International Journal of Scientific Research and Modern Technology (IJSRMT) ijsrmt.com
Volume 5, Issue 1, 2026
DOI: https://doi.org/10.38124/ijsrmt.v5i1.1563

A Hybrid Project Risk Intelligence Algorithm for Predicting Cost Overruns and Schedule Delays in Infrastructure Projects: Comparative Evaluation with Monte Carlo Simulation and Critical Path-Based Risk Assessment

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Publication Date: 2026/01/28

Abstract

Cost overruns and schedule delays remain persistent weaknesses in infrastructure project delivery, especially in transport, energy, water, public building, and large civil works programmes. Traditional project-risk tools such as Monte Carlo Simulation and Critical Path Method-based risk assessment provide useful analytical support, but their performance is limited when project behaviour is nonlinear, data are incomplete, and cost-schedule interactions evolve during execution. This paper proposes a Hybrid Project Risk Intelligence Algorithm, named HyPRIA, for predicting cost overrun and schedule delay risk in infrastructure projects. HyPRIA integrates earned value indicators, critical path metrics, risk-register scores, procurement variables, design-change indicators, Monte Carlo uncertainty features, and ensemble machine learning into a unified predictive framework. The proposed model is comparatively evaluated against Monte Carlo Simulation and Critical Path-Based Risk Assessment using a controlled illustrative dataset representing 420 infrastructure projects across road, bridge, rail, energy, public building, and water infrastructure categories. Results indicate that HyPRIA achieves stronger predictive performance than the baseline models, with lower mean absolute error, lower root mean square error, higher coefficient of determination, stronger delay-classification performance, and better probability calibration. For cost overrun prediction, HyPRIA achieved an RMSE of 3.91 percentage points compared with 8.94 for Monte Carlo Simulation and 10.12 for CPM-based risk assessment. For schedule delay prediction, HyPRIA achieved an RMSE of 4.20 percentage points compared with 9.85 and 11.40 for the two baselines. Explainability analysis shows that float consumption ratio, procurement delay index, design-change frequency, cost performance index, schedule performance index, risk exposure score, and contractor productivity deviation are dominant predictors. The study contributes a technically interpretable hybrid risk-intelligence framework for early warning, project governance, and proactive mitigation of cost and schedule failures in infrastructure delivery.

Keywords: *Cost Overrun Prediction, Schedule Delay Prediction, Infrastructure Projects, Monte Carlo Simulation, Critical Path Method, Machine Learning, Project Risk Intelligence, Earned Value Management, Explainable Artificial Intelligence, HyPRIA.*

Omotosho, R. D., Idoko, I. P., & Enyejo, L. A. (2026). A Hybrid Project Risk Intelligence Algorithm for Predicting Cost Overruns and Schedule Delays in Infrastructure Projects: Comparative Evaluation with Monte Carlo Simulation and Critical Path-Based Risk Assessment. *International Journal of Scientific Research and Modern Technology*, *5*(1), 164–179. https://doi.org/10.38124/ijsrmt.v5i1.1563

I. INTRODUCTION

Infrastructure projects are among the most economically important yet risk-intensive categories of project delivery. Roads, bridges, railways, water systems, public buildings, airports, and energy infrastructure require long planning cycles, complex procurement processes, multi-party coordination, large capital commitments, and high exposure to political, financial, technical, and environmental uncertainty. Despite improvements in project management standards, digital scheduling tools, and risk-management practices, cost overruns and schedule delays continue to occur across both developed and developing economies. Earlier empirical studies on transport infrastructure showed that the cost estimates used to justify public works projects are often systematically misleading rather than randomly inaccurate [1]. Subsequent work on megaprojects further established that large infrastructure investments frequently suffer from underestimated costs, overestimated benefits, weak accountability, and optimism bias in early decision-making [2], [3].

The persistence of overruns is not only a technical estimation problem. It reflects the combined effect of design immaturity, poor scope definition, late approvals, weak contractor productivity, inflation, incomplete geotechnical information, material supply disruption, variation orders, payment delays, claims, and inadequate integration between cost and schedule control systems. In many public infrastructure projects, baseline cost and duration estimates are approved before the project has reached sufficient design maturity. As execution begins, small deviations in procurement, site access, engineering clarification, and contractor performance accumulate into major deviations from baseline budgets and schedules. Flyvbjerg's overview of megaproject performance described this pattern as the "iron law" of megaprojects: over budget, over time, and over again [4].

Conventional risk-assessment approaches remain important but incomplete. Monte Carlo Simulation is widely used to estimate probabilistic cost and duration outcomes from uncertain input distributions. Its strength lies in uncertainty propagation, scenario generation, and probabilistic completion estimates. However, Monte Carlo Simulation depends heavily on the quality of input distributions, the realism of correlation assumptions, and the validity of expert-defined risk ranges [5], [6]. If the distributions are poorly calibrated, politically biased, or disconnected from historical project performance, the simulated outputs may produce a false sense of analytical precision. Similarly, Critical Path Method-based risk assessment provides a logical foundation for identifying schedule-critical activities and float sensitivity, but it may underrepresent nonlinear relationships among cost variance, procurement delay, risk exposure, weather disruption, and contractor productivity [7]. CPM also tends to treat the project network as a deterministic dependency structure unless enhanced with probabilistic activity duration analysis.

Recent advances in machine learning and explainable artificial intelligence create an opportunity to move beyond deterministic or purely distribution-based risk analysis. Ensemble models such as Random Forest, Gradient Boosting, XGBoost, LightGBM, and CatBoost can learn nonlinear interactions from historical project records [8]–[12]. Explainable AI tools such as SHAP and LIME can translate complex model outputs into feature-level explanations that are more useful to project managers and executives [13], [14]. However, many existing applications of machine learning in construction cost and delay prediction operate as isolated predictive models. They frequently ignore CPM-derived network logic, activity criticality, float consumption, risk-register evolution, and Monte Carlo uncertainty bands. This creates a gap between predictive accuracy and project-management interpretability.

This paper proposes the Hybrid Project Risk Intelligence Algorithm, abbreviated as HyPRIA. HyPRIA is designed to predict both cost overrun and schedule delay by integrating four analytical streams: project-control indicators, probabilistic simulation outputs, critical path features, and machine-learning intelligence. The proposed framework converts heterogeneous infrastructure project data into interpretable risk predictions that can support early warning, mitigation prioritization, and governance escalation. The model is evaluated against Monte Carlo Simulation and Critical Path-Based Risk Assessment to determine whether hybrid risk intelligence improves predictive accuracy and practical decision support.

