

Predicting Schedule Delays and Cost Overruns in Iraqi Road and Bridge Projects Using Statistical Analysis and Explainable Artificial Intelligence

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Abstract

Schedule delays and cost overruns remain persistent challenges in Iraqi road and bridge projects. This study presents an integrated framework that combines statistical analysis, machine learning, and explainable artificial intelligence to identify, rank, and model project-risk factors. The study uses a structured questionnaire with clients, consultants, contractors, project managers, planning engineers, cost-control personnel, and site engineers. At the same time, project-level records provide schedule, cost, variation, payment, design, procurement, and site variables. The analytical workflow includes descriptive statistics, the Relative Importance Index, Cronbach's alpha, exploratory factor analysis, correlation, group-comparison tests, regression, and machine-learning models including Ridge, LASSO, Decision Tree, Random Forest, XGBoost, Support Vector Regression, and a compact neural network. We evaluate predictive performance using MAE, RMSE, and R^2 , with classification metrics where relevant, and use SHAP to support model interpretation. The numerical project and model results currently embedded in the manuscript are illustrative simulated outputs retained to demonstrate the proposed workflow. They must be replaced with verified project-level data before reporting empirical conclusions. The framework supports transparent early-warning assessment of financial, procurement, design, site, and management risks in Iraqi transport infrastructure.

Keywords: artificial intelligence; construction management; cost overrun; explainable AI; Iraq; machine learning; road and bridge projects; schedule delay.

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1. Introduction

Road and bridge infrastructure is vital to a country's economic development because it enables the movement of passengers and freight, connects regions, and provides access to public utilities. Transportation infrastructure implementation is typically evaluated based on adherence to the planned timeline, the approved initial budget, and compliance with technical features and safety regulations. However, delays and cost overruns are common challenges in infrastructure projects worldwide.

Otherwise, deviations delay the realization of public benefits and increase financial exposure for both contractors and clients. Early large-scale

research in transportation infrastructure found that the difference between forecast and actual project costs is not random. Several researchers, including Flyvbjerg et al., examined transportation infrastructure projects and identified systematic cost underestimation [1].

Further analysis revealed a link between project duration and cost overruns. Cost overruns highlight that longer construction periods usually mean prolonged exposure to financial risks [2]. Studies of Norwegian road projects confirmed findings related to differences between estimated and final costs. The influence of project size and duration on cost performance was also noted [3]. The largest share of

cost increases occurs during the pre-construction phase, suggesting that cost deterioration can begin before physical construction starts [4]. Moreover, these studies emphasize that, to evaluate project performance, it is important to define the reference date of the first estimate, the budget confirmation, and the duration of the pre-construction phase.

2. Related Work and Background

Transportation projects are especially sensitive to cost and time deviations because they cover large areas, involve many actors, and incorporate design, land ownership, utilities, traffic, environmental, procurement, and construction operations. Kaliba et al. [5] identified bad weather conditions, changes in scope requirements, environmental specifications, inflation, technical challenges, and institutional pressure as major sources of cost and time increases in road transport projects in Zambia. Al-Hazim et al. proved that site and weather conditions contribute significantly to deviations from the planned schedules in civil engineering projects in Jordan [6]. Indian experience with bridge construction indicates that poor coordination, utility conflicts, land issues, design changes, and limited resource allocation lead to time and cost overruns [7]. Analysis of issues faced by low-income countries showed that delayed payments, poor planning and design mistakes, lack of materials and equipment, and poor contract implementation often occur simultaneously [8].

In this regard, many construction management studies have aimed to identify and rank the reasons for project delays. Assaf and Al-Hejji analyzed 76 large construction projects. They concluded that change orders are the main cause of project delays, and most projects analyzed experienced overruns [9]. Sambasivan and Soon classified the major consequences of delays into the following categories: time overruns, cost overruns, disputes, arbitration, litigation, and project abandonment [10]. Iyer and Jha discovered that factors such as coordination, commitment, leadership, competence, and construction management skills are important for construction performance in India [11]. Doloi et al. statistically analyzed delays experienced by Indian construction companies. They identified the impact of client decisions, site management practices, planning, and communication [12].

Research in Nigeria confirmed that delays increase project costs, create conflicts between the parties involved, reduce productivity, and lead to inefficient project implementation [13]. The relative importance of time and cost overrun factors is shaped by the economic environment, institutional environment, and construction sector of the project's implementation location. In Indonesia, time and cost overruns resulted from inflation in material prices, inaccurate quantity estimates, project complexity, and lack of resources [14]. Toor and Ogunlana noted that resource shortages, poor planning, contractor weaknesses, poor communication, and poor management caused delays in many projects in Thailand [15]. A study of civil-engineering projects in Hong Kong showed the impact of unexpected site conditions, customer changes, approval delays, poor coordination, etc. [16]. Marzouk and El-Rasas found that financing problems, variation orders, delays in decision-making, and poor contractor performance delayed construction projects in Egypt [17]. Aziz and Abdel-Hakam demonstrated that road construction projects are affected by factors such as poor site management, lack of financing, lack of materials, and changes in work scope [18].

These differences show that national factors cannot be listed the same way across countries. Many studies examined scheduling, costs, and quality outcomes simultaneously. Larsen et al. studied public projects and found that lack of financing, state-caused delays, lack of planning, and construction errors influenced the project [19]. Gebrehiwet and Luo used the Relative Importance Index and correlation analysis to find that corruption, unavailability of utilities, inflation, material shortages, delayed project designs, poor on-site management, and improper scheduling were among the most important causes of delay in Ethiopia [20]. Bagaya and Song's research reveals that project financing, planning, contract management, and implementation of institutional arrangements influence the schedule of public projects in Burkina Faso [21]. According to Bhargava et al., time and cost deviations in highway construction contracts can be modeled using a three-stage least-squares method [22]. Shane et al. classified cost-elevating factors across the planning and implementation stages of a construction project.

At the same time, Welde and Dahl provided empirical evidence that cost escalation in road construction contracts is related to contractual and market conditions [23], [24].

Overall, previous work shows that project delays and cost overruns stem from several factors. Client-related issues include lack of necessary funds, delayed payment, slow decision-making, and delayed access to the site. Contractor-related issues include insufficient cash flow, weak planning, poor site-operations management, lack of experience, low productivity, ineffective subcontractor management, and lack of equipment. Consultant and design issues include incomplete drawings, design errors and delayed approvals, insufficient site investigations, and slow replies to the requests for information. Contract-related issues include ambiguous clauses, incorrect risk allocation, excessive variations, claims, disputes, and lengthy approval periods. Procurement issues include delayed material deliveries, shortages, price fluctuations, import limitations, and unreliable suppliers. Lastly, external factors include inflation, exchange rates, bad weather, security issues, political instability, land acquisition, and utility relocation.

