



Framework For Dynamic Risk Pricing In Construction Contracts Using Machine Learning on Historical Claims Data

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Abstract : Construction contracts are prepared before all project conditions and financial consequences are fully known. Design errors, unclear contractual responsibilities, inaccurate estimates, scope changes, resource delays and payment problems may generate additional costs or claims. Conventional risk allowances can be useful, but a fixed percentage or an experience-based judgement may not adequately reflect the changing exposure of an individual project. This study examines how professional risk assessment can be linked with a proposed dynamic risk-pricing framework for construction contracts. A structured questionnaire was analysed using 125 valid responses from construction professionals. Descriptive statistics, mean scores and the Relative Importance Index (RII) were used to rank risks across three dimensions: frequency, severity and perceived financial impact. Design errors and incomplete drawings received the highest combined risk-priority score (RII = 0.654), followed by unclear contract conditions and allocation of responsibilities (0.643) and inaccurate cost estimation (0.633). The survey also found that 64.0% of respondents considered fixed allowances insufficiently responsive to changing conditions, while 64.0% supported reviewing allowances when project conditions change. Published studies on construction claims and predictive modelling were reviewed to identify suitable data structures and validation practices. The resulting framework connects survey-based risk prioritisation, project information, historical claims records, conditional machine-learning analysis, contractual risk allocation and professional review. Importantly, the questionnaire dataset did not contain claim-level historical records; therefore, no machine-learning model was trained or validated in this study. The contribution is a data-informed framework and a transparent calculation structure whose predictive component requires future testing on suitable historical claims data.

IndexTerms - Construction contracts; dynamic risk pricing; construction claims; Relative Importance Index; risk allowance; historical claims data; machine learning

I. INTRODUCTION

Construction projects are delivered through contractual arrangements that bring together clients, contractors, consultants, subcontractors and suppliers. These parties work with incomplete information, changing site conditions and commercial constraints. Even when a project is carefully planned, design revisions, delayed approvals, labour shortages, material price movement, payment delays and differences in contract interpretation can affect cost and time. The consequences are not limited to the immediate event. A late design response, for example, may interrupt procurement and site activities, increase overheads and later become the basis for a claim. Risk management in construction therefore needs to consider both the event itself and the financial and contractual consequences that may follow.

Risk management guidance such as ISO 31000:2018 treats risk as something to be identified, analysed, evaluated, treated, monitored and communicated across an organisation. In construction, these activities must connect with commercial decisions. Identifying a risk is not enough when a contractor must decide what allowance to include

in a tender, or when an owner must evaluate whether a proposed contingency is reasonable. A useful assessment should indicate which risks need the greatest attention, how their effects may be expressed financially, and which party is expected to bear those effects under the contract.

Risk pricing remains difficult because project teams often use a mixture of past experience, judgement, general contingency percentages and project-specific adjustments. Such approaches are fast and familiar, and experienced professionals can bring valuable knowledge to the decision. However, the basis for an allowance may be difficult to trace or compare if assumptions are not recorded. An allowance that is reasonable for a short, well-defined project may not be suitable for a complex project with incomplete design information, uncertain ground conditions or a long exposure to market changes. Conversely, adding a large general contingency to every project may reduce tender competitiveness without necessarily addressing the risks that matter most.

Research on construction risk pricing has explored quantitative methods for translating uncertainty into monetary terms. Paek, Lee and Ock (1993), for example, proposed a fuzzy-set approach for risk pricing under uncertainty, while Laryea and Hughes (2008) examined the difference between formal pricing models and actual contractor practices. More recent research has shown that claims and dispute records may help explain the risks experienced on past projects. Such records contain information about causes, contract conditions, amounts requested and final outcomes, although they do not represent every risk or every cost absorbed without a claim (Kumar et al., 2017; Kumar et al., 2021).

Machine learning offers a possible way to analyse large, consistently recorded datasets and estimate defined outcomes, such as the likelihood of a claim, a claim-cost ratio or a dispute outcome. Published construction studies have developed models for particular targets, including variation-claim outcomes, claim tenability and financial losses caused by site accidents (Chaphalkar et al., 2015; Rai et al., 2021; Kim et al., 2022). These examples demonstrate potential, but they also underline a central requirement: the model needs data that match the question being asked. A survey of professional opinions can identify perceived risks; it cannot substitute for historical claim amounts and outcomes when a financial prediction model is to be trained.

This paper develops a practical framework that keeps these evidence sources separate while bringing them together for risk-pricing decisions. It reports the results of a questionnaire survey of construction professionals and uses the survey to rank risks by frequency, severity and perceived financial impact. It then proposes a workflow for incorporating historical claims data and machine learning when suitable records become available. The paper does not claim that a predictive model has been trained or that a numerical risk allowance has been validated for a live contract. Instead, it presents the empirical survey findings, the proposed decision structure and the conditions required for future validation.

II. LITERATURE REVIEW AND RESEARCH GAPS

2.1 Risk assessment and financial pricing

Construction risk assessment commonly separates the identification of an uncertain event from the evaluation of its possible consequences. Frequency or probability measures indicate how likely an event may be, while severity and impact measures describe what may happen if it occurs. These dimensions should not be treated as identical. An event that occurs often may have a relatively manageable cost on each occasion, whereas a less common event may cause significant disruption or a large claim. A combined ranking can assist prioritisation, but it should preserve the underlying dimensions so decision-makers can see why a risk is ranked highly.