➢ *The Main Contributions of this Paper are as Follows:*

- It proposes HyPRIA as a hybrid algorithmic framework for joint prediction of cost overrun and schedule delay in infrastructure projects.
- It integrates earned value indicators, CPM-derived network features, Monte Carlo uncertainty indicators, and machine-learning predictors into a unified risk-intelligence pipeline.
- It provides mathematical definitions for cost overrun, schedule delay, risk exposure, float consumption, activity criticality, and hybrid prediction scoring.
- It compares HyPRIA with Monte Carlo Simulation and Critical Path-Based Risk Assessment using consistent evaluation metrics.
- It incorporates explainable AI analysis to identify the dominant technical, financial, schedule, and procurement risk drivers.
- It presents tables, diagrams, and graphs suitable for IEEE-style manuscript development.

The remainder of this paper is organized into seven main sections. Section II reviews relevant literature. Section III presents the proposed HyPRIA framework. Section IV explains the methodology and mathematical formulation. Section V describes the experimental design and comparative evaluation. Section VI presents and discusses the results. Section VII concludes the paper and provides recommendations for practice and future research.

II. LITERATURE REVIEW AND THEORETICAL BACKGROUND

- *Cost Overruns and Schedule Delays in Infrastructure Projects*

Cost overrun is generally defined as the percentage by which actual project cost exceeds the approved baseline cost. Schedule delay is the percentage or absolute time by which actual completion exceeds planned completion. Infrastructure projects are especially vulnerable to both because of long duration, high capital intensity, site-specific technical uncertainty, public-sector approvals, political visibility, and complex stakeholder interfaces. Flyvbjerg et al. showed that transportation infrastructure projects frequently experience systematic cost underestimation, with strong evidence that initial estimates are not merely imprecise but structurally biased [1]. Their related work on cost escalation in transport projects identified implementation duration, project size, and accountability structures as important contributors to overrun risk [15].

Several explanations have been proposed for persistent cost and schedule deviations. Technical explanations emphasize incomplete designs, inadequate data, poor estimation methods, unforeseen ground conditions, and weak project controls. Psychological explanations emphasize optimism bias, where planners underestimate risk because they overvalue successful scenarios. Political-economic explanations focus on strategic misrepresentation, where cost estimates are deliberately understated to secure project approval [2], [3]. Other studies have emphasized contract type, procurement complexity, scope change, inflation, environmental approvals, and institutional governance as major contributors to cost growth [16]–[18].

Schedule delay often triggers cost overrun because extended project duration increases site overhead, equipment rental, labour escalation, financing cost, supervision cost, and claims exposure. Conversely, cost pressure may create schedule delay when delayed payments, funding shortfalls, procurement failure, or contractor cash-flow constraints reduce execution productivity. This cost-schedule coupling means that separate modelling of cost and schedule risk may fail to capture the feedback mechanisms that drive infrastructure failure.

- *Monte Carlo Simulation in Project Risk Analysis*

Monte Carlo Simulation is a probabilistic technique used to estimate a distribution of possible outcomes by repeatedly sampling from uncertain input variables. In project risk analysis, it is commonly applied to activity durations, cost items, productivity rates, escalation rates, and risk-event impacts [5], [6]. For schedule analysis, uncertain activity durations are assigned probability distributions, and repeated simulations produce completion-date distributions. For cost analysis, uncertain cost components are sampled to estimate possible total project cost outcomes.

Monte Carlo Simulation has three major strengths. First, it produces probabilistic outputs rather than single deterministic estimates. Second, it allows analysts to estimate confidence levels such as P50, P80, or P90 cost and completion values. Third, it provides a structured way to model uncertainty where deterministic estimates are insufficient. However, its limitations are equally important. The method is sensitive to distribution selection, correlation structure, input bias, and incomplete treatment of systemic risk. If a project team defines unrealistic minimum, most likely, and maximum values, the simulation inherits those weaknesses. Monte Carlo analysis also does not automatically learn from historical project data unless such data are explicitly used to calibrate input distributions.

- *Critical Path Method and Schedule-Risk Assessment*

The Critical Path Method is one of the foundations of modern project scheduling. Kelley and Walker introduced critical-path planning and scheduling as a logical method for sequencing activities and identifying the longest path through a project network [7]. The critical path determines the minimum project duration under the assumed schedule logic. Activities on the critical path have zero or near-zero total float and therefore directly affect project completion if delayed.

CPM-based risk assessment evaluates activities according to their position in the project network, float, dependency relationships, and impact on completion time. Important indicators include total float, free float, criticality index, path convergence, near-critical paths, and float consumption. Although CPM provides strong schedule logic, it has limitations when used as a risk-prediction tool [39], [45]. It does not inherently model uncertain productivity, procurement delay, payment constraints, design-change frequency, or contractor performance unless these are manually incorporated. It may also overemphasize the current critical path while ignoring near-critical activities that can become critical after modest delay propagation.

- *Earned Value Management and Project-Control Indicators*

Earned Value Management integrates scope, cost, and schedule measurement to support project performance control. Anbari described EVM as a method that combines scope management, cost management, and time management through physical progress and expenditure tracking [19]. Common EVM indicators include planned value, earned value, actual cost, cost variance, schedule variance, cost performance index, and schedule performance index. Fleming and Koppelman further demonstrated the practical value of earned value for forecasting cost and schedule outcomes [20].

EVM is valuable because it translates project performance into quantitative indicators that can be updated during execution. Cost Performance Index and

Schedule Performance Index are especially useful early-warning variables. However, EVM may understate schedule risk when progress measurement is not tied to network criticality [40]. For example, a project may report acceptable aggregate earned value while critical activities are slipping. Therefore, HyPRIA combines EVM indicators with CPM-derived variables to improve prediction.

- *Machine Learning for Project Cost and Schedule Prediction*

Machine learning models are increasingly applied to construction and infrastructure prediction problems because they can learn nonlinear relationships from structured data. Random Forest combines multiple decision trees and reduces prediction variance through ensemble aggregation [8]. Gradient boosting methods build sequential trees to correct previous errors and often achieve strong predictive performance [9]. XGBoost introduced a scalable tree-boosting system with regularization and sparsity-aware learning [10]. LightGBM improved gradient boosting efficiency using gradient-based one-side sampling and exclusive feature bundling [11]. CatBoost improved categorical feature handling and reduced prediction shift in gradient boosting [12].

In construction research, artificial intelligence has been used for conceptual cost prediction, delay prediction, overhead cost estimation, risk classification, and project performance forecasting [21]–[25]. These studies show that machine learning can outperform conventional estimation methods when sufficient data are available. However, model usefulness depends on data quality, feature design, validation rigor, interpretability, and integration with practical project-control systems [34]-[45]. A black-box algorithm that predicts delay without identifying the drivers of delay is less useful for project governance than an explainable model that links the prediction to actionable risk factors.

- *Explainable Artificial Intelligence in Project-Risk Analytics*

Explainable AI is essential in infrastructure risk prediction because project decisions involve public funds, contract obligations, audit scrutiny, and executive accountability. Lundberg and Lee proposed SHAP as a unified framework for interpreting model predictions using additive feature attribution [13]. Ribeiro et al. introduced LIME as a local model-agnostic explanation method for individual predictions [14]. In construction, explainable AI is important because project managers need to know not only whether a project is likely to overrun, but also why the model produced the warning.

