International Journal of Technology
http://ijtech.eng.ui.ac.id

Research Article

Explainable Artificial Intelligence (XAI) Model for Transparent and Trustworthy Tender Evaluation of Construction Projects

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Abstract: Construction tender evaluation is a high-stakes decision process in which contractor selection is expected to remain transparent and defensible. Although artificial intelligence (AI) effectively enhances analytical decision processing scalability using machine learning, AI adoption in project tender evaluation is constrained by limited interpretability and weak justification of AI insights. This study develops a conceptual Explainable Artificial Intelligence (XAI) tender evaluation model that integrates data preprocessing, predictive modeling, and SHAP explainability within three phases. The model provides decision insights at global and contractor levels through dataset-level feature attribution, contractor-level explanations of evaluation criteria and trade-offs, and project governance insights supporting audit trails and tender award justification. A pilot study was conducted among 10 Malaysian construction sector experts to examine the relevance and practical applicability of the proposed model. The findings indicate XAI strengthens for decision transparency, improves tender ranking interpretability, and supports transparent tender deliberation, whereas professional judgment remains central to a final tender decision award. This study strengthens the link between predictive analytics and procurement governance by explicitly revealing the interaction dynamics of ranking criteria that are often obscured in conventional tender evaluation. This study positions data governance as a prerequisite for credible explanations and decision support. Future research should empirically test the proposed model in live tender evaluation settings and establish sectoral standards for explainability and data governance for construction projects.

Keywords: Artificial intelligence; Construction management; Data driven decision-making; Explainable AI; Tender evaluation

1. Introduction

Artificial intelligence (AI) research in the construction sector has expanded rapidly as organisations seek to transform fragmented and heterogeneous project data into structured decision intelligence. AI refers to computational systems which learn from data, identify patterns, and generate outputs to support decision and action across complex operational environments (Adeyeye and Akanbi, 2024; Datta et al., 2024; Verma and Singhal, 2023). In engineering and construction project management, AI-driven decision making techniques improve project design, evaluation accuracy, and support data-intensive decision processes (Rajalakshmi and Wahab, 2025). AI applications strengthened estimation accuracy, anomaly detection, risk forecasting,

https://doi.org/10.14716/ijtech.v17i3.8288
Received December 2025; Revised December 2025; Accepted April 2026

cost transparency, and multi-criteria decision making across project lifecycles. As construction stakeholders increasingly operate in data-intensive environments, AI is becoming an important decision support capability that reshapes how project information is processed and analysed.

Tender evaluation represents one of the most critical high-stakes settings with huge AI potential (Mostofi et al., 2025). Contractor selection directly influences project cost outcomes, delivery performance, and risk exposure, particularly in public procurement contexts where decisions must remain transparent, auditable, and defensible to multiple stakeholders, including clients, regulators, consultants, and contractors. The conventional tender evaluation relies on structured scoring matrices, staged screening procedures, and expert judgement to compare tender bids across criteria such as cost, technical capability, and past performance. While existing tender evaluation provides an established governance structure, the process is time consuming, susceptible to inconsistency, and reliant on fragmented data, which weakens the traceability of decision rationales (Maaz et al., 2025; Alozie, 2024). Increasing project complexity and organic growth of data volume further intensify these challenges, frequently prolonging assessment cycles and limiting deeper analytical insight into how competing tender evaluation criteria shape final ranking outcomes.

AI-driven tender evaluation is positioned as a response to the limitations of conventional evaluation. Machine learning (ML) and natural language processing (NLP) techniques can effectively process large project datasets, automate scoring, and generate predictive insights to support contractor ranking (Zubair et al., 2024; Sholeh et al., 2023; Ashritha and Reddy, 2023). With integration to multi-criteria decision making approaches, AI can improve analytical scalability and consistency by simultaneously evaluating quantitative and qualitative tender data (Maaz et al., 2026; Khalid et al., 2024; Mensah et al., 2022). However, AI advances subsequently introduce a critical governance challenge as AI models operate as 'black box', generating recommendations without clearly revealing how specific evaluation criteria influence outcomes (Phillips, 2025; Waqar, 2024; Chamola et al., 2023). In the high-stakes construction procurement process, tender award decisions must withstand scrutiny, audit, and possible dispute. Such opacity can weaken stakeholder trust despite strong technical performance.

