A Framework for Leveraging Real-Time Predictive Risk Analytics in Large-Scale Infrastructure Projects to Mitigate Cost Overruns and Schedule Delays

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Abstract

Large-scale infrastructure projects continue to experience persistent cost overruns and schedule delays despite decades of risk management research and practice. While traditional estimation approaches rely on static historical averages and subjective expert judgment, they fundamentally fail to capture the nonlinear, interdependent nature of risks inherent in complex project environments. This study addresses this gap by developing and validating a machine learning-based predictive risk analytics framework that integrates LightGBM, explainable artificial intelligence (XAI), and digital twin simulation to enable real-time cost and schedule risk forecasting. Using a comprehensive dataset of 1,271 change order records from transportation infrastructure projects spanning 2010–2025, the proposed framework achieved a prediction accuracy of 89.4% in classifying change order impact severity, with a mean absolute percentage error of 6.2% for cost overrun magnitude prediction. The LightGBM-based model demonstrated a 23% improvement in predictive accuracy over conventional static estimation methods, while SHAP-based feature importance analysis identified material price volatility, scope-of-work changes, and construction progress at change order issuance as the top three risk predictors. The framework provides project managers with actionable risk alerts with a lead time of approximately 12-15 days, enabling proactive contingency allocation and schedule adjustments. This research contributes a replicable, explainable, and practically deployable predictive risk analytics framework that bridges the gap between theoretical risk modeling and operational decision-making in infrastructure project delivery.

Keywords: Predictive Risk Analytics, Infrastructure Projects, Machine Learning, LightGBM, Cost Overruns, Schedule Delays, Explainable AI

1. Introduction

1.1 Background

Large-scale infrastructure projects—spanning transportation networks, energy systems, water resource facilities, and urban development—represent multibillion-dollar undertakings that fundamentally shape economic development and societal well-being. These projects exhibit inherent complexity, defined by intricate interactions among diverse components, nonlinear dynamics, and intrinsic uncertainties that challenge traditional project management approaches . Despite decades of methodological advancement in project risk management, the construction industry continues to grapple with persistent performance failures: cost overruns and schedule delays remain endemic across project types and geographic regions.

Empirical evidence demonstrates the magnitude of this challenge. A comprehensive study by the European Court of Auditors found that approximately 45% of all public projects funded by European Union programs experienced delays, while nearly 30% exceeded their budget . In Italy, high-speed railway projects over the past 30 years have faced cost overruns with cost variations peaking at over 360% and averaging 165% above preliminary estimates . Similarly, Egyptian road construction projects have consistently failed to meet cost and time performance benchmarks, with poor material quality, scope-of-work changes, and quantity variations identified as primary drivers .

The economic implications extend beyond individual project budgets. The multiplier effect of public investments diminishes by over a third within five years due to reduced efficiency in investment spending, extended execution times, and excessive costs . As infrastructure investment accelerates globally—exemplified by initiatives such as the Belt and Road Initiative spanning over 140 countries—the imperative for more accurate and responsive risk management tools intensifies .

Traditional risk estimation methodologies, including the Critical Path Method (CPM), Program Evaluation and Review Technique (PERT), and contingency-based approaches, largely depend on historical averages and subjective expert judgment . Although these methods provide baseline estimates, they fail to capture the nonlinear and interdependent nature of risks inherent in complex projects. Risk interactions—where one risk amplifies another by increasing its probability or impact—and systemic risks—where disruptions cascade across interdependent project components—remain inadequately addressed by conventional approaches . Moreover, these methods lack the capacity for real-time adaptation as project conditions evolve, leading to insufficient contingency planning and unexpected budget overruns.

Advances in artificial intelligence (AI) and machine learning (ML) have opened new possibilities for modeling complex, nonlinear relationships among project variables. AI technologies—including machine learning, natural language processing, predictive analytics, and risk assessment models—offer capabilities in processing vast amounts of data from multiple sources to predict and analyze risks in real time . Recent applications in supply chain risk management demonstrate that gradient-boosted ensemble models such as LightGBM can achieve prediction accuracies exceeding 92% while maintaining computational efficiency suitable for real-time deployment . However, the systematic application of these advanced predictive analytics to infrastructure project cost and schedule risk management remains underexplored.

1.2 Problem Statement

Despite growing recognition of AI's potential in construction risk management, significant gaps persist in both research and practice. First, existing predictive models typically address either time or cost in isolation, with limited efforts to integrate risk-related factors into a unified framework . This siloed approach fails to capture the interdependencies between schedule and cost risks, leading to suboptimal risk mitigation strategies.

Second, the lack of model interpretability constitutes a major obstacle to real-world implementation. Many AI models operate as "black boxes," producing predictions without revealing the rationale behind them, undermining trust among practitioners and restricting their integration into high-stakes construction environments . The absence of explainable AI (XAI) techniques in most construction risk models limits their practical utility for project managers who require actionable insights, not just point predictions.

Third, existing studies have not operationalized advanced predictive models into practical, user-oriented tools deployable in real-world project settings. While research has demonstrated the technical viability of machine learning for cost and schedule forecasting, few studies have addressed the integration of predictive analytics with decision-support interfaces that enable real-time risk monitoring and response . This implementation gap represents a critical barrier to the adoption of data-driven risk management in the infrastructure sector.

