

Artificial Intelligence in Construction Cost Estimation: Enhancing Budget Accuracy and Controlling Cost Overruns

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ABSTRACT

Construction projects frequently experience cost growth because early estimates are produced under incomplete design information and later exposed to inflation, scope change, productivity variation, supply disruption, contractual claims and managerial bias. Artificial intelligence (AI) offers a data-driven response by learning relationships among project characteristics, market conditions and realized costs. This article critically examines how machine learning, artificial neural networks, case-based reasoning, natural-language processing, computer vision and AI-enabled building information modelling can improve conceptual estimating, quantity take-off, tender analysis and estimate-at-completion forecasting. It argues that the principal benefit of AI is not a single, perfectly accurate estimate but a continuously updated decision system that produces ranges, detects emerging variance and explains the drivers of risk. Evidence from the literature indicates that AI models can represent nonlinear cost relationships and outperform simple parametric approaches in suitable datasets; however, performance is highly dependent on data quality, representativeness and validation. A practical implementation framework is proposed, integrating governed historical data, probabilistic forecasting, human review, drift monitoring and feedback from completed projects. The article concludes that AI can reduce avoidable overruns when embedded in cost governance, but it cannot correct strategic misrepresentation, uncontrolled scope or poor commercial decisions on its own.

INTRODUCTION

Cost estimation is central to feasibility analysis, financing, tendering and project control. Yet the estimate prepared at approval is often treated as a fixed promise even though design maturity, market prices and delivery conditions continue to change. Flyvbjerg, Holm and Buhl (2003) analyzed 258 transport infrastructure projects in 20 countries and found that cost escalation was the rule rather than the exception. Their evidence remains influential because it demonstrates that inaccurate forecasting is not merely a technical inconvenience: it distorts investment selection, weakens public confidence and reduces the value available for other projects.

Traditional estimating remains indispensable. Quantity surveyors decompose work, measure quantities, apply labor, plant and material rates, account for preliminaries and overheads, and price risk. Nevertheless, spreadsheets and deterministic unit-rate models may struggle with nonlinear interactions, incomplete conceptual information and rapidly changing conditions. AI extends rather than abolishes this process. Machine-learning systems can identify patterns across completed projects, compare a proposed scheme with historical analogues, extract risk signals from documents and update final-cost forecasts as progress data arrive. A systematic review by Elmousalami (2020) showed that construction cost prediction has employed statistical, analogy-based and analytical models across buildings, roads, railways, tunnels, power and water projects. More recent reviews similarly locate machine learning, neural networks and hybrid systems at the centre of data-driven estimating (Abioye et al., 2021; Okeke et al., 2025).

This article examines three questions: how AI improves budget accuracy; how predictive tools can support the control of overruns during delivery; and what organizational safeguards are necessary for dependable use. The discussion is conceptual and evidence-based, drawing on peer-reviewed construction-management literature. It does not claim that performance values from one dataset will transfer automatically to another region or asset class.

2. The Cost-Overrun Problem

A cost overrun is commonly measured as the percentage difference between actual completion cost and the estimate at a defined decision point, expressed in constant prices. The baseline must be stated because an estimate at initial approval is less mature than one at contract award. Apparent accuracy can also be manipulated by rebasing, removing scope or

mixing nominal and real prices. Sound AI therefore begins with a consistent target variable and a traceable estimate history.

Overruns arise through interacting technical and institutional causes. Technical uncertainty includes incomplete quantities, ground conditions, design development, productivity variation and estimation error. Market uncertainty includes labour scarcity, commodity volatility, exchange rates and contractor capacity. Delivery factors include delay, rework, change orders, claims and weak interface management. Finally, optimism bias and strategic underestimation can suppress the approved budget. AI can learn recurring patterns in the first three groups when adequate evidence exists, but algorithms cannot by themselves resolve incentives that reward a low opening estimate.