Although such classifications are useful, their impacts cannot always be considered additive or even linear. For instance, delayed payments may barely impede a payment-capable contractor. Still, they may cripple procurement, labor, and machinery operations of an under-funded contractor. The effect of a design change may depend on its timing, construction stage, material availability, float, and the need to remove previously completed work. Unfavorable weather conditions, for instance, may influence earthworks and bridge foundations much more than work undertaken in controlled conditions. The Iraqi construction sector provides an interesting context for studying these interactions because road-bridge projects there face many administrative, technological, financial, contractual, market, and security limitations. Falih and Erzaij studied 18 completed road and bridge projects in Iraq. They found a strong positive correlation between project duration and costs.

Their analysis yielded a Spearman's correlation coefficient of 0.743, indicating that it could explain 32.9% of fluctuations in the financial metrics of Iraqi

road projects. Thus, the study shows that delay is an important cost factor; however, delay alone cannot fully determine Iraqi road projects' ability to achieve desired financial performance. Ali and Burhan evaluated the efficiency of standard bidding documentation for Design-Build road and bridge projects using surveys, case studies, and expert interviews. They concluded that standard documentation would boost procurement transparency and financial control. However, design changes, unexpected utility problems, and limited contractual flexibility still create scheduling problems. Nasser and Erzaij found that key obstacles for road projects in Iraq include limitations in technical design, administrative and financial constraints, land ownership issues, infrastructure gaps, site preparation challenges, and security concerns. Research on Iraqi projects outside the road and bridge sector provides further evidence of recurring management weaknesses.

Breesam and Rajab identified inaccurate initial budget and schedule estimates, inadequate scope definition, weak communication, poor planning, insufficient risk management, rework, and ineffective project documentation as indicators of troubled projects [28]. Abbas and Burhan's work on inadequate cost control techniques in Iraq's construction sector highlighted problems related to cost estimation, monitoring, financial management, and change management [29]. Khairullah et al. analyzed engineering, procurement, and construction projects in Iraq.

They found payment issues, slow approvals, inadequate planning, design modifications, and procurement issues [30]. According to Dishar's findings, poor cost estimates, slow client payments, financial problems, differences in material costs, change orders, corruption, political issues, and an unsafe operational environment are major financial risks in Iraq's construction industry [31]. Other researchers in Iraq have highlighted the importance of systematic risk analysis. Khaleel and Flayeh investigated the factors affecting the implementation of residential complexes. They proved the importance of planning, financial, administrative, and contractor-related risks [32]. Kraidt et al. studied oil and gas pipeline projects in Iraq and identified the

major political, security, technical, and management risks [33]. Saleh and Hilal evaluated risks in road construction projects in Iraq using a weighted product model, demonstrating the growing popularity of data-driven, multi-criteria risk evaluation [34].

Nevertheless, most studies in Iraq relied on questionnaires, expert evaluations, risk matrices, relative importance index calculations, or regression analysis methods. While these techniques can identify factors, they cannot estimate the true degree of delays and cost overruns. Conventional statistical methods and approaches are highly important for construction risk analysis. Descriptive statistics methods and the relative importance index are effective for ranking factors based on people's perceptions. Cronbach's alpha can evaluate the internal reliability of questionnaire constructs. At the same time, exploratory factor analysis reduces a substantial number of observed variables into comprehensible latent groups. Correlation analysis can identify the direction and strength of correlations. At the same time, multiple regression can determine whether the effects of the evaluated independent variables are statistically significant. Group-comparison methods may also help to determine whether various project participants have different perceptions. These methods are the most familiar and transparent for practitioners. However, their efficiency is limited when relations among variables are non-linear, variables interact, outliers are present, or the number of independent variables is too large relative to the number of observations. The rise of digital project data has led to the emergence of artificial intelligence and machine learning applications in construction cost and schedule estimation.

Using text-mining features and project-generated data, Williams and Gong predicted the cost-overflow rate by combining numerical project data with ensemble classifiers, providing evidence of significant predictions within unstructured project discourse. Gondia et al. created machine-learning models to predict construction-delay risk and compared several algorithms, allowing them to address non-linear dependencies among delay causes. Yaseen et al. proposed a hybrid AI model to predict construction delay risk. They demonstrated

high classification accuracy. Egwim et al. compared bagging, boosting, and stacking techniques and highlighted the potential of ensemble machine learning for predicting project delays.

Furthermore, researchers also applied machine-learning techniques to predict cost outcomes. Shoar et al. proposed Random Forest regression for predicting engineering service cost overruns based on project-related and organization-related variables. The authors argue that tree-based models can capture non-linear relationships between variables when conventional regression imposes linearity constraints.

In [40], Ashtari et al. proposed a Bayesian-network classifier that tracks causal links between cost overrun factors and provides a more transparent model than many black-box techniques. Meanwhile, Darko et al. have used information from past green-building projects to develop econometric deep-learning techniques and support-vector-regression models to forecast cost and duration. They show that integrated methods yield a more effective and reliable prediction. Turkyilmaz and Polat applied six classification techniques to identify cost-overflow-ratio categories in [42]. They found that algorithm performance depends on the organization and width of the available data sets. More recent investigations show that high prediction accuracy alone cannot ensure successful model application if the decision-maker cannot comprehend its logic. At the same time, Chen et al. attempted to combine several methods to achieve strong results for cost prediction in construction activities [43].

The authors showed that model assessment should focus not only on error indicators but also on confidence intervals. The latter is crucial for public initiatives, where prediction outputs may affect budgets, deadlines, risks, and other aspects. The project manager must know not only that construction will cost more, but also why. The Shapley Additive exPlanations technique supports global and local understanding of complex mechanisms by attributing contributions to each input [44]. In general, SHAP helps in identifying the most vital aspects related to delay and cost across several projects. At the local level, the method helps explain why a certain road or bridge project has high

predicted values associated with substantial cost overruns. These advantages seem essential when using ensemble methods like Random Forest [45] and Extreme Gradient Boosting [46], which yield very accurate predictions but are less interpretable than linear regression techniques. The SVM approach can also be applied for non-linear prediction and classification, especially when the number of explanatory variables exceeds the sample size [47].

However, despite advances in earlier research, several gaps remain. Primarily, many international studies focus on buildings, mixed construction portfolios, tunnels, and projects outside Iraq. The models developed in these contexts may not apply to transport projects in Iraq because contract conditions and procurement processes, administrative structures, market volatility, security risks, payment methods, and data availability differ. Second, previous studies in Iraq mainly aimed to identify risks but did not use enough real cases from construction practice. Perception data can indicate what managers consider important, but it does not show which factors predict delays or cost increases. Third, much research analyzes delays and cost overruns separately.