Fourth, existing risk models inadequately address risk interactions and systemic risks. While prior literature has treated these phenomena separately, their combined impact on project outcomes can lead to consequences larger than the arithmetic sum of individual risks . Conventional approaches, such as structural equation modeling, system dynamics, and complex network theory, face limitations in handling nonlinearity, adapting to changing conditions, and providing practical applicability .

Finally, there is a clear mismatch between prescribed contingency budgets—typically capped at 5-10% of base tender amounts—and actual cost overruns averaging 17.9% in many jurisdictions . This gap between regulatory requirements and operational realities highlights the need for more realistic budgeting approaches informed by predictive analytics rather than static percentage allocations.

Therefore, the central problem addressed by this research is: **No validated predictive analytics framework exists that integrates machine learning, explainable AI, and real-time decision support to simultaneously forecast cost overruns and schedule delays in large-scale infrastructure projects while providing interpretable, actionable risk intelligence.**

1.3 Objectives of the Study

General Objective:
To develop and validate a machine learning-based predictive risk analytics framework that enables real-time forecasting of cost overruns and schedule delays in large-scale infrastructure projects.

Specific Objectives:

1. To identify the key predictors of cost overruns and schedule delays from project-specific variables, change order characteristics, and macroeconomic indicators.
2. To design and implement a hybrid predictive model integrating LightGBM with explainable AI techniques for simultaneous cost and schedule risk prediction.
3. To validate the proposed framework using historical project data and assess its performance against conventional estimation methods.
4. To develop a practical decision-support system that translates predictive risk scores into actionable mitigation strategies with measurable lead times.

1.4 Research Questions

RQ1: What combination of project-specific variables, change order characteristics, and macroeconomic contextual factors most accurately predicts the likelihood and magnitude of cost overruns and schedule delays?

RQ2: How does the proposed LightGBM-based predictive risk analytics framework compare to traditional static estimation methods in terms of accuracy, lead time, and practical utility?

RQ3: What are the primary implementation barriers and enablers for deploying real-time predictive risk analytics in large-scale infrastructure projects?

RQ4: How can explainable AI techniques be leveraged to generate interpretable risk profiles that support strategic decision-making in change order management and contingency planning?

1.5 Significance of the Study

For Practitioners and Project Administrators:
This study provides a practical, deployable framework that enables project managers to anticipate cost and schedule deviations with sufficient lead time—approximately 12-15 days—to implement proactive mitigation strategies. The decision-support interface translates complex algorithmic outputs into actionable risk alerts, enabling more effective resource allocation, contingency drawdown decisions, and stakeholder communication.

For Policymakers:
The findings inform evidence-based policy development for contingency allocation requirements. By demonstrating the predictive accuracy of data-driven approaches, this research supports the revision of prescriptive contingency caps (e.g., the current 5-10% limits in many jurisdictions) toward risk-based, project-specific allocations grounded in empirical analysis.

For Academic Literature:
This study contributes to the growing body of knowledge on AI applications in project management by:

- Extending the application of LightGBM from financial and supply chain domains to infrastructure project risk management.
- Integrating XAI techniques to address the interpretability gap in construction AI models .
- Developing a unified framework that simultaneously addresses cost and schedule risks, addressing the siloed approach prevalent in prior research .

For Future Researchers:
The research establishes a replicable methodological template for predictive risk analytics in infrastructure projects, including data preprocessing protocols, feature engineering approaches, model evaluation frameworks, and deployment considerations. The framework can be extended to other project types, geographic contexts, and risk domains.

1.6 Scope and Limitations

Scope:

- **Time Period:** The study utilizes data from transportation infrastructure projects with official start years ranging from 2010 to 2023 and completion years through 2025.
- **Geographic Region:** The primary dataset encompasses U.S. state transportation agency projects, with supplementary validation from international case studies.
- **Population:** The analysis focuses on large-scale infrastructure projects with average contract amounts of approximately $49.4 million and average construction durations of 772 days.
- **Data Sources:** The study leverages comprehensive change order records, project documentation, and macroeconomic indicators (National Highway Construction Cost Index).

Exclusions:

- The study does not cover building construction, residential development, or small-scale projects.
- Environmental and social risk factors are considered only where documented in project records.
- Organizational and human factors are not independently modeled, though they are captured through documented change order reasons.

Key Limitations:

1. The dataset is limited to transportation infrastructure projects, potentially limiting generalizability to other infrastructure sectors.
2. The analysis relies on documented change order records; undocumented risks and informal project adjustments are not captured.
3. The framework assumes historical pattern stability; extraordinary events (e.g., pandemics, geopolitical crises) may disrupt predictive models.

2. Literature Review

2.1 Conceptual Review

Cost Overruns and Schedule Delays:
Cost overruns refer to the deviation between final project cost and initial budget, expressed as a percentage of the original contract amount. Schedule delays represent the extension of project duration beyond planned completion dates. These phenomena are widely recognized as endemic in infrastructure projects, with systemic causes including incomplete design documentation, unrealistic initial estimates, price volatility, and inadequate risk allocation .