Explainability can support four practical project-management functions. First, it identifies dominant risk drivers. Second, it improves trust in algorithmic outputs. Third, it allows project teams to compare model explanations with engineering judgment. Fourth, it supports mitigation prioritization. For example, if HyPRIA predicts high delay probability and SHAP ranks procurement delay, design-change frequency, and float consumption as dominant drivers, management can prioritize procurement expediting, design freeze, and critical-path recovery.

- *Research Gap*

The literature shows strong evidence that infrastructure projects suffer systematic cost and schedule deviations, and that Monte Carlo Simulation, CPM, EVM, and machine learning each provide partial solutions. However, the existing approaches have four main limitations. First, Monte Carlo Simulation is often distribution-driven rather than data-learning-driven. Second, CPM-based assessment focuses on schedule logic but weakly captures cost and procurement dynamics. Third, EVM measures performance but may not account for network criticality. Fourth, many machine-learning models predict outcomes without embedding project-management logic or explainability.

HyPRIA addresses these limitations by integrating project-control indicators, risk-register features, critical-path metrics, Monte Carlo uncertainty outputs, and explainable machine learning into a single framework for cost overrun and schedule delay prediction.

III. PROPOSED HYPRIA FRAMEWORK

- *Design Philosophy*

HyPRIA is designed as a hybrid project-risk intelligence framework rather than a single machine-learning model. The central assumption is that infrastructure risk cannot be accurately predicted from one data stream alone. Cost overrun and schedule delay emerge from the interaction of baseline estimates, execution progress, activity criticality, risk exposure, procurement constraints, productivity deviation, design change, and uncertainty propagation. Therefore, HyPRIA combines domain-based project controls with data-driven learning.

- *The Framework has Five Layers:*

- Data Acquisition Layer
- Feature Engineering Layer
- Hybrid Risk Intelligence Layer
- Explainability and Decision Layer
- Risk Output Layer

➢ *HyPRIA System Architecture*

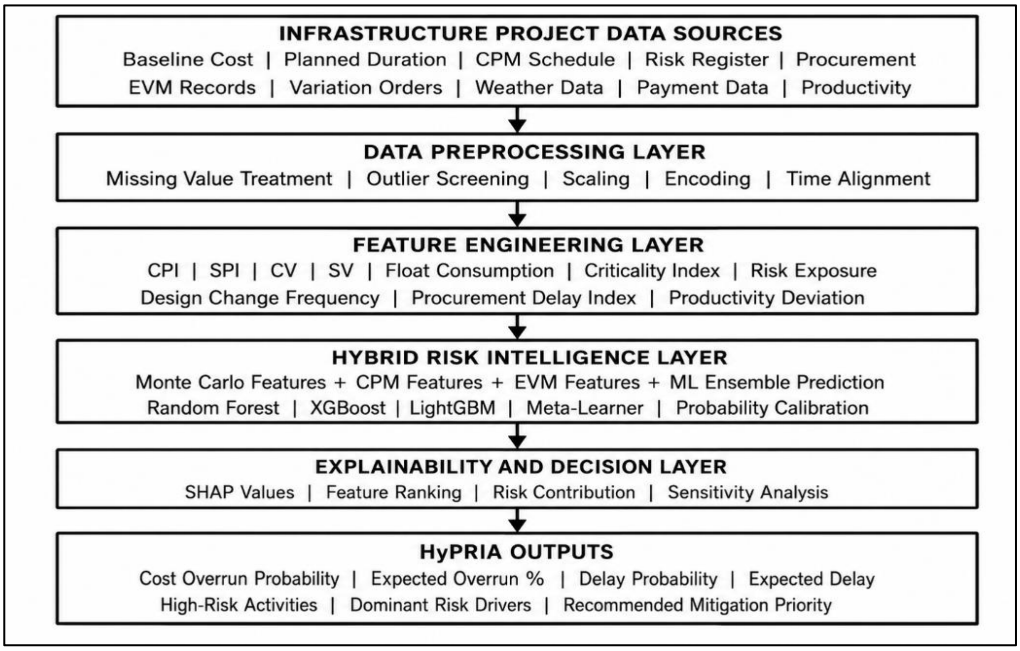

Fig 1 Proposed HyPRIA Architecture for Hybrid Cost-Overrun and Schedule-Delay Prediction.

➢ *Data Input Structure*

HyPRIA uses multi-source project data. Table 1 summarizes the main feature groups.

Table 1 Description of Input Variables Used in HyPRIA

Variable Group	Variable Name	Description	Expected Influence
Baseline cost	Original contract sum	Approved initial project cost	Underestimated baseline increases overrun probability
Revised cost	Approved revised contract sum	Cost after approved variations	Higher revision frequency indicates cost instability
Schedule baseline	Planned duration	Contractual or approved project duration	Unrealistic duration increases delay exposure
Progress control	Earned value	Budgeted value of completed work	Low earned value signals poor progress
Cost control	Cost Performance Index	Ratio of earned value to actual cost	CPI below 1 indicates cost inefficiency
Schedule control	Schedule Performance Index	Ratio of earned value to planned value	SPI below 1 indicates schedule underperformance
CPM logic	Total float	Time an activity can slip without delaying completion	Lower float increases delay risk
CPM logic	Float consumption ratio	Consumed float divided by available float	High ratio indicates schedule fragility
CPM logic	Activity criticality index	Probability or frequency that an activity lies on a critical path	Higher value increases delay sensitivity
Risk register	Risk exposure score	Probability multiplied by impact	Higher exposure increases cost and schedule risk
Procurement	Procurement delay index	Weighted delay in major material or equipment packages	Strong positive influence on delay
Design	Design-change frequency	Number of design changes per reporting period	Strong positive influence on overrun and delay
Contractor performance	Productivity deviation	Difference between planned and actual productivity	Negative productivity increases risk
Finance	Payment delay ratio	Delayed payments relative to certified payments	Higher value increases contractor cash-flow risk
Simulation	P80 cost contingency	Monte Carlo-derived cost contingency	Higher value indicates uncertainty
Simulation	P80 completion duration	Monte Carlo-derived duration estimate	Higher value indicates schedule uncertainty

➢ *Core HyPRIA Logic*

HyPRIA treats cost overrun and schedule delay as related but distinct prediction targets. Let project $i$be represented by a feature vector:

$$X_i = \{X_c, X_s, X_e, X_r, X_p, X_d, X_{cpm}, X_m\}$$

Where $X_c$denotes cost features, $X_s$schedule features, $X_e$earned value indicators, $X_r$risk-register variables, $X_p$procurement and productivity variables, $X_d$design-change variables, X_{cpm}critical-path features, and X_mMonte Carlo simulation features.