Paek et al. (1993) recognised that the pricing decision is complicated by uncertainty in both the likelihood of a risk event and the monetary consequences associated with it. Their fuzzy-set model sought to provide a structured method for evaluating and pricing construction risk. Laryea and Hughes (2008), in turn, found that contractor risk pricing is a commercial decision shaped by more than mathematical models alone. Tender strategy, competition, contractual obligations and professional experience remain relevant. This suggests that a practical framework should support judgement with traceable evidence rather than attempt to replace professional responsibility with a single score.

A review of the field by Osei-Kyei, Narbaev and Ampratwum (2022) mapped a broad research landscape spanning risk processes, analytical methods, contingency, project planning and stakeholder management. This breadth is important because a pricing method is unlikely to work well if it ignores contract structure or how the project is managed. The risk allocation in a contract affects which party is exposed to a loss; the estimate should not automatically price risks that are clearly retained by another party, although shared or ambiguous allocation may itself require review.

2.2 Claims records as evidence of realised risk

Construction claims offer another source of information. A claim generally identifies an event or condition for which a party seeks additional payment, time or another contractual entitlement. The supporting record may contain the cause of the claim, instructions, correspondence, variation details, delay information and an amount claimed or determined. Kumar, Chandrashekhar and Singh (2017) demonstrated how past dispute records could be analysed to classify risk causes and quantify their impacts relative to contract sum. Their approach is valuable because it connects a risk event to a recorded financial consequence instead of relying only on expert ratings.

Kumar, Iyer and Singh (2021) developed a claim-based risk assessment model using 234 claims from 24 settled arbitration awards. Their work emphasises the relationship between risk events and claims and shows how claim records can inform occurrence and cost-impact assessment. Nevertheless, dispute and arbitration files form a selected subset of project experience. They are more likely to capture claims that escalated into formal processes than risks resolved informally or costs absorbed within the contractor's price. Such datasets can support analysis, but the scope of inference must be clearly stated.

Studies focused on claim types and contractual conditions provide further context for the present research. Al-Qershi and Kishore (2017) examined claim causes and types from the contractor's perspective in India. Moza and Paul (2018) analysed claims from public-works contracts and explored their relationship with contract conditions. Shaikh, Zainun and Khahro (2020) reviewed construction-claim research and identified recurring links with delay, extra work, payment, design information, variations and project management. Kalyan et al. (2022), using Indian judicial cases, further examined recurring and interrelated dispute factors. Together, this literature supports more systematic record-keeping and early attention to issues that may later lead to claims.

2.3 Machine learning in construction claims and loss analysis

Machine learning has been applied to specific construction decision problems, but the target variables differ. Hosny, Elbarkouky and Elhakeem (2015) proposed a claims-prediction and decision-awareness framework using artificial neural networks, while Chaphalkar, Iyer and Patil (2015) studied outcomes of variation claims with a multilayer perceptron neural network and data from arbitration awards. Rai, Jagannathan and Venkata Santosh Kumar (2021) used artificial neural network and decision-tree methods to assess claim tenability in Indian real-estate projects; their paper notes that the models could assess tenability but did not predict the extent of the claim. Kim et al. (2022) examined monetary losses associated with apartment construction accidents in South Korea, comparing deep learning with multiple regression. Ün et al. (2025) investigated machine-learning methods for forecasting outcomes of construction contract disputes in Türkiye.

These studies are relevant, but their results are not interchangeable. Claim acceptance or dispute outcome is normally a classification problem; estimating the monetary amount of a claim is a regression problem; and estimating whether a project will experience any claim requires records of both claim and non-claim projects or periods. Financial loss from an accident may also differ from a contractual claim amount. A dynamic risk-pricing system must therefore define its prediction target in advance and build the data to match that target. Reported performance from another country or sector cannot be adopted as evidence that the proposed framework will achieve the same accuracy on Indian construction contracts.

2.4 Research gap

The reviewed work points to three connected gaps. First, survey-based risk rankings and financial pricing are often presented as separate tasks. A risk index helps decide where attention is needed, but it does not directly provide a monetary allowance. Second, claim records can quantify realised impact, yet the availability and consistency of these records may be weak. Third, predictive studies often address one defined outcome, whereas a pricing decision must also account for the contract's risk allocation, the project's current condition and model uncertainty. The present study responds by combining professional risk prioritisation with a proposed process for preparing claims data, predicting a clearly defined outcome, calculating retained exposure and reviewing risk allowances over time. The predictive component remains a proposal because the available questionnaire dataset does not contain claim-level historical records.

III. AIM AND OBJECTIVES

The aim of the study is to develop a practical framework for dynamic risk pricing in construction contracts by linking professional risk assessment with the proposed use of historical claims data and machine learning.

The study addresses the following objectives:

1. To identify major risks associated with construction contracts from the views and experience of construction professionals.
2. To assess the frequency, severity and perceived financial impact of the identified risks.
3. To determine the relative priority of contractual and project-related risks that may affect construction costs and claims.
4. To examine professional views on historical claims information, existing risk-pricing methods and the possible use of machine learning.
5. To propose a dynamic risk-pricing framework that accounts for risk priority, estimated financial exposure, contractual risk allocation and review over time.
6. To examine published construction case studies for lessons about the data and validation needed before the framework is used in practice.