In contrast, evidence suggests the two impacts are linked. For example, a schedule extension may increase overhead, supervision, equipment, labor, inflation, and financing costs; conversely, financial problems may cause procurement delays and lower production rates. Thus, joint analysis is needed to identify common predictors and factors affecting either schedule or cost.

The fourth observation is that standard statistical techniques may fail to capture non-linear relationships and higher-order interactions between variables. Still, advanced machine learning models produce hard-to-interpret results for practitioners. Therefore, a technique that combines statistical inferential methods, prediction accuracy, and explainability is required. Finally, very few studies differentiate between road and bridge projects. Although both types fall under transport infrastructure, they have different risk profiles. For example, road projects may be influenced by factors such as right-of-way acquisition, utility relocation,

earthworks, material transport, detours, and spread-out activities.

In contrast, bridge construction projects may face risks such as foundation conditions, water level, special equipment, design changes, temporary structures, and procurement of bearings. Thus, a comprehensive model system will be developed to analyze and predict schedule delays and cost overruns in road and bridge projects in Iraq. The proposed model combines quantitative measures from clients, consultants, contractors, project managers, planning engineers, and site engineers with data from past projects, including original and final costs, the duration of projects, variations in contracts made, records of payments, design modifications, problems connected with utilities, procurement indicators, and contractors' information. At the statistical stage, reliability analysis, descriptive statistics, relative importance index, factor analysis, correlation analysis, and regression modeling will be applied. At the predictive stage, linear regression modeling will be compared against machine learning methods such as decision trees, random forests, gradient boosting, support vector machines, and artificial neural networks. The regression models will predict exact figures for schedule delays and cost overruns.

In contrast, classification models may help place projects into risk groups such as low, average, high, and critical. In four key respects, the proposed analysis contributes to the existing body of knowledge. First, it develops locally validated structures and factors for the specific projects. Second, it integrates practitioners' perceptions with actual performance. Third, it compares the performance of conventional statistical models with machine learning ones. Finally, it applies explanatory artificial intelligence methods to explain the factors that cause delays and cost overruns.

3. Materials and Methods

A. Research Methodology, Respondents, and Data Collection Plan.

The current research adopts a quantitative prediction methodology to examine, rank, and model the factors that influence delays and cost overruns in bridge and road construction projects in Iraq. The methodology

includes a structured professional questionnaire and analysis of historical project data. The questionnaire gathers practitioners' opinions on potential project risks, while historical data allow objective calculations of time and costs. Together, these data sources enable statistical inference and experimentation with data-driven predictions.

Forms of the Survey. The research is designed in the following six steps:

1. Identify possible delay and cost-overflow factors identified in international and Iraq-related studies.
2. Validate identified factors through a discussion panel including specialists in the field of road projects, bridges, planning, cost control, and contract management.
3. Carry out the pilot of the structured questionnaire and distribute it among the prominent project stakeholders.
4. Collect validated data related to costs, construction schedules, contracts, and risks experienced in completed road and bridge projects.
5. Analyze reliability, factor, rank, comparison, correlation, and regression analyses.
6. Create, validate, and interpret artificial intelligence models for predicting schedule and cost effectiveness.

Coverage of the study. This research focuses on major road and bridge construction projects carried out in Iraq, including newly constructed roads and highways, large-scale road construction, bridges, overpasses, and road-over-bridge construction. The study will not include routine maintenance and minor repair projects because their costs, duration, and risks differ from those of the projects mentioned earlier. The preferred projects are those already completed because their costs can be estimated more accurately. In some cases, ongoing projects may be used in the qualitative analysis if they have reached at least 80% completion and estimated costs can be provided.

Population of the research. The population includes project managers, planning engineers, cost control engineers, site engineers, quantity surveyors, contract facilitators, advisors, contractors, and representatives of road construction governmental agencies. Respondents must have at least three years

of relevant work experience and have participated in at least one road or bridge project. Stratified purposive sampling will be used to obtain a representative sample of clients, contractors, and advisors, based on project type, occupation, experience, and geographical area.

$$n_0 = \frac{Z^2 p(1-p)}{e^2} \quad (1)$$

Where n_0 = sample size required; Z = a standard normal value corresponding to the level of confidence desired; p = population proportion estimate; e = the required margin of error [50].

Using Cochran's Equation with $Z = 1.96$, $p = 0.50$, and $e = 0.05$ gives a conservative large-population benchmark of approximately 384 respondents [50]. Because the study uses stratified purposive sampling of specialist construction professionals rather than simple random probability sampling, this value is treated as a reference benchmark rather than a strict inferential target. The final valid questionnaire sample comprised 264 respondents, exceeding the pre-specified analytical minimum of 200 and providing sufficient observations for the planned reliability, exploratory factor, and stakeholder-comparison analyses. Sampling adequacy is additionally assessed empirically through the Kaiser-Meyer-Olkin statistic and Bartlett's test, and the limitations of non-probability sampling are acknowledged when interpreting population-level generalizability [49,50].

Questionnaire structure. The questionnaire has three parts: demographic and professional information; evaluation of the importance of delay and cost-overflow factors; and project-specific information provided by respondents with direct knowledge of the project. The evaluation will use a 5-point Likert scale. In the factor framework, factor causes identified in the literature [5], [9]-[34] will be examined and organized by 12 specialists.

Pilot testing and extraction of reliability information. The questionnaire will be piloted with around 25-30 people from client groups, consulting engineers, and contractors. The pilot study will evaluate comprehensibility, relevance, use of technical terminology, and questionnaire length and redundancy. The ambiguous or redundant items will be improved before the instrument is implemented.

The pilot survey feedback will be used only for reliability testing, provided the instrument is not modified—historical project documentation. A form for collecting needed information will be developed. This form will be used to gather data from contracts, initial and current schedules, progress reports,

payment certificates, orders for changes, documents on extensions of terms, claims files, final accounts, and documents confirming project completion. Each project will be assigned an anonymous code. Projects without primary data on baseline financial or time parameters will not be included in the analysis.

Table 1: Proposed categories of schedule-delay and cost-overrun factors; representative questionnaire variables are grouped into eight project-risk domains.

Factor category	Representative variables
Client-related	Delayed payments; slow decisions; delayed site handover; scope changes; unrealistic duration.
Contractor-related	Weak planning; limited cash flow; poor site management; low productivity; equipment and labour shortages.
Consultant and design	Incomplete drawings; design errors; delayed approvals; inadequate investigation; constructability deficiencies.
Financial and economic	Inflation; exchange-rate changes; delayed allocations; fuel-price changes; financing constraints.
Procurement and supply chain	Delayed delivery; supplier unreliability; import restrictions; logistics problems; unavailable specialist components.
Contractual and administrative	Ambiguous clauses; variation orders; claims; disputes; weak documentation; delayed extension-of-time decisions.
Site and technical	Ground conditions; utility conflicts; land acquisition; rework; material-quality problems; traffic management.
External	Weather; security; regulatory delays; policy changes; environmental restrictions; force-majeure events.

