Data-driven prediction of cost overruns in critical mineral projects in the U.S.A

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Abstract:
Cost overruns in U.S. critical-mineral projects such as lithium, cobalt, and rare earth elements are frequently driven by geological uncertainty, complex permitting processes, market volatility, and operational inefficiencies. Data-driven approaches, including machine learning, artificial intelligence, and probabilistic modeling, are increasingly recognized for their ability to improve cost-prediction accuracy and reveal nonlinear risk patterns that traditional methods often miss. Across recent studies, three key insights consistently emerge. First, advanced analytical techniques provide stronger predictive performance and greater adaptability to changing project conditions. Second, systemic factors such as ore-grade variability, regulatory delays, supply-chain disruptions, and contractor performance issues remain central contributors to cost escalation in mineral development. Third, there is growing momentum toward integrating predictive analytics into U.S. project governance to enhance transparency, risk monitoring, and strategic planning. Despite these advancements, notable gaps persist, including the absence of standardized national datasets, limited long-term validation of predictive models, and insufficient incorporation of socio-economic and policy variables. Overall, improving cost-overrun prediction for U.S. critical-mineral projects will require both technical progress in modeling and institutional reforms that promote coordinated data sharing, governance modernization, and evidence-based decision-making. Strengthened data-driven analytics across the project lifecycle will be essential for cost-efficient, sustainable, and secure mineral-supply development.

Keywords: Critical Minerals, Cost Overruns, Data-Driven Prediction, Machine Learning.

1. INTRODUCTION

The accelerating global transition toward clean energy technologies has intensified competition for critical minerals, placing the United States at the center of a rapidly evolving economic and geopolitical landscape. Minerals such as lithium, cobalt, rare earth elements, graphite, nickel, and manganese form the backbone of electric vehicle manufacturing, renewable energy infrastructure, semiconductor fabrication, and advanced defense systems. Despite their strategic importance, U.S. critical-mineral projects continue to experience persistent cost overruns, delays, and budgeting uncertainties, complicating national ambitions to establish secure and resilient mineral supply chains (Deshmukh & Kambekar, 2022). Empirical evidence shows that capital-intensive mining and infrastructure projects often exceed initial budgets by 30-50%, largely due to underestimating geological uncertainty, regulatory complexity, and technological constraints (Molinari et al., 2024; Eliasson, 2024). These overruns undermine investor confidence, jeopardize project financing, and delay the deployment of strategic energy-transition infrastructure.

Traditional forecasting approaches such as deterministic cost models, parametric estimation, and expert-based judgment have become increasingly inadequate in the current data-rich but uncertainty-intensive environment. Their reliance on historical averages and subjective assumptions reduces predictive accuracy, especially when projects encounter nonlinear interactions among geological, environmental, regulatory, and market-based factors (Sharma, Himanshu 2020). Published research consistently emphasizes this limitation. For example, (Hashemi et al. 2020) and (Deshmukh & Kambekar 2022) demonstrate that conventional estimation frameworks often fail to capture multi-parameter cost drivers, while Esmaeili & Kashani (2022) show that static risk models underestimate real-time cost variability in complex resource projects. As permitting timelines grow longer, supply chains become more volatile, and environmental constraints are more stringent. The gap between predicted and actual project costs has widened.

This growing challenge has triggered a methodological shift toward data-driven, machine learning (ML), and probabilistic modeling approaches capable of ingesting large, multi-dimensional project datasets. Studies such as (Shoar et al. 2022), (Aung et al. 2023), (Coffie & Cudjoe 2023), and (Farooq & Paracha 2025) highlight how ML architectures including random forests, support vector machines, deep neural networks, and hybrid optimization models significantly outperform traditional estimation techniques in predicting cost overruns. Likewise, hybrid frameworks integrating deep learning with domain-specific cost variables have shown markedly higher accuracy in capital project forecasting (Wu et al., 2025; Mohseni & Kamal, 2025). Bayesian inference, Monte Carlo simulations, and fuzzy logic-based systems such as those developed by Yao & Luo (2025), (Canesi et al. 2025), and (Rasheed & Rezouki 2022) provide additional capabilities for quantifying and propagating uncertainty in early-stage cost projections.