IV. METHODOLOGY

4.1 Research design

The research used a descriptive and analytical survey design. Primary information was collected through a structured questionnaire, while published academic studies were reviewed to inform the proposed framework and to examine examples of claims-based risk assessment and construction prediction. The questionnaire analysis described the respondents and ranked risk factors; it did not provide the outcome labels or project-level claim amounts required to train a machine-learning model.

4.2 Respondents and data collection

The study population consisted of professionals involved in construction planning, site execution, project management, contracts, quantity surveying, billing, consultancy and related activities. The questionnaire was distributed through online and offline modes. The thesis records 200 questionnaires distributed and a final analytical dataset of 125 valid responses, equivalent to a 62.5% response yield. The completed dataset contained 125 response rows and the fields used in the descriptive analysis were populated. The results should be understood as the views of the surveyed professional group, not as a statistically representative estimate for the entire Indian construction industry.

Respondents were asked to assess 12 risk factors across three dimensions: frequency, severity and potential financial impact. Further items asked about the availability of historical claims information, use of previous claims, existing risk-pricing practices, attitudes towards dynamic allowances, preferred review stages, perceived usefulness of machine learning, challenges in data use, confidence and willingness to use the proposed framework. The questionnaire used five-point rating scales for the risk assessment items.

4.3 Data analysis

The responses were organised and tabulated in Microsoft Excel and analysed using descriptive statistics and the Relative Importance Index (RII). Frequencies and percentages were used for respondent characteristics and categorical responses. Mean scores were calculated for the rating-scale items. The risk data were reverse-coded so that higher adjusted values consistently represented higher frequency, severity, or potential financial impact. If X is the original five-point score, the adjusted value was $X^* = 6 - X$.

For each risk item, RII was calculated as the sum of adjusted ratings divided by the highest possible rating multiplied by the number of valid numerical responses:

$$RII_i = \Sigma W_i / (A \times N_i) = \text{Mean}_i / 5$$

where ΣW_i is the sum of adjusted ratings for risk i , A is the maximum possible rating (5), and N_i is the number of valid numerical responses for that item. The analysed risk items had $N = 125$. The overall risk score was calculated as the arithmetic mean of frequency, severity and financial-impact mean scores. The combined RII was then calculated by dividing the overall score by 5. Equal weighting was used because the questionnaire did not establish a different weighting scheme. The combined RII is a comparative risk-priority indicator; it is not a probability of loss, a model prediction or a monetary allowance.

4.4 Scope of the machine-learning component

The questionnaire workbook contained survey responses only. No separate claim-level historical dataset with project characteristics, claim causes, claimed amounts and final settlement or award outcomes was supplied for the study. Accordingly, no classifier or regression model was trained, no train-test split was performed, and no

predictive accuracy, MAE, RMSE or R^2 value is reported as a result of this study. Machine learning is treated as a proposed component of the framework that can be implemented after suitable historical records have been collected, cleaned and approved for use.

IV. RESULTS

5.1 Profile of respondents

The survey included 125 valid responses from professionals working in construction planning, site execution, project management, contracts, quantity surveying and consultancy. The largest age group was 36–45 years (38 respondents; 30.4%), followed by 26–35 years (31; 24.8%); together, these groups accounted for 55.2% of the sample. In terms of professional experience, 80.8% reported at least six years in construction, including 47.2% with more than ten years. Civil/site engineers formed the largest occupational group (20.0%), while project managers and consultants/PMCs each represented 17.6%. The sample was predominantly male (85.6%). These characteristics suggest that the responses include substantial practical experience, but the uneven gender distribution and lack of evidence of random sampling mean the results should be interpreted as the views of the surveyed group rather than as a statistically representative estimate for the entire construction industry.

Table 5.1. Respondent Demographic profile

Profile variable	Category	Frequency	Percentage
Age	18–25 years	9	7.2%
	26–35 years	31	24.8%
	36–45 years	38	30.4%
	46–55 years	24	19.2%
	Above 55 years	23	18.4%
Gender	Male	107	85.6%
	Female	18	14.4%
Professional role	Civil/site engineer	25	20.0%
	Project manager	22	17.6%
	Consultant/PMC	22	17.6%
	Quantity surveyor/billing engineer	21	16.8%
	Contract engineer	18	14.4%
	Contractor/subcontractor	11	8.8%
	Other	6	4.8%
Experience	Less than 2 years	6	4.8%
	2–5 years	18	14.4%
	6–10 years	42	33.6%
	11–15 years	31	24.8%
	More than 15 years	28	22.4%

Source: Questionnaire results reported in the dissertation. Percentages are calculated within the total sample ($N = 125$).

5.2 Risk frequency, severity and perceived financial impact

Across the 12 risks, unclear contract conditions ranked first for frequency (mean = 3.320; RII = 0.664). Procurement and labour delays ranked first for severity (mean = 3.360; RII = 0.672), while design errors and inaccurate cost estimation jointly ranked first for perceived financial impact (mean = 3.448; RII = 0.690). Table 2 reports the complete values for all risks and dimensions.

The equal-weight combined ranking places design errors and incomplete drawings first (score = 3.269; RII = 0.654), unclear contract conditions second (3.213; 0.643), and inaccurate cost estimation third (3.163; 0.633). The first six risks range from RII 0.654 to 0.622, a difference of 0.032. The index is therefore best treated as a screening priority, not as a claim probability or a direct estimate of loss.