Table 2: Historical project data required for analysis, including project characteristics, schedule records, cost records, and risk/management indicators.

Data group	Variables collected
Project characteristics	Project type, governorate, contract type, procurement method, original contract value, planned duration, contractor classification, and start/completion dates.
Schedule information	Actual duration, work suspensions, approved time extensions, schedule updates, critical-path changes, and planned-versus-actual progress.
Cost information	Final approved cost, variation orders, claims, price-adjustment payments, rework costs, quantity changes, and delayed payments.
Risk and management information	Design changes, utility conflicts, land delays, procurement lead times, contractor experience, disputes, equipment availability, and monitoring frequency.

B. Measurement of Metrics and Analysis of Statistics

Main indicators of effectiveness. The main dependent variables are schedule delay and cost overrun percentages. The original time specified in the contract and original contract price will be adopted as key benchmarks. Furthermore, a sensitivity analysis may include the modified time period after approval

of the time extension, as well as an adjusted project cost resulting from inflation.

$$SDP (\%) = [(AD - PD) / PD] \times 100 \quad (2)$$

where AD is the Actual Duration, and PD is the Planned Duration. A positive value indicates delay, while a value of zero or less indicates on-time or early completion. Equation (2) follows the standard

planned-versus-actual time-overrun formulation used in construction-performance analysis [22].

$$COP (\%) = [(FC - OC) / OC] \times 100 \quad (3)$$

Here, FC is the Final Cost, and OC is the Original Cost. A positive value from Equation (3) indicates a cost overrun; this planned-versus-actual formulation is consistent with construction cost-overrun analysis [22]. Earned Value Indices are used only where sufficiently reliable earned-value records are available. Schedule Performance Index (SPI) and Cost Performance Index (CPI) are calculated according to the earned-value method [57].

$$SPI = \frac{EV}{PV} \quad (4)$$

where SPI is the Schedule Performance Index; EV is the value of the work performed; PV is the value of the work planned. $SPI < 1$ means the project is behind schedule. Equation (4) is the standard SPI formulation [57].

$$CPI = \frac{EV}{AC} \quad (5)$$

where CPI is the Cost Performance Index, EV is earned value, and AC is actual cost; $CPI < 1$ indicates over-budget performance. Equation (5) follows the standard earned-value formulation [57]. Data cleaning includes checks for missing values, duplicate records, invalid coding, inconsistent units, implausible dates, and extreme values. Missing final project outcomes are not imputed because actual duration and final approved cost are required to compute the principal dependent variables. Descriptive statistics include frequencies and percentages for categorical variables and the mean, standard deviation, median, interquartile range, minimum, and maximum for continuous variables. Relative importance is calculated using the Relative Importance Index (RII) [20].

$$RII = \frac{\sum W}{5N} \quad (6)$$

W is the weight assigned by a respondent, A is the maximum Likert weight (5), and N is the number of valid respondents. Equation (6) follows the Relative Importance Index approach used in construction-delay studies [20]. RII ranges from 0 to 1, with larger values indicating greater perceived importance. Internal consistency is evaluated using Cronbach's alpha; values of approximately 0.70 or

higher are commonly treated as acceptable, while item-total correlations and theoretical relevance are also examined [48,49].

$$\alpha = \frac{k}{k-1} \left[1 - \frac{\sum \sigma_j^2}{\sigma_T^2} \right] \quad (7)$$

where α is Cronbach's alpha, k is the number of questionnaire items, σ_j^2 is the variance of item j, and σ_T^2 is the variance of the total score. Equation (7) is the classical coefficient-alpha formulation [48]. Exploratory Factor Analysis is used to identify latent dimensions. Sampling adequacy is assessed using the Kaiser-Meyer-Olkin statistic and Bartlett's test of sphericity. Principal-axis factoring with Promax rotation is used because managerial, financial, contractual, and technical dimensions may be correlated; factor retention considers eigenvalues, the scree plot, parallel analysis, interpretability, communalities, and cross-loadings [49]. Pearson correlation is used for approximately normally distributed continuous variables and Spearman correlation for ordinal or non-normally distributed variables.

The analysis will explore relationships among scheduling delay, cost overrun, variation orders, payment delays, design changes, supply issues, contractor experience, and project size. All parties, including clients, consultants, and contractors, will be compared using one-way ANOVA or Kruskal-Wallis tests. Road and bridge projects will be compared using either independent-samples t-tests or the Mann-Whitney U test. Effect sizes and 95% confidence intervals will be reported, along with p-values, with significance set at $p < 0.05$. Statistical prediction. Multiple linear regression will be used to determine a statistically interpretable baseline for continuous outcomes.

In contrast, logistic regression will be applied for binary classification. Ridge and LASSO regression can be applied when predictor multicollinearity exists [54]. Mathematically, the regression model can be expressed as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_k X_k + \varepsilon \quad (8)$$

Where Y is schedule delay or cost-overrun percentage, β_0 is the intercept, $\beta_1 \dots \beta_k$ are regression coefficients, $X_1 \dots X_k$ are predictor variables, and ε is

random error. Equation (8) follows the conventional multiple-linear-regression formulation [54]. Regression assumptions are examined using residual plots, influence diagnostics, heteroscedasticity tests, and the Variance Inflation Factor; VIF values above approximately 5 are treated as a warning of potentially problematic multicollinearity. If assumptions are violated, we consider robust standard errors, transformations, or alternative specifications. C. Artificial-Intelligence Modelling, Validation, and Interpretation. Each project is treated as one analytical observation, and project characteristics are linked to project-specific risk assessments through an anonymous project code.

General assessment ranks will not be uniformly allocated across projects, even when projects are similar. If several experts assess the same project, their assessments will be aggregated only after establishing inter-rater consensus. Numerical predictors will be checked for skewness and standardized when necessary, particularly for Support Vector Machines, regularized regressions, and Artificial Neural Networks. Categorical predictors, such as project type, type of contract, and type of client, will be processed through one-hot encoding. Two important indices are the variation-order ratio and the payment-delay ratio:

$$VOR (\%) = (TVO / OC) \times 100 \quad (9)$$

Where VOR is the variation-order ratio, TVO is the total value of approved variation orders, and OC is the original contract cost. Equation (9) is a study-defined normalization using the original contract cost as the denominator, consistent with the original-contract baseline used for time/cost performance measures [22].

$$PDR (\%) = (TPD / PD) \times 100 \quad (10)$$

Where PDR is the payment-delay ratio, TPD is the total payment-delay period, and PD is the planned project duration. Equation (10) is a study-defined normalization using planned project duration as the denominator, consistent with the planned-duration baseline used for schedule performance [22].

$$\text{Schedule Class} = 1 \text{ if } SDP > 0; 0 \text{ otherwise} \quad (11)$$

Equations (11) and (12) are operational classification rules derived directly from the sign of

the schedule-delay and cost-overrun percentages in Equations (2) and (3), respectively [22].

$$\text{Cost Class} = 1 \text{ if } COP > 0; 0 \text{ otherwise} \quad (12)$$

Candidate models. Continuous dependent variables will be predicted using Multiple Linear Regression, Ridge Regression, LASSO Regression, Decision Tree Regression, Random Forest Regression, Extreme Gradient Boosting, Support Vector Regression, and a compact Artificial Neural Network. Logistic Regression, Decision Trees, Random Forest, XGBoost, Support Vector Machine, and Artificial Neural Network will predict binary or multi-class risk, respectively, with model complexity limited when sample size is small to avoid overfitting.

