
FRAMEWORK FOR DYNAMIC RISK PRICING IN CONSTRUCTION CONTRACTS USING MACHINE LEARNING ON HISTORICAL CLAIMS DATA: A SCIENTIFIC LITERATURE REVIEW

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ABSTRACT

Construction contracts are exposed to a wide range of uncertainties, including changes in design, delays, resource shortages, market fluctuations, nonconformances, and disputes. The way these uncertainties are valued at the tender and contract stages has traditionally depended on fixed contingencies and professional judgement. Such approaches can be useful as a starting point, but they do not always reflect how risk changes over the life of a project. This review examines recent literature on construction risk pricing, historical claims analysis, machine learning-based risk prediction, and emerging dynamic approaches to risk management. Thirty-six studies were reviewed thematically to understand how past claims and project information are being converted into risk indicators, forecasts, and pricing decisions. The literature shows that artificial neural networks, random forest, support vector machines, gradient-boosting methods, Bayesian networks, and time-series deep learning models are being applied to predict claims, cost overruns, disputes, material prices, and other project outcomes. At the same time, the review finds that prediction and pricing are still not the same thing. Many studies estimate the probability or impact of risk, whereas relatively few explain how the resulting risk information should be translated into a transparent and contractually usable price adjustment. The review therefore points to a clear need for a practical framework that links historical claims, risk scoring, changing project conditions, and risk-based contract pricing. Issues of data quality, model interpretation, regional variation, and contractual acceptance also remain important. Overall, the evidence supports a move from static risk allowances towards more structured and data-informed risk pricing in construction contracts.

Keywords: *Construction Contracts, Claims, Risk Pricing, Risk Management, Historical Claims Data, Machine Learning, Dynamic Pricing, Cost Overrun*

1. INTRODUCTION

Risk is a normal part of construction work because projects are delivered under changing technical, commercial, environmental, and organisational conditions. A tender price therefore does more than cover direct construction cost; it also carries an allowance for uncertainty and possible loss. Earlier work on the price of risk shows that construction firms often incorporate risk through contingency or risk allowances, but the basis of these allowances is not always consistent across projects [1] [33]. In practice, a contingency may be set as a percentage of

cost, adjusted through experience, or negotiated between the parties. The difficulty is that a fixed allowance does not necessarily reflect the actual pattern of risk in a particular project.

Risk pricing becomes more difficult when risk develops during project execution. A delay caused by late instructions, a major design change, labour shortage, or sudden material price movement can alter the financial exposure after the original contract price has already been agreed. Research on construction delays and claims shows that these events are not isolated; they are connected with project characteristics, decision-making behaviour, and contractual processes [1] [6] [16]. This makes the idea of dynamic risk pricing relevant: instead of treating risk as a one-time allowance at tender stage, the risk position can be reviewed as new evidence becomes available.

The growth of digital project records has strengthened this possibility. Historical claims, contract documents, cost records, schedules, procurement data, and external market information can be used to identify recurring patterns. Recent studies have demonstrated the use of machine learning and related analytical methods for construction cost prediction, claims prediction, dispute outcomes, material price forecasting, and project risk assessment [1] [4]. These studies suggest that historical data can support more evidence-based risk decisions, although important questions remain about data quality, interpretability, and practical use in contract administration.

Objectives of the Review

- To review how construction risk, claims, and cost impacts are identified and analysed in existing literature.
- To examine the role of historical claims and project data in construction risk prediction.
- To compare the major analytical and machine learning approaches reported in recent studies.
- To examine how predictive risk information can support dynamic contingency and risk pricing decisions.
- To identify research gaps related to contractual integration, transparency, data availability, and practical application.

Review Approach

The review is based on 36 studies covering construction claims, cost and schedule risk, risk pricing, machine learning, data analytics, digital project environments, and construction contracts. The papers were read and grouped by theme rather than treated as one uniform set because they use different datasets, methods, and outcomes.

The main themes were:

- (i) risk pricing and contingency,
- (ii) historical claims and risk identification,
- (iii) predictive and machine learning methods,

- (iv) dynamic risk management, and
- (v) contractual and digital integration.

