recognition of emerging risk patterns. AI-based classification can complement expert judgment by detecting combinations of variables that indicate elevated risk exposure. This result is in line with studies on digital twins, BIM-based intelligent platforms, and Construction 4.0 technologies, which emphasize the use of integrated data environments for monitoring, prediction, and proactive control (Afzal et al., 2023; Kor et al., 2022; Sun & Liu, 2022). It also corresponds with research on cloud-based AI in construction, where scalable digital environments are presented as tools for improving data processing, collaboration, and decision-making across project stakeholders (Wang et al., 2024).

Feature importance analysis further clarified the predictive structure of the models. Schedule deviation had the highest contribution, followed by design revision frequency, number of BIM clashes, material cost fluctuation, BIM maturity level, procurement delay, cost-related change orders, project complexity, rework cost ratio, and subcontractor performance. The prominence of schedule deviation confirms that time instability is one of the strongest signals of cost and risk escalation. Delays often generate additional indirect costs, resource inefficiencies, subcontractor conflicts, extended site overhead, and contractual disputes. Therefore, schedule deviation should be treated not only as an outcome of poor planning but also as a predictive variable for financial and risk outcomes. This finding is supported by recent work on autonomous resource-loaded scheduling and machine-learning-based BIM scheduling, which emphasizes the need for intelligent schedule generation and resource-aware planning in construction projects (Al-Sinan et al., 2024a, 2024b). It also aligns with research on digital twin and BIM-based dispatching systems, where time-sensitive project data are used to support more responsive project control (Sun & Liu, 2022).

The importance of design revision frequency and BIM clashes in the predictive models indicates that design instability is a critical driver of construction risk. Frequent design revisions disrupt cost baselines, change procurement requirements, affect subcontractor sequencing, increase the probability of rework, and reduce the reliability of project schedules. BIM can help identify and manage these problems, but only when design models are updated, coordinated, and linked with project control systems. The present findings are consistent with studies that emphasize AI-supported architectural design, digitally enabled design management, and automated recognition of BIM objects as mechanisms for improving design quality and reducing later-stage errors (Amer, 2023; Kim, 2022; Rane et al., 2023). They are also compatible with studies on sustainable architecture and healthy built environments, which indicate that AI and BIM can support more informed, performance-oriented design decisions when used early in the project life cycle (Bernstein et al., 2022; Krausková & Pifko, 2021).

The role of material cost fluctuation and procurement delay in the models reflects the importance of external market conditions and supply-chain reliability in construction project performance. Even when design coordination and BIM maturity are acceptable, volatile material prices and delayed procurement can generate significant cost and schedule deviations. This is particularly relevant in urban construction markets where projects depend on multiple suppliers, subcontractors, approval processes, and financial conditions. Intelligent construction techniques and integrated digital platforms can help project teams monitor these uncertainties more systematically and update forecasts as new information becomes available (Chashyn et al., 2024; Guo, 2024). The results also align with research on advanced civil integrated management, large-span structure monitoring, and digital twin applications in infrastructure, which shows that the integration of BIM, IoT, AI, and related technologies can improve the management of complex assets and construction processes (Salzgeber et al., 2024; Taheri & Sobanjo, 2024; Xing, 2024).

Overall, the results support the argument that BIM-AI integration can transform project management from reactive reporting into predictive control. Traditional reporting systems often identify cost overrun and risk after they have already affected the project, whereas AI-supported BIM analytics can detect early signals of deviation before they become severe. The findings confirm that schedule deviation, design revisions, BIM clashes, material price instability, and BIM maturity are among the most important predictors of cost and risk outcomes. They also show that ensemble AI models are more suitable than conventional models for analyzing the complexity of construction project data. This conclusion is consistent with the growing literature on BIM-AI integration, Construction 4.0, digital twins, cloud computing, intelligent scheduling, and smart construction management (Bassir et al., 2023; Özturk & Tunca, 2020; Zakaria et al., 2024; Zawada et al., 2024; Zhang et al., 2022). The practical implication is that construction organizations should not treat BIM and AI as separate technologies; rather, BIM should serve as a structured project information environment, while AI should function as the analytical engine that converts this information into predictive insight.

The present study had several limitations. First, the sample was limited to construction projects in Tehran, and although the selected projects represented different building types, project sizes, and professional roles, the findings may not be fully generalizable to other cities, rural construction contexts, infrastructure projects, or countries with different regulatory, economic, and technological conditions. Second, the dataset was based on available BIM records, cost documents, schedule reports, risk assessment forms, and expert validation, and therefore the accuracy of the models depended on the completeness and reliability of project documentation. Third, some variables, such as subcontractor performance, project complexity, and risk severity, required expert judgment and may have been influenced by subjective interpretation despite the use of structured assessment procedures. Fourth, the cross-sectional and retrospective nature of part of the project data limited the ability to examine how predictions change dynamically throughout the entire project life cycle. Finally, while several artificial intelligence models were compared, the study did not include real-time sensor data, live site monitoring data, or fully operational digital twin feedback loops.

Future research should expand the dataset to include construction projects from different cities, climatic regions, contract types, and project delivery systems in order to improve the generalizability and robustness of BIM-AI prediction models. Longitudinal studies are recommended to examine how cost and risk predictions change from conceptual design to design development, procurement, construction, commissioning, and operation. Future studies should also integrate real-time data from site monitoring systems, IoT sensors, procurement platforms, financial dashboards, and digital twin environments to create continuously updated predictive models. In addition, comparative studies can examine the performance of more advanced algorithms, including explainable artificial intelligence methods, hybrid optimization models, deep learning architectures, and probabilistic risk forecasting systems. Another useful direction would be to investigate organizational, behavioral, and managerial factors affecting the successful implementation of BIM-AI systems, including digital readiness, resistance to change, data governance, training quality, and stakeholder collaboration.

From a practical perspective, construction companies, project managers, BIM specialists, and cost control teams should integrate BIM-based information with artificial intelligence analytics as part of routine project planning and control. BIM models should be developed with sufficient information quality to support quantity extraction, clash detection, design coordination, scheduling, cost analysis, and risk assessment. Project teams should continuously monitor the most influential predictive variables identified in this study, especially schedule deviation, design revisions, BIM clashes, material cost fluctuation, procurement delay, change orders, and rework cost ratio. Organizations should also invest in data standardization, BIM execution planning, staff training, model auditing, and integrated dashboards that connect design, cost, schedule, procurement, and risk information. By doing so, construction firms can move from delayed corrective action toward early warning, preventive decision-making, and more accurate control of cost and risk throughout the project life cycle.

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.

Acknowledgments

We would like to express our gratitude to all individuals helped us to do the project.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethics Considerations

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

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