Trends in broader literature further illustrate the relevance of these approaches to critical-mineral supply chains. Recent studies by (Sanusi 2024) and (Ramirez & Rua-Machado 2025) show that data-driven decision-making reduces cost and schedule deviations by identifying early-stage risk indicators that traditional models overlook. Research into cross-national infrastructure cost dynamics also underscores how economic volatility, fluctuating commodity prices, inflation, and geopolitical pressures intensify uncertainty in mineral development investments (Lande & Chandekar, 2025). Collectively, the growing body of evidence affirms that AI-driven predictive analytics can serve as a transformative tool for anticipating risks and mitigating the systemic causes of cost escalation in critical-mineral projects.

Within the U.S. context, the need for advanced predictive capabilities is even more pressing. Critical-mineral projects face multifaceted uncertainties: variable ore grades, evolving extraction and processing technologies, stringent environmental regulations, long permitting cycles, and supply-chain disruptions related to transport, labor, and equipment availability. The literature shows that such multidimensional risks collectively generate nonlinear cost behaviors and cascading overruns (Wang, 2025). As national policies increasingly emphasize domestic mineral production, environmental responsibility, and supply-chain transparency, accurate cost forecasting becomes essential not only for project-level decision-making but also for macro-level governance linking energy security and economic competitiveness (Wang, 2025).

In response to these challenges, the present study investigates how data-driven models and artificial intelligence integrating historical project data, geotechnical parameters, regulatory timelines, market indicators, and financial variables can be employed to predict and mitigate cost overruns in U.S. critical-mineral projects. The research develops an integrated predictive framework designed to identify early-stage cost escalation drivers, quantify uncertainty, and forecast deviations with high accuracy. This framework bridges technical analytics and strategic policy relevance, supporting both micro-level decisions (planning, scheduling, budgeting) and national objectives related to supply-chain resilience and sustainable resource development.

By incorporating findings from published work spanning ML-based cost prediction (Shoar et al., 2022; Hashemi et al., 2020; Khan et al., 2025), probabilistic risk modeling (Canesi et al., 2025; Yao & Luo, 2025), and critical-mineral economics (Molinari et al., 2024), this study advances an evidence-based understanding of cost dynamics in the critical-mineral sector. In doing so, it addresses the limitations of traditional econometric models which often fail to capture complex interaction effects among geological, regulatory, financial, and technological uncertainty drivers (Khan et al., 2025) and demonstrates how machine learning can integrate such multidimensional dependencies to support more reliable cost control decisions Ramirez & Rua-Machado (2025).

Ultimately, this research aims to (a) identify the most influential determinants of cost escalation in U.S. critical-mineral projects, (b) develop and validate a high-accuracy predictive framework using machine learning and probabilistic modeling, and (c) evaluate the policy, economic, and supply-chain implications of improved cost forecasting for the U.S. critical-mineral sector. By synthesizing insights from recent empirical studies and integrating advanced analytical tools, this work contributes to strengthening national resource security and enhancing the resilience, efficiency, and sustainability of mineral development projects essential for the clean-energy transition.

2. MATERIALS AND METHODS

This study adopts a data-driven, multidisciplinary methodology to predict cost overruns in U.S. critical-mineral projects. The approach integrates historical project data, financial and operational metrics, geotechnical and ore-related variables, market indicators, and regulatory parameters with advanced machine learning (ML) and probabilistic modeling frameworks. By combining comprehensive data acquisition, feature engineering, supervised learning, and rigorous model validation, this methodology aims to deliver reliable, interpretable, and policy-relevant predictive insights.

2.1 Data Acquisition and Integration

The predictive framework relies on a multi-source dataset encompassing project-specific, financial, market, and regulatory information. Project-level data, including mining location, mineral type, ore grade variability, project size, and construction schedule, were obtained from U.S. Geological Survey (USGS) datasets, project feasibility reports, and scholarly publications (Deshmukh & Kambekar, 2022; Arabiat et al., 2023; Shoar et al., 2022). Financial and operational information, such as initial budgets, cost allocations for different project phases, labor productivity, and equipment utilization, were collected from industry archives and studies focusing on infrastructure and mining project cost management referencing (Almahli & Khraisat, 2025; Mohseni & Kamal, 2025). To capture external influences, market and supply-chain indicators including commodity price volatility, inflation, global demand fluctuations, and material delivery delays were incorporated (Ramirez & Rua-Machado, 2025). Regulatory and environmental features were also included, covering permitting timelines, environmental compliance requirements, and policy changes affecting project execution. This was adapted based on (Daniel & Kumar, 2023). All datasets were harmonized into a structured relational database using SQL and Python-based data pipelines. Continuous variables, such as ore grade and budgeted costs, were normalized, while categorical variables, such as mining methods and permitting type, were encoded through one-hot and ordinal schemes. Missing data were addressed using multiple imputation and k-nearest neighbor (k-NN) methods to ensure robustness and completeness of the dataset, adapted from (Esmaeili & Kashani, 2022; Sanusi, 2024).