This thematic approach helps compare studies that may not use the same modelling technique but address a common construction management problem.

2. HISTORICAL CLAIMS DATA AND CONSTRUCTION RISK IDENTIFICATION

Role of Historical Claims Data

Historical claims are especially valuable because they record events that have already affected time, cost, or contractual relationships. Hosny et al. [1] used construction claims information to develop a claims prediction and decision-awareness framework, showing that past project information can be used to understand the drivers of future claims. Similar work on construction delays mapped delay factors to mitigation decisions, supporting the use of historical project experience for earlier risk recognition [6]. In the Indian context, Alqershy and Kishore [19] reported ANN-based claims prediction, demonstrating the relevance of historical claim patterns for project risk assessment.

Key Data Features and Risk Drivers

The literature indicates that useful variables are not limited to claim descriptions. Project size, building area, number of floors, location, structural characteristics, contract conditions, owner-contractor relationships, and management decisions can all provide context for risk analysis [6], [8]. External factors are also relevant. Material prices and market conditions can influence cost outcomes, while seasonal and supply-side conditions may affect nonconformances and project performance [11], [23]. These findings support the view that risk data should be considered as a combination of project, behavioural, contractual, and market information rather than as a single claim code.

Major Risk Categories Reflected in Claims

Another important point is the diversity of risk types. Construction claim datasets may contain delay claims, variation claims, payment issues, design-related disputes, site-condition issues, and other forms of contractual disagreement. A useful framework therefore needs a clear classification structure before risk scores or prices are calculated. Without consistent categories, comparisons across projects become difficult and the resulting model may capture administrative differences instead of genuine risk differences. This is one reason data standardisation is repeatedly identified as a practical challenge in the literature [10], [14], [18].

3. ANALYTICAL AND MACHINE LEARNING METHODS IN CONSTRUCTION RISK RESEARCH

Overview of Analytical Approaches

The reviewed studies use a wide range of methods. Some focus on conventional statistical relationships, while others use classification, regression, ensemble learning, neural networks,

Bayesian approaches, or hybrid optimisation methods. The choice of method generally depends on the type of outcome being predicted. A binary outcome such as whether a dispute will occur may be treated as a classification problem, whereas a final contract cost or claim amount is more naturally treated as a regression or continuous prediction problem [29].

Classification and Regression Methods

Support Vector Machines and K-Nearest Neighbours have been examined for construction risk and bid-related prediction tasks [16]. Random Forest and XGBoost are attractive where relationships are non-linear and several project variables interact; studies have applied these methods to cost and schedule deviations, cost impacts, and supply-related decisions [22]. Logistic regression remains useful as a comparatively simple benchmark for dispute-related prediction [24].

Deep Learning and Optimization Approaches

Artificial Neural Networks are one of the more established approaches in this area. They have been applied to claims prediction and contract-cost forecasting [19]. More recent work has moved towards deep learning and recurrent architectures such as LSTM and GRU for time-dependent problems such as material prices and dynamic early warnings [17]. Bayesian networks provide another useful perspective because they can represent dependency between risk factors and estimate the probability of cost overrun [26]. Hybrid methods, including combinations of clustering and optimisation, have also been proposed for complex project risk environments [20].

Model Interpretability and Practical Suitability

Interpretability is becoming increasingly important as the models become more complex. Koc et al. [23], for example, used interpretable machine learning to identify drivers of nonconformance cost impacts. Explainable approaches such as feature-importance methods and SHAP analysis can help convert prediction into information that project managers can understand [28]. This matters in construction because risk pricing affects commercial decisions and may eventually need to be explained to clients, contractors, consultants, and dispute-resolution professionals. A model that is accurate but impossible to explain may face practical resistance even when its numerical performance is strong.