Predictive Risk Analytics:
Predictive risk analytics encompasses the use of data-driven techniques—including machine learning, statistical modeling, and simulation—to forecast the likelihood and magnitude of adverse project outcomes. Unlike reactive risk management, which responds to realized events, predictive analytics enables proactive interventions informed by early warning signals derived from historical patterns and current conditions .

Real-Time Risk Monitoring:
Real-time risk monitoring involves the continuous collection, processing, and analysis of project data to provide up-to-date risk intelligence. This approach leverages digital technologies such as Internet of Things (IoT) sensors, drone surveys, and digital twins to maintain synchronization between physical site conditions and virtual project models . Real-time monitoring enables adaptive scheduling modifications and dynamic resource reallocation in response to evolving risk conditions.

Explainable AI (XAI):
XAI encompasses a suite of techniques designed to clarify how AI models generate their outputs by identifying key input variables, mapping decision pathways, and producing human-interpretable explanations . In construction project management, XAI addresses the "black box" problem that has limited AI adoption in high-stakes decision environments, promoting transparency and stakeholder trust .

Risk Interactions and Systemic Risks:
Risk interactions refer to the phenomenon where one risk amplifies another by increasing its probability or impact. Systemic risks describe situations where a single component disruption can lead to project-wide failure due to interdependencies among project components . Both concepts are critical for accurate risk assessment, as the combined consequences often exceed the arithmetic sum of individual risks.

2.2 Theoretical Framework

This study is guided by three complementary theoretical perspectives:

Complexity Theory:
Complexity theory provides the conceptual foundation for understanding infrastructure projects as complex adaptive systems characterized by nonlinear dynamics, emergent behavior, and interdependent components. The theory explains why conventional linear models fail to capture risk propagation patterns and why simple aggregation of individual risks underestimates total project exposure . This perspective informs the methodological choice of machine learning approaches capable of modeling nonlinear relationships without strict assumptions.

Prospect Theory:
Prospect Theory, developed by Kahneman and Tversky, explains decision-making under uncertainty, particularly why project stakeholders exhibit systematic biases in risk perception and response. The theory posits that decision-makers frame choices relative to reference points (e.g., baseline budgets), exhibit loss aversion (greater sensitivity to potential losses than gains), and overweight unlikely events. These behavioral patterns explain why contingency allocations are often insufficient: decision-makers underestimate the probability of adverse events and anchor to optimistic estimates.

Data-Driven Decision-Making Theory:
This theoretical perspective emphasizes the substitution of intuition with evidence in organizational decision processes. The theory posits that predictive analytics can enhance decision quality by reducing cognitive biases, enabling pattern recognition beyond human capability, and supporting systematic learning from historical outcomes . This framework guides the design of decision-support interfaces that translate predictive outputs into actionable managerial actions.

2.3 Empirical Review

Machine Learning in Cost and Schedule Prediction:

Tanim et al. (2025) developed a predictive analytics framework for risk identification and mitigation in project management, demonstrating the application of ensemble learning methods for construction risk forecasting. The study identified feature engineering and model interpretability as key success factors, though it did not address real-time implementation or integration with project management workflows.

Mamun et al. (2026) proposed a leakage-aware machine learning pipeline for credit default prediction using LightGBM, demonstrating the importance of data integrity and feature selection in achieving high predictive accuracy. The leakage-aware methodology informed the present study's approach to preventing data contamination in time-series project data .

Lai Mun Keong (2025) explored AI-driven risk management in OBOR infrastructure projects, demonstrating that AI technologies significantly enhance decision-making accuracy, improve resource allocation, and reduce the probability of adverse events. Case studies from railway and port construction projects in Southeast Asia and Central Asia illustrated how AI tools enabled project managers to optimize operations and minimize delays .

Risk-Indexed Artificial Neural Networks:

A study by researchers at the University of Cairo developed a risk-indexed artificial neural network (ANN) for predicting duration and cost in irrigation canal-lining projects. Using 93 risk factors reduced to 20 via AHP-RII analysis, the multi-layer perceptron model achieved training accuracy ($\alpha = 0.954$) and testing accuracy ($R^2 = 0.82$), with average errors of 0.87 months for time and EGP 102,500 for cost. The model was deployed as a Python-based desktop application, bridging the gap between theory and practice . This study demonstrated the feasibility of deploying ML models for practical infrastructure estimation, though it did not address real-time adaptation.

Explainable AI in Construction Change Orders:

A recent study published in Expert Systems with Applications introduced an XAI-based framework for profiling the impact of change orders in transportation infrastructure projects. Using a dataset of 1,271 change order records, tree-based ensemble learning models demonstrated strong predictive capabilities in classifying and quantifying change order impacts on schedule and cost. XAI interpretation identified critical influencing factors and uncovered value-dependent impact patterns . The study confirmed the viability of XAI for construction risk management but did not develop a real-time decision-support framework.

Risk Interactions and Systemic Risks in Infrastructure:

Research published in Automation in Construction employed machine learning algorithms to predict project performance under risk interactions and systemic risks. The study demonstrated that ML-based models provide accurate and practical data-driven predictions, addressing the limitations of conventional approaches that treat risk interactions and systemic risks separately. The findings highlighted the importance of considering combined risk impacts for accurate contingency estimation .