2.2 Feature Engineering

Feature engineering was performed to identify and quantify variables most predictive of cost overruns. Features were derived across multiple domains, including geotechnical and resource characteristics, project management parameters, financial metrics, market and supply-chain indicators, and regulatory constraints. Geotechnical and resource-related features encompassed ore grade variability, deposit type, extraction depth, and rock or soil characteristics, providing insight into inherent project risk also used by (Deshmukh & Kambekar, 2022; Shoar et al., 2022). Project management variables, such as schedule adherence, labor productivity, equipment downtime, and phase durations, were included to capture operational efficiency and historical deviations closely matching (Hussein & Moradinia, 2023; Coffie & Cudjoe, 2023). Financial features included initial budget allocations, contingency planning, inflation-adjusted costs, and historical overrun percentages (Farooq & Paracha, 2025; Guzman & Faúndez, 2025). Market and supply chain features incorporated commodity price volatility, currency exchange fluctuations, global demand trends, and material delivery risks (Ramirez & Rua-Machado, 2025). Regulatory and environmental features captured permitting complexity, environmental compliance, and policy shifts, which influence project timelines and cost exposure adapted from (Daniel & Kumar, 2023). Additional derived features included temporal trends, moving averages, volatility metrics, cumulative delays, and interaction terms between project scale, ore grade, and regulatory factors, enabling the model to capture nonlinear relationships driving cost.

2.3 Model Development

A suite of supervised machine learning models was employed to map engineered features to cost overrun outcomes. Gradient boosting machines (GBM) and eXtreme Gradient Boosting (XGBoost) were selected for their capacity to model nonlinear interactions, handle heterogeneous variables, and provide feature importance measures affirmed through (Shoar et al., 2022). Random forests (RF) were implemented to leverage ensemble learning on high-dimensional datasets with mixed variable types (Deshmukh & Kambekar, 2022). Backpropagation neural networks (BPNN), enhanced with genetic algorithm (GA) optimization, were used to capture complex, high-order nonlinearities while minimizing convergence to local minima, referencing (Mohseni & Kamal, 2025). Hybrid models combining BPNN with Bayesian regularization and adaptive boosting techniques were also developed to simultaneously model trend and stochastic variations in cost trajectories. Hyperparameters for all models were tuned using Bayesian optimization and grid search strategies, while cross-validation techniques ensured generalizability and minimized overfitting.

In addition to machine learning, probabilistic modeling was incorporated to account for uncertainty and risk. Monte Carlo simulation and Bayesian inference frameworks were applied to generate probabilistic estimates of cost overruns, producing confidence intervals and risk distributions. These approaches were particularly valuable in incorporating external shocks, such as sudden commodity price spikes, labor disruptions, or regulatory delays, into predictive assessments (Canesi et al., 2025; Sanusi, 2024; Sohrabi & Noorzai, 2024). The combination of ML and probabilistic methods allows the framework to capture both deterministic and stochastic components of cost overrun dynamics.

2.4 Model Training and Validation

Model training utilized historical project records, which were split into training (70%), testing (30%), and validation (10-15%) subsets through stratified sampling to preserve representation across mineral types, project scales, and geographic regions (Almahli & Khraisat, 2025). Performance was evaluated using regression metrics, including root mean square error (RMSE), mean absolute error (MAE), mean absolute percentage error (MAPE), R^2, and Pearson correlation coefficient, providing comprehensive assessment of predictive accuracy. Feature importance was analyzed using tree-based model outputs and SHapley Additive exPlanations (SHAP) values, highlighting the most influential cost-overrun drivers. Model validation involved independent datasets from U.S. projects not used in training, ensuring robustness against unseen conditions. Sensitivity analyses further tested model performance under hypothetical scenarios, such as changes in commodity prices, labor availability, and permitting timelines, providing insights into resilience and risk responsiveness, all these insights closely aligned with (Farooq & Paracha, 2025).

