

Article

Assessing the Influence of Risk Maturity Level on Construction Delay Factors: A Machine Learning-Based Model

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Abstract

Construction project delays remain a persistent challenge in the construction industry, yet existing studies have generally examined delay risk prioritisation and organisational risk management maturity as separate research domains. This study addresses this gap by investigating how organisational risk management maturity influences the evaluation and prioritisation of construction delay risks in the Australian construction context. A structured survey instrument based on the Generic Risk Maturity Model was used to assess maturity across five dimensions: management commitment and leadership, organisational risk culture, risk identification, risk analysis, and standardised risk management processes. Expert judgements were used to derive impact severity, probability of occurrence, and composite criticality scores for 22 construction delay risk factors. Extreme Gradient Boosting (XGBoost) models with SHapley Additive exPlanations (SHAP) were then applied to explain how maturity dimensions influence risk evaluations. The results show that maturity is associated with changes in both the level and pattern of delay risk prioritisation. Owner's late decisions remained the top-ranked composite risk across all maturity levels, while other risks exhibited maturity-related shifts, with the composite risk weight of poor project cost estimation declining from 0.079 at maturity Level 1 to 0.041 at maturity Levels 3–4, and rainfall and weather conditions becoming more prominent at higher maturity levels. The proposed XGBoost–SHAP framework provides a transparent, data-driven diagnostic tool for linking organisational capability with delay risk prioritisation and supporting more consistent and evidence-based delay risk management. The results further indicate that weaker organisational risk culture and lower process standardisation are associated with greater perceived exposure to planning-, coordination-, and decision-related delay risks. Within the sampled Australian construction organisations, the XGBoost–SHAP framework provides a transparent analytical approach for examining associations between organisational capability and delay risk prioritisation.

Keywords: organisational risk management maturity; construction delay risk management; schedule risk; explainable artificial intelligence; XGBoost; SHAP; Australian construction industry

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1. Introduction

Construction is a critical sector that drives economic growth, infrastructure development, and social advancement. However, construction projects are inherently complex

and often face numerous risks that can compromise their success [1]. Among these challenges, schedule delay remains particularly persistent because it can generate cost escalation, contractual disputes, productivity losses, resource disruption, and reduced stakeholder confidence [2]. Effective delay risk management therefore requires more than the identification of potential risk factors; it also requires organisations to evaluate their probability of occurrence and schedule impact consistently and to prioritise management actions according to the relative criticality of each risk.

Several studies have examined the factors that contribute to risks in construction projects. Risk factors are often evaluated based on project-specific characteristics such as size, location, complexity, and type, as well as external influences like regulatory requirements, market conditions, and environmental factors [3]. Understanding these risk factors allows organisations to develop mitigation strategies, allocate resources effectively, and prioritise management efforts where they are most needed [4].

Organisational risk management maturity models have been widely adopted to assess and enhance a company's capability in identifying, evaluating, and responding to project risks. By improving processes, structures, and decision-making practices, these models help organisations strengthen their risk management practices over time. The literature suggests that increasing maturity levels generally leads to better risk assessment, more informed prioritisation of critical risks, and improved overall project performance [5]. However, existing maturity studies have predominantly focused on benchmarking overall organisational capability or identifying areas requiring improvement.

Despite the extensive evaluation of risk factors and the use of maturity models, there is limited research exploring the relationship between an organisation's maturity levels and the perceived probability of occurrence and impact of specific risk factors. In other words, while risk factors are assessed based on project characteristics, no studies have explicitly investigated how maturity in different dimensions influences the prioritisation of these risks. This gap limits our understanding of how organisational capability shapes risk perception and decision-making in construction projects.

Machine learning techniques provide opportunities to investigate this relationship because they can capture complex interactions and non-linear associations that may not be adequately represented by conventional linear models. Recent construction and project management studies have applied machine learning to duration forecasting, project control, cost estimation, safety assessment, and risk prediction [6,7]. At the same time, explainable artificial intelligence has emerged in response to concerns regarding the limited transparency of high-performing machine learning models. Recent research has demonstrated the value of XAI in construction by using SHapley Additive exPlanations (SHAP) to interpret project-control models, identify construction cost drivers, explain construction risk predictions, and support transparent project risk decision-making [8,9]. However, these studies have largely concentrated on explaining project outcomes or the contribution of conventional project-level variables. They have not examined how multidimensional organisational risk management maturity shapes the evaluation and prioritisation of individual construction delay risks.

This study addresses this gap by applying an explainable machine learning framework to examine the relationship between organisational risk management maturity and construction delay risk prioritisation in the Australian construction industry.

The study addresses the following research objectives:

- To compare the rankings of construction delay risks according to impact, probability, and composite criticality across different overall organisational maturity levels.
- To use XGBoost to model the relationships between the five organisational risk management maturity dimensions and the impact, probability, and composite criticality of individual delay risks.

- To use SHAP to explain the direction and magnitude of these relationships and identify the maturity dimensions that contribute most strongly to the evaluation of specific delay risks.

Based on the premise that organisational capability influences how construction delay risks are assessed and prioritised, this study examines two hypotheses:

H1. *The prioritisation of construction delay risks differs across overall organisational risk management maturity levels.*

H2. *Organisational risk management maturity dimensions are differentially associated with the evaluation of individual construction delay risks.*

The study contributes by integrating multidimensional risk maturity assessment with explainable machine learning to provide a transparent framework for understanding maturity-informed delay risk prioritisation and supporting targeted organisational improvement.

2. Literature Review

2.1. Construction Project Delays and Risk Prioritisation

Construction project delays remain among the most persistent challenges affecting industry performance, contributing to cost escalation, contractual disputes, productivity losses, and reduced stakeholder confidence. A substantial body of international research has therefore examined the causes of delay across countries, project types, and procurement environments [10]. This research consistently demonstrates that delays rarely arise from a single cause; instead, they emerge through interactions among technical, organisational, financial, and external conditions [11]. However, the relative importance of these factors varies considerably across contexts because of differences in governance structures, market maturity, institutional arrangements, labour availability, regulatory requirements, and project-delivery practices [12]. Consequently, delay risk rankings developed in one setting may not be directly transferable to another without appropriate contextual calibration [13].

In response, many construction delay studies adopt expert-judgement approaches, through surveys, interviews, or case-based evaluation, to identify and prioritise delay risk factors in specific settings [14]. To support decision-making, researchers have applied multi-criteria decision-making (MCDM) and related prioritisation techniques such as the Relative Importance Index (RII), Analytic Hierarchy Process (AHP), Best–Worst Method (BWM) and fuzzy extensions, and Probability–Impact matrices [15,16]. These methods help structure expert knowledge and produce comparative rankings that can guide managerial attention under limited resources [17]. Nevertheless, much of the existing prioritisation literature remains descriptive, presenting ranked lists without explaining why risk evaluations differ across organisations or governance environments. As a result, observed variation in expert judgement is often aggregated, potentially masking systematic differences linked to organisational capability and risk governance.

A related methodological concern is that schedule-delay risk is sometimes represented through a single aggregated measure or assessed using only one dimension. Probability of occurrence and schedule impact represent conceptually distinct components of risk and may exhibit different patterns across delay factors [18,19]. For example, some risks occur frequently but generate recoverable disruptions, whereas others are less frequent but trigger severe downstream schedule impacts. Treating such risks as equivalent through single-score measures may distort mitigation priorities and reduce decision usefulness [20]. Consequently, there is growing recognition that probability and impact

should be evaluated separately, while still being integrated within a coherent analytical structure that supports prioritisation and risk zoning. These limitations are particularly relevant in the Australian construction context, where existing studies have commonly focused on identifying and categorising delay causes and often produce extensive, context-specific lists [21]. Figure 1 summarises the study's contextual scoping process, through which globally reported delay factors were localised to the Australian construction environment and subsequently examined across organisations with different levels of risk management maturity.

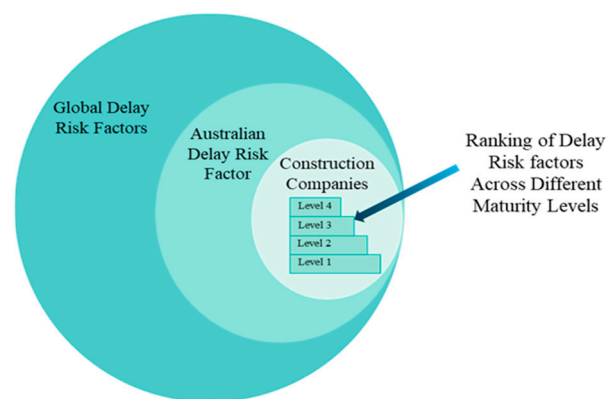


Figure 1. Contextual narrowing of construction delay risk factors from global evidence to organisations by risk maturity level.

2.2. Risk Management Maturity in the Construction Industry

Construction organisations are increasingly adopting formalised frameworks for the systematic identification, assessment, treatment, monitoring, and communication of project risks [22]. In support of these structured practices, Risk Maturity Models (RMMs) are utilised within the construction industry to assess the effectiveness of organisational risk management and to highlight opportunities for enhancement. Several frameworks have been applied in construction, including Generic Risk Maturity Model (GRMM), construction-specific adaptations of GRMM, project management-oriented models such as PMI's OPM3, and other sector-focused maturity models developed in different national contexts [23–28].

Among these frameworks, the construction-adapted GRMM is particularly suitable for empirical maturity assessment because it provides a validated, multidimensional structure that integrates managerial, cultural, analytical, and procedural capabilities in a form that is readily operationalised through standardised survey instruments. Earlier studies, including Zou et al. [24], mainly assessed risk maturity at an overall or group level, without analysing individual factors or items. As a result, they offered limited insight into which specific capabilities, such as leadership, communication, or analytical skills, contribute most to organisational improvement. In addition, prior research did not examine relationships among risk management dimensions, leaving interdependencies largely unexplored. Furthermore, maturity was treated as a static state rather than a dynamic process, with little attention given to how organisations evolve across maturity levels over time. Building on this foundation, Zagia et al. [29] provided a data-driven benchmark of risk management maturity in the Australian construction industry using a GRMM-based instrument operationalised through 25 assessment criteria across five maturity dimensions. However, existing maturity studies typically treat organisational capability and project risk assessment as separate analytical domains, overlooking their potential interaction. This gap constrains the practical value of maturity assessments, as higher

maturity levels are implicitly assumed to improve risk outcomes without being directly tested against project-specific risk indicators.

Accordingly, there remains a clear need for integrated empirical studies that link organisational risk maturity with data-driven delay risk modelling. Addressing this gap can provide deeper insight into whether and how mature risk governance systems translate into more consistent, reliable, and accurate assessment of construction delay risks. This integration forms a central motivation of the present study.

2.3. Machine Learning in Construction Risk and Delay Analysis

Machine learning (ML) has become an increasingly important analytical approach for modelling complex and potentially non-linear relationships in engineering and construction management research [30,31]. Unlike traditional statistical approaches that rely on predefined functional forms, ML algorithms learn directly from data and iteratively improve their predictive performance through experience [32]. Depending on the learning objective and data structure, ML techniques are commonly classified into supervised, unsupervised, and reinforcement learning approaches [33]. Among these, supervised learning is particularly relevant to construction management research, as it enables the prediction of project outcomes based on observed explanatory variables and expert assessments [34,35].