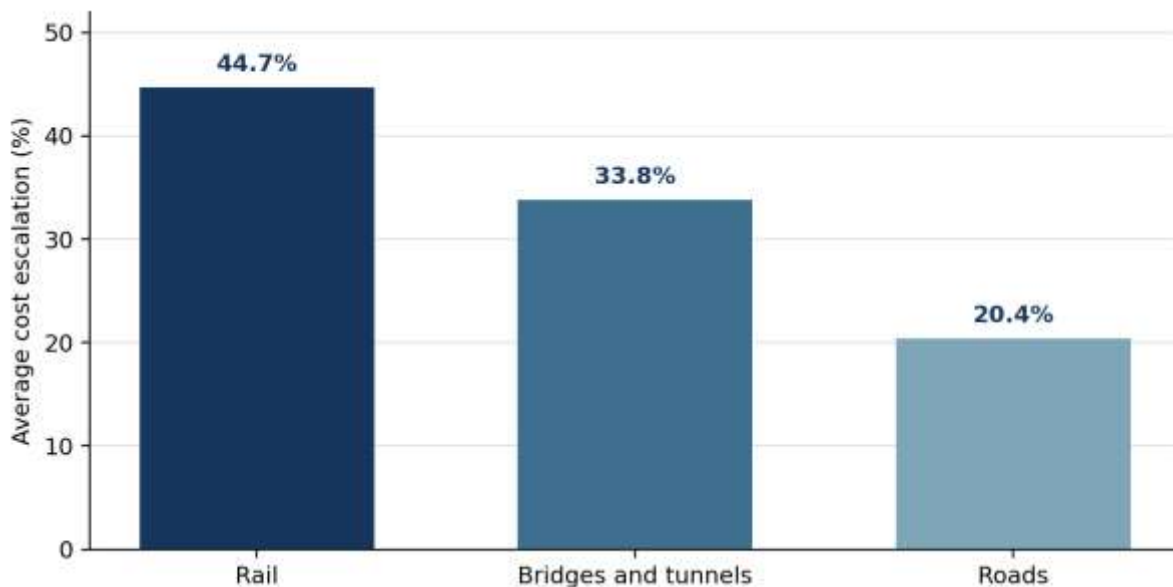


Figure 1. Average cost escalation by transport infrastructure type

Figure 1 shows why cost models should be segmented by project type. Rail projects in the cited sample averaged 44.7% escalation, compared with 33.8% for fixed links and 20.4% for roads. A generic model trained across these categories without asset-type controls could conceal materially different risk distributions. Project class, geography, procurement route, scale and estimate stage should therefore be represented explicitly or modelled through carefully selected peer groups.

3. AI Techniques for Construction Cost Estimation

Supervised learning maps input variables to a known output, such as tender price, final account value, cost per square metre or percentage overrun. Linear regression provides a transparent baseline, while decision trees capture thresholds and interactions. Random forests and gradient-boosting models combine multiple trees and often perform strongly on structured project data. Support-vector regression is useful in smaller, nonlinear datasets, whereas artificial neural networks can approximate complex relationships when sufficient observations are available. Rafiei and Adeli (2018), for example, developed an advanced machine-learning model for construction-cost estimation that incorporated economic variables and indices. The appropriate model is therefore selected through validation, not fashion.

Accuracy must be assessed with out-of-sample evidence. Mean absolute error and mean absolute percentage error communicate typical error, root mean squared error penalises large misses, and R-squared indicates explained variation but does not measure calibration. Cross-validation should respect time and project grouping: randomly mixing records from the same programme between training and testing can exaggerate generalisation. Prediction intervals are also essential. A point estimate of 100 million has a very different decision meaning if the credible range is 98-103 million rather than 75-140 million.

BIM, Computer Vision and Language Models

Building information modelling supplies geometry, object properties and design revisions that can be linked to cost codes. In a 5D BIM workflow, quantities and prices are connected so that design changes trigger-controlled cost updates. Ma, Liu and Mills (2022) described a machine-learning-integrated 5D BIM informatics framework that automated the estimation of building elements and linked model information to standardized cost items. Likewise, Juszczak et al. (2023) combined BIM properties with deep learning for construction-cost prediction. These approaches

reduce manual quantity-transfer errors, but only when model completeness, classification and level of development are verified.