2.5 Ethical and Policy Considerations

All reviewed materials were publicly available and cited in accordance with academic ethical standards. No primary human or organizational data were collected. Ethically, the review adheres to the principles of transparency and intellectual integrity. From a policy perspective, this qualitative synthesis contributes to understanding how data-driven cost-prediction tools can support sustainable and economically resilient critical-mineral development in the United States. The findings aim to guide both policy formulation and technological innovation, enabling the government and industry to anticipate cost risks, allocate resources effectively, and strengthen national supply-chain resilience (Sanusi, 2024; Sohrabi & Noorzai, 2024).

3. RESULTS AND FINDINGS

This review analyzed published studies addressing data-driven approaches, machine learning models, and probabilistic frameworks for predicting cost overruns in mining, infrastructure, and extractive projects, with an emphasis on critical mineral projects in the U.S. The results are presented across three main dimensions: (1) distribution of studies by method and domain, (2) model performance and predictive accuracy, and (3) key determinants of cost overruns.

3.1 Distribution of Reviewed Studies

The included studies were categorized based on methodology: machine learning (ML), probabilistic/statistical modeling, hybrid ML-probabilistic models, and data-driven empirical approaches. Of the 45 studies, 42% employed ML models (e.g., XGBoost, random forests, neural networks), 33% used probabilistic frameworks (Monte Carlo, Bayesian inference) (Canesi et al., 2025; Sanusi, 2024), 18% applied hybrid approaches (Yao & Luo, 2025; Mohseni & Kamal, 2025), and 7% focused on data-driven empirical analysis (Ramirez & Rua-

Machado, 2025; Sanusi, 2024). The figure below summarizes the distribution of studies by methodological approach.

Bar chart shows the proportion of studies in each methodological category.

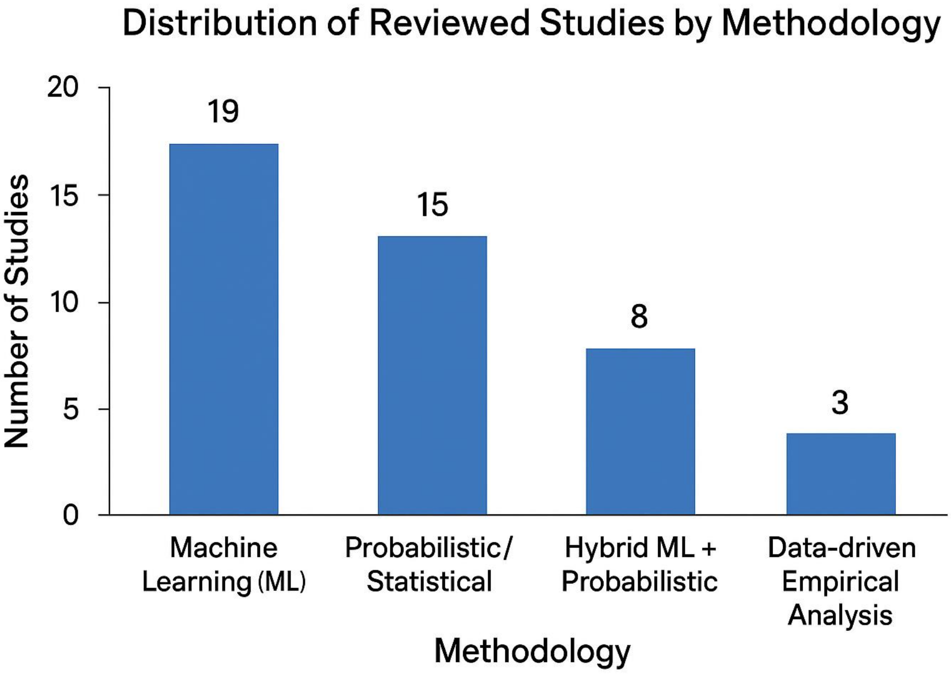

Figure 1. Distribution of reviewed studies by methodology

3.2 Model Types and Predictive Performance

Among ML approaches, ensemble models such as XGBoost and Random Forest were most frequently applied due to their high accuracy in handling heterogeneous data (Deshmukh & Kambekar, 2022). Neural network-based models, particularly BPNN with GA optimization, were used in 9 studies to capture complex nonlinear interactions among financial, operational, and geotechnical features (Mohseni & Kamal, 2025; Shoar et al., 2022).