Supervised learning methods are generally divided into classification and regression models. Classification techniques assign observations to predefined categories, whereas regression models predict continuous numerical values [36,37]. In construction delay research, key performance indicators such as duration overruns, impact severity, probability of occurrence, and composite risk scores are typically expressed on continuous scales. Consequently, regression-based supervised learning provides a suitable analytical framework for modelling delay-related phenomena. Recent studies demonstrate growing adoption of ML techniques in construction risk and delay analysis. Researchers have applied decision trees, random forests, gradient boosting models, and other ensemble methods to predict construction duration, schedule deviation, and delay occurrence using historical project data and operational indicators [38,39].

Among ensemble learning techniques, gradient boosting decision trees have attracted considerable attention for their strong predictive capability and flexibility. Random Forest, XGBoost, and LightGBM are tree-based ensemble methods capable of modelling non-linear relationships and interactions; however, they differ in their learning mechanisms and principal advantages. Random Forest constructs multiple decision trees independently using bootstrapped samples and averages their predictions, thereby providing a robust mechanism for reducing prediction variance with relatively limited parameter tuning [40]. However, because its trees are constructed independently, Random Forest does not sequentially focus on residual errors that remain unexplained by previously developed trees. LightGBM, by contrast, is a gradient boosting implementation designed primarily to improve computational efficiency and scalability. Its histogram-based learning, gradient-based one-side sampling, exclusive feature bundling, and leaf-wise tree-growth strategy are particularly advantageous for very large or high-dimensional datasets [41,42]. Although these properties make LightGBM computationally efficient, computational scale was not the principal concern in the present study, which uses a structured survey dataset with five theoretically defined maturity predictors and multiple continuous delay risk outcomes.

Extreme Gradient Boosting (XGBoost), introduced by Chen and Guestrin [43], is an ensemble learning algorithm that uses sequential tree construction to iteratively correct prediction errors and refine the model structure. This enables XGBoost to effectively capture highly non-linear relationships while maintaining robustness against overfitting [44].

It also incorporates an explicitly regularised objective function, shrinkage through the learning rate, row and column subsampling, and controls over tree depth and complexity [45]. This capability is important in the present study because the relationships between maturity dimensions and delay risk evaluations may include threshold, increasing, decreasing, and non-monotonic patterns that cannot be represented adequately through a single predefined functional form.

Empirical construction research also supports the suitability of XGBoost for delay- and schedule-related prediction. Sahu et al. [46] evaluated multiple ML algorithms for construction delay prediction, including logistic regression, decision trees, random forests, and gradient boosting models, and reported that XGBoost achieved superior predictive accuracy and stability. Similarly, Cho et al. [39] employed XGBoost within an automated framework for highway delay risk management and demonstrated its effectiveness in identifying critical schedule risks. These studies indicate that XGBoost is particularly well suited for analysing construction datasets characterised by heterogeneous variables and complex dependency structures.

Despite their strong predictive capabilities, tree-based ensemble models such as XGBoost are often criticised for their limited interpretability, as they provide little transparency regarding how input variables influence model outputs [47]. This limitation is important in the present study because the objective is not only to predict delay risk evaluations but also to explain how each organisational maturity dimension contributes to impact severity, probability of occurrence, and composite criticality. To address this limitation, explainable artificial intelligence (XAI) techniques have been developed to enhance model interpretability [45]. Among these, SHapley Additive exPlanations (SHAP) has emerged as a theoretically grounded and practically validated approach for interpreting machine learning models. Lundberg and Lee [48] established the theoretical foundation of SHAP, presenting it as a unified framework that assigns feature importance values with desirable mathematical properties derived from cooperative game theory.

SHAP is not an alternative predictive algorithm to Random Forest, XGBoost, or LightGBM; rather, it is an explanatory framework that can be applied after a predictive model has been developed. Conventional feature importance measures can indicate which variables are influential overall, but they do not always reveal whether a feature increases or decreases a specific prediction, the magnitude of that contribution, or whether its effect changes across different feature values [49]. SHAP addresses these limitations through feature attributions that satisfy properties such as local accuracy and consistency. The TreeSHAP implementation additionally enables efficient explanation of tree-based ensemble models and supports both local and global interpretation through summary plots, dependence plots, feature rankings, and interaction analysis [48,50].

These capabilities are directly aligned with the present study. SHAP enables the analysis to determine whether a specific maturity dimension increases or decreases a predicted delay risk measure, quantify the magnitude of that contribution, and identify non-linear, threshold, or maturity-insensitive relationships. Accordingly, combining XGBoost with SHAP provides both the modelling flexibility required to capture complex maturity-risk relationships and the interpretability required to translate those relationships into meaningful organisational and managerial insights.

Recent research has demonstrated SHAP's effectiveness in construction-related domains. Chen et al. [51] applied SHAP in construction cost prediction and successfully identified critical cost drivers while maintaining transparent model interpretation. Similarly, Ekanayake et al. [52] employed SHAP in predicting concrete compressive strength and reported that SHAP-based interpretations aligned with engineering domain knowledge. Beyond construction, SHAP has been applied in building energy systems and

data centre operations to reveal model weaknesses and enable systematic feature importance ranking [53].

2.4. Research Gap and Positioning of the Present Study

The review of existing literature reveals several important limitations in current research on construction delay risk management. First, although numerous studies have identified and prioritised delay risk factors using expert judgement and multi-criteria decision-making techniques, most of these studies implicitly assume homogeneous organisational capability and aggregate expert opinions without considering how organisational maturity influences risk perception and prioritisation. Consequently, variations arising from differences in leadership practices, risk culture, and governance structures remain largely unexplored.

Second, while risk management maturity models have been widely applied to assess organisational capability, existing studies are predominantly descriptive and cross-sectional in nature. These assessments provide useful benchmarks for maturity levels but rarely examine how maturity is reflected in operational behaviour, particularly in relation to the evaluation and prioritisation of project-specific risks. As a result, the behavioural mechanisms through which maturity influence managerial decision-making remain insufficiently understood.

Third, although machine learning techniques have been increasingly adopted in construction risk and delay research, their application has largely focused on project-level outcome prediction, such as estimating delay duration or classifying delay types. Limited attention has been given to using advanced machine learning methods as analytical tools for investigating organisational capability and expert-based risk evaluation processes. Moreover, the integration of ensemble learning techniques with structured maturity assessment frameworks and systematically quantified risk prioritisation outputs remains scarce.

Taken together, these limitations indicate the absence of an integrated analytical framework that links organisational risk management maturity with expert-derived construction delay risk prioritisation using explainable data-driven methods. Through this integrated perspective, the study contributes to both theory and practice by advancing understanding of risk management behaviour and offering a diagnostic tool to support continuous improvement in organisational risk maturity. Figure 2 illustrates the identified research gap at the intersection of delay risk prioritisation, risk maturity assessment, and explainable machine learning.

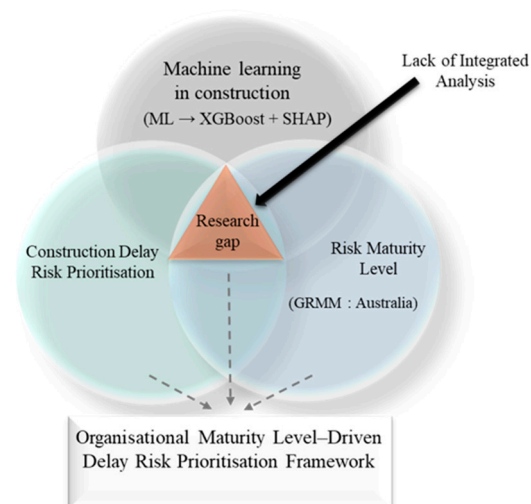


Figure 2. Research gap and conceptual positioning of the proposed framework.

3. Research Methodology

3.1. Research Design and Overall Framework

This study adopts an integrated survey-based and explainable machine learning framework to investigate the relationship between risk management maturity levels and construction delay risk factors within the Australian construction industry. The methodology combines expert-based risk assessment with data-driven modelling to capture both the quantitative relationships and the underlying influence mechanisms between organisational maturity and delay risk outcomes. The overall framework consists of four main stages:

- i. Risk maturity assessment;
- ii. Quantification of construction delay risk factors;
- iii. Machine learning modelling using XGBoost regression;
- iv. Model interpretation using SHapley Additive exPlanations (SHAP).

This approach enables not only accurate prediction of delay risk metrics, but also transparent interpretation of how different dimensions of risk maturity influence construction delay risks. Figure 3 outlines the sequential research process.

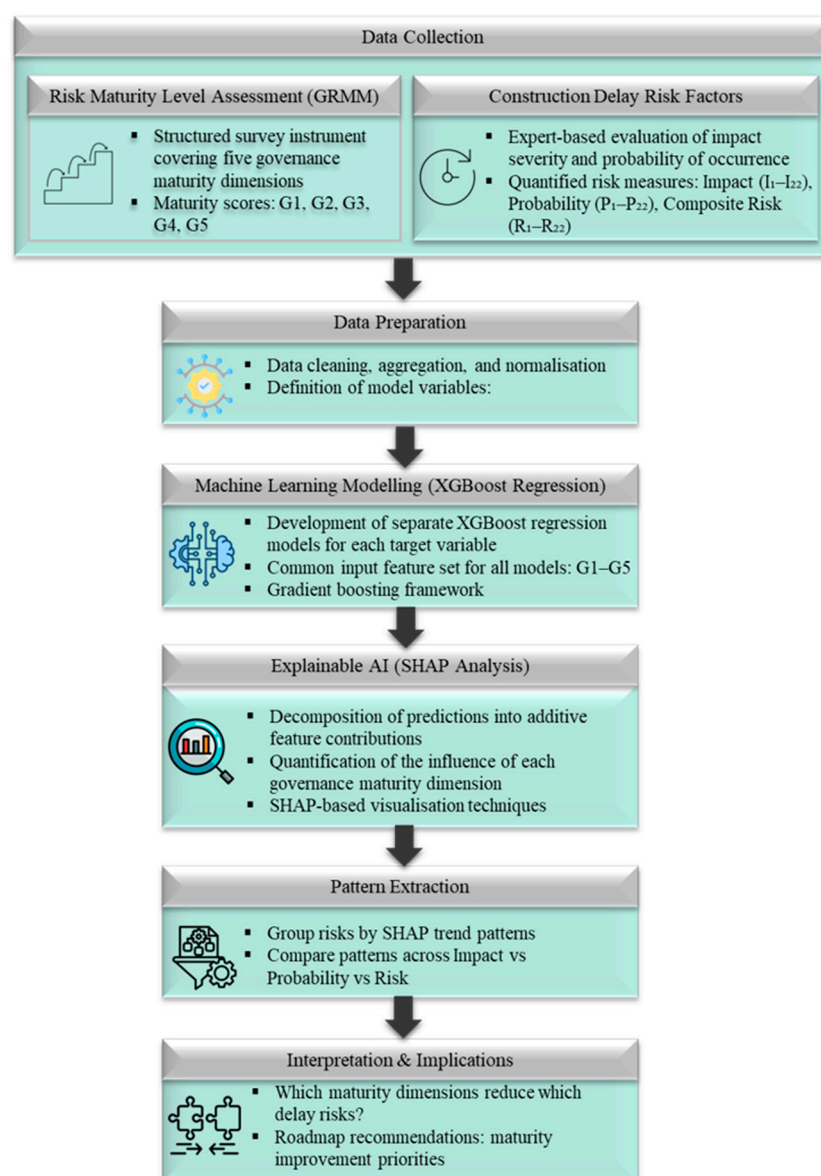


Figure 3. Research framework.

3.2. Data Collection and Survey Instrument

The collected data comprised two main categories: organisational maturity levels and the perceived importance of project risk factors, using a questionnaire as follows.