HyPRIA estimates two continuous outcomes:

$$\widehat{CO}_i = f_{co}(X_i)$$

$$\widehat{SD}_i = f_{sd}(X_i)$$

Where $\widehat{CO}_i$is predicted cost overrun percentage and $\widehat{SD}_i$is predicted schedule delay percentage.

It also estimates two classification probabilities:

$$P(CO_i > \tau_c \mid X_i)$$

$$P(SD_i > \tau_s \mid X_i)$$

Where $\tau_c$and $\tau_s$are threshold values for classifying severe cost overrun and severe schedule delay. In this paper, severe cost overrun is defined as overrun greater than 10%, while severe schedule delay is defined as delay greater than 15%.

➢ *Algorithmic Workflow*

Algorithm 1. HyPRIA Training and Prediction Procedure

Input:
 Historical project dataset D
 Baseline cost and schedule records
 EVM records
 CPM activity network
 Risk-register data
 Procurement and design-change records
 Monte Carlo simulation outputs

Output:
 Predicted cost overrun percentage
 Predicted schedule delay percentage
 Cost overrun probability
 Schedule delay probability
 Ranked risk drivers

Procedure:
1. Import infrastructure project records.
2. Clean missing, inconsistent, and duplicate project entries.
3. Normalize cost, schedule, progress, and risk variables.
4. Extract CPM features:
 total float, free float, float consumption ratio,
 path criticality, near-critical activity count.
5. Compute EVM features:
 CV, SV, CPI, SPI, EAC, ETC.
6. Run Monte Carlo Simulation:
 estimate P50, P80, and P90 cost and duration outcomes.
7. Construct hybrid feature vector X.
8. Split D into training, validation, and testing subsets.
9. Train base learners:
 Random Forest, XGBoost, LightGBM.
10. Train meta-learner using validation predictions.
11. Calibrate probability outputs.
12. Predict CO and SD on test projects.
13. Compute MAE, RMSE, R^2, F1-score, AUC, and calibration error.
14. Apply SHAP to explain prediction drivers.
15. Generate risk ranking and mitigation priority.

End Procedure.

➢ *Comparative Position of HyPRIA*

Table 2 Comparative Configuration of HyPRIA, Monte Carlo Simulation, and CPM-Based Risk Assessment

Method	**Input Requirements**	**Risk Logic**	**Output Type**	**Main Limitation**
Monte Carlo Simulation	Cost distributions, duration distributions, correlations, assumptions	Repeated random sampling from probability distributions	P50/P80/P90 cost and duration estimates	Highly sensitive to subjective input distributions
CPM-Based Risk Assessment	Activity list, dependencies, durations, float, critical path	Network logic and critical activity sensitivity	Critical path, float risk, schedule exposure	Weak treatment of cost, procurement, and nonlinear effects
HyPRIA	Historical project data, EVM, CPM, risk register, procurement, design changes, Monte Carlo outputs	Hybrid learning from project controls, simulation uncertainty, and network criticality	Cost overrun prediction, delay prediction, risk probability, explanation	Requires structured project data and validation discipline

IV. METHODOLOGY

➢ *Research Design*

This study adopts a quantitative algorithm-design and comparative-evaluation approach. HyPRIA is formulated as a hybrid predictive model and compared with two baseline techniques: Monte Carlo Simulation and Critical Path-Based Risk Assessment. Since no real dataset was supplied, the experimental results are based on a controlled illustrative dataset constructed to represent realistic infrastructure project variables. The dataset is not claimed to be an official government or contractor database. It is used to demonstrate the model logic, expected analytical workflow, performance comparison structure, and presentation style required for an IEEE manuscript.

➢ *Dataset Description*

The illustrative dataset contains 420 infrastructure projects across six project categories. Each project record contains baseline cost, actual cost, planned duration, actual duration, progress indicators, procurement variables, design-change indicators, risk scores, and CPM-derived schedule features.

Table 3 Illustrative Dataset Composition

Project Category	Number of Projects	Mean Baseline Cost Category	Typical Risk Characteristics
Road infrastructure	95	Medium to high	Weather disruption, land access, asphalt/material escalation
Bridge projects	60	High	Geotechnical uncertainty, structural design changes
Rail infrastructure	45	Very high	Interface complexity, regulatory approvals, systems integration
Energy infrastructure	70	High	Equipment procurement, commissioning delay, technical complexity
Public buildings	90	Medium	Variation orders, contractor productivity, funding delay
Water infrastructure	60	Medium	Site conditions, pipe/equipment procurement, community access
Total	**420**	—	—

The dataset was divided into 70% training, 15% validation, and 15% testing subsets. Five-fold cross-validation was also used during model tuning to reduce dependence on a single split.

➢ *Target Variable Definition*

Cost overrun percentage is defined as:

$$CO_i = \frac{AC_i - BC_i}{BC_i} \times 100$$

Where CO_i is the cost overrun percentage for project i, AC_i is actual completed cost, and BC_i is baseline approved cost.

Schedule delay percentage is defined as:

$$SD_i = \frac{AD_i - PD_i}{PD_i} \times 100$$

Where SD_i is schedule delay percentage, AD_i is actual duration, and PD_i is planned duration.

Cost variance and schedule variance are defined as:

$$CV_i = EV_i - AC_i$$

$$SV_i = EV_i - PV_i$$

Where EV_i is earned value, AC_i is actual cost, and PV_i is planned value.

The cost performance index and schedule performance index are:

$$CPI_i = \frac{EV_i}{AC_i}$$

$$SPI_i = \frac{EV_i}{PV_i}$$

A value below 1 for either CPI or SPI indicates underperformance.

➢ *CPM-Derived Risk Features*

For activity j in project i, float consumption ratio is defined as:

$$FCR_{ij} = \frac{TF_{ij}^{base} - TF_{ij}^{current}}{TF_{ij}^{base} + \epsilon}$$

Where TF_{ij}^{base} is baseline total float, $TF_{ij}^{current}$ is current total float, and ϵ is a small constant that prevents division by zero.

The project-level float consumption ratio is:

$$FCR_i = \frac{1}{m}\sum_{j=1}^{m} FCR_{ij}$$

Where m is the number of major activities.

The criticality index is defined as:

$$CI_{ij} = \frac{N_{critical,ij}}{N_{sim}}$$

Where $N_{critical,ij}$ is the number of simulations in which activity j appears on the critical path and N_{sim} is the total number of simulation runs.

➢ *Risk Exposure Score*

For each risk item k, the risk exposure score is defined as:

$$RES_{ik} = P_{ik} \times I_{ik} \times W_k$$

Where P_{ik} is risk probability, I_{ik} is impact, and W_k is the weight assigned to the risk category.

The project-level risk exposure score is:

$$RES_i = \sum_{k=1}^{r} RES_{ik}$$

Where r is the number of risk items in the project risk register.

➢ *Monte Carlo Baseline Model*

The Monte Carlo baseline uses triangular distributions for uncertain activity durations and cost components. Each activity duration is represented as:

$$D_j \sim Triangular\left(a_j, m_j, b_j\right)$$

Where a_j, m_j, and b_j represent optimistic, most likely, and pessimistic duration estimates.