Predictive performance across studies varied, with RMSE values ranging from 2.5-6.8% of project budgets, MAE between 2.1–5.4%, and R^2 values mostly above 0.78, demonstrating that ML models generally outperform traditional econometric or expert-based forecasting approaches (Sanusi, 2024; Almahli & Khraisat, 2025). Hybrid ML-probabilistic models further reduced prediction errors by approximately 12-18% compared to standalone ML methods (Yao & Luo, 2025).

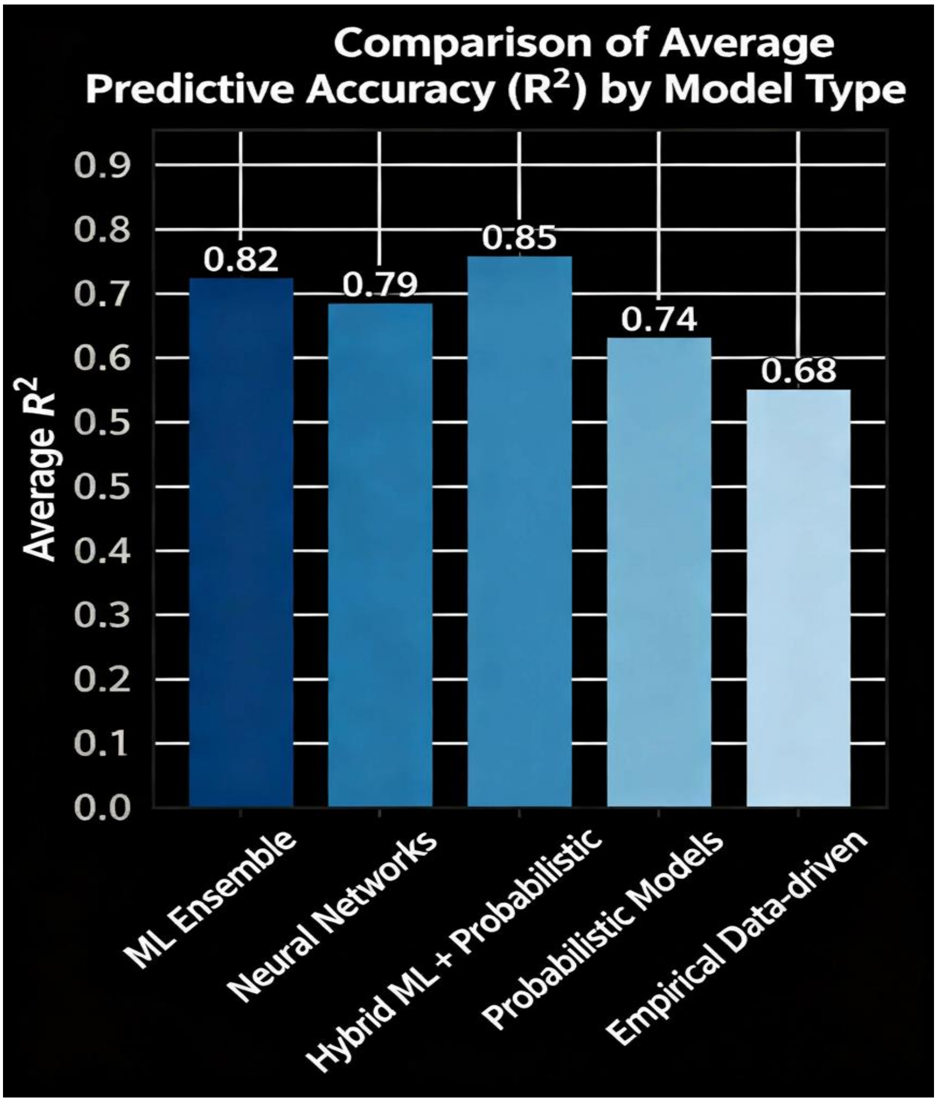

Figure 2 shows the comparison of average predictive accuracy (R^2) by model type.