3.2.1. Operationalisation of Organisational Risk Maturity Variables

Organisational risk management maturity was assessed using a structured questionnaire based on the Generic Risk Maturity Model (GRMM), which provides a systematic framework for evaluating the extent to which risk management practices are embedded within organisational processes and culture. The instrument evaluates maturity across five core dimensions: management commitment and leadership, organisational risk culture, risk identification, risk analysis, and standardised risk management processes [24]. Together, these dimensions capture both the technical and behavioural aspects of organisational risk management capability.

In this study, maturity level refers to the extent to which risk management is embedded, consistently applied, and continuously improved within an organisation; it does not represent a phase of project development. The four levels describe progressively stronger organisational capability [54]. Level 1 (Initial/Ad Hoc) represents informal and reactive practices that depend largely on individual experience. Level 2 (Repeatable) indicates that basic practices, such as maintaining risk registers and conducting periodic risk reviews, are applied on some projects but are not yet consistently standardised across the organisation. Level 3 (Managed) represents formally defined and organisation-wide practices, including assigned risk responsibilities, systematic risk analysis, and regular monitoring and reporting. Level 4 (Optimised) reflects fully integrated, data-informed, and continuously improved risk management embedded in both project and strategic decision-making [24,55]. For example, risk identification may progress from being conducted mainly after problems arise at Level 1, to using basic project risk registers at Level 2, standardised risk workshops and reporting across projects at Level 3, and continuous learning from organisational risk data and lessons learned at Level 4. The levels therefore describe organisational risk management capability throughout the project lifecycle rather than sequential project-development phases.

Data were collected from experienced construction professionals occupying senior managerial, technical, project management, planning, and risk-related roles. A purposive sampling strategy was adopted to ensure that respondents had sufficient experience and organisational knowledge to provide informed assessments of risk management practices. The survey was distributed to 78 construction professionals working in Australian construction organisations, and 62 responses were received, corresponding to a response rate of 79.5% (62/78). Following data screening, 48 fully complete questionnaires were retained for analysis, while 14 questionnaires containing one or more missing responses were excluded. The selected participating organisations included contractors, consultants, clients, and subcontractors and covered a range of organisational sizes and tiers, including Tier 1, Tier 2, Tier 3 from small, medium, and large organisations. The final sample represented organisations operating across infrastructure (56%), commercial construction (21%), industrial construction (10%), residential construction (5%), and other construction sectors (8%). This sampling approach was intended to capture organisation-level risk management practices across different segments of the Australian construction industry rather than individual personal attitudes. Of the 48 valid organisational assessments, 1 was classified as Level 1 (2.1%), 27 as Level 2 (56.3%), and 20 as the combined Levels 3–4 group (41.7%).

Respondents rated the extent to which each criterion was implemented within their organisation using a four-point maturity scale. The questionnaire was designed to focus

on documented procedures, established routines, organisational behaviours, and formal risk governance arrangements rather than individual perceptions alone.

Before analysis, all responses were screened for completeness and consistency. Responses were considered incomplete and excluded if more than 10% of maturity assessment items were missing or if one or more full maturity dimensions had no valid response. In addition, consistency checks were conducted to identify response patterns that could indicate unreliable answers, such as straight-lining across all items, contradictory responses across related criteria, or responses with unusually high variation within the same maturity dimension. Based on these screening procedures, 14 responses were excluded, resulting in a final analytical sample of 48 responses.

For each valid response, item-level scores were first grouped under their corresponding maturity dimensions. The average score of the criteria within each dimension was then calculated to generate five maturity indices for each participating organisation. These indices represented the relative strength of organisational capability in each major area of risk management practice. The resulting five-dimensional maturity profile was used as the set of independent variables in the subsequent XGBoost regression models. Because all maturity criteria were measured using the same four-point scale, the maturity scores were retained in their original scale to preserve interpretability. Where required for machine learning implementation, the dataset was organised into a respondent-by-variable structure, with each row representing one valid organisational assessment and each column representing either a maturity dimension or a quantified delay risk outcome.

In the present study, the five-dimensional maturity indices serve as independent variables in the XGBoost regression models. By operationalising organisational risk management capability through validated and systematically derived maturity measures, this approach enables an empirical examination of how variations in leadership, culture, analytical capability, and procedural standardisation influence the evaluation and prioritisation of construction delay risks.

3.2.2. Measurement of Construction Delay Risk Variables

The construction delay risk factors employed as dependent variables in this study were derived from a multi-stage identification, localisation, and quantification process conducted within the Australian construction context. Initially, a PRISMA-guided systematic review of 92 international studies was undertaken to identify a comprehensive pool of 103 global construction delay factors [10]. These factors were subsequently contextualised through semi-structured interviews with senior Australian construction professionals, during which overlapping items were consolidated and factors considered irrelevant to local delivery environments were removed. This process resulted in a validated and context-specific set of 22 construction delay risk factors. These factors were subsequently contextualised in a preceding localisation study involving semi-structured interviews with 11 senior Australian construction professionals conducted between March and July 2024. A pre-designed interview protocol guided the 60–90 min interviews, during which participants evaluated the relevance and severity of 55 globally identified delay factors, commented on their applicability to the Australian construction context, identified overlapping or irrelevant factors, and proposed additional context-specific considerations. The interviews were approved by the University Human Research Ethics Committee (approval no. LR 2024-7852-19920) and were conducted in accordance with requirements concerning participant consent, confidentiality, anonymisation, and appropriate data handling.

These risk factors were then subjected to a structured expert evaluation process in which experienced industry practitioners assessed each factor separately in terms of its probability of occurrence and its impact on project time performance. Expert judgements

were elicited using a standardised questionnaire and analysed using the Fuzzy Best–Worst Method (FBWM), which allowed for the derivation of consistent, ratio-scale weights while minimising respondent burden and improving consistency in expert judgement. The resulting probability and impact weights were subsequently integrated using a Probability–Impact (P–I) matrix to determine the overall criticality of each delay risk factor.

Through this procedure, quantitative estimates of impact severity, probability of occurrence, and composite risk scores were obtained for all 22 delay risk factors. These metrics provide empirically grounded measures of schedule risk criticality that reflect expert knowledge and the operational realities of the Australian construction industry. These quantified risk measures are adopted as dependent variables in the machine learning models.

3.3. Data Preparation

The GRMM was applied to the collected maturity data to evaluate the maturity levels of companies across five key business dimensions: management commitment and leadership, organisational risk culture, risk identification, risk analysis, and standardised risk management processes. To identify noise and ensure the validity of the results, a cross-validation approach was employed.

Simultaneously, based on the collected data for the importance and probability of the selected risk factors, the Best–Worst Method (BWM) was applied to determine the weights of each factor for every respondent. The overall risk value for each factor was then computed by multiplying the corresponding importance and probability weights.

Based on these procedures, the main dataset was constructed. Each row corresponds to a single respondent and includes the following variables:

- Five columns representing maturity levels across the five dimensions;
- Twenty-two columns containing the importance weights of each risk factor;
- Twenty-two columns containing the probability weights of each risk factor;
- Twenty-two columns for the calculated risk values of each factor.

Figure 4 presents a conceptual illustration of the structured dataset, which provides a comprehensive foundation for subsequent machine learning analysis, enabling the investigation of how maturity levels influence the perceived importance, probability, and overall risk of construction project factors. The five maturity dimensions represent distinct but interrelated components of organisational risk management capability, capturing leadership commitment, cultural alignment, systematic identification of risks, analytical evaluation processes, and the degree of procedural standardisation.

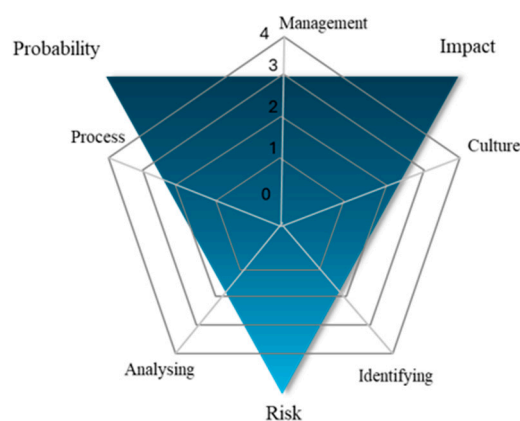


Figure 4. Conceptual representation of the organisational maturity dimensions and delay risk variables included in the analysis.

All responses were screened for completeness and consistency prior to analysis. Aggregated maturity scores and delay risk metrics were standardised where required to ensure comparability across respondents. The final dataset consisted of paired observations of five maturity dimensions and corresponding delay risk metrics for each participating organisation.

3.4. Machine Learning Modelling Using XGBoost

Extreme Gradient Boosting (XGBoost) regression was employed to model the relationship between organisational risk management maturity and construction delay risk factors. XGBoost was chosen for its ability to capture complex non-linear relationships and feature interactions while maintaining strong predictive performance [56,57].

For each selected delay risk factor, separate models were developed to predict three outcomes:

- Impact severity, representing the potential consequences of the risk if it occurs;
- Probability of occurrence, reflecting the likelihood of the risk event;
- Composite risk score, calculated as the product of impact and probability, providing an overall measure of risk significance.

For each respondent $i = 1, \dots, n$, the input vector consisted of the five GRMM maturity indices:

$$x_i = [G1_i, G2_i, G3_i, G4_i, G5_i]$$

The five maturity dimensions (G1–G5), management commitment and leadership, organisational risk culture, risk identification, risk analysis, and standardised risk management processes, were used as input features in all models. Hyperparameters were selected conservatively to balance model complexity, predictive accuracy, and out-of-sample stability.

Separate XGBoost regression models were trained for each delay risk factor j and for each of the three risk outcomes:

Impact severity: $y_{i,j}^{(I)}$

Probability of occurrence: $y_{i,j}^{(P)}$

Composite risk score (criticality): $y_{i,j}^{(R)}$

The composite risk score was calculated as:

$$y_{i,j}^{(R)} = y_{i,j}^{(I)} \times y_{i,j}^{(P)} \quad (1)$$

XGBoost represents the prediction as an additive ensemble of regression trees [43]:

$$\hat{y}_i = \sum_{t=1}^T f_t(x_i), \quad f_t \in F \quad (2)$$

where T is the number of boosting iterations (trees), and each $f_t(\cdot)$ is a decision tree that maps the input x_i to a leaf value. In this study, the same five maturity dimensions were used as predictors for all models, while the target y varied depending on whether impact, probability, or composite risk was being estimated.

XGBoost learns the set of trees $\{f_t\}_{t=1}^T$ by minimising a regularised objective function:

$$L = \sum_{i=1}^n l(y_i, \hat{y}_i) + \sum_{t=1}^T \Omega(f_t) \quad (3)$$

where $l(\cdot)$ is the loss function for regression (commonly the squared error), and $\Omega(f)$ penalises model complexity. The standard regularisation form used in XGBoost is:

$$\Omega(f) = \gamma K + \frac{1}{2} \lambda \sum_{k=1}^K (w_k^2) \quad (4)$$

where K is the number of terminal leaves in the tree, w_k is the prediction score assigned to leaf k , γ penalises adding more leaves (controlling tree size), and λ applies L2 regularisation on leaf weights. This combination reduces the risk of overfitting by discouraging overly complex trees and extreme leaf scores.

Model performance was assessed using cross-validation techniques and standard regression metrics R^2 to ensure reliability and avoid overfitting. Predictive accuracy was evaluated using the coefficient of determination [58]:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (5)$$

where $\bar{y}$ represents the mean of the observed outcomes. Hyperparameters were selected conservatively to balance predictive performance and out-of-sample stability. In particular, the maximum tree depth, learning rate, and regularisation terms were controlled to avoid overly complex models and to improve stability across folds.