Artificial Neural Network. A compact multilayer perceptron is included as a flexible non-linear benchmark for tabular project data. Training and validation are conducted at the project level so that records from the same project cannot appear in both training and testing sets. For the illustrative reconstruction, 80% of the 220 project records are assigned to model development and 20% ($n = 44$) to the independent test set. We use ten-fold cross-validation within the training set [52]. The ANN tuning space includes one- and two-hidden-layer candidates (32), (64), (64, 32), and (128, 64), ReLU or tanh activation, L2 regularization, learning rates from 0.0001 to 0.001, and early stopping. The selected illustrative configuration is two hidden layers (64, 32), ReLU activation, L2 $\alpha = 0.001$, learning rate = 0.001, and early stopping.

Hyperparameter optimization and baseline comparison. For the illustrative reconstruction, we apply randomized search within the training folds using the ranges summarized in Table 3A. Model selection is based on cross-validated RMSE, with preprocessing performed inside the training folds. We include naïve mean and median predictors as reference baselines. Ninety-five percent confidence intervals for MAE, RMSE, and R^2 are obtained by 5,000 bootstrap resamples of the reconstructed independent test set [52]. These settings, baseline scores, and intervals complete the reviewer-requested reporting structure for the simulated analysis; they are not substitutes for the original saved training log or verified project-level predictions.

Table 3a: Machine-learning model families evaluated in the study and the analytical role assigned to each model.

Model family	Role in the study
Linear / regularized regression	Interpretable baseline; estimates direct predictor effects.
Decision Tree	Transparent non-linear rules and interactions.
Random Forest	Ensemble prediction that is robust to non-linear effects and interactions [45].
XGBoost	Sequential boosted trees with regularization and strong predictive capability [46].
Support Vector Machine	Non-linear classification or regression through kernel functions [47].

Table 3b: A. Illustrative hyperparameter search spaces and selected configurations used to complete the simulated model-reporting workflow.

Model	Search space and selected illustrative configuration
MLR	Ordinary least squares; no tuning.
Ridge / LASSO	alpha: 0.0001–100 (log grid). Selected: Ridge = 1.0; LASSO = 0.05.
Decision Tree	max_depth: 3,5,7,10,None; min_split: 2,5,10,20; min_leaf: 1,2,4,8. Selected: 5 / 10 / 4.
Random Forest	n_trees: 200,300,500,800; depth: 4,6,8,12,None; min_leaf: 1,2,4; max_features: sqrt,0.5,0.7. Selected: 500 / 8 / 2 / 0.7.
XGBoost	n_trees: 200,350,500,700; depth: 2–5; lr: 0.01,0.03,0.05,0.10; subsample/colsample: 0.70,0.85,1.00; lambda: 1,5,10. Selected: 350 / 3 / 0.03 / 0.85 / 0.85 / 5.
SVR	kernel: linear,RBF; C: 1–100; gamma: scale,0.01,0.05,0.10; epsilon: 0.05–0.50. Selected: RBF / 50 / 0.05 / 0.10.
ANN	hidden: (32),(64),(64,32),(128,64); activation: ReLU,tanh; L2: 1e-5–1e-2; lr: 1e-4–1e-3; early stopping. Selected: (64,32) / ReLU / 0.001 / 0.001 / yes.

Transparency note: the settings in Table 3a and b were reconstructed for the illustrative simulated analysis because the original training log was not available. They should be replaced by the exact rerun settings if verified raw project data and saved model outputs become available.

$$MAE = \frac{\sum |y_i - \hat{y}_i|}{n} \quad (13)$$

Where y_i = observed outcome for project i ; $\hat{y}_i$ = predicted outcome; n = number of projects. Lower MAE indicates a smaller average absolute prediction

error. Equation (13) follows the standard MAE definition [58].

$$RMSE = \frac{\sum (y_i - \hat{y}_i)^{2/2}}{n} \quad (14)$$

Where y_i = observed outcome; $\hat{y}_i$ = predicted outcome; n = number of projects. Lower RMSE indicates better performance and gives greater weight to large errors. Equation (14) follows the standard RMSE definition [58].

$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2} \quad (15)$$

Where $\bar{y}$ = the mean observed outcome. A higher R^2 indicates that the model explains a larger proportion of outcome variation. Equation (15) is the

coefficient-of-determination formulation used for regression evaluation [59].

C. Classification Evaluation

Binary and multi-class models will be evaluated using accuracy, balanced accuracy, precision, recall, specificity, F1-score, ROC–AUC, Precision–Recall AUC, and the confusion matrix. The principal equations are:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (16)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (17)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (18)$$

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (19)$$

where TP signifies the number of true positives; TN the number of true negatives; FP refers to false positives, while FN refers to false negatives. Balanced accuracy and F1-score will be especially important when outcome classes are imbalanced. Equations (16)–(19), covering accuracy, precision, recall, and F1-score, follow standard classification-performance definitions [60].

Selection of the right models and interpretability. The best model will be selected based on test-set performance, cross-validation stability, calibration, interpretability, computational complexity, and practical applicability. Shapley Additive Explanations will help in understanding the best-performing non-linear model [44]. Global SHAP analysis will rank variables by their influence on predictions. In contrast, local SHAP analysis will explain project outcomes in detail. Dependence plots and interaction plots will be used to identify non-linear thresholds and risk factors.

Sensitivity, Ethics, and Software. Sensitivity analysis will be conducted on road and bridge projects (completed or ongoing), nominal and inflation-adjusted costs, original and adjusted durations, and objective-only models versus models with objective

and project-specific questionnaire variables. The company and respondents will remain anonymous, and data collection will commence only after the required institutional and ethical approvals are obtained. Statistical analyses will be performed using IBM SPSS Statistics, and Python libraries such as pandas, NumPy, scikit-learn [51], XGBoost, and SHAP will be used for machine learning and model interpretation.