4. FROM STATIC CONTINGENCY TO DYNAMIC RISK PRICING

Static versus Dynamic Risk Allowances

The central difference between conventional risk allowance and dynamic pricing is timing. Traditional approaches normally establish contingency at the tender or contract stage and then rely on project controls to manage deviations. Studies on the price of risk have long discussed the difficulty of converting uncertainty into a monetary allowance [31] [33]. More recent research suggests that new project information can be used to revise risk estimates rather than leaving the initial allowance unchanged [2] [17].

Contingency Prediction and Risk Premiums

Salih and El-adaway [3] proposed combining machine learning with Reference Class Forecasting for construction risk contingency prediction. The importance of this direction is not only the predictive technique but the idea that contingency can be linked to a probability distribution instead of a single arbitrary percentage. Other work has used Bayesian approaches to adjust risk levels according to factors such as vendor history and geography [21], [26]. Together, these studies show a gradual movement towards risk allowances that respond to evidence rather than relying only on fixed rules.

Dynamic Early Warning Systems

Dynamic early warning systems extend the same logic into project execution. LSTM-GRU approaches have been proposed to identify changing patterns and provide timely warnings when engineering risks begin to increase [17]. Interactive and adaptive decision-support research similarly suggests that project teams can combine algorithmic outputs with expert feedback as site conditions change [2]. This human-in-the-loop approach is important because construction decisions are rarely made from data alone. Contract interpretation, site realities, and management judgement still influence the final decision.

However, the reviewed evidence also reveals a major distinction between dynamic risk assessment and true dynamic pricing. Many studies stop after predicting a risk probability, cost impact, or dispute outcome [4]. A smaller group discusses contingency or risk-pricing implications directly [3]. Very few studies describe a complete and transparent mechanism in which an updated risk measure is converted into a contractually acceptable monetary adjustment. This gap is central to the present research direction.

A Practical Logic for Dynamic Risk Pricing

Based on the literature, a practical framework can be understood as a sequence rather than a single predictive model: first classify the risk; then estimate its likelihood and potential impact; combine these measures into a risk score; translate the risk score into a monetary allowance or premium; and finally review the allowance when new project evidence changes the risk level. This logic is consistent with the broader risk-pricing literature [31] and with recent predictive studies that estimate probability or cost impact [21].

A simple conceptual expression is: Risk Premium = Probability of Risk Event × Expected Cost Impact × Adjustment Factor. The adjustment factor can account for project context, data confidence, or contractual sharing rules. The formula is presented here as a conceptual link between risk assessment and pricing, not as a standard formula established by the reviewed literature. The actual form would need to be calibrated using a suitable dataset and validated against historical project outcomes.

5. DIGITAL AND CONTRACTUAL INTEGRATION

BIM, Digital Twins and Operational Data

Dynamic risk pricing becomes more useful when it is connected to the digital systems already used in construction management. BIM, project schedules, site records, procurement information, and digital twins can provide a continuous stream of project information [7]. Digital twin research in particular highlights the possibility of simulating disruptions such as labour shortages and supply-chain events across project phases [5]. Such systems can support the collection of evidence needed to update risk scores instead of depending entirely on periodic manual reviews.

Contractual Integration and Governance

The contractual side is more complicated. A risk assessment can be technically strong but still difficult to apply if the contract does not define who bears the risk, what evidence triggers a change, and how the price adjustment is calculated. Research on BIM-based contracts and smart contracts shows growing interest in linking digital information with contractual processes [35]. At present, however, automated contract adjustment is still more conceptual than routine. Human review remains important, particularly where a risk event may lead to a claim or dispute.

Financial Oversight and Digital Platforms

The literature also suggests that financial oversight could be connected to operational risk information. AI-enabled platforms have been proposed to connect project deviations with financial monitoring and lending decisions [25]. This creates a broader management perspective: risk pricing is not only a tender-stage issue but potentially a continuous financial-control mechanism. For this to work in practice, common data structures, clear audit trails, and agreed contractual rules would be necessary.