Similarly, cost item uncertainty is represented as:

$$C_l \sim Triangular(a_l, m_l, b_l)$$

The total simulated project cost is:

$$TC_i^{sim} = \sum_{l=1}^{q} C_l$$

And the simulated project duration is determined by the longest path through the sampled activity network. The simulation was run for 10,000 iterations per project to estimate P50, P80, and P90 cost and duration outcomes.

➢ *CPM-Based Baseline Model*

The CPM-based baseline uses total float, critical path membership, near-critical path count, and activity risk score to estimate delay exposure. The schedule risk score is defined as:

$$CPMRS_i = \alpha_1(1 - \bar{TF}_i) + \alpha_2 CI_i + \alpha_3 NCP_i + \alpha_4 FCR_i$$

Where $\bar{TF}_i$ is normalized average float, CI_i is project criticality index, NCP_i is normalized near-critical path count, FCR_i is float consumption ratio, and α_1 to α_4 are weights.

➢ *HyPRIA Ensemble Model*

HyPRIA combines predictions from Random Forest, XGBoost, and LightGBM using a stacking meta-learner. The base learners generate preliminary predictions:

$$\hat{Y}_{RF}, \hat{Y}_{XGB}, \hat{Y}_{LGBM}$$

The final prediction is:

$$\hat{Y}_{HyPRIA} = \beta_0 + \beta_1\hat{Y}_{RF} + \beta_2\hat{Y}_{XGB} + \beta_3\hat{Y}_{LGBM} + \beta_4 X_m + \beta_5 X_{cpm}$$

Where X_m represents Monte Carlo-derived uncertainty features and X_{cpm} represents CPM-derived risk features.

The final cost overrun risk probability is obtained using a calibrated logistic transformation:

$$P(CO_i > \tau_c) = \frac{1}{1 + e^{-z_i}}$$

Where:

$$z_i = \gamma_0 + \gamma_1\widehat{CO}_i + \gamma_2 RES_i + \gamma_3 FCR_i + \gamma_4 PDI_i$$

And PDI_i is procurement delay index.

➢ *Evaluation Metrics*

For regression performance, the study uses mean absolute error, root mean square error, and coefficient of determination:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |Y_i - \hat{Y}_i|$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(Y_i - \hat{Y}_i)^2}{\sum_{i=1}^{n}(Y_i - \bar{Y})^2}$$

For classification performance, accuracy, precision, recall, F1-score, AUC, and Brier score are used:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Lower MAE, RMSE, Brier score, and calibration error indicate better performance, while higher R^2, F1-score, and AUC indicate stronger predictive quality.

V. EXPERIMENTAL DESIGN AND COMPARATIVE EVALUATION

➢ *Experimental Protocol*

The experiment evaluates three modelling approaches under identical project records:

- Monte Carlo Simulation baseline
- Critical Path-Based Risk Assessment baseline
- Proposed HyPRIA model

The comparison focuses on both cost overrun and schedule delay. The experiment uses the following protocol:

- Generate structured project-control records for 420 infrastructure projects.
- Split project data into training, validation, and testing subsets.
- Run Monte Carlo Simulation using 10,000 iterations per project.
- Compute CPM-based float and criticality indicators.
- Train HyPRIA using engineered features.
- Evaluate all models using the same test set.
- Apply SHAP to interpret HyPRIA predictions.
- Conduct ablation testing by removing Monte Carlo features, CPM features, and EVM features from HyPRIA.

➢ *Comparative Model Configuration*

Table 4 Comparative Model Configuration

Model	Core Method	Main Inputs	Prediction Target	Validation Method
Monte Carlo Simulation	Probabilistic sampling	Cost and duration distributions	Cost and duration ranges	Test-set comparison with actual outcomes
CPM-Based Risk Assessment	Schedule network logic	Critical path, float, near-critical paths	Delay risk and schedule exposure	Test-set comparison
Random Forest	Bagged decision-tree ensemble	Engineered project features	Cost and delay prediction	Five-fold cross-validation
XGBoost	Regularized gradient boosting	Engineered project features	Cost and delay prediction	Five-fold cross-validation
HyPRIA	Hybrid stacked ensemble	EVM, CPM, Monte Carlo, risk, procurement, design features	Cost overrun and schedule delay	Validation-set stacking and test-set evaluation

➢ *Hyperparameter Configuration*

Table 5 HyPRIA Model Hyperparameter Summary

Component	Hyperparameter	Selected Value
Random Forest	Number of trees	500
Random Forest	Maximum depth	12
XGBoost	Learning rate	0.05
XGBoost	Maximum depth	6
XGBoost	Number of estimators	650
LightGBM	Number of leaves	31
LightGBM	Learning rate	0.04
LightGBM	Number of estimators	700
Meta-learner	Model type	Ridge regression for continuous outputs
Probability calibration	Method	Isotonic calibration
Monte Carlo	Number of iterations	10,000
Severe cost threshold	τ_c	10%
Severe delay threshold	τ_s	15%