Table 5.2. Detailed numerical ranking of construction risks across four measures (N = 125)

Construction risk factor	Frequency (rank; mean; RII)	Severity (rank; mean; RII)	Financial impact (rank; mean; RII)	Combined (rank; score; RII)
Design errors and incomplete drawings	Rank 2 Mean 3.256 RII 0.651	Rank 8 Mean 3.104 RII 0.621	Rank 1 Mean 3.448 RII 0.690	Rank 1 Score 3.269 RII 0.654
Unclear contract conditions and improper allocation of responsibilities	Rank 1 Mean 3.320 RII 0.664	Rank 4 Mean 3.224 RII 0.645	Rank 8 Mean 3.096 RII 0.619	Rank 2 Score 3.213 RII 0.643
Inaccurate cost estimation and quantity calculations	Rank 6 Mean 2.976 RII 0.595	Rank 9 Mean 3.064 RII 0.613	Rank 1 Mean 3.448 RII 0.690	Rank 3 Score 3.163 RII 0.633
Changes in project scope and client requirements	Rank 4 Mean 3.096 RII 0.619	Rank 3 Mean 3.312 RII 0.662	Rank 11 Mean 3.008 RII 0.602	Rank 4 Score 3.139 RII 0.628
Poor contractor or subcontractor performance	Rank 12 Mean 2.632 RII 0.526	Rank 2 Mean 3.352 RII 0.670	Rank 3 Mean 3.400 RII 0.680	Rank 5 Score 3.128 RII 0.626
Delays in payments and cash-flow problems	Rank 8 Mean 2.864 RII 0.573	Rank 7 Mean 3.152 RII 0.630	Rank 6 Mean 3.320 RII 0.664	Rank 6 Score 3.112 RII 0.622
Inadequate documentation and contractual notices	Rank 7 Mean 2.872 RII 0.574	Rank 5 Mean 3.192 RII 0.638	Rank 7 Mean 3.248 RII 0.650	Rank 7 Score 3.104 RII 0.621
Delays in material procurement and labour availability	Rank 9 Mean 2.824 RII 0.565	Rank 1 Mean 3.360 RII 0.672	Rank 10 Mean 3.016 RII 0.603	Rank 8 Score 3.067 RII 0.613
Delays in approvals and site handover	Rank 3 Mean 3.112 RII 0.622	Rank 10 Mean 2.992 RII 0.598	Rank 9 Mean 3.088 RII 0.618	Rank 9 Score 3.064 RII 0.613
Material price escalation	Rank 9 Mean 2.824 RII 0.565	Rank 11 Mean 2.920 RII 0.584	Rank 4 Mean 3.392 RII 0.678	Rank 10 Score 3.045 RII 0.609
Unforeseen site and ground conditions	Rank 5 Mean 3.024 RII 0.605	Rank 12 Mean 2.680 RII 0.536	Rank 5 Mean 3.360 RII 0.672	Rank 11 Score 3.021 RII 0.604
Poor communication and coordination among project stakeholders	Rank 11 Mean 2.728 RII 0.546	Rank 6 Mean 3.168 RII 0.634	Rank 12 Mean 2.896 RII 0.579	Rank 12 Score 2.931 RII 0.586

Note: RII = mean score / 5. Tied ranks are retained from the dissertation (frequency: ranks 9 for material escalation and procurement/labour delays; financial impact: rank 1 for design errors and inaccurate cost estimation). The combined score is the equally weighted average of the three dimension means. These are survey-based perceptions, not observed claim probabilities or monetary loss ratios.

The full spread in combined RII was 0.068 (0.654–0.586). The narrow 0.021 gap among the top three items supports using the index to guide attention rather than as a precise forecast of monetary loss.

5.3 Historical claims information and the perceived role of machine learning

Eight types of claims information were assessed (Table 3). Final claim or dispute outcomes received the highest availability rating (77 respondents; 61.6%), whereas claim submission and settlement dates received the lowest (59; 47.2%), a gap of 14.4 percentage points.

Table 5.3. Availability of historical claims information (N = 125)

Claims information field	Mean	RII	Available / very available (n)	Percentage
Final outcome of claims or disputes	3.832	0.766	77	61.6%
Variations and additional-work records	3.552	0.710	70	56.0%
Type and cause of each claim	3.544	0.709	73	58.4%
Claimed amount and final settled amount	3.544	0.709	72	57.6%
Original contract value	3.544	0.709	73	58.4%
Contract type and risk-allocation conditions	3.448	0.690	67	53.6%
Project delay and extension-of-time information	3.432	0.686	66	52.8%
Claim submission and settlement dates	3.360	0.672	59	47.2%

No listed field exceeded 61.6% on the combined “available/very available” measure. This indicates that access or completeness may limit future modelling. Each record would therefore need checks for missing dates, claim status, amount claimed, amount settled, contract value and risk allocation before inclusion in a training dataset.

Previous claims were used “always” or “often” by 81 respondents (64.8%). Existing pricing methods were rated adequate or very adequate by 84 respondents (67.2%), while 20 (16.0%) selected inadequate or very inadequate and 21 (16.8%) selected the middle response. These results point to an improvement opportunity rather than proving that current practice is universally ineffective. The most important allowance factors and additional response distributions are reported in Table 6.

Table 5.4 Perceived usefulness of machine learning for risk and claims management

Proposed use	Mean	RII	Useful / very useful (n)	Percentage
Identify construction risks associated with higher claim costs	3.576	0.715	72	57.6%
Estimate the potential cost impact of identified risks	3.520	0.704	69	55.2%
Support decisions about suitable risk allowances	3.512	0.702	71	56.8%
Identify projects that may face higher claim risk	3.488	0.698	70	56.0%
Estimate the likely financial value of future claims	3.256	0.651	51	40.8%

Note: Ratings describe respondents’ perceived usefulness; they are not model performance measures. No machine-learning model was trained or tested using the questionnaire data.