Figure 1 presents a comparison of conventional, AI-driven, and explainable artificial intelligence (XAI) on the tender evaluation process to clarify the evolution and position the contribution of this study. Conventional evaluation provides procedural transparency but limited analytical scalability. AI-driven evaluation improves efficiency and predictive capability but often obscures decision logic. XAI extends the AI explainability dimension to clarify how project data and tender evaluation criteria influence contractor rankings. By linking automated analysis with interpretable justification and auditable pathways, XAI offers the potential to retain AI's efficiency benefits while strengthening transparency and accountability in high-stakes project tendering decisions.

Explainability in construction tender evaluation must account for the diverse stakeholder environment in which procurement decisions are made. The project team, namely, quantity surveyors, project managers, client representatives, and regulatory representatives, possesses varying levels of technical literacy and distinct accountability responsibilities. Accordingly, AI decision explanations should operate at multiple levels: providing technical insight into criteria influence for evaluators, summarized rationale for decision committees, and traceable audit documentation for governance oversight. The purpose of such explainability extends beyond understanding to both immediate decision support and institutional learning across procurement cycles. Without a structured explanation, AI outputs may be misinterpreted (Humer et al., 2024). For instance, a contractor may be ranked highly due to cost efficiency while sustainability or risk factors are implicitly underweighted, or a lower ranking may result from missing data fields rather than substantive performance weaknesses. The proposed model reduces the risk of misplaced confidence, enhances defensibility, and strengthens transparency in high-stakes construction procurement decisions by embedding explainability mechanisms within the evaluation workflow.

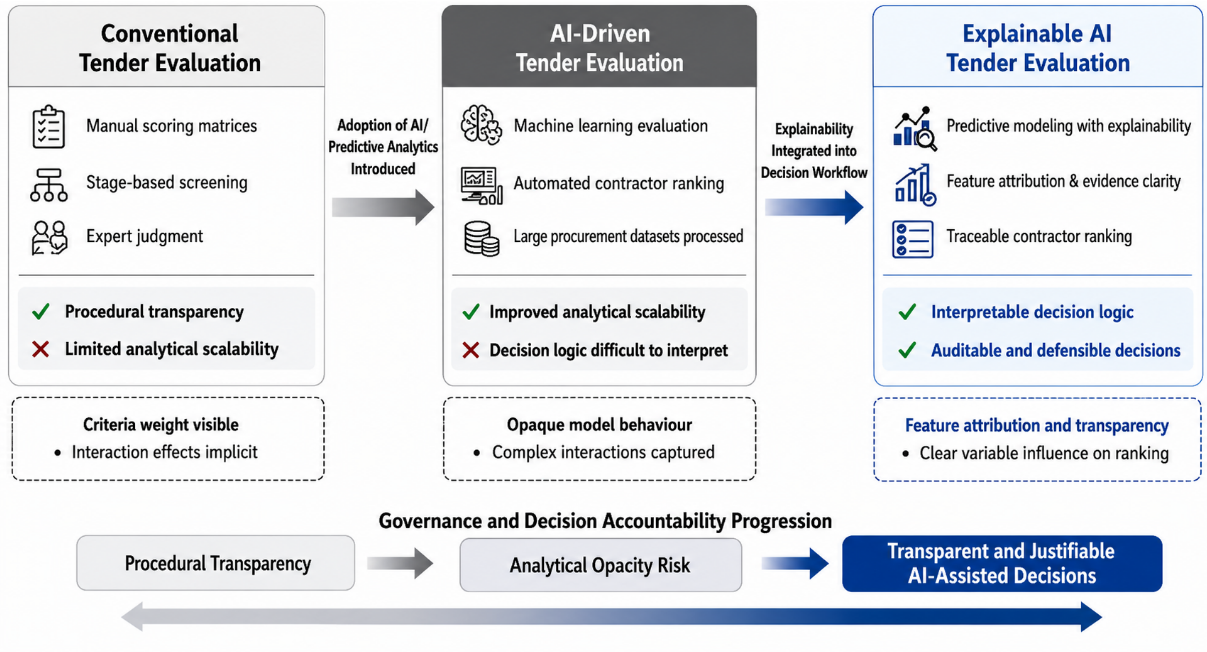

Figure 1 Comparison of conventional, AI-driven, and Explainable Artificial Intelligence (XAI) on tender evaluation process

Explainable Artificial Intelligence (XAI) provides potential to align advanced analytics with project governance requirements. By exposing relationships between input data, model logic, and outputs, XAI enables stakeholders to interpret and scrutinize recommendations for automated tendering and procurement insights. In the healthcare and finance sectors, XAI is increasingly used to support decisions requiring both predictive accuracy and accountability (Phillips, 2025; Nicora et al., 2022). However, within construction, XAI remains at an early stage of development. Shehadeh and Abuaddous, 2025, Zhan et al., 2024; Chen and Mason, 2024; Love et al., 2023 studied XAI in the construction and built environment sector. They primarily explored its applications in delay and cost risk prediction, geotechnical and safety risk analysis, sustainability and building energy analytics, and broader model interpretability for engineering decision support, with comparatively limited attention to its integration into procurement and contractor selection processes. Research on how explainability mechanisms can be systematically integrated into tender evaluation processes to support transparency, auditability, and institutional learning remains scarce.