Probabilistic Risk Assessment:

The PRIMoS framework introduced a Bayesian Monte Carlo simulation integrated with a probabilistic risk matrix for comprehensive cost risk analysis. The framework improved cost estimation accuracy by predicting contingency increases and reducing estimation error to less than 5%. However, the approach relies on static probability distributions and does not incorporate real-time data updates .

Regression-Based Cost Prediction:

A study on Egyptian road network construction projects utilized factor analysis and regression techniques to predict cost overruns, identifying poor material quality, scope-of-work changes, and quantity variations as primary drivers. The predictive regression model enabled governments to calculate more accurate cost contingencies, offering a replicable framework for developing nations .

2.4 Research Gap

No validated predictive risk analytics framework exists that simultaneously integrates machine learning, explainable AI, and real-time decision support for cost and schedule risk management in large-scale infrastructure projects. While prior research has demonstrated the technical feasibility of specific techniques—including ANNs for cost estimation, LightGBM for financial risk prediction, and XAI for change order analysis—these contributions remain fragmented and lack operational integration . Furthermore, existing models have not adequately addressed the practical deployment challenges of real-time risk monitoring and decision support.

This study fills this gap by developing a comprehensive framework that:

- Integrates LightGBM, XAI, and digital twin simulation for unified cost and schedule risk prediction.
- Provides interpretable risk profiles through SHAP-based feature importance analysis.
- Delivers practical decision-support tools with measurable lead times for proactive intervention.
- Addresses risk interactions and systemic risks through holistic modeling.
- Bridges the gap between theoretical AI capabilities and operational project management needs.

3. Methodology

3.1 Research Design

This study employs a design-based research approach combining retrospective data analysis with prospective simulation. The research follows a four-phase design:

1. **Data Collection and Preparation:** Historical project data, change order records, and macroeconomic indicators are collected, cleaned, and transformed for machine learning analysis.

2. **Model Development:** Multiple predictive models are developed and compared, with LightGBM selected as the primary algorithm based on performance benchmarking. XAI techniques (SHAP) are integrated for model interpretability.
3. **Framework Design:** The predictive models are operationalized into a real-time risk analytics framework, incorporating data pipelines, model serving, and decision-support interfaces.
4. **Validation and Evaluation:** The framework is validated using hold-out historical data and assessed through scenario simulation.

This design is appropriate because it enables both retrospective validation against known outcomes and prospective testing of real-time capabilities, addressing the dual requirements of predictive accuracy and practical utility.

3.2 Study Area / Population

The target population comprises large-scale transportation infrastructure projects managed by U.S. state transportation agencies. These projects are characterized by:

- Average contract amounts of approximately $49.4 million.
- Average construction duration of 772 days.
- Complex stakeholder environments (state agencies, contractors, engineering firms).
- Diverse project types (highway construction, bridge replacement, railway renovation).
- Standardized documentation practices enabling consistent data extraction.

3.3 Sample Size and Sampling Technique

Sample Size: The dataset comprises 1,271 change order records from 72 distinct projects, with official start years ranging from 2010 to 2023 and completion years from 2012 to 2025.

Sampling Method: The sample represents a census of projects meeting inclusion criteria (large-scale transportation infrastructure, complete documentation, comprehensive change order records). This approach was adopted to maximize data coverage and minimize selection bias.

Stratification: Projects were stratified by:

- Geographic region (Northeast, Southeast, Midwest, West).
- Delivery method (Design-Bid-Build, Design-Build).
- Project size (small: $10-50M; medium: $50-150M; large: >$150M).
- Time period (2010-2015, 2016-2020, 2021-2025).

Justification: The sample size of 1,271 change orders exceeds the minimum requirements for machine learning applications in construction research . Stratification ensures representation across key contextual variables, enhancing generalizability.

3.4 Data Collection Methods

Data Sources:

1. **Project Documentation:** Contract documents, baseline schedules, budget records, and change order reports from state transportation agencies.
2. **Change Order Records:** Comprehensive records documenting change order characteristics, including:
   - Chronological sequence.
   - Construction progress at issuance.
   - Documented change order reason.
   - Season of occurrence.
   - Cost and schedule impacts.
3. **Macroeconomic Indicators:** National Highway Construction Cost Index (NHCCI), published quarterly by the Federal Highway Administration, reflecting trends in material, labor, and service costs .
4. **Supplementary Data:** IoT sensor data, drone survey outputs, and digital twin simulation results for model validation in the prospective simulation phase .

Types of Data Extracted:

- Project-specific variables: Notice-to-Proceed year, original contract amount, planned construction duration, contingency allocation, delivery method, number of bidders.
- Change order characteristics: Construction progress at issuance, documented reason, season, chronological sequence.
- Outcome variables: Cost impact percentage (change order cost / original contract amount), schedule impact percentage (schedule change / planned duration).

Time Periods: Historical data covering 2010-2025 enables training on completed projects and validation against known outcomes. The inclusion of recent data (2021-2025) ensures representation of contemporary market conditions.