Respondents rated identifying risks linked with higher claim costs highest (mean = 3.576; RII = 0.715; 72 respondents, 57.6%, selected useful/very useful). Estimating the monetary value of future claims scored lowest (mean = 3.256; RII = 0.651; 51, 40.8%). The difference suggests a stronger preference for risk prioritisation and decision support than for an exact claim-value forecast.

5.4 Views about changing risk allowances

For each of the three dynamic-pricing statements, 80 respondents (64.0%) gave a positive response. However, for the statement that fixed allowances may not reflect changing risk, 21 respondents (16.8%) were neutral and 24 (19.2%) disagreed or strongly disagreed. Table 7 provides the complete positive, neutral and negative distributions; periodic review is a decision control and does not itself amend a signed contract price.

The three leading implementation challenges—limited records (22; 17.6%), lack of skills/software (21; 16.8%) and incomplete or inconsistent data (18; 14.4%)—accounted for 48.8% of responses. Although 77 respondents (61.6%) were confident or very confident in validated and explainable estimates, 59 (47.2%) were definitely or probably willing to use the framework and 34 (27.2%) remained undecided.

The most frequently selected outputs were a recommended allowance and comparison of predicted costs with actual claims (22 responses each; 17.6%), followed by cost-impact estimation (20; 16.0%). An estimated monetary value for a potential claim was selected by 10 respondents (8.0%). Full counts for outputs and other preferences appear in Table 6.

Table 5.5 Claims use, current practices, confidence and willingness (N = 125)

Survey indicator	Response	Frequency	Percentage
Use of previous claims information	Always	46	36.8%
	Often	35	28.0%
	Sometimes	31	24.8%
	Rarely	10	8.0%
	Never	3	2.4%
Assessment of existing risk-pricing methods	Very adequate	42	33.6%
	Adequate	42	33.6%
	Moderately adequate	21	16.8%
	Inadequate	9	7.2%
	Very inadequate	11	8.8%
Confidence in machine-learning estimates*	Very confident	44	35.2%
	Confident	33	26.4%
	Moderately confident	26	20.8%
	Slightly confident	10	8.0%
	Not confident	12	9.6%
Willingness to use the proposed framework	Definitely willing	33	26.4%
	Probably willing	26	20.8%
	Undecided	34	27.2%
	Probably unwilling	17	13.6%
	Definitely unwilling	15	12.0%

*Confidence question framed around estimates that are validated and explainable. Percentages are calculated from the 125 valid responses.

Table 5.6 Other survey preferences and implementation priorities (N = 125)

Survey item	Response category	Frequency	Percentage
Most important factor when estimating risk allowance	Project duration and complexity	26	20.8%
	Contract value and contract conditions	20	16.0%
	Frequency of potential risks	20	16.0%
	Severity of potential risks	17	13.6%
	Professional judgement and past experience	15	12.0%
	Expected financial impact of risks	14	11.2%
	Historical claims and dispute records	13	10.4%
Preferred stage for reviewing risk assessment	Before finalising the contract	24	19.2%
	During claim or variation assessment	24	19.2%
	During tender preparation	21	16.8%
	At all major project stages	20	16.0%
	When major risks or conditions change	19	15.2%
	During regular project reviews	17	13.6%
Main challenge to applying claims data and ML	Limited availability of historical claims records	22	17.6%
	Lack of technical expertise and suitable software	21	16.8%
	Incomplete or inconsistent claims information	18	14.4%
	Confidentiality and access restrictions	14	11.2%
	Concerns about model reliability	13	10.4%
	Differences between past and current project conditions	13	10.4%

Most useful output from a risk-pricing framework	High implementation cost	13	10.4%
	Difficulty interpreting ML results	11	8.8%
	Recommended risk allowance	22	17.6%
	Comparison of predicted costs with actual claims	22	17.6%
	Estimated cost impact of a specific risk	20	16.0%
	Estimated likelihood of a claim	19	15.2%
	Ranking of major contract risks	17	13.6%
	Identification of risks needing immediate attention	15	12.0%
	Estimated financial value of a potential claim	10	8.0%

Source: Questionnaire results in the dissertation. Each block reports one response per respondent; percentages are based on $N = 125$ and may differ from 100% only because of rounding.

Table 5.7 Respondents' views on dynamic risk pricing ($N = 125$)

Statement	Positive response	n	%	Neutral (%)	Negative response n (%)
A fixed allowance may not reflect changing risks during a project	Agree / strongly agree	80	64.0 %	21 (16.8%)	24 (19.2%)
Risk allowances should be reviewed when project conditions change	Important / very important	80	64.0 %	24 (19.2%)	21 (16.8%)
Historical claims data can improve consistency in financial-impact assessment	Agree / strongly agree	80	64.0 %	28 (22.4%)	17 (13.6%)

"Positive" means agree/strongly agree for agreement statements and important/very important for the review statement. Neutral and negative categories follow the dissertation's original tabulation.