Accordingly, this study develops a conceptual Explainable Artificial Intelligence (XAI) model for construction project tender evaluation. The model integrates data preprocessing, predictive modelling, and SHapley Additive exPlanations (SHAP) explainability in a three-phased model to strengthen transparency, interpretability, trustworthiness, and justification in contractor selection. The model intended to advance conventional tender evaluation beyond opaque scoring and black box prediction toward a transparent decision support process in which contractor rankings can be traced to identifiable evaluation criteria and explained through global and contractor-level insights. The study incorporates a pilot study with ten (10) Malaysian construction experts to explore the relevance and practical applicability of the proposed XAI model across tender evaluation stages.

This study makes two contributions. First, the role of XAI in high-stakes project tender evaluation is conceptualized by linking predictive analytics with procurement governance requirements. Second, an XAI model linking data, model, and explanation layers is proposed, supported by an exploratory pilot study with construction experts. In doing so, the study advances understanding of how XAI can support transparent and trustworthy tender evaluation while reinforcing the continued centrality of professional judgement in final tender award decisions.

2. Explainable Artificial Intelligence Potential for Tender Evaluation of Construction Projects

2.1 Tender Evaluation Issues for Construction Projects

Tender evaluation is a fundamental element of procurement, requiring systematic and objective assessment frameworks to select the most suitable contractor. Table 1 summarizes tender evaluation issues for construction projects. Limited transparency in tender evaluation undermines public procurement where impartiality and accountability are imperative (Ismail et al., 2021). Conventional systems, including AI evaluation techniques, produce scores without elucidating the rationale behind decisions, resulting in fragmented audit trails that are difficult to reconstruct (Fawzy et al., 2024; Khoso et al., 2021). Bilal and Oyedele, 2020 highlight opacity issues undermine the confidence of stakeholders in AI recommendations to justify potential costly delays and budget overruns. Evaluation frameworks that not only automate scoring but also furnish clear and human-readable explanations for how criteria influence evaluation decisions are urgently needed.

Publicly tendered construction projects often attract hundreds of bidders, each submitting rich datasets ranging from structured financial returns to unstructured sustainability reports or BIM models (Khoso et al., 2021; Taylan et al., 2018). Conventional Excel workflows lack the capacity to handle large data volumes, resulting in superficial reviews or lengthy backlogs. The evaluation mechanisms also face difficulties in decomposing interrelated criteria, such as lifecycle cost versus environmental performance, into prioritized insights (Khoso et al., 2021). Without advanced analytic support, construction stakeholders struggle to transparently balance conflicting objectives (cost, time, quality, and sustainability), impairing the ability to align contractor selection with impartial and broader strategic goals (Fawzy et al., 2024).

Furthermore, prequalification stages frequently employ rigid pass/fail thresholds, treating all compliant bidders as equivalent and masking the difference between marginally acceptable and exceptional proposals (Zhang et al., 2015). Jain et al., 2024 argued the binary approach and manual record lead to variations in spreadsheet versions and inconsistent documentation, which inhibits institutional learning across procurement cycles. Although standardized scoring matrix mitigates overt evaluator bias, qualitative assessments, such as team competence, remain susceptible to subtle subjective influences when structured guidance is insufficient (Fawzy et al., 2024; Khoso et al., 2021). Collectively, these shortcomings highlight the need for more adaptive, transparent, and analytically robust evaluation paradigms in public construction tendering.

2.2 Artificial intelligence techniques

The exploration of Artificial Intelligence (AI) is revolutionizing traditional tender management in construction, particularly in contractor selection and bid evaluation. Conventional tender evaluation predominantly relies on multi-criteria decision-making models, such as the analytical hierarchy process, fuzzy theory, and ELECTRE III, which systematically rank contractors using multiple weighted qualitative and quantitative criteria (Fawzy et al., 2024). For instance, fuzzy TOPSIS and fuzzy SAW enhance decision-making under uncertainty by addressing subjective attributes such as reputation and reliability (Taylan et al., 2018). However, conventional methods heavily depend on manual assessments and expert-driven criteria, rendering the process time-consuming and susceptible to subjective biases. This prompted a shift toward AI techniques, including machine learning (ML), big data analytics, and case-based reasoning (CBR), for automated, data-driven alternatives that reduce subjectivity while improving decision accuracy (Jain et al., 2024; Bilal and Oyedele, 2020).