3.5. Model Interpretation Using SHAP

While XGBoost provides strong predictive performance, it does not directly reveal how each maturity dimension influences the predicted delay risk outcomes. To achieve this, SHAP (SHapley Additive exPlanations) values were employed to interpret the model results. SHAP is based on cooperative game theory and decomposes a model prediction into additive contributions of each input feature [59,60]. For each observation i , the prediction can be expressed as:

$$\hat{y}_i = \phi_0 + \sum_{k=1}^p \phi_k(x_i) \quad (6)$$

where

- $\hat{y}_i$ = predicted value (impact, probability, or composite risk),
- ϕ_0 = baseline prediction (mean model output),
- ϕ_k = SHAP value representing the contribution of feature k ,
- p = 5 maturity dimensions (G1–G5).

In this study, SHAP values were calculated for each maturity dimension (G1–G5) across all models predicting impact severity, probability of occurrence, and composite risk scores for the selected delay risk factors. Each SHAP value ϕ_k quantifies how much the corresponding maturity dimension increases or decreases the predicted risk relative to the baseline. This analysis enabled the identification of:

- Which maturity dimensions most strongly influence the perception of risk;
- How increases or decreases in specific maturity levels affect the predicted importance or likelihood of different risks; and
- Potential interactions between maturity dimensions that amplify or mitigate specific risk outcomes.

In this study, SHAP was used at two complementary levels. Global explanations, obtained by examining SHAP values across all observations, identify the maturity dimensions that contribute most strongly to each delay risk outcome and reveal general patterns across maturity levels. Local explanations decompose an individual organisation's predicted risk into the separate contributions of management commitment and leadership (G1), organisational risk culture (G2), risk identification (G3), risk analysis (G4), and standardised risk management processes (G5). This organisation-specific decomposition enables the model output to be linked to the particular capability dimensions associated with an elevated or reduced risk prediction, thereby providing an analytical basis for

targeted risk management improvement. All computational analyses were conducted using Python 3.14.6, with XGBoost 3.3.0 used for regression modelling and SHAP 0.52.0 used for model interpretation.

Figure 5 illustrates the modelling process linking maturity dimensions (G1–G5) to delay risk predictions and SHAP-based interpretation.

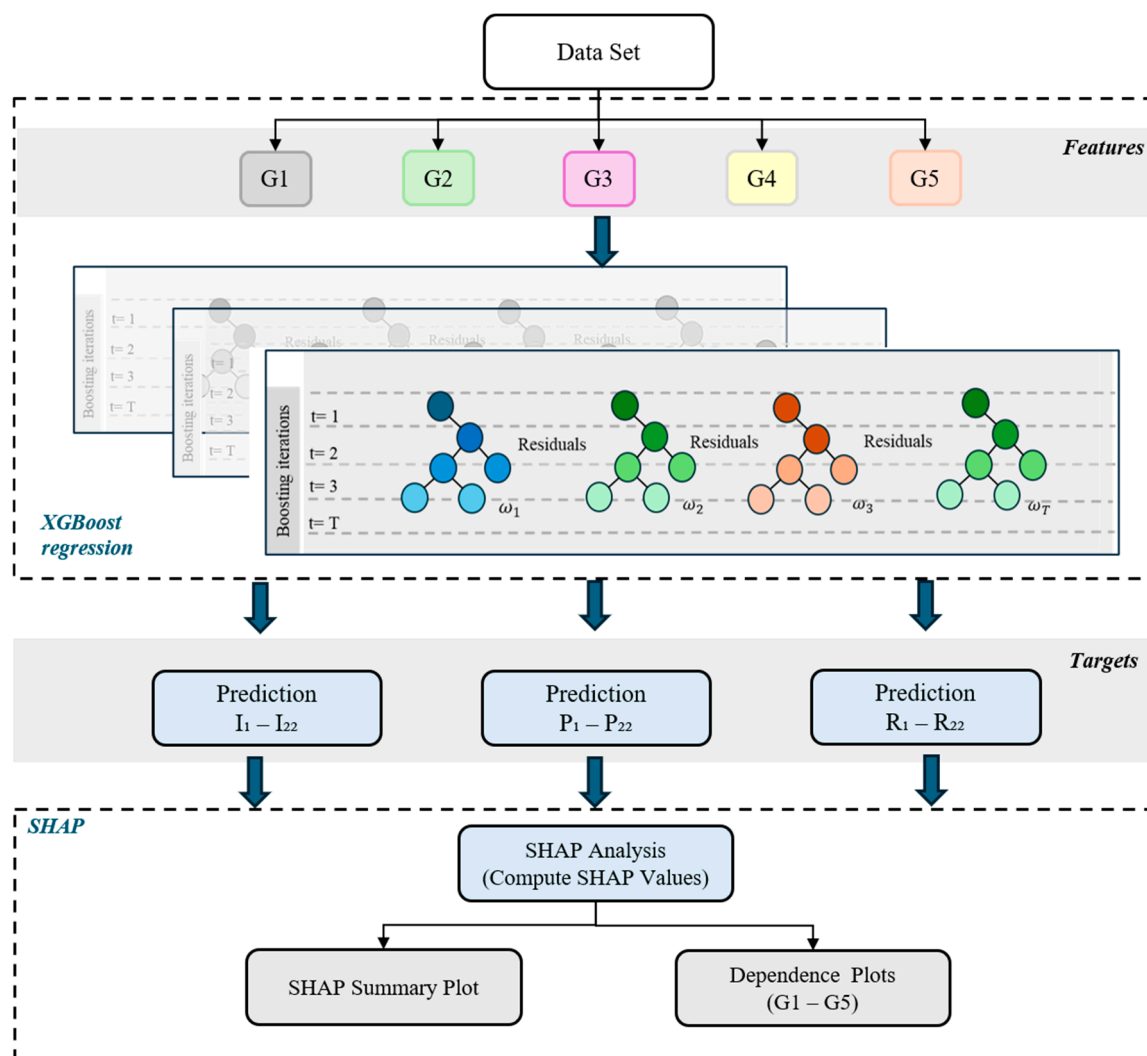


Figure 5. XGBoost–SHAP modelling and interpretation framework.

4. Results

4.1. Risk Factor Prioritisation Across General Organisational Maturity Levels

The risk factors were prioritised separately for each maturity level, and the results are summarised in Table 1. This table presents the normalised weights of impact, probability, and composite risk value for each risk factor across different maturity levels. The maturity-level comparisons were based on Level 1 (2.1%), Level 2 (56.3%), and combined Levels 3–4 (41.7%). For each maturity level, the sum of weights within each column equals one, allowing the results to be interpreted as relative weights. Accordingly, this table illustrates the relative importance of each risk factor based on the three criteria, impact, probability, and overall risk, independently for each maturity level.

Table 1. Normalised impact, probability, and composite risk weights of delay factors across maturity levels.

Delay Risk Factor	Maturity Level 1			Maturity Level 2			Maturity Level 3 & 4		
	Impact	Probability	Risk	Impact	Probability	Risk	Impact	Probability	Risk
Consultant's Lack of Experience	0.02	0.03	0.01	0.02	0.04	0.02	0.03	0.05	0.03
Poor qualification of the contractor's technical staff	0.03	0.05	0.03	0.03	0.04	0.03	0.03	0.07	0.04
Owner's Lack of Experience	0.05	0.07	0.06	0.05	0.04	0.04	0.04	0.05	0.05
Owner's financial problems	0.07	0.02	0.03	0.05	0.02	0.02	0.06	0.02	0.02
Owner's Late Decisions	0.09	0.09	0.17	0.07	0.06	0.08	0.07	0.07	0.11
Owners change in requirements	0.08	0.05	0.06	0.05	0.04	0.05	0.05	0.04	0.04
Delay in changes approval	0.05	0.07	0.06	0.05	0.07	0.07	0.05	0.05	0.04
Contractor's financial problems	0.07	0.05	0.05	0.04	0.05	0.04	0.06	0.04	0.04
Delay in subcontractors work	0.06	0.06	0.09	0.05	0.05	0.05	0.06	0.05	0.06
Shortage of labour	0.03	0.05	0.03	0.04	0.04	0.04	0.04	0.03	0.03
Labor Productivity	0.03	0.05	0.03	0.04	0.04	0.04	0.04	0.04	0.03
Poor project cost estimation	0.06	0.06	0.08	0.05	0.06	0.07	0.05	0.05	0.04
Poor and improper Planning	0.06	0.03	0.04	0.05	0.05	0.05	0.04	0.06	0.04
Complexity in project design	0.04	0.03	0.02	0.05	0.05	0.05	0.04	0.05	0.04
Late in revising and approving design documents	0.04	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Unclear and inadequate details in drawings	0.03	0.03	0.02	0.05	0.05	0.05	0.04	0.05	0.06
Lack of Coordination	0.04	0.04	0.03	0.05	0.05	0.05	0.05	0.05	0.05
Mistakes during the execution of works	0.03	0.03	0.02	0.05	0.04	0.04	0.05	0.05	0.05
Injuries on Site	0.04	0.02	0.02	0.03	0.03	0.02	0.04	0.03	0.03
Poor project management and supervision	0.04	0.03	0.02	0.05	0.05	0.07	0.03	0.04	0.03
Inflation	0.03	0.04	0.03	0.04	0.05	0.05	0.05	0.03	0.03
Rainfall and Weather conditions	0.04	0.05	0.06	0.05	0.05	0.05	0.06	0.04	0.08

To facilitate comparison and interpretation, Table 2 converts these relative weights into rankings. Focusing on impact severity, the results indicate clear shifts in risk prioritisation as organisational maturity increases. At maturity Level 1, risk factors 5, 6, and 4 are identified as the most critical in terms of impact. As organisations progress to maturity Level 2, risk factor 9 emerges as the second most important factor, while risk factor 6 drops to the seventh position, indicating a reduced perceived impact.

Table 2. Ranking of delay risk factors by impact, probability, and composite risk across maturity levels.

Delay Risk Factor	Maturity Level 1			Maturity Level 2			Maturity Level 3 & 4		
	Impact	Probability	Risk	Impact	Probability	Risk	Impact	Probability	Risk
Consultant's Lack of Experience	22	20	22	22	15	22	22	13	21
Poor qualification of the contractor's technical staff	21	11	13	20	19	19	20	2	9
Owner's Lack of Experience	8	2	5	14	16	14	15	4	5
Owner's financial problems	3	22	14	3	22	20	3	22	22
Owner's Late Decisions	1	1	1	1	3	1	1	1	1
Owners change in requirements	2	12	6	7	14	7	7	15	13
Delay in changes approval	9	3	4	6	1	2	10	10	14
Contractor's financial problems	4	7	8	18	8	16	5	17	12
Delay in subcontractors work	6	6	2	2	13	5	4	7	3
Shortage of labour	16	10	11	17	18	15	17	19	18
Labor Productivity	19	8	12	16	17	17	16	18	17
Poor project cost estimation	7	4	3	5	2	3	9	8	15
Poor and improper Planning	5	16	10	13	4	11	19	3	11
Complexity in project design	15	15	17	15	9	12	13	5	10
Late in revising and approving design documents	13	5	9	8	11	6	6	12	8
Unclear and inadequate details in drawings	20	18	21	9	7	10	18	9	4
Lack of Coordination	12	13	15	10	6	8	11	11	7
Mistakes during the execution of works	18	17	20	12	20	18	12	6	6
Injuries on Site	11	21	19	21	21	21	14	21	20
Poor project management and supervision	14	19	18	4	5	4	21	16	19
Inflation	17	14	16	19	12	13	8	20	16
Rainfall and Weather conditions	10	9	7	11	10	9	2	14	2

This trend becomes more pronounced at higher maturity levels. For organisations at maturity Levels 3 and 4, risk factors 4 and 6 are ranked among the least important in terms of impact, whereas risk factors 22 and 9 become two of the most critical. These results demonstrate that improvements in organisational maturity are associated with substantial changes in how construction delay risks are perceived and prioritised. Specifically, higher maturity levels correspond to a shift away from traditionally dominant risk factors toward risks that may require more advanced organisational capabilities to identify and manage.