VI. PROPOSED DYNAMIC RISK – PRICING FRAMEWORK

6.1 Framework logic

The proposed framework links three information sources with a series of decision steps. The first source is the survey-derived risk register, which gives a starting point for prioritising risks based on professional views. The second source is historical project and claims data, which—once available—can support statistical or machine-learning estimates of defined outcomes. The third source is the current project record, including contract conditions, risk allocation, design status, variations, approvals, payment conditions and mitigation actions. These sources have different functions and should be labelled accordingly: perceived risk is not the same as observed claim experience, and neither one alone is a monetary allowance.

Figure 1 summarises the workflow. The survey risk ranking helps determine which risks deserve attention, but financial forecasting requires additional historical records. At the project stage being assessed, the team should define a prediction target before selecting a model. If the target is whether a claim will occur, the dataset must include eligible projects or project periods with no claim as well as those with claims. If only claim files are available, the task may be limited to estimating the cost or outcome of observed claims, and the result must not be described as the probability that any project will generate a claim.

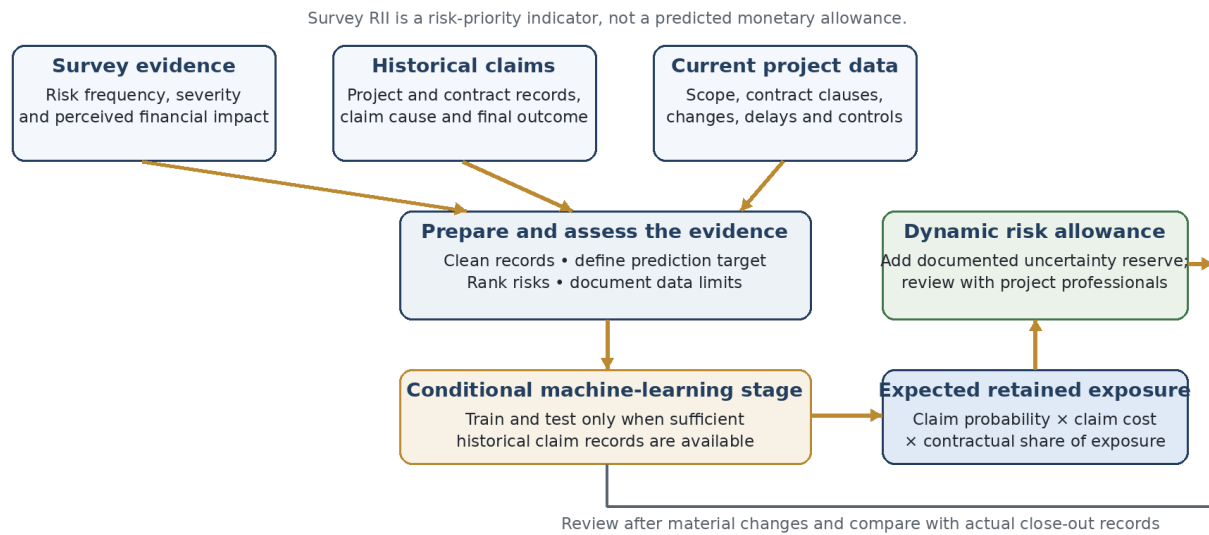


Figure 6.1. Proposed workflow for dynamic risk pricing. The machine-learning stage is conditional on suitable historical claims data and out-of-sample validation.

6.2 Dataset requirements and preparation

A usable historical claims dataset should connect each claim to the project, contract, risk event and financial outcome. At minimum, the dataset should include an anonymous project identifier; project type and contract type; original contract value and planned duration; relevant clauses and risk allocation; cause and type of claim; event and claim dates; delay, extension-of-time and variation information; amount claimed; amount settled or awarded; currency and price date; claim status; and the information that was available at the intended prediction stage. Identifiers and confidential information should be protected, and records should be used only where the necessary authorisation exists.

Before model development, duplicate records, inconsistent dates, missing values and incompatible claim categories should be checked. Financial amounts recorded in different years may need a documented price adjustment if they are to be compared. Unresolved, withdrawn or partially settled claims should not be assigned a final outcome that is not supported by the records. Most importantly, information that became known after the prediction date must not be used as a model input for a prediction intended to be made earlier. This would create information leakage and produce an overly optimistic performance estimate.

Table 6.1. Recommended historical claims fields for future implementation

Data group	Example fields	Purpose
Project profile	Anonymous project ID, project type, region, project value, duration	Define the setting and compare cases
Contract context	Contract form, clauses, payment terms, variation and notice procedures	Interpret the relevant contractual responsibilities
Risk event	Risk category, cause, event date, design/approval/site/payment issue	Connect project conditions with the claim
Time and change records	Delay duration, extension of time, approved variations, design revisions	Describe the schedule and scope effects
Financial outcome	Claimed amount, settled/awarded amount, currency, price date	Define a consistent outcome for cost analysis
Status and review timing	Resolved/unresolved status, date resolved, information available at pricing stage	Avoid mixing final outcomes with earlier inputs
Actual project outcome	Final cost, completion date, approved change orders	Support comparison with final project performance

6.3 Prediction tasks and validation

A classification model may be appropriate for a clearly defined event such as claim occurrence or a specified dispute outcome. Candidate methods could include logistic regression, decision trees, random forest, gradient boosting or support vector machines, chosen according to the dataset size, structure and target. A regression model may be more suitable for a continuous value such as settled claim cost or claim cost as a proportion of

contract sum. Linear regression can provide a baseline before more complex methods are considered. This paper does not identify a best-performing algorithm because no historical dataset has been trained or tested for this study.