Computer vision can measure installed work from site images or scans and compare progress with modelled quantities. Natural-language processing can classify bill items, extract scope obligations from specifications and identify risk language in tender or contract documents. Williams and Gong (2014) demonstrated that text mining combined with numerical project data could predict construction cost overruns, illustrating the value of information that conventional numeric tables omit. Generative language models can help draft assumptions and retrieve comparable items, but their outputs require source verification because fluent text is not evidence of a correct quantity, rate or contractual interpretation.

Table 1. AI applications across the construction cost-management cycle

Application	Typical inputs	Primary contribution	Suitable methods	Main control
Conceptual estimate	Area, capacity, location, asset type, indices	Rapid range and option comparison	Regression; random forest; neural network	Peer-group validation
Quantity and rate build-up	BIM objects, cost codes, rate libraries	Automated take-off and consistent classification	BIM rules; NLP; classification	Model and code audit
Tender assessment	Bid breakdowns, qualifications, market history	Detects anomalies and unbalanced pricing	Clustering; anomaly detection; NLP	Commercial review
Overrun early warning	Progress, commitments, changes, schedule and EVM	Forecasts final cost and variance drivers	Boosting; time-series; hybrid EVM-ML	Monthly recalibration

Source: Author's synthesis of Elmousalami (2020), Ma et al. (2022), Juszczak et al. (2023), Williams and Gong (2014), and Wauters and Vanhoucke (2023).

4. Enhancing Budget Accuracy

AI improves an estimate through consistency, scale and conditional comparison. First, it can normalize historical costs by location, time, currency, specification and capacity before retrieving comparable projects. Second, it can incorporate variables simultaneously rather than relying on a single cost-per-area factor. Third, feature-importance methods can show whether floor area, structural system, duration, location index or procurement route drives the prediction. Interpretable models are particularly important for public approval and professional sign-off; recent work on metro and power-project estimation reflects the move toward explainable machine learning rather than opaque accuracy alone (Chakraborty et al., 2024; Mahjoubi et al., 2025).

The strongest estimate is a distribution rather than a deterministic number. Quantile regression, Bayesian models or conformal prediction can produce P50 and P80 budgets, enabling the client to separate expected base cost from risk allowance. Scenario analysis can then test inflation, productivity and design alternatives. Reference-class data can provide an outside view, while project-specific modelling provides the inside view. Combining both reduces the danger that a sophisticated algorithm simply reproduces the optimism embedded in the organization's historical baselines.

AI also supports estimate reconciliation. When a bottom-up quantity estimate differs materially from a top-down model, the system can flag the packages, assumptions or rates contributing most to the gap. This directs expert attention to high-impact uncertainty rather than encouraging indiscriminate contingency. However, a lower model error does not automatically imply a better approved budget: contingency policy, exclusions, escalation basis and client risk appetite remain governance decisions.

5. Controlling Cost Overruns During Delivery

Overrun control requires a shift from a one-off preconstruction estimate to continuous forecasting. Actual costs, commitments, approved changes, pending changes, progress quantities, schedule status and risk-register movements should feed a monthly or near-real-time cost model. Earned value management (EVM) supplies cost and schedule performance indicators, but conventional estimate-at-completion formulas rely on fixed assumptions. Wauters and Vanhoucke (2023) showed how machine learning can improve cost and duration prediction alongside EVM by learning from prior project trajectories.

An effective early-warning model predicts both the likely final variance and its drivers. For example, it may detect that procurement delay, declining productivity and a rising volume of unresolved requests for information jointly precede package overruns. Managers can then act by freezing design, resequencing work, expediting procurement, renegotiating

scope or allocating contingency. The model creates value only when alerts are tied to owners, thresholds and response times. A dashboard with no decision protocol merely automates observation.

Change control is another high-value use. AI-BIM comparison can identify revised elements, recalculate affected quantities and trace them to work packages. NLP can screen instructions and correspondence for potential change events, while anomaly detection can identify unusual unit rates or commitment patterns. Human commercial teams must confirm entitlement, causation and valuation. In this hybrid arrangement, AI accelerates detection and prioritisation; accountable professionals determine the contractual and financial response.