4.2. Risk Factor Prioritisation Across Dimensional Organisational Maturity Levels

To examine how risk management maturity levels in each dimension influence construction delay risks, a series of XGBoost regression models were developed. These models used the five maturity dimensions (G1–G5) as explanatory variables and the quantified delay risk metrics, impact, probability, and composite risk score, as response variables to identify recurring relationship patterns between maturity dimensions and delay risk measures.

Hyperparameter tuning was conducted by testing a predefined set of candidate values for the main XGBoost parameters and selecting the combination that provided stable predictive performance. The tuned parameters included maximum tree depth, learning rate, number of estimators and regularisation terms. The candidate search space included maximum tree depth values of [2, 3, 4, 5], learning rates of [0.01, 0.05, 0.10], numbers of estimators of [50, 100, 200, 300], gamma values of [0, 0.1, 0.5], reg_alpha values of [0, 0.01, 0.1], and reg_lambda values of [1, 5, 10].

Considering the relatively limited sample size, model complexity was carefully controlled to reduce the risk of overfitting. Based on the hyperparameter tuning process, the final XGBoost regression models were implemented using a maximum tree depth of 3, a learning rate of 0.05, and 100 estimators. The regularisation parameters were set as gamma = 0.1, reg_alpha = 0.01, and reg_lambda = 5. These settings provided a balance between predictive performance and model complexity while maintaining sufficient flexibility to capture potential non-linear relationships between organisational maturity dimensions and delay risk outcomes.

Model validation was conducted using five-fold cross-validation. Under this procedure, the dataset was divided into five subsets, with each subset used once as the validation fold while the remaining subsets were used for model training. The same cross-validation procedure was applied across all models to ensure consistency in model performance assessment. Model performance was evaluated using R^2 , calculated for each validation fold and averaged across folds. The final hyperparameter combination was selected based on the highest average cross-validated R^2 , while also considering model stability across folds and avoiding unnecessarily complex model structures. Across all developed models, the cross-validated R^2 values ranged between 0.821 and 0.932, with a mean value of 0.892, indicating consistently strong explanatory performance across the evaluated delay risk outcomes.

For each of the 22 delay risk factors, three XGBoost regression models were developed: one for impact severity, one for probability of occurrence, and one for composite risk criticality. In total, 66 XGBoost models were estimated. In all models, the same five organisational risk maturity dimensions were used as predictor variables, while the target variable changed according to the specific delay risk factor and risk metric being analysed.

Figures 6–8 illustrate how changes in maturity across the five dimensions affect the impact, probability, and composite risk weights of each delay factor.

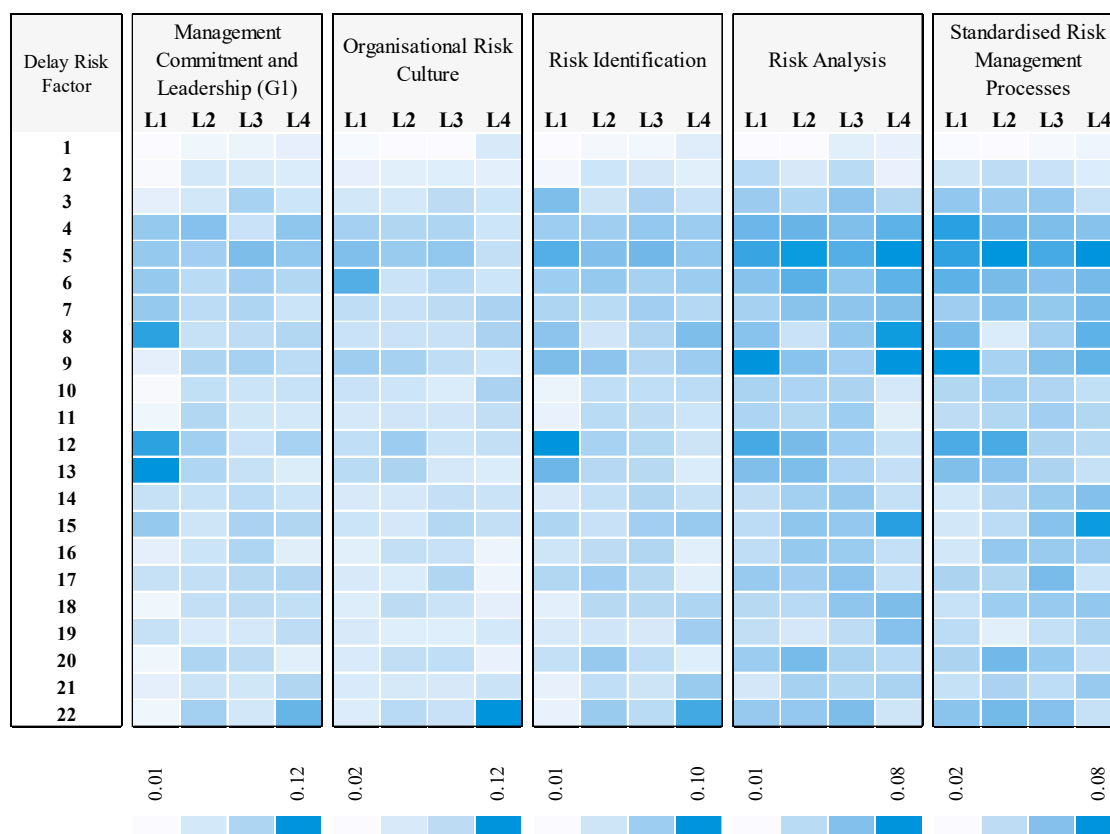


Figure 6. Effects of maturity dimensions on delay risk impact across maturity levels.

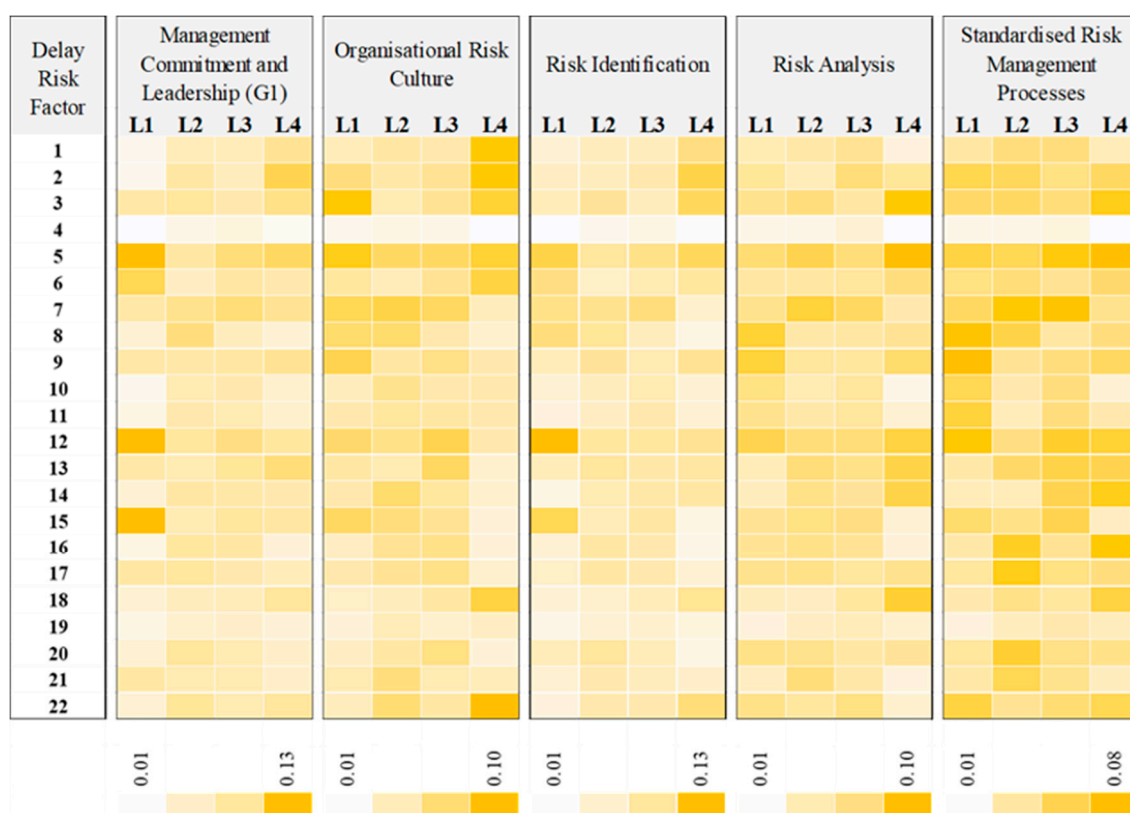


Figure 7. Effects of maturity dimensions on delay risk probability across maturity levels.

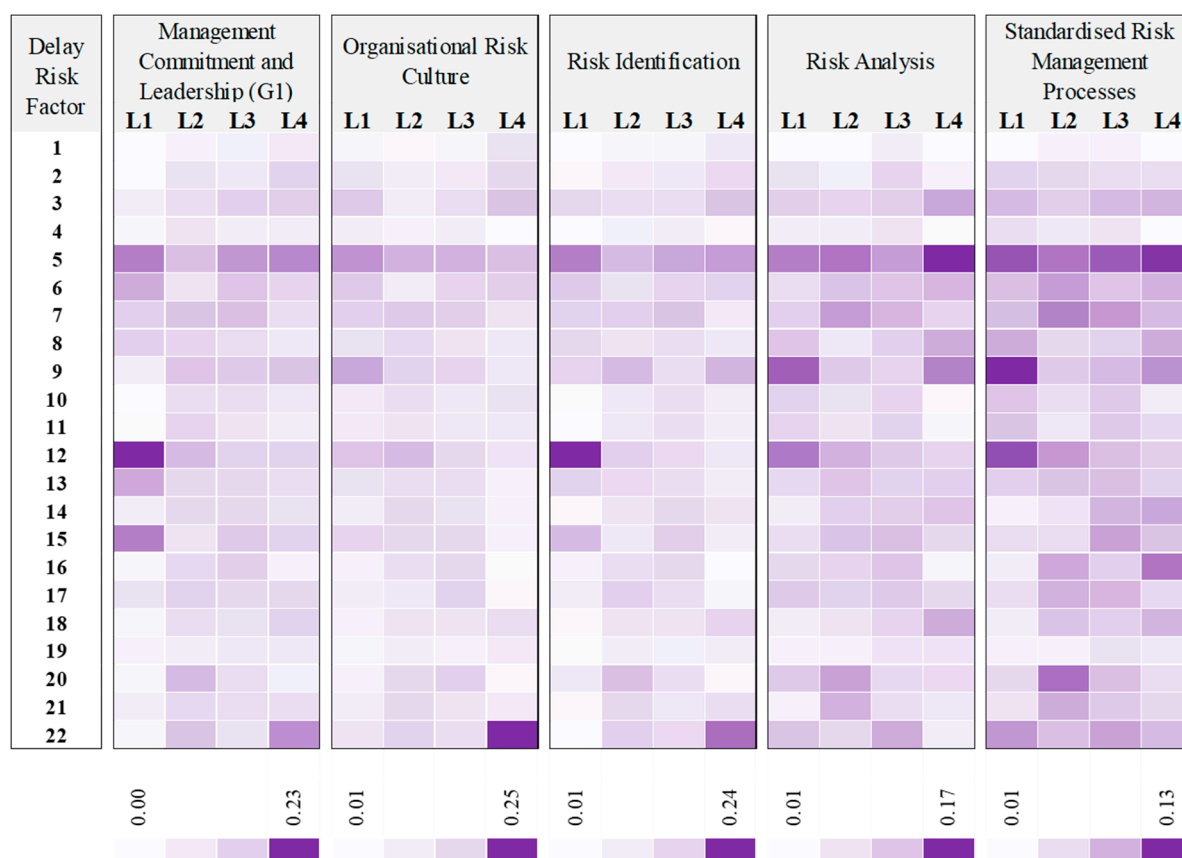


Figure 8. Effects of maturity dimensions on composite delay risk across maturity levels.