When records are available, the final test set should remain separate from model training and tuning. If several claims belong to the same project, a project-level split may be needed so that claims from one project do not appear in both the training and test sets where that would create leakage. For monetary estimates, MAE and RMSE can be reported with the units and scale of the outcome; R-squared may be useful for some regression problems but should not be used alone. For classification, accuracy should be accompanied by measures such as precision, recall and F1-score when class frequencies are unbalanced. Any model should be compared with a simple baseline to determine whether added complexity provides a genuine improvement.

6.4 Translating predictions into risk allowance

The financial calculation should begin only after the model output has been defined. If the model separately estimates the probability of a claim and the cost conditional on that claim occurring, the expected exposure for risk i at review time t can be written as:

$$E_{i,t} = P_{i,t} \times C_{i,t}$$

where $E_{i,t}$ is expected exposure, $P_{i,t}$ is the estimated probability of the defined claim event and $C_{i,t}$ is the expected cost conditional on the event. If the model predicts a claim-cost ratio $Q_{i,t}$ instead of a monetary cost, the expected exposure can be represented as $P_{i,t} \times Q_{i,t} \times V_t$, where V_t is the contract value defined for that analysis. The prediction and pricing formula must match the same risk category, population and review period.

The pricing party does not necessarily bear the full exposure. If $A_{i,t}$ represents the proportion of the exposure allocated to that party under the contract, the proposed dynamic allowance is:

$$RA_t = \sum_i (P_{i,t} \times C_{i,t} \times A_{i,t}) + U_t$$

Here RA_t is the proposed risk allowance at time t and U_t is an uncertainty reserve determined through a documented method, model error or approved contingency policy. The allocation factor $A_{i,t}$ should be based on the actual contract terms rather than chosen arbitrarily. If a model directly predicts expected claim cost across the entire eligible population, multiplying the estimate by claim probability again may count the probability effect twice. The model target must therefore be understood before applying the pricing equation.

The sum also assumes that risk exposures are defined consistently and are not counted twice. Risks often interact: a design revision may generate a variation, delay and additional cost. If the same loss is represented in more than one category, simple addition could overstate exposure. The uncertainty reserve must not be chosen to force a desired final figure, and a contingency already included in the base estimate should be checked to avoid duplication. Survey RII scores can prioritise risk review; they cannot be inserted into the equation as if they were probabilities or cost ratios.

6.5 Dynamic review during the contract life cycle

The allowance should be reviewed at decision points where meaningful new information becomes available. During tender preparation, the team can examine scope, drawings, contract type, value, duration, market conditions and records from comparable projects. Before award, it should confirm the final contract clauses, exclusions and responsibility for each major risk. During execution, the review may consider progress, design changes, variation orders, approvals, payments, market conditions and mitigation measures. After a major change, the current assessment can be compared with the previous one; the reason for any difference should be documented. At close-out, actual claims and cost outcomes can be compared with earlier estimates to inform future datasets.

A change in a recommended internal risk allowance does not automatically amend a signed contract price. Any adjustment to contractual payments, compensation or the contract sum must follow the relevant contractual mechanism and agreement between the parties. The framework is intended to support decisions and improve the traceability of assumptions, not to override contract terms or professional responsibility.

VII. EVIDENCE FROM PUBLISHED CONSTRUCTION CASE STUDIES

The paper reviewed published case studies to establish whether historical project and claim records have been used for risk quantification or prediction. Their value is illustrative: they show possible data structures and modelling targets. They are not a direct validation of the proposed framework, and their performance measures should not be compared as though the studies predicted the same output.

Table 7.1 Selected published evidence and its relevance to the framework

Study and setting	Evidence base	Method / target	Implication and limitation
Kumar et al. (2017), India	276 claims from 28 CPWD dispute cases	Content analysis and risk impact relative to contract sum	Connects claim causes with realised financial impact; formal disputes are a selected record source.
Kumar et al. (2021), India	234 claims from 24 settled arbitration awards	Claim-Based Risk Assessment Model (C-RAM)	Shows the potential of claim data for occurrence and cost-impact assessment.
Chaphalkar et al. (2015), India	204 variation claims from 72 arbitration awards	Multilayer perceptron for claim outcome	Demonstrates outcome prediction for a defined claim type, not direct claim-cost estimation.
Rai et al. (2021), India	Project and claim information from 275 real-estate projects	ANN and decision tree for claim tenability	Highlights the role of drawing/specification consistency; tenability is not claim amount.
Moza and Paul (2018), India	22 public-works arbitration disputes	Analysis of claim types and contract conditions	Shows why contractual clauses and claim records should be linked.
Kim et al. (2022), South Korea	930 apartment construction accident-loss records	Deep learning compared with multiple regression for financial loss	Illustrates monetary-loss modelling, but accident losses differ from contractual claims.
Ün et al. (2025), Türkiye	Arbitration-case records	Comparison of five machine-learning classifiers for dispute outcomes	Shows potential for dispute-outcome analysis while reinforcing the importance of a clearly defined target.

The Indian claim-based studies are particularly relevant because they examine local contract and dispute settings. They also show that records should distinguish the initial amount claimed from the amount settled or awarded. A model using claimed amounts as if they were final losses may give an inaccurate picture of financial exposure. Likewise, a model that predicts whether an arbitrator accepts a claim cannot be assumed to predict the expected loss at tender stage. The South Korean accident-loss study is useful as an example of financial prediction, but it deals with a different process and cannot provide performance expectations for construction contract claims. The published evidence therefore supports the proposed direction, while project-specific validation remains necessary.