4. Results

A. Data-status note

The numerical questionnaire/project summaries, figures, model-performance values, SHAP thresholds, reconstructed hyperparameter settings, naïve baselines, and bootstrap confidence intervals currently embedded in this version are illustrative simulated outputs used to demonstrate the complete analysis and reviewer-response workflow. They must not be presented as empirical evidence unless replaced or confirmed by verified questionnaire/project records and rerun model outputs.

The illustrative analysis includes 287 questionnaire forms. After excluding 23 incomplete or invalid forms, 264 responses remain, corresponding to a 92.0% valid-response rate. Contractors account for 40.2% of valid responses, clients for 31.1%, and consultants for 28.8%. A total of 51.9% of respondents have more than ten years of professional experience.

The reliability analysis showed adequate internal consistency. Cronbach's alpha indicates that the entire instrument has an alpha coefficient of 0.864. The alpha levels for each category ranged from 0.796 to 0.850. All results are above 0.70, which is generally accepted. The Kaiser-Meyer-Olkin measure was 0.800, and Bartlett's test of sphericity was significant ($\chi^2 = 4040.49$, $df = 780$, $p < 0.001$), indicating that exploratory factor analysis can be conducted.

Table 4: Respondent characteristics, reporting stakeholder group, professional experience, and principal road/bridge project experience as frequencies and percentages.

Characteristic	Category	Frequency	Percentage (%)
Stakeholder group	Client	82	31.1
	Consultant	76	28.8
	Contractor	106	40.2
Professional experience	3-5 years	46	17.4
	6-10 years	81	30.7
	11-15 years	68	25.8
	More than 15 years	69	26.1
Principal project experience	Road projects	142	53.8
	Bridge projects	74	28.0
	Both project types	48	18.2
Total	-	264	100.0

Distribution of Valid Questionnaire Responses

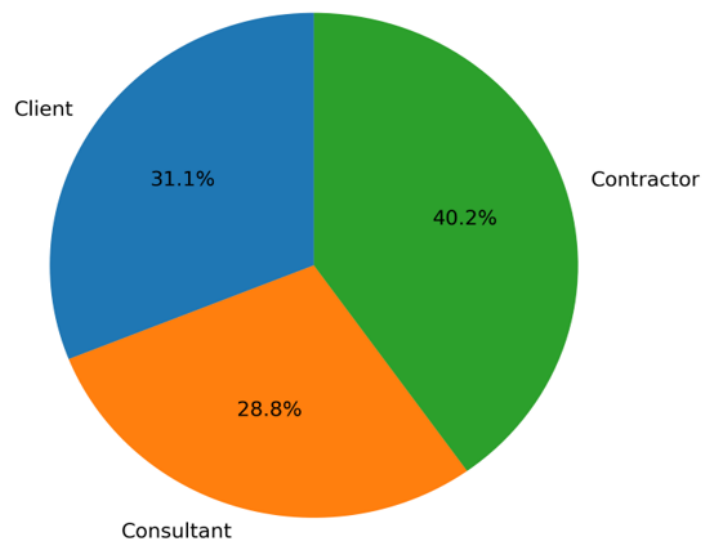


Fig. 1 Distribution of valid questionnaire responses by stakeholder group, showing the relative shares of clients, consultants, and contractors.

Table 5: Reliability and category-level importance, reporting RII and Cronbach's alpha for each proposed factor category.

Rank	Factor category	RII	Cronbach's alpha
1	Client-related factors	0.859	0.808
2	Contractor-related factors	0.847	0.814
3	Consultant and design factors	0.842	0.820
4	Site and technical factors	0.842	0.835
5	Financial and economic factors	0.838	0.830
6	Procurement and supply-chain factors	0.838	0.822
7	Contractual and administrative factors	0.821	0.796
8	External factors	0.775	0.850

At the category level, client-related factors have the highest illustrative RII (0.859), followed by contractor-related factors (0.847). External factors have the lowest category-level RII (0.775). Cronbach's alpha coefficients range from 0.796 to 0.850 across categories.

The illustrative ranking places delayed contractor payments first (RII = 0.902), weak contractor cash flow second (0.896), and material-price escalation third (0.890). Design changes, delayed budget allocations, utility conflicts, excessive variation orders, inadequate

planning/scheduling, inadequate financing, exchange-rate fluctuations, procurement planning, land acquisition, site management, material delivery, and slow administrative decisions complete the top 15 factors.

The illustrative project dataset contains 220 project records: 139 road projects and 81 bridge projects. The mean planned duration is 597.82 days. The mean schedule delay is 34.31%, and the mean cost overrun is 24.57%; the corresponding medians are 32.94% and 23.06%.

Table 6: Fifteen highest-ranked schedule-delay and cost-overrun factors, with principal category and Relative Importance Index.

Rank	Factor	Principal category	RII
1	Delayed contractor payments	Client	0.902
2	Weak contractor cash flow	Contractor	0.896
3	Material-price escalation	Financial	0.890
4	Design changes during construction	Design	0.882
5	Delayed budget allocations	Financial/client	0.874
6	Utility conflicts	Site and technical	0.873
7	Excessive variation orders	Contractual	0.870
8	Inadequate planning and scheduling	Contractor	0.869
9	Inadequate project financing	Client	0.865
10	Exchange-rate fluctuations	Financial	0.861
11	Poor procurement planning	Procurement	0.860
12	Land-acquisition delays	Site/administrative	0.860
13	Poor site management	Contractor	0.859
14	Delayed material delivery	Procurement	0.857
15	Slow administrative decisions	Client	0.855