Machine learning (ML), which uses historical data to predict contractor reliability and improve selection accuracy, is one of the key AI methods in tender evaluation (Jain et al., 2024). Multi-linear regression, decision trees, and support vector machines (SVM) are used to identify complex patterns in bid outcomes, performance, and risks, enabling data-driven contractor ranking (Shi et al., 2016). These algorithms are adaptable and continuously improve with new data, making them ideal for dynamic procurement environments. However, high-quality and structured data are required to ensure reliability, interpretability, and fairness, as they may inherit biases from historical records.

Table 1 Issues of tender evaluation for construction projects

Issue	Details	Authors
Limited transparency and justification	Limited understanding of AI decisions challenges impartiality, accountability, and transparency in public projects	Ghezzi and Mikkonen, 2023; Khoso et al., 2021; Khaderi et al., 2019
Inefficient processing of large volumes	Integration of diverse data and selection from large pools of bidders	Kusumarukmi and Adi, 2019; Dello and Yoshida, 2017
Complexity in the evaluations	Balancing conflicting criteria in complex multi-attribute systems is difficult	Khoso et al., 2021; Bilal and Oyedele, 2020
Numerical cut-off thresholds	Inability to differentiate highly qualified contractors from those who barely meet minimum requirements	Kusumarukmi and Adi, 2019
Difficulties in tracking and managing data	Limitations in manual processes and the need for accurate data for effective model development	Cheaitou et al., 2019
Subjectivity and bias	Influence of personal biases on expert evaluations and inadequate consideration of qualitative factors	Khoso et al., 2021; Kusumarukmi and Adi, 2019

Deep neural networks (DNNs) and artificial neural networks (ANNs) are increasingly vital in tender evaluation, contractor benchmarking, and bid assessment (Zhu et al., 2022; Bilal and Oyedele, 2020). DNN and ANN effectively capture complex, nonlinear relationships within data for detecting bid collusion, fraud prevention, and profitability benchmarking. DNNs support comprehensive contractor ranking, whereas ANNs assist in subcontractor evaluation by simultaneously considering multiple selection criteria (Jain et al., 2024; Fachrurrazi et al., 2017). Nevertheless, the black box nature of AI models poses concerns on transparency and accountability, particularly in public procurement where explainability and auditability are critical for trust and compliance (Akhtar et al., 2024).

Beyond predictive modelling, Big Data Analytics (BDA) is revolutionizing tender evaluation by analysing extensive bid records, cost databases, and project characteristics to identify pricing trends, anomalies, and competitive bid ranges (Zhang et al., 2015). While these insights improve procurement transparency and competitiveness, BDA introduces challenges related to data security, real-time data integration, and bias in historical records, necessitating ethical data practices and regulatory compliance to prevent misuse or unfair competitive advantages (Safa et al., 2015).

Finally, CBR is gaining traction in automating tender document generation to recommend pre-filled bid templates based on similar historical projects (Zhou et al., 2021). Consequently, CBR reduces manual workload and ensures compliance with evolving industry standards and regulations. However, the effectiveness of CBR depends on high-quality past cases and weakens when handling unique or customized tenders.

2.3 Explainable Artificial Intelligence Dimensions

Explainable Artificial Intelligence (XAI) is an emergent domain focused on demystifying the "black box" of complex AI models to ensure transparent and interpretable insights that are trusted by human stakeholders (Phillips, 2025; Waqar, 2024). Chamola et al., 2023 highlight the difference between AI and XAI, where AI models deliver insights without revealing decision logic, and XAI explicitly exposes the relationships between input data and algorithmic processes resulting from the decisions. XAI facilitates informed and justifiable decision-making by providing clear rationales and evidence accompanying each decision (Phillips, 2025). Thus, XAI permits targeted human oversight and enables intervention when systemic or contextual anomalies are detected.