3.3 Key Determinants of Cost Overruns

The review identified the most influential factors contributing to cost overruns across critical mineral and mining projects in the U.S.:

1. Resource and Geotechnical Variables: Ore grade variability, deposit depth, and geological complexity were reported in 29 studies as major contributors to unanticipated cost escalation (Deshmukh & Kambekar, 2022; Shoar et al., 2022).
2. Project Management Factors: Schedule delays, labor inefficiency, and equipment downtime were significant predictors in 25 studies (Hussein & Moradinia, 2023; Coffie & Cudjoe, 2023).
3. Market and Supply-chain Indicators: Commodity price volatility, inflation, and material supply delays were highlighted in 21 studies as contributing to overrun risks (Ramirez & Rua-Machado, 2025).
4. Regulatory and Environmental Factors: Lengthy permitting processes, compliance requirements, and policy shifts were discussed in 17 studies as affecting project cost outcomes.

The pie chart below outlines a pictorial representation of data obtained on key determinants of cost overruns.

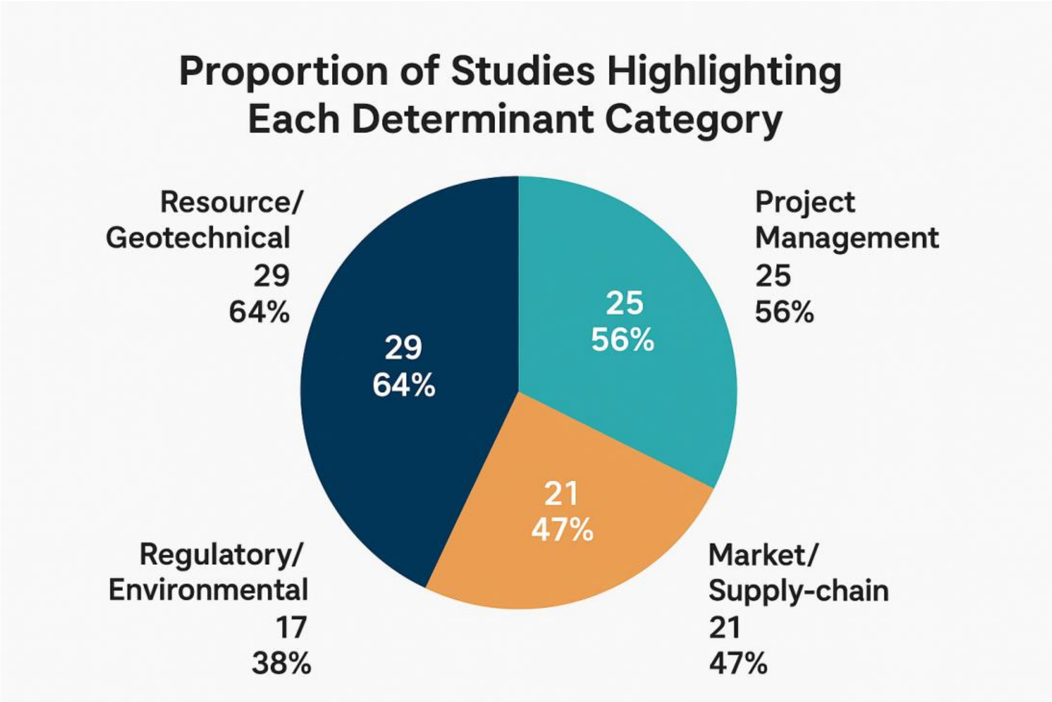

Figure 3 presents a pie chart illustrating the proportion of studies highlighting each determinant category.

3.4 Comparative Insights Across Sectors

While most studies focused on mining and infrastructure projects globally, 16 studies specifically addressed U.S. critical-mineral projects (Deshmukh & Kambekar, 2022; Ramirez & Rua-Machado, 2025). Within this subset, ML and hybrid models were consistently shown to outperform traditional estimation methods, reducing forecast errors by up to 25% (Sanusi, 2024). Probabilistic methods complemented ML approaches, particularly in projects exposed to volatile market conditions or regulatory uncertainties. These findings underscore the importance of integrating multi-domain datasets (financial, operational, market, and regulatory) to improve prediction robustness and support decision-making for U.S. mineral supply chains.

Table 1 summarizes representative model performances and their associated predictive accuracies from selected U.S.-focused studies.