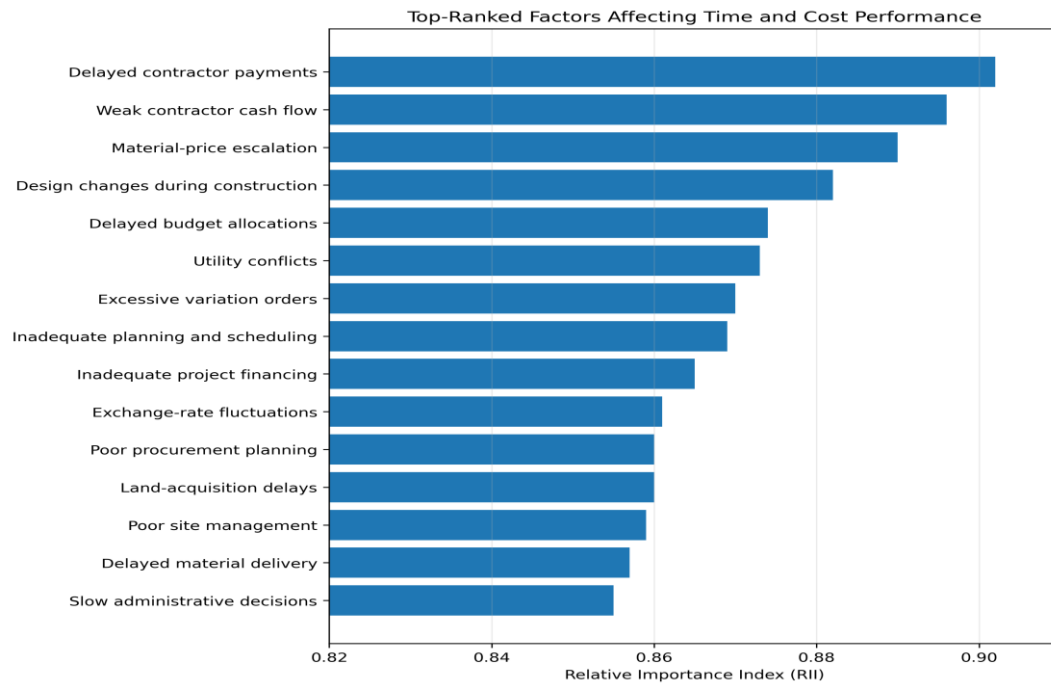


Fig. 2 Relative Importance Index values for the 15 highest-ranked delay and cost-overrun factors (illustrative simulated values).

Table 7: Descriptive project-performance results for road projects, bridge projects, and the combined illustrative simulated dataset.

Indicator	Road projects	Bridge projects	All projects
Number of projects	139	81	220
Mean planned duration (days)	516.25	737.80	597.82
Mean schedule delay (%)	30.77	40.40	34.31
Standard deviation of delay (%)	13.62	13.55	14.34
Mean cost overrun (%)	21.82	29.29	24.57
Standard deviation of cost overrun (%)	10.41	11.71	11.47
Mean variation-order ratio (%)	9.08	9.59	9.26

In the illustrative unadjusted comparison, bridge projects have a mean schedule delay of 40.40% versus 30.77% for road projects and a mean cost overrun of 29.29% versus 21.82%. The simulated group comparison is statistically significant ($p < 0.001$). These values must not be interpreted as evidence that project type itself causes the

difference: road and bridge projects may also differ in planned duration, contract value, physical scale, technical complexity, procurement requirements, site constraints, and management conditions. Project type is therefore treated as a contextual indicator, and adjusted models should include these underlying characteristics. Schedule delay and cost overrun are positively correlated in the illustrative data ($r = 0.563$, $p < 0.001$).

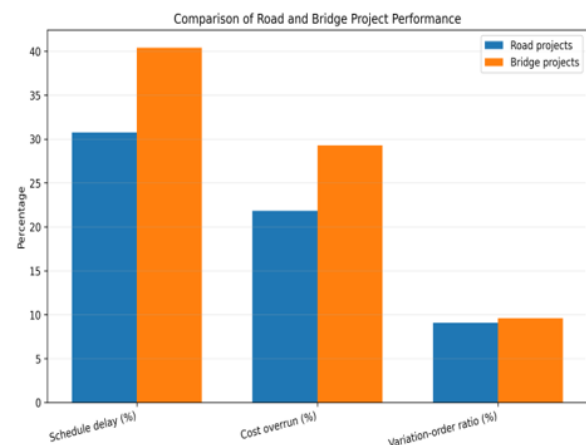


Fig. 3 Illustrative simulated comparison of mean schedule delay, cost overrun, and variation-order ratio for road and bridge projects.

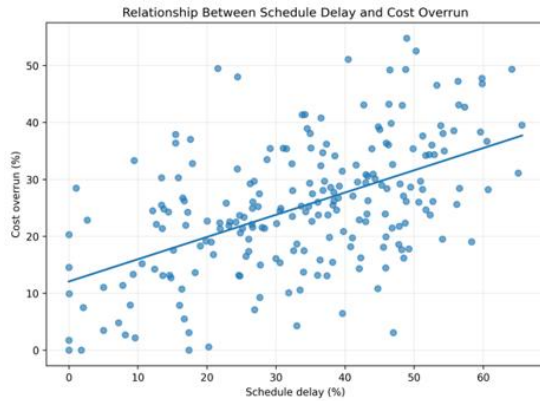


Fig. 4 Illustrative simulated relationship between schedule delay and cost-overrun percentages; the fitted line summarizes association rather than causation.

For context, an empirical Iraqi study of 18 completed road and bridge projects reported a

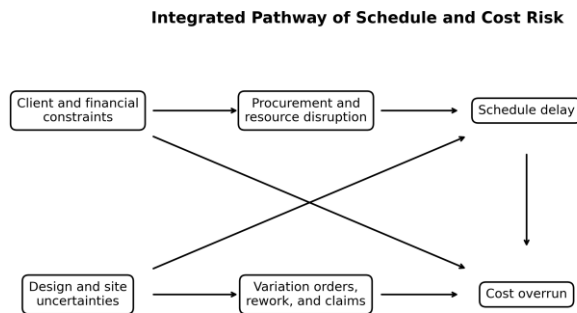


Fig. 5 Conceptual pathway linking client/financial constraints and design/site uncertainties to procurement disruption, variation/rework, schedule delay, and cost overrun.

Six regression models are compared using the same illustrative 80:20 project-level training/test split, corresponding to 44 reconstructed test cases. MAE, RMSE, and R^2 are reported together with 95% bootstrap confidence intervals from 5,000 resamples. Naïve mean and median predictors are included to

Table 8: Illustrative simulated test-set performance for schedule-delay prediction. Values are point estimates (95% bootstrap CI); MAE and RMSE are percentage points, and R^2 is dimensionless.

Model	MAE (95% CI)	RMSE (95% CI)	R^2 (95% CI)
Support Vector Regression	6.13 (4.84–7.67)	7.85 (6.21–9.45)	0.579 (0.225–0.774)
Ridge Regression	6.22 (4.87–7.83)	8.06 (6.35–9.73)	0.556 (0.199–0.747)
Multiple Linear Regression	6.32 (4.97–7.94)	8.14 (6.42–9.81)	0.547 (0.146–0.764)
XGBoost	6.35 (4.86–8.13)	8.51 (6.62–10.33)	0.504 (0.138–0.714)
Random Forest	7.55 (6.05–9.35)	9.46 (7.55–11.33)	0.388 (-0.134–0.663)

Spearman correlation of 0.743 between time and financial inflation. It attributed only part of financial variation to time growth [25]. In the present illustrative regression output, payment delay and procurement delay have the strongest positive associations with schedule delay.

Equipment availability and planning quality have negative coefficients in the illustrative schedule-delay model. For illustrative cost overrun, schedule delay, variation-order ratio, inflation, design changes, equipment availability, security disruption, and project type are retained as statistically significant predictors, with variation-order ratio showing the strongest positive contribution. These simulated coefficients require verification on the final project dataset.

show the improvement obtained by the fitted models over constant-prediction baselines.