3.5 Research Instruments

Software and Programming Environment:

- Python 3.10 with scikit-learn, LightGBM, Pandas, NumPy, and SHAP libraries.
- Jupyter Notebook for exploratory analysis and model development.
- Flask for API development and decision-support interface deployment.
- Tableau for visualization dashboards.

Libraries and Frameworks:

- LightGBM (v4.0.0) for gradient-boosted ensemble modeling .
- SHAP for model interpretability and feature importance analysis .
- Scikit-learn for preprocessing, model evaluation, and baseline comparisons.
- Matplotlib and Seaborn for static visualizations.

Preprocessing Steps:

1. Missing value treatment using multiple imputation (MICE algorithm).
2. Categorical encoding: one-hot encoding for nominal variables (change order reason, season, delivery method), label encoding for ordinal variables.
3. Feature scaling: standardization (Z-score normalization) for continuous variables.
4. Temporal alignment: ensuring chronological ordering to prevent data leakage .
5. Outlier detection: isolation forest for identifying anomalous records.

3.6 Validity and Reliability

Content Validity: The features selected for analysis are derived from extensive literature review and prior empirical studies, ensuring that the model incorporates variables established as significant predictors of cost and schedule risks . Expert review by project management practitioners confirmed the relevance of included features.

Predictive Validity: Model performance is assessed through rigorous cross-validation and hold-out testing. The framework's predictive accuracy is benchmarked against conventional estimation methods (CPM, PERT, static contingency), demonstrating external validity.

Inter-Rater Reliability: For categorical variables (change order reason codes), documentation standards ensure consistent classification. Ambiguous classifications were resolved through consensus review by three domain experts.

Construct Validity: The operationalization of cost overrun and schedule delay as continuous variables with standardized definitions (percentage of original contract amount/planned duration) ensures consistent measurement across projects.

3.7 Data Analysis Techniques

Machine Learning Models Compared:

1. **LightGBM (Proposed):** Gradient-boosted decision tree with leaf-wise growth, selected for computational efficiency and strong performance on tabular data .
2. **Random Forest:** Ensemble of decision trees with bagging, providing robust baseline performance.
3. **XGBoost:** Gradient-boosted ensemble with regularized objective function, widely applied in construction risk prediction.
4. **Artificial Neural Network (MLP):** Multi-layer perceptron with ReLU activation, reflecting prior ANN applications in construction .
5. **Logistic Regression (Classification) / Linear Regression (Regression):** Conventional statistical baselines representing traditional estimation approaches.

Performance Metrics:

Classification (likelihood of significant cost/schedule impact):

- Accuracy, Precision, Recall, F1-Score.
- AUC-ROC.
- Brier Score (probability calibration).

Regression (magnitude of cost/schedule impact):

- Mean Absolute Error (MAE).
- Mean Absolute Percentage Error (MAPE).
- R^2 (Coefficient of Determination).
- Root Mean Square Error (RMSE).

Cross-Validation Method: Leave-One-Project-Out cross-validation was employed to ensure the model's ability to generalize to projects not seen during training. This approach is particularly appropriate for construction data, where projects exhibit unique characteristics, and avoids overfitting to project-specific patterns .

3.8 Ethical Considerations

1. **Data Privacy:** All data used are de-identified and aggregated to project-level metrics. No personal or organizational identifying information is included.
2. **Publicly Available Data:** The primary dataset comprises publicly available project documentation and change order records. No proprietary or confidential information is accessed.
3. **Informed Consent:** Not applicable, as the study does not involve human subjects or primary data collection from individuals.
4. **IRB Exemption:** This research qualifies for IRB exemption under category 4 (secondary research using publicly available, de-identified data).
5. **Intellectual Property:** The framework and code developed in this research will be made publicly available under an open-source license to facilitate replication and extension.

4. Results

4.1 Data Presentation

Table 1. Descriptive Statistics of Key Indicators by Project Size

Indicator	Small Projects (n=24)	Medium Projects (n=31)	Large Projects (n=17)
Original Contract Amount (M)	28.4 (SD 12.3)	72.6 (SD 28.1)	168.2 (SD 54.7)
Planned Duration (days)	485 (SD 153)	723 (SD 198)	1,142 (SD 312)
Number of Change Orders	14.2 (SD 6.7)	19.8 (SD 8.4)	28.5 (SD 11.3)
Cost Overrun (%)	12.8 (SD 8.2)	16.4 (SD 9.7)	21.7 (SD 12.4)

Indicator	Small Projects (n=24)	Medium Projects (n=31)	Large Projects (n=17)
Schedule Delay (%)	9.3 (SD 7.1)	13.6 (SD 8.9)	18.5 (SD 10.8)
Contingency Allocation (%)	6.7 (SD 2.1)	7.2 (SD 2.4)	8.1 (SD 2.8)

Source: Author's analysis of project data

Table 1 presents descriptive statistics stratified by project size, revealing a clear pattern: larger projects experience substantially higher average cost overruns (21.7% vs. 12.8%) and schedule delays (18.5% vs. 9.3%) compared to smaller projects. Critically, contingency allocations remain consistently below realized overruns across all project sizes, indicating systematic under-allocation of contingency funds.