To examine the potential interrelationships among the organisational maturity dimensions and assess the dependency structure of the predictor variables, a correlation analysis was conducted among G1–G5. Figure 9 presents the correlation matrix of the five maturity dimensions. The results indicate that all dimensions are positively correlated, with correlation coefficients ranging from 0.558 to 0.803. The strongest correlation was observed between G4 (risk analysis) and G5 (standardised risk management processes) ($r = 0.803$), followed by the correlation between G3 (risk identification) and G5 ($r = 0.736$). Other dimensions demonstrated moderate positive associations, including G2–G4 ($r = 0.641$), G1–G2 ($r = 0.615$), and G1–G3 ($r = 0.614$). These findings confirm the expected conceptual relationship among maturity dimensions, as organisations with higher levels of maturity in one capability area tend to demonstrate stronger performance across other related areas. However, none of the correlation coefficients exceeded the commonly used threshold of 0.90, suggesting that although the maturity dimensions are highly interconnected, they represent distinct aspects of organisational risk management maturity rather than redundant measures. Therefore, all five dimensions were retained as predictor variables in the XGBoost models.



Figure 9. Correlation of predictor variables.

4.3. SHAP Results

To enhance the interpretability and readability of the XGBoost results, SHAP (SHapley Additive exPlanations) was applied to the trained XGBoost models. Accordingly, the results can be systematically compared based on observed patterns and SHAP value distributions.

In terms of patterns, five dominant patterns in the relationship between maturity levels and risk factor importance were identified, as illustrated in Figure 10:

1. monotonic decreasing relationships, where increasing maturity was associated with a consistent reduction in predicted impact, probability, or overall risk;
2. monotonic increasing relationships, where higher maturity corresponded to increased predicted values, often reflecting enhanced risk visibility or reporting;
3. threshold effects, in which maturity improvements yielded limited influence until a critical maturity level was reached;
4. non-linear or inverted-U relationships, indicating an initial amplification of risk recognition followed by mitigation at higher maturity levels;
5. maturity-insensitive relationships, where predicted outcomes remained largely unaffected by changes in maturity.

In terms of magnitude, the SHAP analysis illustrates the relative strength of the influence of each maturity dimension on the predicted importance of risk factors. Larger absolute SHAP values indicate a stronger contribution of a maturity dimension to the model output, while smaller values suggest a limited effect. The results demonstrate that certain maturity dimensions consistently exhibit greater influence on risk evaluation, highlighting their dominant role in shaping how organisations perceive the severity and likelihood of construction delay risks.

Considering both magnitude and pattern for all maturity dimensions, the SHAP summary plots in Figure 11 show the distribution of SHAP values for each maturity dimension. In these plots, factor importance is represented through colour coding, where blue indicates lower feature values and red indicates higher feature values. The horizontal distribution of SHAP values illustrates how variations in maturity levels influence the predicted importance of risk factors. Positive SHAP values indicate that increasing maturity in a specific dimension increases the perceived importance of a risk factor, while negative values indicate a reduction in its importance.

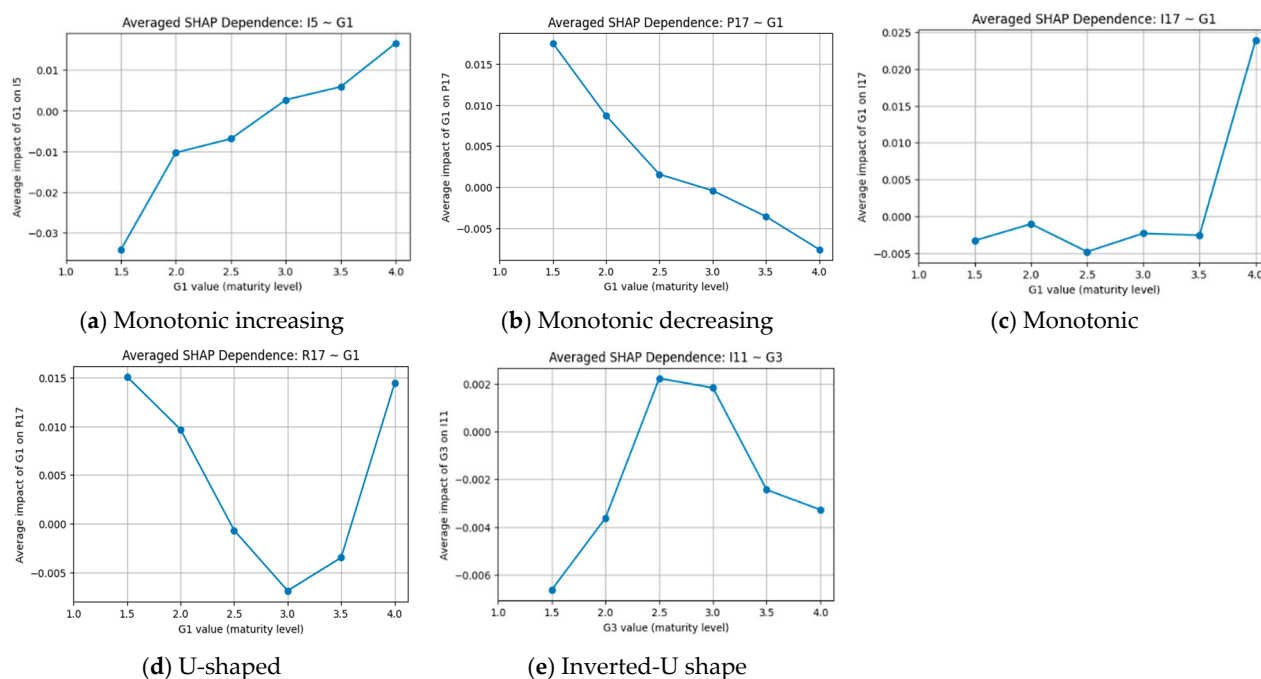


Figure 10. Dominant SHAP dependence patterns between maturity dimensions and delay risk outcomes.

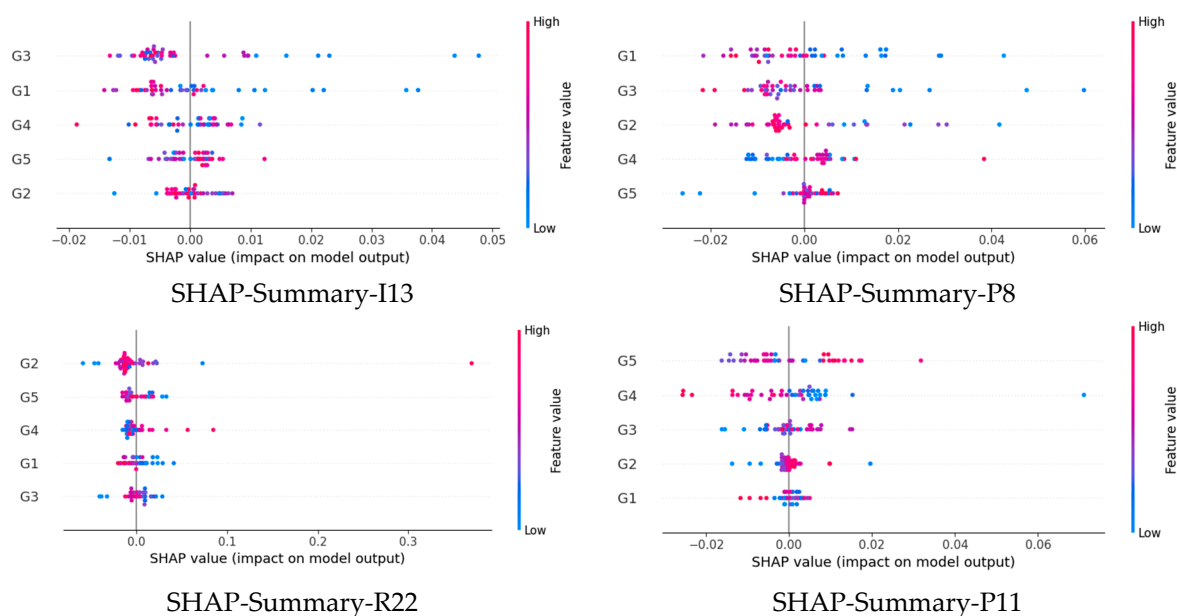


Figure 11. SHAP summary plot showing the relative influence of maturity dimensions on representative delay risk models.

5. Discussion

5.1. G1: Management Commitment and Leadership

Impact

In terms of impact, several trends are noticeable as the maturity level of G1 (management commitment and leadership) increases. Risk factors such as F1 (consultant's lack of experience) and F2 (Poor qualification of contractors' technical staff) show a gradual increase in weight from lower to higher maturity levels, indicating that organisations with higher leadership maturity assign greater importance to capability-related risks. This pattern is consistent with organisational risk governance theories, which suggest that

stronger managerial commitment improves risk awareness and encourages a more systematic evaluation of knowledge and competency gaps.

Conversely, factors such as F4 (Owner's financial problems) and F6 (Owner's change in requirements) decrease slightly or fluctuate across maturity levels, suggesting that these risks become relatively less dominant in the overall risk profile as leadership maturity develops. However, this does not necessarily imply that leadership directly reduces these risks; rather, mature organisations may have stronger governance mechanisms, contingency planning, and stakeholder management practices that influence how these risks are assessed and prioritised.

High initial impact factors such as F8 (Contractor's financial problems) and F12 (Poor project cost estimation) show a decreasing trend, which may reflect improved organisational capability in monitoring, planning, and controlling project-related uncertainties. This interpretation aligns with construction risk management frameworks, where management commitment is recognised as an enabling factor for establishing effective planning, monitoring, and control processes. Some factors, like F5 (Owner's late decisions) and F9 (Delay in subcontractors' work), fluctuate slightly across maturity levels, indicating that while leadership may influence awareness, certain delays are less controllable and remain moderately important across all maturity levels.

Probability

For probability, the trends indicate that stronger management commitment generally increases attention to the likelihood of risks associated with human factors and technical expertise. For example, F1 (consultant's lack of experience), F2 (poor qualification of the contractor's technical staff), and F3 (Owner's lack of experience) increase in probability weight as maturity rises, suggesting that mature organisations may develop a more comprehensive understanding of human-related uncertainties. From an organisational learning perspective, increased maturity can improve the ability to identify and record previously underestimated risk sources, resulting in higher perceived probabilities rather than necessarily higher actual occurrence rates.

Conversely, factors such as F4 (Owner's financial problems) and F19 (Injuries on site) remain low or decrease slightly in weight, indicating that leadership commitment may reduce the perceived likelihood of financial or safety-related issues through better planning, monitoring, and enforcement of policies.