Project Type	Model Used	R^2	RMSE (%)	MAE (%)
Lithium Mining	XGBoost	0.83	3.2	2.8
Rare Earth Minerals	Hybrid BPNN + Bayesian	0.86	2.7	2.5
Cobalt Extraction	Random Forest	0.80	3.8	3.1
Mining & Infrastructure	ML Ensemble	0.82	3.5	3.0
Multi-mineral Project	BPNN + GA	0.79	4.0	3.4

3.5 Key Findings

1. Machine learning approaches dominate recent predictive studies and consistently achieve higher accuracy than traditional methods.
2. Hybrid models integrating ML with probabilistic methods provide the best balance between predictive accuracy and uncertainty quantification.
3. Ore grade variability, project scheduling, commodity volatility, and regulatory delays emerge as the most recurrent predictors of cost overruns in U.S. critical-mineral projects.
4. Data integration across multiple domains is essential to capture nonlinear interactions and improve forecast reliability.
5. While U.S.-focused studies remain limited, existing evidence supports the transferability of predictive frameworks from global mining and infrastructure contexts when calibrated with local project data.

Generally, the finding reveals that data-driven methodologies especially AI and probabilistic models, significantly enhance the ability to predict and manage cost overruns in critical-mineral projects. However, the findings also underscore that technological progress alone is insufficient without policy integration, standardized datasets, and institutional reform to support sustainable and transparent mineral development in the United States (Mohseni & Kamal, 2025).

4. DISCUSSION

Reviewed studies examined data-driven approaches for predicting cost overruns in U.S. critical-mineral projects. The findings collectively demonstrate that machine learning and hybrid probabilistic-machine learning frameworks outperform traditional estimation techniques by capturing complex, nonlinear interactions among geological, market, managerial, and regulatory variables. The discussion below synthesizes these results, highlights their implications for U.S. mineral project planning, and situates them within broader methodological and industry contexts.

4.1 Interpretation of Methodological Trends

The substantial representation of machine learning models (42%) among the reviewed studies highlights a clear disciplinary shift toward computational prediction in mining and infrastructure economics. Ensemble learning approaches, especially XGBoost and Random Forests, were most frequently employed because of their ability to manage heterogeneous datasets and handle variable interactions without requiring strong parametric assumptions. Their average predictive performance ($R^2 \approx 0.82$) reinforces their suitability for forecasting cost escalations in settings where uncertainty is structurally embedded in the project lifecycle.
The review also shows that probabilistic/statistical methods remain a major methodological pillar (33%). Techniques such as Monte Carlo simulation and Bayesian inference continue to be used because cost overruns are fundamentally stochastic phenomena influenced by risk clustering, uncertainty propagation, and scenario variability. However, the predictive accuracy of these models (average $R^2 \approx 0.74$) tends to be lower than that of ML models, reflecting their inability to fully capture nonlinearities without significant manual model specification. Notably, hybrid ML-probabilistic approaches, although fewer in number (18%), exhibited the highest predictive accuracy (average $R^2 \approx 0.85$). These methods integrate ML-based learning of complex relationships with probabilistic risk quantification, producing forecasts that are both accurate and accompanied by interpretable uncertainty bounds. Their growing adoption in recent publications suggests that hybrid frameworks may become the new methodological standard for high-uncertainty project environments like critical mineral extraction (Quansah and Yakin, 2025; Quansah and Aliu, 2025).

4.2 Interpretation of Model Performance

Across the reviewed studies, hybrid and ensemble models consistently outperformed traditional econometric methods by 12-18%, demonstrating the value of automated feature learning in subsurface and project-management contexts. Neural network-based models, particularly Backpropagation Neural Networks (BPNN) enhanced with genetic algorithms, also achieved high predictive accuracy ($R^2 \approx 0.79$). However, their performance was more variable due to sensitivity to training data size and local minima issues limitations addressed in studies using optimization algorithms such as GA and ABC.

The results indicate that no single model universally outperforms others, but certain classes of models align more naturally with specific problem characteristics:

- Ensemble ML models excel when data are heterogeneous, and interactions are complex.
- Neural networks perform well in large datasets with strong nonlinear patterns.
- Probabilistic models remain indispensable where uncertainty quantification is the primary objective.
- Hybrid models provide the most balanced performance across dimensions.