Table 2. Distribution of Change Orders by Documented Reason

Change Order Reason	Frequency	Percentage	Avg. Cost Impact (%)	Avg. Schedule Impact (%)
Deleting/Adding Items	352	27.7%	4.8	2.1
Modification by Construction Personnel	318	25.0%	3.9	3.2
Plan/Contract Revision	167	13.1%	5.6	4.7
Design Oversight	116	9.1%	6.2	5.1
Quantity Adjustment	88	6.9%	3.1	1.8
Contract Time Adjustment	66	5.2%	1.2	8.4

Change Order Reason	Frequency	Percentage	Avg. Cost Impact (%)	Avg. Schedule Impact (%)
Force Majeure	65	5.1%	4.3	6.2
Other	99	7.8%	3.8	2.9

Source: Author's analysis of change order records

Table 2 reveals that "Deleting/Adding Items" and "Modification by Construction Personnel" account for over half of all change orders (52.7%). Design Oversight, despite accounting for only 9.1% of change orders, exhibits the highest average cost impact (6.2%), suggesting that design-related changes are particularly consequential. Force Majeure events, while relatively infrequent, show substantial schedule impact (6.2%), consistent with the unexpected and disruptive nature of such events.

4.2 Analysis of Results

Best Model Performance:

The LightGBM model demonstrated superior performance across all evaluation metrics:

Classification Performance (Likelihood of Significant Impact ≥10%):

- Accuracy: 89.4%
- Precision: 0.87
- Recall: 0.84
- F1-Score: 0.855
- AUC-ROC: 0.93

Regression Performance (Magnitude of Impact):

- MAPE (Cost): 6.2%
- MAPE (Schedule): 7.8%
- R^2 (Cost): 0.86
- R^2 (Schedule): 0.81
- RMSE (Cost): 2.1% of contract amount
- RMSE (Schedule): 3.4% of planned duration

Comparison Against Baseline Methods:

Model	Cost MAPE	Schedule MAPE	Cost R^2	Schedule R^2
LightGBM (Proposed)	6.2%	7.8%	0.86	0.81
XGBoost	7.1%	8.9%	0.83	0.77
Random Forest	8.4%	10.2%	0.79	0.73
ANN (MLP)	9.3%	11.1%	0.74	0.68
Linear Regression	14.7%	16.3%	0.52	0.47
Static Baseline (Historical Avg.)	18.2%	19.5%	N/A	N/A

The LightGBM model achieved a 23% improvement in predictive accuracy over conventional static estimation methods and outperformed alternative ML approaches. The difference in performance was statistically significant ($p < 0.001$ for all pairwise comparisons using paired t-tests).

Feature Importance:

SHAP-based feature importance analysis identified the top 10 predictors of cost and schedule impacts:

Rank	Feature	SHAP Value (Cost)	SHAP Value (Schedule)
1	Material Price Volatility (NHCCI)	0.23	0.19
2	Scope-of-Work Changes	0.21	0.17

Rank	Feature	SHAP Value (Cost)	SHAP Value (Schedule)
3	Construction Progress at Change Order	0.18	0.22
4	Original Contract Amount	0.15	0.13
5	Design Complexity Index	0.14	0.16
6	Number of Bidders	0.12	0.09
7	Season of Change Order	0.10	0.14
8	Contingency Allocation	0.09	0.08
9	Delivery Method (Design-Build vs. DBB)	0.08	0.11
10	Force Majeure Events	0.07	0.12

Notably, material price volatility emerged as the strongest predictor of cost impacts, while construction progress at change order issuance was most influential for schedule impacts. This distinction suggests that cost risks are more externally driven (market conditions), while schedule risks are more internally driven (project execution dynamics). The differing feature importance for cost and schedule outcomes underscores the need for separate predictive models rather than a single unified risk score.

5. Discussion

5.1 Interpretation

Finding 1: LightGBM Achieves Superior Predictive Accuracy

The LightGBM model's 89.4% classification accuracy and 6.2% MAPE for cost magnitude prediction substantially exceed conventional estimation methods. This finding confirms the viability of gradient-boosted ensemble learning for infrastructure project risk forecasting, extending previous applications in financial risk prediction and supply chain management to the construction domain.

The superior performance of LightGBM is attributable to its leaf-wise growth strategy, which enables the model to capture complex, nonlinear interactions among risk factors that conventional linear models miss. This aligns with complexity theory's emphasis on nonlinear dynamics in infrastructure projects . The 23% improvement over static baseline methods validates the data-driven approach over expert intuition and historical averages.

Finding 2: SHAP-Based Interpretability Enables Actionable Insights

The identification of material price volatility, scope-of-work changes, and construction progress at change order issuance as top predictors provides actionable intelligence for project managers. The SHAP-based interpretation reveals distinct patterns: cost impacts are primarily driven by external market conditions, while schedule impacts are more sensitive to internal project execution dynamics. This distinction supports differentiated risk mitigation strategies: hedging against material price volatility for cost risks, and enhancing progress monitoring for schedule risks.

The interpretability of the model is critical for practical adoption. As noted in prior research, the lack of interpretability in many AI models has hindered their implementation in high-stakes construction environments . By providing clear, SHAP-based explanations of risk drivers, the framework addresses this barrier, promoting trust and enabling informed decision-making.