6. Limitations, Governance and Ethical Issues

Data quality is the principal constraint. Historical final accounts may use inconsistent cost codes, omit failed bids, conceal scope transfers or lack information about design maturity. Inflation indices cannot fully correct structural changes in supply chains. Small datasets encourage overfitting, while imported models may fail under different regulations, labour markets and procurement systems. Elmousalami (2020) therefore emphasised the need for adequate datasets, and broad construction-AI reviews identify interoperability, fragmented information and implementation capability as persistent obstacles (Abioye et al., 2021).

Governance should include a data dictionary, baseline rules, documented exclusions, access controls, versioned models and reproducible validation. Training data must be screened for leakage, and performance should be reported separately by project type, size and stage. Drift monitoring is essential when prices, standards or delivery methods change. Explainability tools such as SHAP values can expose influential variables, but explanations do not prove causality. Independent quantity-surveyor review should remain mandatory for material decisions.

Ethical concerns include confidentiality of bids and subcontractor rates, cybersecurity of BIM and commercial systems, and bias against unfamiliar project types or smaller contractors. Procurement teams should avoid treating a model score as an unquestionable ranking. Every estimate should retain an audit trail identifying data sources, model version, human adjustments and approval authority. Professional responsibility cannot be delegated to software.

7. Implementation Framework

A staged implementation reduces technical and organizational risk. The organization should first define the estimate target and baseline point, then create a governed dataset linking scope, quantities, rates, indices, schedule, risks and final outcomes. A transparent benchmark model should be compared with one or more advanced models using time-based holdout testing. Outputs should include prediction intervals and a concise explanation of major drivers. Pilot use should run in parallel with the existing estimating process, allowing teams to measure error, review exceptions and identify workflow changes before relying on the model.

After deployment, estimate performance should be measured as a learning system. Recommended indicators include absolute error at each design stage, interval coverage, frequency of manual overrides, lead time for producing estimates, value of changes detected early and realised final variance. Post-project reviews must feed corrected data back into the repository. Senior governance should review drift, material model changes and cases where commercial judgement overrides the prediction. This socio-technical approach is more robust than purchasing an isolated AI tool.

DISCUSSION

The literature supports a balanced conclusion. AI is well suited to repetitive classification, nonlinear prediction, anomaly detection and rapid updating. It can make uncertainty more visible and can connect information that is usually separated across estimates, schedules, BIM models, procurement records and site reports. These capabilities improve the speed and internal consistency of cost decisions. Yet construction projects are temporary organizations with changing scopes and contractual incentives. Historical data encode past management behavior as well as engineering relationships. Consequently, a model may be statistically accurate while reinforcing a poor baseline culture.

The most defensible role for AI is therefore augmented estimating. The estimator defines cost logic and verifies quantities; the model supplies evidence from comparable outcomes, calculates conditional ranges and highlights anomalies; management sets contingency and acts on warnings. This division protects professional accountability while exploiting computational capacity. It also reframes the objective from eliminating all overruns, an unrealistic promise, to reducing avoidable error, detecting variance earlier and making residual uncertainty explicit.

CONCLUSION

Artificial intelligence can enhance construction budget accuracy by modelling complex cost relationships, automating quantity and document processing, reconciling estimates and generating probabilistic ranges. During delivery, AI can extend EVM, (Earned Value Management) detect emerging variance and support faster evaluation of scope and design

changes. These capabilities are most valuable when BIM (Building Information Modelling) cost, schedule, procurement and risk data share consistent identifiers.

AI alone will not control cost overruns. Poor baselines, strategic underestimation, weak scope governance and delayed management action can defeat even an accurate model. Successful adoption requires clean and representative data, out-of-sample validation, uncertainty reporting, explainability, human sign-off and continuous performance monitoring. Used within these controls, AI becomes not a replacement for the quantity surveyor or cost engineer, but a disciplined forecasting partner that improves transparency, directs attention and supports timely corrective action.

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