Intermediate factors like F5, F6, and F7 (Owners' late decisions and changes, Delay in change approvals) fluctuate slightly, reflecting that while leadership awareness may shift probability perceptions, some external dependencies remain uncertain and are harder to control.

Risk

When considering the overall risk (impact $\times$ probability), several rational patterns emerge. Risk factors associated with technical capability and project management, such as F5 (Owner's late decisions), F8 (Contractor's financial problems), and F12 (Poor project cost estimation), show a clear decrease in overall risk weight as maturity rises. This trend suggests that mature leadership environments may place greater emphasis on structured governance, planning, and control mechanisms, which are recognised components of construction risk management maturity frameworks. Conversely, risk factors linked to human experience and expertise, like F1 (consultant's lack of experience), F2 (poor qualification of the contractor's technical staff), and F3 (Owner's lack of experience), tend to maintain or slightly increase their overall risk weights. Rather than indicating that leadership maturity increases these risks, this finding suggests that mature organisations may recognise competency-related vulnerabilities more explicitly through improved risk identification and assessment processes.

Factors such as F22 (Rainfall and weather conditions) see a slight increase at higher maturity levels in overall risk. Although environmental risks are largely uncontrollable, their increased weighting may indicate that mature organisations incorporate external uncertainties more systematically into risk assessments. This interpretation is consistent with Risk Maturity Models, where advanced organisations are expected to consider a broader range of internal and external risk sources.

5.2. G2: Organisational Risk Culture

Impact

In terms of impact, several patterns emerge as the organisational risk culture (G2) improves:

- F1 (consultant's lack of experience) shows a slight increase at higher maturity levels, indicating that organisations with stronger risk culture pay more attention to expertise-related risks.
- F6 (Owner's change in requirements) and F5 (Owner's late decisions) gradually decrease, suggesting that a mature risk culture enables companies to anticipate and manage owner-driven uncertainties more effectively.
- F8 (Contractor's financial problems) and F7 (Delay in change approvals) increase slightly, reflecting a heightened sensitivity to coordination and contractor-related risks in organisations with more developed risk awareness.
- F22 (Rainfall and weather conditions) exhibits a notable increase in weight at higher maturity levels, implying that companies with a mature risk culture are more deliberate in recognising uncontrollable environmental risks.

Other factors such as F2 (Poor qualification of contractors' technical staff) and F3 (Owner's lack of experience) remain relatively stable, suggesting that organisational culture does not strongly alter the perceived impact of personnel-related issues in the project.

Probability

For probability, clear trends can also be observed:

- F1 (consultant's lack of experience), F2 (poor qualification of the contractor's technical staff), and F3 (Owner's lack of experience) gradually increase in probability weight, showing that stronger risk culture makes organisations more aware of the likelihood of risks related to human expertise and owner inexperience.
- F4 (Owner's financial problems) decreases slightly, indicating that a mature risk culture reduces the perceived likelihood of risks that can be mitigated through proactive monitoring and financial planning.
- F22 (Rainfall and weather conditions) shows a strong increase at the highest maturity level, suggesting that organisations with a well-developed risk culture are better at accounting for environmental risks in probability assessments.
- Moderate increases are also observed for F5, F6, and F7, highlighting that as organisations focus more on risk culture, they become more sensitive to process-related delays and owner-induced uncertainties.
- Factors such as F14 (Complexity in project design) and F20 (Poor project management and supervision) fluctuate slightly but remain generally stable, suggesting that risk culture alone does not significantly affect the perceived likelihood of these technical risks.

Risk

Considering the overall risk (impact $\times$ probability), several relational trends are apparent:

- F22 (Rainfall and weather conditions) shows a sharp increase in overall risk at higher maturity levels, reflecting that mature organisations systematically incorporate external and uncontrollable risks into their assessments.
- F1, F3 (Consultant/Owner experience) increase moderately, highlighting that human-capability risks remain critical despite improvements in risk culture.
- F5, F6, and F9 (Owner decisions and subcontractor delays) decrease gradually, suggesting that enhanced risk culture allows organisations to anticipate and reduce the overall effect of these predictable, controllable risks.
- Factors like F12 (Poor project cost estimation) and F15 (Late in revising/approving design documents) show slight decreases in overall risk, indicating that a strong risk culture improves awareness and control over planning and procedural risks.

5.3. G3: Risk Identification

Impact

In terms of impact, several trends emerge as the maturity level in risk identification (G3) increases:

- F1 (consultant's lack of experience) and F2 (Poor qualification of contractors' technical staff) show a gradual increase in weight, indicating that organisations with mature risk identification practices pay more attention to expertise-related risks that could critically affect project outcomes.
- F3 (Owner's lack of experience) decreases slightly after an initial increase, suggesting that while early improvements in risk identification highlight owner-related risks, further maturity allows mitigation through structured evaluation processes.
- F12 (Poor project cost estimation) decreases significantly with higher maturity, reflecting that better risk identification reduces the perceived impact of foreseeable estimation errors.
- F22 (Rainfall and weather conditions) increases substantially at the highest maturity level, showing that organisations with advanced risk identification processes recognise environmental and uncontrollable risks as having higher potential impact.
- Some mid-range risks, such as F8 (Contractor's financial problems) and F9 (Delay in subcontractors' work), remain relatively stable or slightly increase, indicating that identification processes bring attention to operational uncertainties without significantly changing their perceived severity.

Probability

For probability, the trends suggest that stronger risk identification leads to heightened awareness of likely risk events:

- F1 (consultant's lack of experience), F2 (poor qualification of the contractor's technical staff), and F3 (Owner's lack of experience) increase in probability, indicating that organisations with robust risk identification are more aware of the likelihood of risks related to personnel and human capability.
- F22 (Rainfall and weather conditions) also shows a notable increase at higher maturity levels, highlighting that environmental risks are perceived as more likely when risk identification processes are mature and systematic.
- Risks associated with controllable processes, such as F5 (Owner's late decisions) and F6 (Owner's change in requirements), remain moderately stable or slightly increase, suggesting that organisations recognise the likelihood but also understand these risks can be managed through procedures.
- F4 (Owner's financial problems) shows minimal changes across maturity levels, implying that identification alone does not drastically alter perceptions of risks controlled externally.

Risk

Considering overall risk (impact $\times$ probability), clear relational trends emerge:

- F12 (Poor project cost estimation) and F13 (Poor and improper planning) decrease in overall risk, reflecting that advanced risk identification reduces both perceived impact and likelihood for predictable planning and estimation errors.
- F1, F2, and F3 increase moderately, indicating that human-capability risks remain critical even in mature organisations, as their likelihood and impact are now better assessed.
- F22 (Rainfall and weather conditions) rises sharply, demonstrating that environmental risks, which are uncontrollable yet identifiable, become more prominent in overall risk prioritisation as maturity increases.

Some operational delays, such as F8 (Contractor's financial problems) and F9 (Delay in subcontractors' work), fluctuate slightly but remain mid-ranked, suggesting that improved identification highlights these risks without significantly altering prioritisation.

5.4. G4: Risk Analysis

Impact

For impact, several trends emerge as the risk analysis maturity level increases:

- F1 (consultant's lack of experience) remains relatively low but shows a slight increase at higher maturity levels, indicating that mature analysis processes bring attention to expertise-related risks, even if their overall severity is low.
- F5 (Owner's late decisions) fluctuates slightly but generally decreases with higher maturity, suggesting that strong risk analysis allows organisations to anticipate owner-driven delays and reduce their perceived impact.
- F8 (Contractor's financial problems) and F9 (Delay in subcontractors' work) increase slightly at higher maturity levels, reflecting that mature analysis highlights potential operational disruptions that could influence project timelines.
- F12 (Poor project cost estimation) decreases steadily, showing that improved analytical processes reduce the relative impact of predictable financial risks.
- F22 (Rainfall and weather conditions) shows an irregular trend, with a slight decrease at the highest maturity level, suggesting that while initially considered high impact, mature analysis may contextualise environmental risks relative to controllable factors.
- Moderate-impact factors, such as F3 (Owner's lack of experience) and F6 (Owner's change in requirements), remain relatively stable, indicating that risk analysis mainly affects perception of controllable process risks rather than external uncertainties.

Probability

For probability, the trends reveal the influence of more sophisticated risk analysis practices:

- F1, F2, and F3 show small increases, suggesting that organisations with higher analytical maturity are slightly more aware of human-capability risks and their likelihood.
- F5, F6, and F7 (Owner delays and change approvals) remain mostly stable, indicating that while analysis helps anticipate these events, their probability is constrained by external factors.
- F22 (Rainfall and weather conditions) decreases slightly in probability, suggesting that improved analytical maturity allows organisations to contextualise and model environmental risks more realistically.

- F8 (Contractor's financial problems) fluctuates moderately, reflecting that risk analysis highlights operational vulnerabilities without dramatically altering likelihood perceptions.
- Other factors, such as F12 (Poor project cost estimation) and F15 (Late revision of design documents), remain stable, indicating that probability perceptions for procedural risks are less sensitive to analytical maturity.

Risk

When considering overall risk (impact $\times$ probability), clear rational patterns emerge:

- F5 (Owner's late decisions) and F9 (Delay in subcontractors' work) maintain moderate risk weights, reflecting that analytical maturity cannot fully eliminate external or operational delays but helps organisations anticipate them.
- F12 (Poor project cost estimation) decreases in overall risk, confirming that improved analytical processes reduce both perceived impact and likelihood for predictable financial errors.
- F22 (Rainfall and weather conditions) shows a slight decrease overall, highlighting that better analysis allows organisations to place environmental risks in context relative to controllable project elements.
- F1–F3 (Consultant/Owner experience) slightly increase, reflecting continued recognition that personnel-related risks remain relevant even as analytical sophistication improves.

5.5. G5: Standardised Risk Management Processes

Impact

For impact, the maturity level in G5 shows interesting trends:

- F1 (consultant's lack of experience) remains consistently low across all levels, reflecting that standardised processes reduce the perceived impact of human-related inexperience.
- F5 (Owner's late decisions) remains high but stable, indicating that even with strong standardisation, late decision-making by owners continues to have a significant perceived impact.
- F9 (Delay in subcontractors' work) shows a small increase at higher maturity levels, highlighting that advanced standardisation allows organisations to detect operational risks that could affect project schedules.
- F12 (Poor project cost estimation) decreases gradually, suggesting that standardised processes mitigate the impact of predictable estimation errors.
- F22 (Rainfall and weather conditions) decreases slightly at the highest maturity level, showing that well-established procedures allow organisations to contextualise uncontrollable environmental risks relative to other factors.

Moderate-impact factors, like F6 (Owner's change in requirements) and F8 (Contractor's financial problems), remain relatively stable, indicating that standardised processes primarily influence procedural and predictable risk perception rather than external uncertainties.

Probability

For probability, key trends indicate that stronger standardised processes improve the understanding of likely risks:

- F1–F3 (Consultant/Owner experience) remain low but slightly increase at mid-level maturity, suggesting that standardised procedures detect human-capability risks more consistently.

- F5 (Owner's late decisions) increases slightly at higher levels, reflecting recognition of persistent likelihood of delays even in standardised environments.
- F22 (Rainfall and weather conditions) remains relatively stable, indicating that environmental risks are understood but not strongly influenced by standardisation.
- F7 (Delay in change approvals) shows minor fluctuations, demonstrating that procedural risks are better anticipated, but external dependencies still limit probability reduction.
- Other procedural risks, such as F12 (Poor project cost estimation) and F15 (Late revision of design documents), remain stable or slightly decrease, showing the stabilising effect of standardisation on predictable project risks.