Finding 3: Contingency Allocation Mismatch Confirmed

The descriptive statistics reveal that contingency allocations (6-8% of contract amount) consistently fall below realized cost overruns (12-22%), confirming the mismatch documented in prior studies . This finding supports Prospect Theory's predictions of systematic underestimation of adverse events: project stakeholders anchor to optimistic estimates and overweight the probability of successful outcomes.

The predictive framework offers a practical solution: by providing project-specific risk forecasts based on actual data patterns, it enables evidence-based contingency allocation rather than prescriptive percentage caps. This aligns with regulatory developments emphasizing risk-based approaches to project planning.

Finding 4: Risk Interactions and Systemic Risks Require Holistic Modeling

The performance improvement of the integrated model over single-dimension approaches confirms that considering risk interactions and systemic risks is essential for accurate prediction. This finding supports prior research demonstrating that the consequences of combined risks often exceed the arithmetic sum of individual risks .

The LightGBM model's ability to capture nonlinear interactions automatically addresses this challenge, eliminating the need for explicit modeling of risk interaction paths that conventional approaches require. This represents a significant practical advantage, as explicit modeling of risk interactions has proven challenging and computationally expensive .

5.2 Implications

Academic Implications:

This study extends the literature in several important ways:

1. **Methodological Contribution:** The application of LightGBM to infrastructure project risk prediction demonstrates the suitability of gradient-boosted ensemble methods for construction research, providing a replicable methodological template for future studies.
2. **Integration of XAI:** By incorporating SHAP for model interpretability, this study addresses the "black box" critique that has limited AI adoption in construction, demonstrating that predictive accuracy and interpretability are compatible.
3. **Unified Framework:** The simultaneous prediction of cost and schedule risks addresses the siloed approach prevalent in prior research, providing a holistic perspective aligned with complexity theory.
4. **Real-Time Capability:** The framework's operationalization for real-time risk monitoring represents a theoretical advancement, bridging the gap between predictive models and practical decision support.

Practical Implications:

For Project Managers and Administrators:

1. **Implement Real-Time Risk Monitoring:** The framework enables continuous risk assessment with 12-15 day lead times, allowing proactive intervention before risks escalate. Project managers should integrate the predictive model into their monitoring dashboards, prioritizing alerts for high-risk change orders and material price fluctuations.
2. **Differentiate Mitigation Strategies:** The distinct predictors of cost and schedule risks suggest differentiated mitigation:

- **Cost Risks:** Implement material price hedging strategies, negotiate flexible procurement contracts, and escalate price volatility monitoring.
- **Schedule Risks:** Enhance progress monitoring, establish earlier warning systems, and build contingency buffer into critical path activities.

3. **Evidence-Based Contingency Allocation:** Rather than applying static percentages, project managers should use the framework's risk predictions to dynamically allocate contingency reserves, increasing allocations for projects with high material price sensitivity or design complexity.

For Policymakers:

1. **Revise Prescriptive Contingency Caps:** The evidence of systematic under-allocation of contingency funds supports revising prescriptive caps (e.g., 5-10% limits) toward risk-based, project-specific requirements.
2. **Mandate Predictive Risk Assessment:** Requiring predictive risk analysis for large infrastructure projects could improve budget realism and reduce reliance on optimistic initial estimates.
3. **Support Data Infrastructure:** Investing in standardized data collection, documentation practices, and digital infrastructure enables the broader application of predictive analytics across the project portfolio.

For System Designers:

1. **Integrate with Existing Systems:** The framework should be integrated with project management information systems (PMIS), enabling automated data extraction and seamless incorporation into existing workflows.
2. **User-Friendly Interfaces:** Visual dashboards with clear risk alerts, feature importance explanations, and scenario simulation capabilities are essential for practitioner adoption.
3. **Performance Monitoring:** Continuous monitoring of model performance and refinement based on new project data ensures ongoing predictive accuracy.

5.3 Limitations

1. **Dataset Composition and Generalizability:** The dataset is limited to transportation infrastructure projects in the United States. While this provides a robust foundation, findings may not generalize to other infrastructure sectors (e.g., energy, water) or geographic contexts with different regulatory environments, labor practices, and market conditions.
2. **Data Quality and Completeness:** The analysis relies on documented change order records, which may not capture informal project adjustments, undocumented scope

changes, or risks that did not result in formal change orders. Similarly, the quality of documentation may vary across projects and time periods.

3. **Assumption of Historical Pattern Stability:** The framework assumes that historical patterns will persist into the future. Extraordinary events (e.g., pandemics, geopolitical crises, major policy shifts) may disrupt these patterns and reduce model accuracy.

4. **Limited Handling of Human Factors:** While the model captures documented human decisions (e.g., change order reasons, contingency allocations), it does not independently model psychological biases, organizational culture, or communication patterns that influence risk perception and response.

5. **Causality vs. Correlation:** The predictive model identifies statistical associations, not causal relationships. While SHAP analysis provides interpretability, it does not establish causality, and interventions based on identified predictors may not always achieve intended outcomes.

6. **Computational Resource Requirements:** Real-time implementation requires appropriate computational infrastructure (data pipelines, model serving, visualization dashboards), which may be challenging for organizations with limited IT resources.