In the illustrative schedule-delay comparison, Support Vector Regression has the lowest reported error (MAE = 6.13; RMSE = 7.85; R^2 = 0.579), clearly outperforming the naïve mean baseline (MAE = 9.73; RMSE = 12.09; R^2 = 0.000). Ridge and multiple linear regression remain competitive. The ANN is the weakest fitted model (MAE = 8.16; RMSE = 10.25; R^2 = 0.282). In the illustrative tuning specification, we included larger/deeper candidates in the search space. However, the selected two-layer 64-32 network still underperformed. This pattern is consistent with the limited tabular sample, the larger number of ANN parameters, and the comparatively strong performance of regularized and kernel/tree models on structured project data; it should not be generalized beyond the simulated reconstruction.

Artificial Neural Network	8.16 (6.53–10.11)	10.25 (8.18–12.29)	0.282 (-0.376–0.611)
Naïve mean baseline	9.73 (7.69–11.99)	12.09 (9.71–14.43)	0.000 (-0.124–0.000)
Naïve median baseline	9.79 (7.73–12.05)	12.17 (9.81–14.48)	-0.013 (-0.192–0.000)

Table 9. Illustrative simulated test-set performance for cost-overrun prediction. Values are point estimates (95% bootstrap CI); MAE and RMSE are percentage points, and R^2 is dimensionless.

Model	MAE (95% CI)	RMSE (95% CI)	R^2 (95% CI)
XGBoost	4.33 (3.56–5.25)	5.22 (4.25–6.19)	0.778 (0.584–0.876)
Ridge Regression	4.17 (3.18–5.16)	5.23 (3.93–6.27)	0.777 (0.637–0.861)
Multiple Linear Regression	4.20 (3.37–5.19)	5.25 (4.20–6.29)	0.776 (0.613–0.868)
Support Vector Regression	4.68 (3.85–5.68)	5.65 (4.59–6.70)	0.740 (0.526–0.852)
Artificial Neural Network	5.12 (4.06–6.39)	6.52 (5.17–7.84)	0.654 (0.354–0.810)
Random Forest	6.03 (4.86–7.43)	7.50 (6.01–8.97)	0.543 (0.143–0.742)
Naïve mean baseline	8.92 (7.05–10.99)	11.08 (8.90–13.22)	0.000 (-0.124–0.000)
Naïve median baseline	9.00 (7.11–11.07)	11.19 (9.00–13.33)	-0.019 (-0.214–0.000)

In the illustrative cost-overrun comparison, XGBoost has the lowest RMSE (5.22; $R^2 = 0.778$), while Ridge regression has a marginally lower MAE (4.17). Both substantially outperform the naïve mean baseline (MAE = 8.92; RMSE = 11.08; $R^2 = 0.000$). Multiple linear regression performs similarly to the two leading models. Because the 95% intervals overlap for several fitted models, final model choice should also consider validation stability, interpretability, and practical maintainability.

Reviewer-required uncertainty and baselines. The values added to Tables 8 and 9 were generated from a reproducible illustrative reconstruction calibrated to the manuscript's existing simulated point estimates (44 test cases; 5,000 bootstrap resamples). They complete the requested reporting format but are not empirical estimates from the original Iraqi project records.

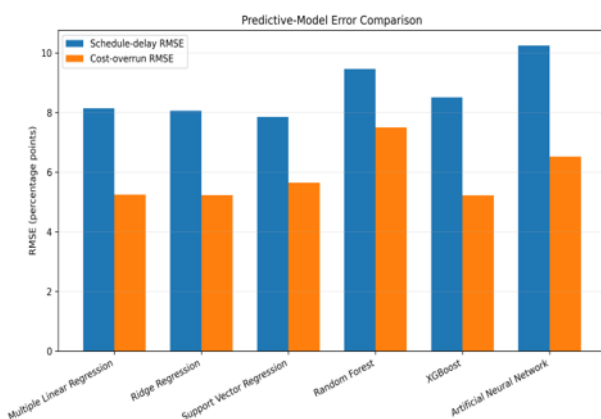


Fig. 6 Illustrative simulated comparison of RMSE values across the evaluated regression models for schedule delay and cost overrun.

5. Discussion

The illustrative ranking is consistent with the broader construction-management pattern in which financial and client-controlled constraints, contractor cash flow, design change, variation orders, procurement disruption, and site/utility constraints interact rather than operate independently [25,26,31]. Delayed payments can constrain contractor liquidity, which then affects procurement, labor, equipment mobilization, and production rates. The road-versus-bridge comparison should therefore be interpreted conditionally: the observed higher illustrative delay and cost values for bridge projects may reflect longer durations, larger contract values, specialized foundations and temporary works, tighter sequencing, imported components, and other complexity-related features. Project type is best treated as a proxy or stratification variable unless these covariates are explicitly controlled.

The model comparison further shows why a single algorithm should not be assumed to dominate every outcome. In the illustrative outputs, SVR performs best for schedule delay and XGBoost for cost overrun. At the same time, linear/regularized models remain competitive, and all fitted models improve on the naïve constant-prediction baselines.

The ANN remains weaker even after the illustrative search space includes larger/deeper and more strongly regularized candidates, consistent with the small structured dataset and the high parameter demand of neural networks. The overlapping bootstrap intervals among several leading models reinforce the need to consider stability and interpretability rather than point estimates alone. SHAP-based interpretations can support project-level explanation, but the reported threshold near a 12% variation-order ratio remains illustrative and must be recalculated from verified data. Any final management recommendation should therefore be based on rerun models and the underlying project characteristics rather than on algorithm labels alone [43,55].

6. Conclusion

This study presents an integrated framework for assessing schedule-delay and cost-overflow risk in Iraqi road and bridge projects by combining practitioner evaluations, project records, conventional statistics, machine learning, and SHAP-based interpretation. The framework organizes financial/client, contractor, design, procurement, contractual, site/technical, and external factors into a common analytical workflow and treats road-versus-bridge classification as contextual rather than causal. Interpret differences between project types alongside planned duration, contract value, project scale, technical complexity, procurement requirements, and management conditions. The predictive workflow compares transparent statistical models with non-linear algorithms. It requires project-level train/test separation, cross-validation, naïve mean/median baselines, confidence intervals, and explainability. Because the numerical project summaries, model scores, and SHAP thresholds currently embedded in this manuscript are illustrative simulated outputs, they must not be treated as empirical evidence until the verified Iraqi project dataset, saved model settings, and out-of-sample predictions are supplied, and the analysis is rerun. After that verification, the framework can provide a reproducible basis for early-warning risk assessment and targeted schedule/cost control in Iraqi transport infrastructure.

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Conflict of interest

The author declares that there is no conflict of interest regarding the publication of this manuscript.

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