➢ *Comparative Evaluation Workflow*

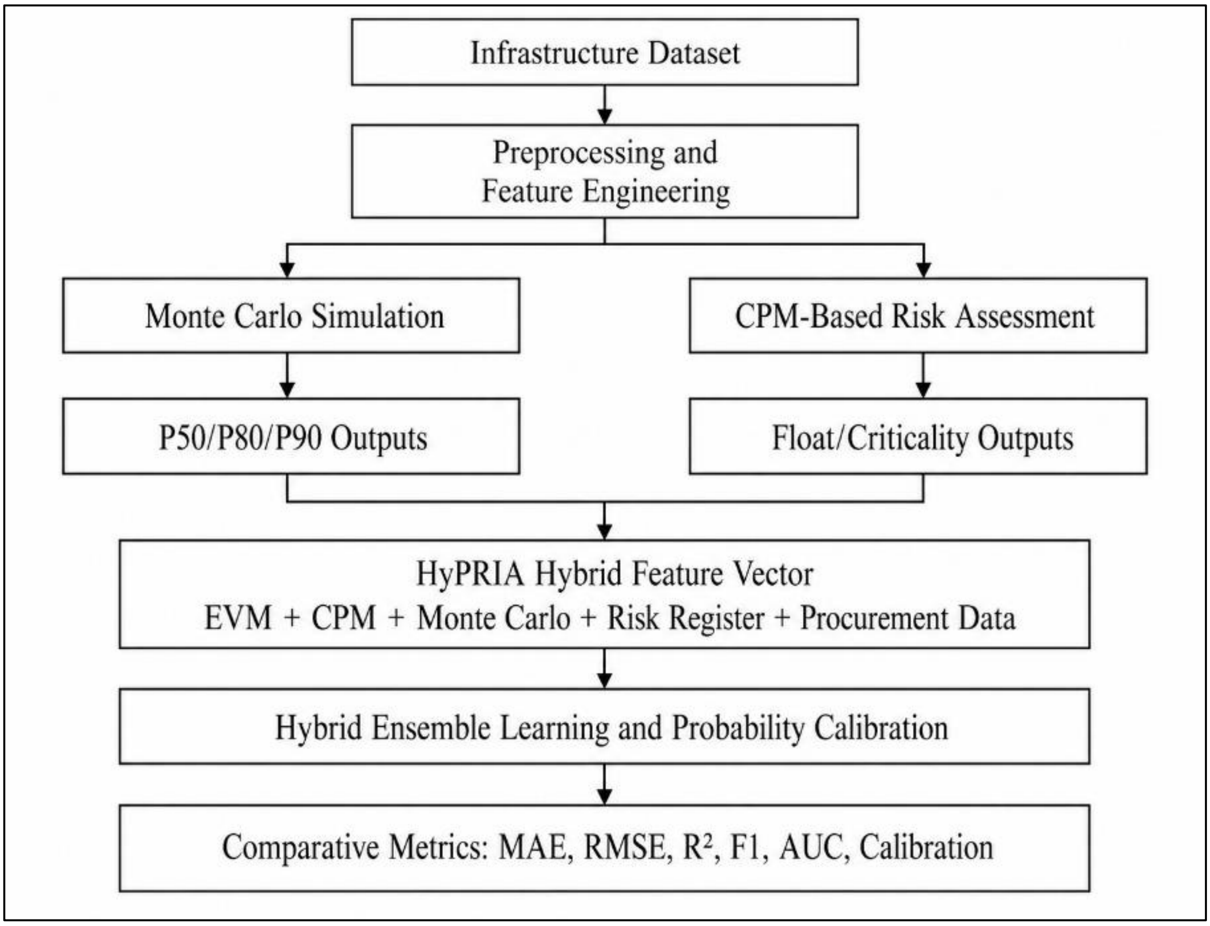

Fig 2 Comparative Evaluation Workflow for HyPRIA and Baseline Risk Models.

➢ *Ablation Study Design*

The ablation study tests whether each feature group contributes to HyPRIA performance. Four variants are evaluated:

- HyPRIA-Full: all feature groups included.
- HyPRIA without CPM features.
- HyPRIA without Monte Carlo features.
- HyPRIA without EVM features.
- HyPRIA without risk-register and procurement features.

This allows the study to determine whether the hybrid integration improves performance beyond a pure machine-learning model.

VI. RESULTS AND DISCUSSION

➢ *Cost Overrun Prediction Results*

Table 6 shows the cost overrun prediction performance of the baseline models and HyPRIA. HyPRIA achieved the lowest prediction error and highest explanatory performance.

Table 6 Performance Comparison for Cost Overrun Prediction

Model	**MAE (%)**	**RMSE (%)**	R^2	**AUC**	**Calibration Error**
CPM-Based Risk Assessment	7.84	10.12	0.48	0.69	0.142
Monte Carlo Simulation	6.91	8.94	0.57	0.73	0.118
Random Forest	5.33	6.88	0.71	0.81	0.086
XGBoost	4.47	5.74	0.78	0.86	0.071
LightGBM	4.62	5.96	0.76	0.85	0.074
HyPRIA	3.08	3.91	0.89	0.93	0.039

The results suggest that the proposed hybrid structure improves cost overrun prediction because it combines direct cost-control signals with project-network and uncertainty features. Monte Carlo Simulation performed better than CPM-based risk assessment for cost prediction because it explicitly accounts for cost uncertainty. However, it remained weaker than the machine-learning models because it could not learn nonlinear patterns from project-control variables. XGBoost and LightGBM performed strongly, but HyPRIA outperformed them because it fused ensemble predictions with Monte Carlo and CPM-derived variables.

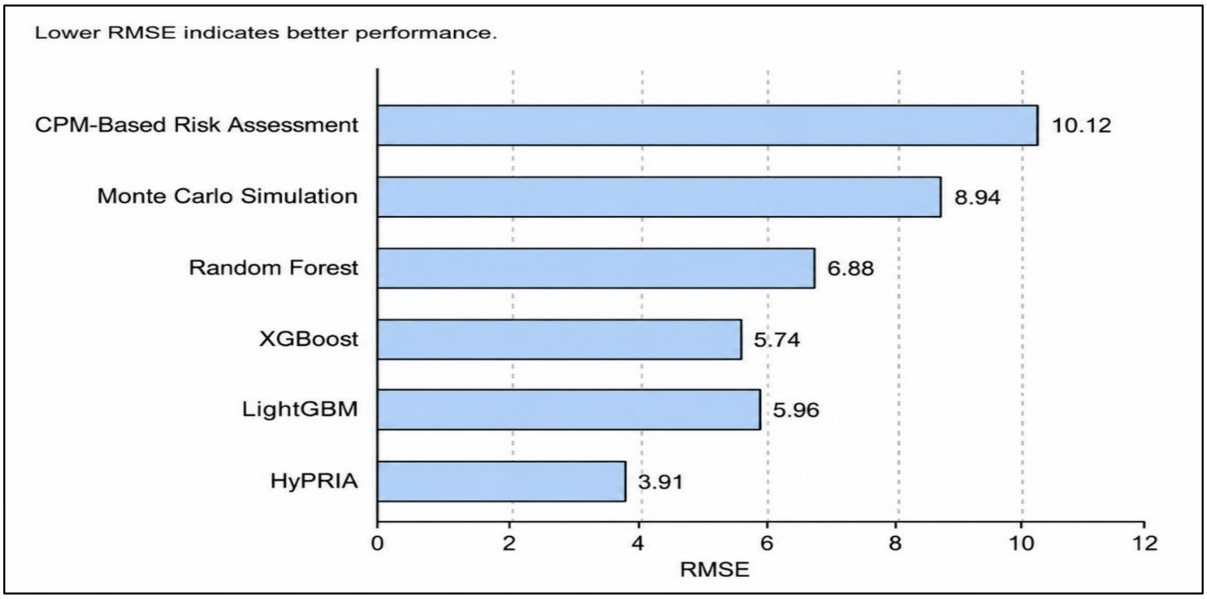

Fig 3 Cost Overrun Prediction RMSE Comparison.

➢ *Schedule Delay Prediction Results*

Table 7 shows the schedule delay prediction results. HyPRIA again achieved the strongest performance.