5.4 Future Research Directions

1. **Extension to Other Infrastructure Sectors:** Replicating the framework for energy projects (renewable, nuclear, oil/gas), water resource projects, and urban development would enhance generalizability and identify sector-specific risk patterns.

2. **Longitudinal Studies on Decision-Making:** Longitudinal research examining how predictive risk intelligence influences administrator decision-making, risk mitigation effectiveness, and project outcomes would provide evidence on the framework's practical impact.

3. **Integration of Real-Time Sensor Data:** Incorporating IoT sensor data, drone surveillance outputs, and digital twin simulations could enhance prediction accuracy by providing current project conditions as model inputs .

4. **Human Factors Integration:** Developing hybrid models that integrate behavioral factors (cognitive biases, organizational culture, communication quality) with technical risk factors would provide a more comprehensive risk assessment.

5. **Causal Inference Approaches:** Applying causal inference methods (e.g., instrumental variables, difference-in-differences) could establish causal relationships between risk factors and project outcomes, enabling more targeted interventions.

6. **Multi-Modal Data Integration:** Future research should explore the integration of text data (contract language, stakeholder communications) and image data (site photographs) using natural language processing and computer vision techniques.
7. **Benchmarking and Standardization:** Development of standardized benchmarks, public datasets, and performance metrics for predictive risk analytics in construction would facilitate systematic comparison and improvement of models.

6. Conclusion

This study developed and validated a machine learning-based predictive risk analytics framework for real-time forecasting of cost overruns and schedule delays in large-scale infrastructure projects. The proposed framework, integrating LightGBM with explainable AI techniques, achieved 89.4% classification accuracy in predicting significant impacts and a 6.2% mean absolute percentage error in cost magnitude prediction, representing a 23% improvement over conventional static estimation methods. The framework provides project managers with actionable risk intelligence with approximately 12-15 days of lead time, enabling proactive risk mitigation and evidence-based contingency allocation.

The primary contribution of this research is a replicable, explainable, and practically deployable framework that bridges the gap between theoretical risk modeling and operational decision-making. By incorporating SHAP-based interpretability, the framework addresses the critical barrier of AI "black boxes" that has hindered practitioner adoption, promoting transparency and trust. The practical takeaway for administrators is clear: implementing real-time predictive risk analytics can reduce reliance on static contingency percentages, enable differentiated mitigation strategies for cost versus schedule risks, and enhance project delivery performance.

As infrastructure investment continues to accelerate globally, the need for more sophisticated, data-driven risk management tools becomes increasingly urgent. This framework represents a step toward intelligent project management, where predictive analytics informs strategic decision-making, reduces waste, and enables successful project delivery despite inherent uncertainty.

References

1. Lai Mun Keong. (2025). AI-Driven Risk Management in OBOR Infrastructure Projects. *International Journal of Research and Innovation in Social Science, 9*(2), 1221-1232.
2. Risk-indexed artificial neural network for predicting duration and cost of irrigation canal-lining projects using survey-based calibration and python validation. (2025). *Scientific Reports, 15*, 40316.
3. Explainable AI-driven expert system for impact profiling of contract modifications in construction projects. (2026). *Expert Systems with Applications*.
4. Tanim, S. H., Ahmad, M. S., Mithun, M. M. U., Tarannum, R., Refat, F., & Sunny, M. N. M. (2025). Leveraging Predictive Analytics for Risk Identification and Mitigation in Project Management. *Journal of Information Systems Engineering and Management, 10*(43s), 1041-1052.
5. Digital Twin Technology for Smart Project and Risk Management. (2026). *IEEE Xplore*.
6. Predicting and managing risk interactions and systemic risks in infrastructure projects using machine learning. (2024). *Automation in Construction*.
7. Application of the LightGBM algorithm in cross-border supply chain risk management: prediction and mitigation strategy development. (2026). *Scientific Reports, 16*, 16194.
8. Using factor analysis and regression technique to predict cost overrun in road network construction projects. (2026). *Scientific African, 31*, e03172.
9. Stock Return Forecasting Using SHAP-Based Feature Selection and Risk-Controlled Portfolio Construction. (2025). *Proceedings of ICIAI-25*.
10. Design of an AI-Based Decision Support Framework for Operational Risk Mitigation in Contract Logistics. (2026). *IEEE Xplore*.
11. Mamun, A. A., Shahiduzzaman, M., Kabtia, M., Hossain, M. S., Akter, S., & Kabir, M. F. (2026). A Leakage-Aware machine learning pipeline for credit default prediction using LightGBM. *Journal of Computer Science and Technology Studies, 8*(6), 143–160.
12. Probabilistic risk assessment framework for cost overruns predictions in infrastructure projects using randomized simulations. (2026). *Journal of Infrastructure Systems*.
13. AI-Driven Risk Management in OBOR Infrastructure Projects. (2025). *International Journal of Research and Innovation in Social Science*.

14. Design of an AI-Based Decision Support Framework for Operational Risk Mitigation in Contract Logistics. (2026). *IEEE Xplore*.

15. Framework for Leveraging Real-Time Predictive Risk Analytics in Large-Scale Infrastructure Projects. (2025). *EconPapers*.