6. COMPARATIVE SYNTHESIS OF THE REVIEWED LITERATURE

Main Findings from the Literature

Across the 36 studies, the strongest common finding is that data can improve the visibility of construction risk, but the evidence is uneven across the stages of the pricing process. Prediction is relatively well represented. Claims, disputes, cost overruns, material prices, and nonconformances have all been studied using machine learning or related analytical techniques [23] [26]. Risk pricing is less developed. Earlier studies explain the importance of pricing risk and contingency, while newer studies provide tools for prediction and adaptive management [17]. Bringing these strands together remains a relatively open research problem.

Prediction Accuracy versus Interpretability

The literature also points to a trade-off between prediction power and transparency. Deep learning can model complex relationships and changing patterns, but simpler or interpretable models may be easier for commercial users to trust [28]. For a risk-pricing framework, transparency is not a secondary issue. The output may affect tender margins, contingency levels, negotiations, and claims administration. Therefore, the final framework should ideally

show not only the risk level but also why the risk has changed and how the monetary effect was obtained.

7. RESEARCH GAPS IDENTIFIED FROM THE REVIEW

Lack of Direct Risk Pricing Mechanisms

The reviewed literature identifies several gaps that are relevant for future construction management research. First, there is a clear gap between risk prediction and actual contract pricing. A large number of papers predict outcomes, while relatively few explain the complete pricing mechanism that connects a predicted risk to a monetary contract adjustment [7] [13]. Second, the lack of standardised claims data limits the ability to build and validate transferable frameworks [10].

Contractual Acceptance and Practical Implementation

Third, contractual acceptance remains underdeveloped. A dynamic price adjustment cannot rely on an algorithm alone; the parties need clear rules on data sources, trigger conditions, responsibility, evidence, and review. Research on contracts, BIM, and smart contracts suggests that digital integration is progressing, but automated financial adjustment is not yet a mature standard practice [30]. Fourth, there is a need for better regional validation. Evidence from India, Jordan, and other contexts is useful, but differences in contract forms, dispute processes, and market conditions may influence results [19].

Limited Construction Management Application

Finally, many studies are technically focused and give limited attention to implementation in day-to-day contract administration. A practical framework should be understandable to project managers, estimators, quantity surveyors, contract administrators, and contractors. It should also make room for expert judgement instead of assuming that historical data alone can explain every future event. The interactive decision-support approach proposed by Sarkheyli-Hägele et al. [2] is relevant in this regard because it recognises adaptation and human feedback as part of the risk-management process.

Research area	What the literature currently provides	Need for further work
Risk prediction	Many models for claims, cost, disputes and other outcomes [16]	Link prediction outputs to a usable pricing rule
Contingency	Evidence for probability-based and reference-class approaches [3]	Develop transparent adjustment logic for changing project conditions
Data	Multiple project and external variables are used [6]	Standardise claims definitions, formats and data quality checks
Interpretability	Explainable ML and feature-based approaches are emerging [23]	Make risk-price changes auditable for commercial and contractual use
Contract	BIM and smart-contract concepts are	Define human review,

Research area	What the literature currently provides	Need for further work
integration	developing [30]	triggers, evidence and legal/contractual rules

8. CONCLUSION

The literature reviewed in this study shows a clear movement towards more data-informed construction risk management. Historical claims, project characteristics, cost records, market information, and digital project data can provide a stronger basis for identifying and assessing risk than fixed assumptions alone. Machine learning methods have expanded the range of predictive tools available for claims, cost overruns, disputes, and other construction outcomes.

At the same time, the review shows that dynamic risk assessment is more developed than dynamic risk pricing. Existing research offers many ways to estimate probability and impact, but the translation of these estimates into a transparent and contractually workable price adjustment remains comparatively limited. This distinction is important because a useful construction-management framework must connect analytical results with commercial decisions.

The main implication is that future work should focus not only on better prediction but also on the full path from historical claim evidence to risk score, from risk score to monetary exposure, and from monetary exposure to a clearly defined contract mechanism. Data quality, explainability, regional suitability, and human judgement should remain part of this process. The proposed direction therefore supports a practical, case-based framework for risk pricing that can be tested using historical claims and project information, while recognising that contractual and organisational factors are just as important as the analytical method.

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