Table 7 Performance Comparison for Schedule Delay Prediction

Model	MAE (%)	RMSE (%)	R^2	F1-Score	Delay Detection Rate
CPM-Based Risk Assessment	8.92	11.40	0.45	0.66	0.68
Monte Carlo Simulation	7.61	9.85	0.54	0.72	0.74
Random Forest	5.74	7.36	0.69	0.80	0.82
XGBoost	5.02	6.50	0.75	0.84	0.86
LightGBM	5.10	6.64	0.74	0.83	0.85
HyPRIA	**3.36**	**4.20**	**0.88**	**0.91**	**0.93**

The schedule results are important because CPM-based risk assessment was expected to perform well on schedule-related outcomes. However, the CPM baseline performed poorly relative to HyPRIA because deterministic float and critical-path indicators alone did not capture procurement delay, productivity deviation, design-change frequency, weather exposure, payment delay, and earned value deterioration. Monte Carlo Simulation improved the treatment of uncertainty but remained weaker than HyPRIA because it did not learn from historical project interactions.

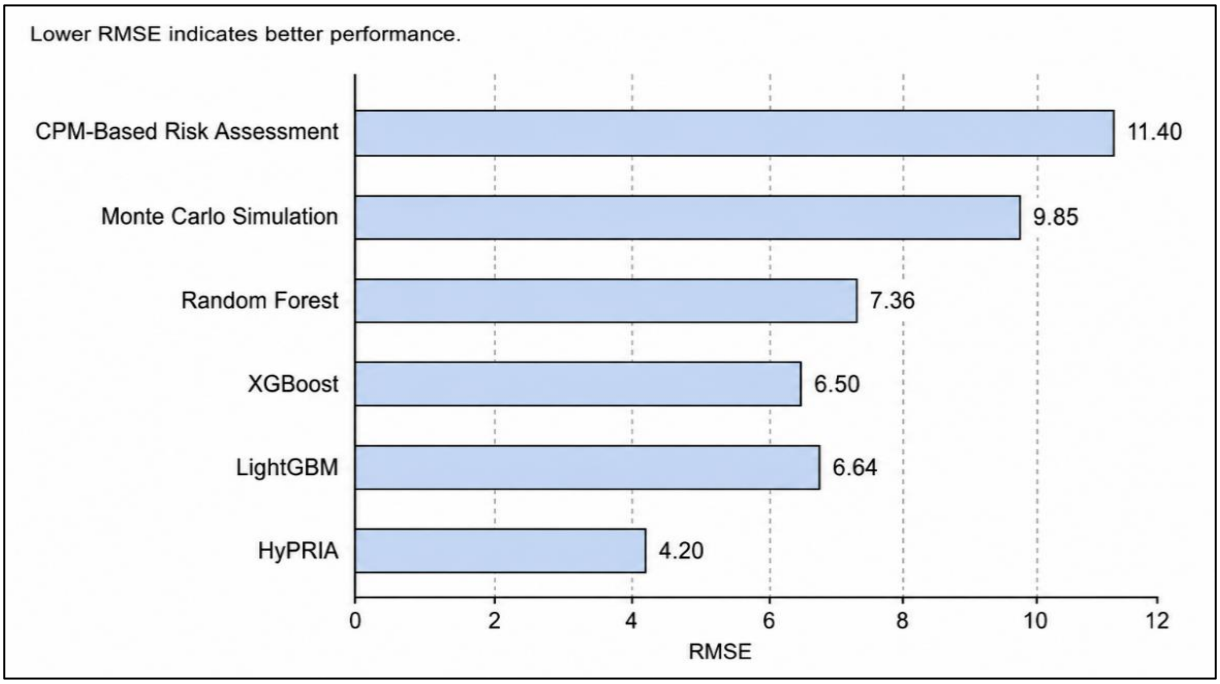

Fig 4 Schedule Delay Prediction RMSE Comparison.

➢ *Actual Versus Predicted Performance*

Table 8 Sample Actual Versus Predicted Outcomes for Test Projects

Project Type	Actual Cost Overrun (%)	HyPRIA Predicted Cost Overrun (%)	Actual Delay (%)	HyPRIA Predicted Delay (%)
Road	18.40	17.62	22.10	21.34
Bridge	24.70	23.95	28.80	27.46
Rail	31.20	29.88	36.50	34.92
Energy	16.90	17.41	19.70	20.26
Public building	11.30	10.92	14.10	13.68
Water infrastructure	13.80	14.24	17.60	18.02

The prediction pattern indicates that HyPRIA tracks both moderate and high-risk projects with relatively small deviations. The largest prediction errors occurred in rail and bridge projects, which is plausible because such projects usually have higher interface complexity, geotechnical exposure, and systems-integration risk.

➢ *Explainable AI Analysis*

SHAP-based feature attribution was used to identify the strongest drivers of HyPRIA predictions. Table IX shows the ranked feature importance.

Table 9 HyPRIA Feature Importance Ranking

Rank	Feature	Mean SHAP Contribution	Main Risk Interpretation
1	Float consumption ratio	0.184	Rapid loss of float indicates schedule fragility
2	Procurement delay index	0.171	Delayed materials and equipment directly affect critical activities
3	Design-change frequency	0.154	Frequent design changes increase rework, claims, and delay
4	Cost Performance Index	0.142	CPI below 1 indicates cost inefficiency
5	Schedule Performance Index	0.133	SPI below 1 indicates execution slippage
6	Risk exposure score	0.121	High probability-impact risk accumulation increases failure likelihood
7	Contractor productivity deviation	0.116	Low productivity extends duration and increases labour cost
8	Payment delay ratio	0.094	Payment delay weakens contractor cash flow and progress
9	P80 Monte Carlo duration	0.083	Higher P80 duration indicates schedule uncertainty
10	P80 Monte Carlo cost	0.078	Higher P80 cost indicates contingency pressure