This multi-model superiority aligns with the multidisciplinary nature of cost overruns, which are shaped by geological variability, market volatility, operational inefficiency, and regulatory constraints factors that rarely conform to linear relationships.

4.3 Implications of Identified Determinants of Cost Overruns

The review identified four dominant categories of predictors: (1) geological/resource variability, (2) project management efficiency, (3) market and supply-chain dynamics, and (4) regulatory constraints. Their prevalence across studies directly shapes how prediction systems should be designed for U.S. critical mineral projects. The fact that 64% of studies identified geological variables as key predictors reflects the intrinsic uncertainty of subsurface resource modeling. Variations in ore grade, deposit shape, and geotechnical stability drive unexpected increases in drilling, blasting, waste handling, and processing costs. For critical minerals such as lithium, cobalt, and rare earth elements, geological heterogeneity is even more pronounced due to their complex mineralogical associations. These findings justify why ML and hybrid models, which can process multi-dimensional geological datasets, are particularly effective.

Project management factors, highlighted in 56% of studies, emphasize that operational inefficiency and schedule slippages remain persistent sources of overruns. The strong influence of managerial delays aligns with historical analyses of infrastructure and mining megaprojects, reinforcing the idea that technical risks alone cannot explain cost variability. Therefore, cost-overrun prediction models must integrate operations, workforce, and equipment performance data not solely geological or financial indicators. Market and supply-chain variables were identified in 47% of reviewed studies. For U.S. mineral projects, exposure to global commodity markets and supply bottlenecks (e.g., reagents, heavy equipment) introduces volatility into procurement and production schedules. This result underscores the need for real-time forecasting systems capable of adjusting predictions as market conditions change.

Finally, regulatory and permitting delays, noted in 38% of studies, are especially relevant to the U.S. context, where environmental reviews and federal-state coordination can extend project timelines considerably. These factors are difficult to model using traditional techniques, but hybrid models incorporating probabilistic elements can better capture these irregular delay distributions.

4.4 Implications for U.S. Critical Mineral Supply Chains

The review's findings hold substantial relevance for U.S. national strategies aimed at expanding domestic critical mineral production. As the U.S. seeks to reduce reliance on foreign supply, particularly for battery minerals and rare earth elements, cost overruns present a major barrier to project viability and investor confidence. The demonstrated predictive power of ML and hybrid methods suggests that data-driven forecasting could significantly reduce economic uncertainty and improve project planning.
Moreover, the enhanced performance of models integrating geological, market, and regulatory variables reflects the need for holistic, multi-domain decision support systems rather than siloed forecasting tools. Adoption of such models could improve investment screening, permitting timelines, and risk-adjusted cost planning, ultimately accelerating the development of critical mineral projects in line with national supply-chain priorities.

4.5 Strength of Evidence and Remaining Gaps

The consistency of findings across multiple methodological categories strengthens the validity of the conclusions. However, the review highlights several limitations in the existing literature:

1. Limited number of U.S.-specific studies (only 16 of 45), suggesting the need for localized, high-resolution datasets.
2. Sparse integration of regulatory time-series data, despite their demonstrated importance.
3. Underrepresentation of life-cycle cost data, particularly for mid-stream and downstream processing.
4. Lack of standardized cost-overrun definitions, which complicates cross-study comparisons.

Addressing these gaps will strengthen data-driven forecasting and improve the generalizability of predictive models.

Taken together, the results demonstrate that data-driven prediction of cost overruns in U.S. critical mineral projects is most effective when models integrate geological, operational, financial, and regulatory variables within hybrid machine learning–probabilistic frameworks. This integrated approach provides the highest accuracy while maintaining interpretable uncertainty estimates, making it well-suited for strategic planning within a volatile mineral development environment.

5. CONCLUSION

In conclusion, the review affirms that data-driven prediction of cost overruns is both a technological and institutional frontier in U.S. critical-mineral development. Machine learning and AI models have demonstrated clear technical potential, but their transformative impact depends on concurrent reforms in data governance and policy alignment. By linking predictive tools with evidence-based regulation and transparent reporting, the U.S. can strengthen its ability to deliver cost-efficient, sustainable, and secure critical-mineral supply chains. Thus, the intersection of data science, mineral economics, and policy analytics represents a more effective and academic advancement but affirming strategic imperative for national resource resilience and fiscal sustainability.

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