Risk

When combining impact and probability into overall risk:

- F5 (Owner's late decisions) and F9 (Delay in subcontractors' work) remain among the highest risks, showing that some operational and external risks cannot be fully mitigated by standardised processes.
- F12 (Poor project cost estimation) and F13 (Poor and improper planning) decrease, reflecting that standardisation effectively reduces both impact and likelihood of procedural errors.
- F22 (Rainfall and weather conditions) decreases slightly overall, indicating that environmental risks are better contextualised but still recognised.
- F1–F3 (Consultant/Owner experience) remain low to moderate, showing that human-capability risks are identified but not dominant in overall risk prioritisation.

Figure 12 focuses on the five delay risk factors that were ranked as most critical based on composite risk values under the general condition where risk prioritisation was conducted without considering organisational maturity. This baseline ranking represents the conventional industry-wide perception of delay risks derived from aggregated expert judgement. By tracking how these initially dominant risks evolve across maturity levels, the figure provides insight into how organisational capability reshapes established risk priorities.

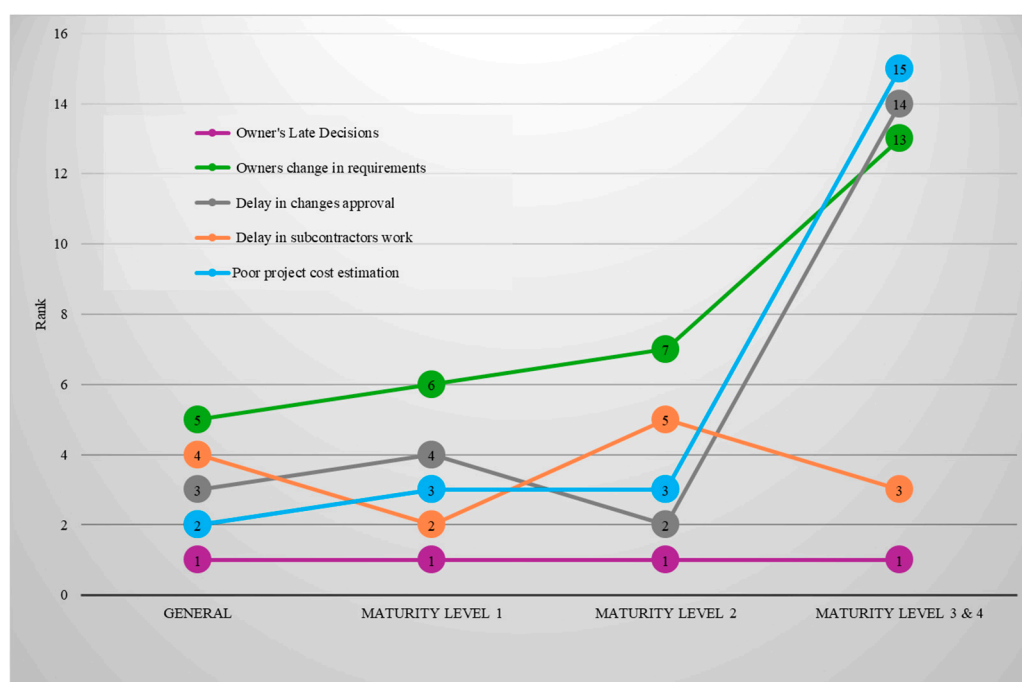


Figure 12. Changes in ranking of selected delay risk factors across organisational maturity levels.

At lower maturity levels, these top-ranked risks remain largely stable, indicating that less mature organisations tend to rely on generic industry perceptions and reactive management approaches. In particular, owner-related uncertainties and coordination-related delays continue to dominate risk prioritisation, reflecting limited institutional capacity for early intervention and systematic governance.

As maturity increases, substantial reordering of these baseline risk profiles becomes evident. Controllable risks associated with estimation and approval processes, including poor project cost estimation and delays in change approval, become less prominent in the composite rankings, suggesting that stronger analytical and procedural capabilities are associated with a reduced relative emphasis on these risks. Conversely, external and less controllable risks, particularly rainfall and weather conditions, receive greater relative attention at higher maturity levels. This pattern indicates that mature organisations develop a more differentiated risk profile in which internal process-related vulnerabilities are increasingly distinguished from risks requiring contractual, stakeholder, or project-resilience responses.

Notably, the persistent high ranking of owner's late decisions across all maturity levels highlights the enduring influence of external stakeholders on project schedules. Even in highly mature organisations, client-driven uncertainties remain difficult to fully mitigate, indicating inherent limitations in contractual governance and risk transfer mechanisms.

Overall, by re-evaluating baseline high-risk factors through progressively advanced governance systems, mature organisations exhibit more strategic, proactive, and internally focused approaches to delay risk management. This finding supports the argument that risk management maturity enhances not only technical competence but also the cognitive and organisational processes that underlie managerial decision-making.

6. Practical Implications

From a practical perspective, the proposed framework provides construction organisation with a diagnostic tool for linking maturity assessments to operational risk outcomes. Rather than treating maturity improvement as an abstract organisational objective, the framework identifies how variations in leadership, analytical capability, risk culture, risk identification, and procedural standardisation are associated with differences in delay risk evaluation and prioritisation. This information can support more targeted investments in leadership development, analytical systems, governance arrangements, and process integration. The XGBoost models can identify delay risks associated with elevated predicted impact, probability, or composite criticality, while SHAP indicate which maturity dimensions contribute most strongly to each prediction. These results may support more targeted consideration of leadership development, analytical systems, governance arrangements, and process integration within comparable Australian construction settings. However, application in other sectors or national contexts would require locally collected data, model recalibration, and independent validation.

An organisation-specific application can be illustrated through poor project cost estimation (F12). For a contractor exhibiting comparatively low maturity in risk analysis (G4) and standardised risk management processes (G5), a local SHAP explanation decomposes the predicted composite criticality of F12 into the individual contributions of the five maturity dimensions. Where low G4 and G5 values produce the largest positive SHAP contributions, limited analytical capability and process standardisation can be identified as the organisational characteristics most strongly associated with the elevated prediction. This evidence provides an analytical basis for prioritising independent cost reviews, standardised estimating and contingency procedures, systematic use of historical project data, and formal integration of lessons learned. A contrasting application arises in

relation to rainfall and weather conditions (F22), for which higher maturity may be associated with greater recognition of an external and largely uncontrollable source of delay. In this case, the appropriate managerial response would focus on project-level resilience measures, including wet-weather allowances, schedule contingencies, alternative activity sequencing, and suitable contractual provisions. Within the present dataset, local SHAP interpretation illustrates how capability-related and externally driven delay risks may be differentiated and how potential mitigation measures may be aligned with the organisational conditions associated with each prediction.

7. Recommendations for Future Research

The analysis relies on expert judgement and cross-sectional survey data, which may not fully capture temporal changes in organisational behaviour. In addition, while the study focuses on schedule-related risks, other performance dimensions such as cost, quality, and safety warrant similar investigations. Future research could adopt longitudinal designs to examine how maturity development influences risk prioritisation over time, integrate objective project performance data, and extend the framework to different construction sectors, project types (e.g., infrastructure, residential, and commercial projects), and international contexts.

Although the analytical procedure may be replicable in other settings, the empirical relationships identified in this study are specific to the sampled Australian construction organisations. The findings may reflect context-specific regulatory conditions, organisational characteristics, market environments, and industry practices. Future research should therefore independently validate and recalibrate the framework using datasets from different construction sectors, organisational categories, and national contexts before conclusions regarding its external generalisability or transferability can be established.

8. Conclusions and Research Limitations

This study developed an integrated framework combining the Generic Risk Maturity Model, expert-based risk quantification, XGBoost regression, and SHAP interpretation to examine how organisational risk management maturity is associated with construction delay risk prioritisation in Australia.

Within the sampled Australian construction organisations, different levels of risk management maturity were associated with different patterns of delay risk perception and prioritisation. Lower-maturity organisations tend to emphasise more visible and conventional delay risks, reflecting reactive management approaches and limited analytical capability. In contrast, higher-maturity organisations demonstrate more differentiated risk prioritisation patterns, with greater attention directed towards underlying and interconnected risk sources that require stronger governance structures, systematic processes, and proactive decision-making capabilities. These findings indicate that organisational maturity represents not only an improvement in risk management procedures but also a fundamental shift in how organisations interpret uncertainty and allocate attention to potential project threats.

The findings indicate that differences in maturity were associated with differences in how construction delay risks were perceived, evaluated, and prioritised within the present sample. While previous maturity models have primarily focused on evaluating the existence and sophistication of risk management practices, this research demonstrates that maturity levels influence the way organisations perceive, evaluate, and prioritise risks. The integration of explainable machine learning further contributes by revealing the mechanisms through which different maturity dimensions influence risk outcomes,

providing empirical insights into the relationship between organisational capability and risk decision-making in the Australian construction context.

Methodologically, the XGBoost–SHAP framework demonstrates the potential of explainable artificial intelligence to support construction risk research beyond prediction. Although machine learning models are often applied to improve forecasting accuracy, this study shows that interpretable machine learning can provide deeper insights into organisational behaviour by identifying how maturity dimensions contribute to changes in risk evaluation. This creates a transparent link between organisational characteristics and risk outcomes, supporting more evidence-based and proactive risk management decisions. Organisations can consequently align maturity-development initiatives with controllable planning, analytical, cultural, and procedural weaknesses, while applying project- and contract-level resilience measures to risks that cannot be substantially reduced through internal capability improvement alone.

Several limitations should be considered when interpreting the findings. First, the study was conducted within one national and industry context using a purposive sample of Australian construction professionals. Although the sample included different organisational types, tiers, and construction segments, it was not designed to establish independently generalisable findings for infrastructure, commercial, industrial, residential, consulting, or other project-based sectors. Differences in regulatory systems, market conditions, procurement practices, organisational structures, and risk cultures may produce different maturity–risk relationships in other settings.

Second, the relatively limited sample size should be acknowledged as a limitation. However, this research relies on expert-based assessments of organisational risk management maturity and construction delay risks, where obtaining responses from experienced professionals with sufficient organisational knowledge is inherently challenging. To enhance the reliability of the analysis, response screening, consistency checks, controlled model complexity through hyperparameter optimisation, and five-fold cross-validation were applied. Nevertheless, future studies with larger datasets are recommended to further validate the identified relationships and improve the generalisability of the findings.

Third, organisational maturity was assessed using a four-point ordinal scale, and item-level scores were aggregated within each maturity dimension to generate composite maturity indices. This approach was adopted to represent broader organisational risk management capabilities rather than individual assessment criteria and is consistent with established maturity assessment practices. However, treating these aggregated ordinal scores as continuous predictors introduces an inherent simplification. In particular, the limited number of discrete maturity levels may constrain the resolution of the identified relationships, and the SHAP dependence patterns should therefore be interpreted as directional trends and comparative influences rather than precise continuous effects across all maturity values. Future research could investigate these relationships using larger datasets and more granular maturity measurement scales.

Fourth, organisational maturity and delay risk evaluations were derived from expert judgements. Although structured assessment instruments, consistency screening, and systematic aggregation procedures were applied to improve reliability, the assessments may still involve a degree of subjective judgement. Furthermore, the cross-sectional nature of the dataset limits the ability to examine how organisations evolve between maturity levels and how maturity improvements influence project outcomes over time. Future research could address these limitations by collecting longitudinal data, expanding the sample across different geographic contexts, and validating the proposed relationships using larger datasets.

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