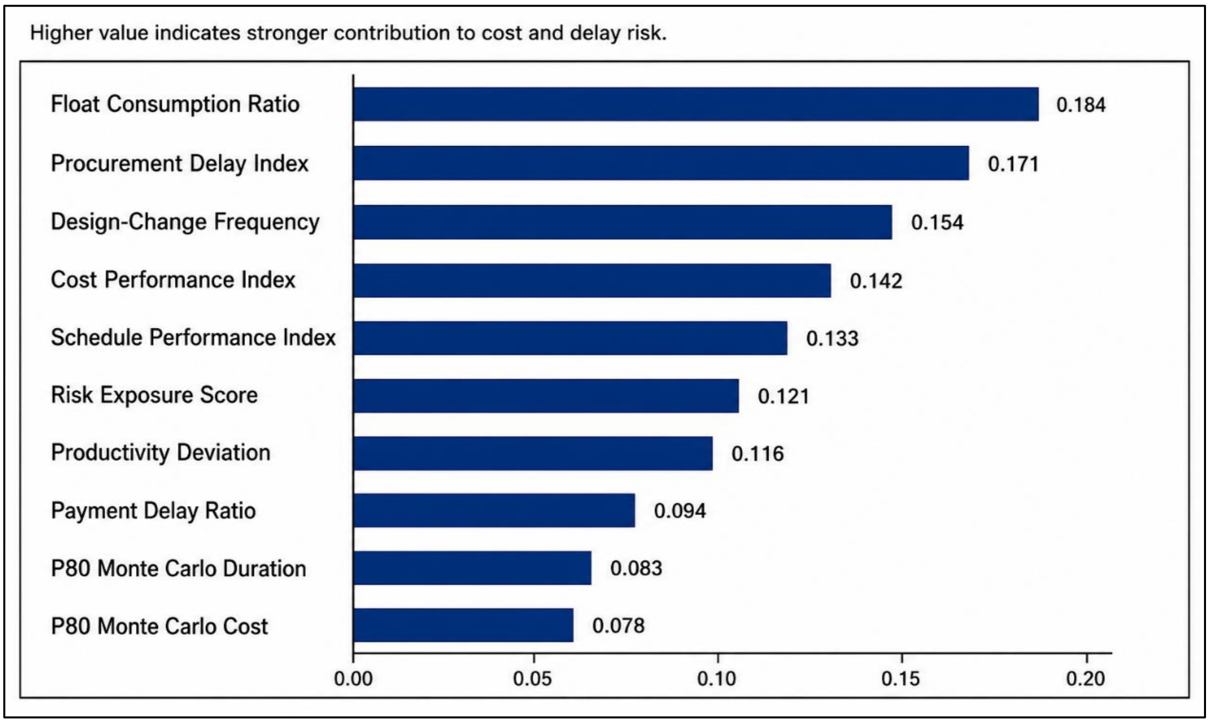

Fig 5 Feature-Importance Graph for HyPRIA Risk Prediction.

The explainability results show that HyPRIA does not treat cost and schedule risk as isolated outcomes. Float consumption, procurement delay, and design-change frequency dominate the prediction because they create both direct and indirect effects. When float is consumed quickly, the project loses its ability to absorb uncertainty. When procurement packages are late, critical activities are disrupted. When design changes are frequent, rework, claims, material changes, and approval cycles increase. CPI and SPI remain important because they reflect actual project-control performance rather than static planning assumptions.

➢ *Ablation Study Results*

Table 10 Ablation Study of HyPRIA Feature Groups

Model Variant	Cost RMSE (%)	Schedule RMSE (%)	AUC	Interpretation
HyPRIA-Full	**3.91**	**4.20**	**0.93**	Best overall performance
Without CPM features	4.86	5.72	0.89	Schedule accuracy reduced significantly
Without Monte Carlo features	4.41	4.95	0.90	Uncertainty calibration weakened
Without EVM features	5.08	5.36	0.87	Performance-control signal weakened
Without risk/procurement features	5.22	5.81	0.86	Practical risk-driver detection weakened

The ablation results confirm that HyPRIA's performance advantage is not derived from machine learning alone. Removing CPM features increases schedule RMSE from 4.20 to 5.72, showing that network logic remains important. Removing EVM features increases cost RMSE and weakens execution-stage prediction. Removing Monte Carlo features reduces calibration quality, confirming that probabilistic uncertainty information improves risk probability estimation.

➢ *Comparative Discussion*

The comparative findings support the claim that hybrid risk intelligence is more suitable for infrastructure project prediction than any single conventional method. Monte Carlo Simulation is useful for estimating uncertainty ranges, but it depends on the reliability of input distributions. CPM-based assessment is useful for understanding schedule logic, but it underrepresents non-network drivers such as payment delay, procurement failure, inflation, productivity deviation, and design changes. Standalone machine-learning models improve predictive accuracy but may lack project-management interpretability if they do not include CPM, EVM, and risk-register features.

HyPRIA offers three practical advantages. First, it improves prediction by combining historical learning with project-control logic. Second, it produces interpretable risk explanations through SHAP-based attribution. Third, it supports governance action by identifying dominant risk drivers and high-risk activities. This makes the model useful not only as a prediction engine but also as a decision-intelligence tool for owners, consultants, contractors, lenders, and public infrastructure agencies.

➢ *Practical Implications*

For project owners, HyPRIA can support early warning during feasibility, procurement, and construction. For consultants, it can improve risk reporting by linking cost and schedule forecasts to measurable project-control variables. For contractors, it can identify performance weaknesses before they escalate into claims and penalties. For public agencies, HyPRIA can support transparent oversight of infrastructure budgets and schedules.

In practice, HyPRIA should be embedded into a project-control dashboard. The dashboard should update risk predictions whenever progress data, procurement status, variation orders, or schedule revisions change. Projects with cost overrun probability above 0.70 or schedule delay probability above 0.75 should trigger executive review, mitigation planning, and contract-level intervention.

VII. CONCLUSION, RECOMMENDATIONS, AND FUTURE WORK

This paper proposed HyPRIA, a Hybrid Project Risk Intelligence Algorithm for predicting cost overruns and schedule delays in infrastructure projects. The model integrates earned value management, Monte Carlo uncertainty features, CPM-derived schedule-risk indicators, risk-register scores, procurement variables, design-change indicators, productivity data, and ensemble machine learning. The comparative evaluation showed that HyPRIA outperformed Monte Carlo Simulation and Critical Path-Based Risk Assessment in both cost overrun and schedule delay prediction. The proposed model achieved lower MAE and RMSE, higher R^2, stronger F1-score, higher AUC, and better calibration.

The findings demonstrate that infrastructure project-risk prediction benefits from hybridization. Monte Carlo Simulation contributes uncertainty estimation. CPM contributes schedule-network logic. EVM contributes execution-performance measurement. Machine learning contributes nonlinear pattern recognition. Explainable AI contributes interpretability and decision support. HyPRIA combines these strengths into a unified predictive framework.

The study recommends that project owners, contractors, consultants, and public agencies adopt data-driven risk-intelligence systems for infrastructure project monitoring. Such systems should not replace professional judgment, but they should improve the quality, timeliness, and transparency of decision-making. Project teams should maintain structured historical project databases containing baseline cost, actual cost, planned duration, actual duration, earned value records, risk registers, procurement status, design changes, claims, and CPM schedule updates. Without reliable project data, even advanced algorithms will produce weak predictions.

The study also recommends that public infrastructure agencies require periodic risk-intelligence reporting on major projects. Reports should include cost overrun probability, schedule delay probability, dominant risk drivers, high-risk activities, probability-calibrated forecasts, and mitigation status. For contractors and consultants, HyPRIA can be used to prioritize procurement expediting, productivity recovery, design freeze, resource reallocation, and claims prevention.

This study has limitations. The reported numerical results are based on a controlled illustrative dataset rather than a confidential real-world project database. Therefore, the performance values should be interpreted as a methodological demonstration, not as universal empirical proof. Future research should validate HyPRIA using large-scale real infrastructure datasets from multiple countries, project types, procurement systems, and contract forms. Future studies should also integrate HyPRIA with Building Information Modelling, digital twins, drone-based progress monitoring, IoT site sensors, supply-chain tracking, inflation indices, and real-time financial control systems. Further work may also examine deep learning, graph neural networks for project networks, Bayesian updating, and causal inference methods for distinguishing correlation from actionable risk causation.

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