VIII. DISCUSSION

The results confirm that risk priority depends on the dimension measured. Unclear contract conditions led frequency (RII = 0.664); procurement and labour delays led severity (0.672); and design errors plus inaccurate cost estimation jointly led perceived financial impact (0.690). A single ranking would conceal these differences. For pricing decisions, frequency, severity and financial impact should therefore remain visible separately before they are combined.

The top three combined RII values were 0.654, 0.643 and 0.633. They point to different controls: drawing coordination and change control for design risk; clear responsibilities, notices and variation procedures for contract ambiguity; and quantity verification and transparent assumptions for estimating risk. Scope change, contractor performance, payment and procurement remain relevant and should not be excluded merely because they rank below the first three.

The strongest data-availability result was for final claim/dispute outcomes (61.6%); submission and settlement dates were rated available/very available by only 47.2%. This matters because a claim amount without event timing and the information available at the pricing stage may be insufficient for a valid forecast. Data preparation should standardise claim status, claimed and settled amounts, contract value, time effects and risk allocation.

Respondents preferred decision-support uses—identifying higher-cost risks (RII = 0.715), estimating risk cost impact (0.704) and supporting allowances (0.702)—over estimating future claim value directly (40.8% useful/very useful). The top three barriers represented 48.8% of responses. A realistic implementation order is therefore to standardise claim records, test a transparent baseline, and only then assess whether a model improves estimates on unseen projects.

The framework is a proposed decision-support design, not a validated predictive model. Its next empirical step is to assemble claim-level historical data, define the target outcome, and compare predictions against projects not used in training. Until that testing is completed, no model accuracy or monetary pricing performance can be claimed.

IX. PRACTICAL IMPLICATION

For contractors, the risk rankings can be used as a checklist during tender preparation, especially for design completeness, contractual responsibility, quantity estimation, scope change and performance-related risks. A tender review should record the information used to set an allowance and explain how each major risk is assigned to the contractor, client or shared responsibility. This creates a clearer basis for comparing bids and revisiting assumptions when the scope or contract terms change.

For clients and consultants, the framework can improve discussion about whether a proposed contingency is linked to the actual project conditions. Review should focus on both the likelihood of an event and the scale of the financial consequence, and it should be supported by documented contractual allocation. Teams should also maintain records of notices, instructions, variations, delay events, payment status and claim outcomes. Better records can improve current contract administration and make later analysis of historical claims more reliable.

For organisations considering machine learning, the immediate priority is a dependable dataset rather than selecting an algorithm first. A consistent register of projects, contract terms, risk events and financial outcomes should be created, with clear definitions for claimed, accepted, settled and awarded amounts. Any model should be tested against a simple baseline, evaluated on unseen projects or periods, and reviewed for errors and bias. The proposed output should support—not replace—professional and contractual judgement.

X. LIMITATION AND FUTURE RESEARCH

Several limitations should guide interpretation. First, the empirical analysis is based on 125 questionnaire responses, and the respondent profile is uneven, particularly by gender. The study does not establish that the respondents represent the wider construction industry. Second, the risk scores measure respondents' perceptions and are not calculated from claim-level loss records. The combined RII is a descriptive priority measure, not a calibrated estimate of claim probability or money. Third, a separate historical claims dataset was not available for training and testing a machine-learning model; the proposed predictive component has therefore not been validated. Fourth, the published case studies involve different countries, project types, contract arrangements and prediction targets. Their numerical findings cannot be transferred directly to the present framework.

Future work should collect an authorised dataset that links projects, contract conditions, risk events and final financial outcomes. It should include both projects with claims and eligible projects or periods without claims if claim occurrence is the target. The research should define whether the aim is to predict claim occurrence, claim tenability, dispute outcome, settled claim amount or expected financial exposure. These tasks should not be combined into one ambiguous target. Further work can then compare a baseline with suitable classification or regression models, test performance on held-out projects, examine prediction uncertainty and evaluate whether the calculated allowance improves on conventional contingency methods. A later field application should also compare estimated exposure with the actual results at project close-out.

VIII. CONCLUSION

This study examined the risks that construction professionals consider important when pricing and managing construction contracts and proposed a framework for reviewing risk allowances as project conditions change. Based on 125 questionnaire responses, design errors and incomplete drawings received the highest combined risk-priority ranking (RII = 0.654), followed by unclear contract conditions (0.643) and inaccurate cost estimation (0.633). The separate rankings further showed that procurement and labour availability was rated highest for severity, while design errors and cost estimation shared the highest perceived financial-impact score. These differences support a multidimensional approach to risk assessment rather than relying on frequency alone.

The respondents also indicated that fixed allowances may not always reflect changing project conditions and that historical claims data could improve consistency in assessing financial impact. The proposed framework responds by linking survey-based prioritisation, structured claims records, current project information, a clearly defined prediction task, contractual risk allocation and professional review. Published research demonstrates that claims and project records can support risk quantification or prediction, but each application depends on the quality of the data and the target being modelled.

The present study does not establish the predictive accuracy of a machine-learning model because the available data contain questionnaire responses rather than historical claim-level records. Its contribution is a structured framework and a set of practical requirements for future implementation. Before the framework is used to recommend a monetary allowance, it must be tested on suitable historical data and compared with actual outcomes. When supported by reliable data, transparent calculations and contract-aware review, dynamic risk pricing may provide a more consistent basis for discussing and updating financial exposure in construction contracts.

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