XAI has been successfully implemented in the healthcare and finance sectors. In healthcare, during the COVID-19 pandemic, XAI-driven diagnostic tools not only predict disease onset but also outline the weight of clinical indicators in mortality forecasting (Phillips, 2025; Nicora et al., 2022). Similarly, financial institutions leverage XAI to detect anomalies in anti-money laundering transactions and highlight credit risk models, revealing variable interdependencies during borrower assessments (Phillips, 2025). In construction, the potential of XAI is explored to enhance project risk management by applying fuzzy logic to assign linguistic risk labels with the capability to explain the contributing factors, providing an understanding of how project cost estimation is established using rule-based decision paths and clarity through interpretable site sensor data for proactive hazard identification (Waqar, 2024).

2.3.1 Explainable Artificial Intelligence Attributes

The potential of XAI adheres to the following four foundational attributes: transparency, interpretability, justification, and trustworthiness:

Transparency. The extent to which an artificial intelligence (AI) system reveals internal data flows and decision logic (Waqar, 2024; Albahri et al., 2023). The XAI model clarifies the decision nature by detailing the input data, algorithms, and transformations applied, and clarifies the sequential steps linking inputs to outputs. Transparency on AI insights enables rigorous auditability and increases stakeholders' confidence in AI usage to assist decision-making (Phillips, 2025).

Interpretability. Humans can understand the degree of the decision process and insights from the AI model (Chamola et al., 2023). The interpretability principle emphasizes translating complex mathematical processes into simplified forms, such as rule-based summaries or visual representations. Kamath and Liu, 2021 highlight the importance of XAI in facilitating understanding by technical and non-technical users.

Trustworthiness. Reliability and alignment of the AI model with human values (Chamola et al., 2023). A trustworthy AI model delivers consistent and reproducible results across varying conditions, proactively identifies and discloses potential bias sources, and ensures alignment with ethical and regulatory standards. The trustworthiness AI principle underpins user confidence in AI to facilitate decision-making (Jou et al., 2026; Waqar, 2024).

Justification. AI decisions are accompanied by explicit evidence or reasoning, enabling stakeholders to scrutinize, challenge, or override outcomes (Albahri et al., 2023). Techniques such as feature importance analysis and rule-based explanations present details on why specific conclusions were reached and which factors contributed most significantly (Waqar, 2024). This mechanism ensures that AI models remain transparent and subject to human governance.

3. Explainable Tender Evaluation Conceptual Model of Artificial Intelligence

The development of an XAI tender evaluation model aims to improve the tender evaluation process's efficiency, interpretability, trustworthiness, and justification, thereby optimizing contractor selection.

3.1 Phase 1: Data collection and preprocessing

3.1.1 Data collection

The data collection phase aggregates multiple source datasets, including historical tender data (i.e., bid price, contractor information, material costs, and labor costs), project specifications (i.e., size, complexity, and location), market conditions (i.e., inflation rates), risk factors (i.e., weather conditions and geopolitical risks), contractor performance records (project completion rates, budget monitoring, and project quality report), and tender evaluation scores from previous tenders. This aggregated dataset provides a data-driven view of contractor performance, and preprocessing steps are applied to maintain data integrity with strict privacy and security measures to protect sensitive information (Bahameish et al., 2022).

3.1.2 Preprocessing of Data

Data preprocessing is required to clean and structure data for ML training due to the multiple-source data collection (Obinna and Kess-Momoh, 2024; Konnerth, 2023; Gredell et al., 2019). Data pre-processing involves several key steps to prepare raw data for ML models (Kadhim, 2018). Data cleaning is the initial step, which focuses on detecting and correcting or removing inaccurate, irrelevant, or noisy data from the dataset (Maharana et al., 2022). This process addresses issues such as removing duplicate data that may arise from combining data from different sources, fixing data errors caused by mislabeling or inconsistent naming, and handling missing values through imputation methods such as mean, median, or mode values. Maharana et al., 2022 highlighted that fractured data is a significant issue if data are collected from several groups or different platforms, as data standards for managing the data have high varying potential. Data validation is crucial to ensure that data adhere to specific rules and that high-quality data meet the thresholds of validity, accuracy, completeness, consistency, and uniformity (Dalavai et al., 2024). Data integration further combines data from heterogeneous sources to create a unified data lake for ML model development (Le et al., 2020).

3.2 Phase 2: Development of an Explainable Artificial Intelligence Model

3.2.1 Feature Engineering

Feature engineering ensures that the tender evaluation criteria are analytically meaningful and suitable for integration with the proposed XAI model. Tender evaluation variables are derived from structured tender and procurement datasets (e.g., bid price, contractor experience, financial positions, historical project performance indicators) and unstructured tender documentation data. Natural language processing (NLP) techniques are incorporated to extract evaluative indicators from technical proposals, construction methods, project plans, and financial positionings (Recep et al., 2026). Textual features are transformed into structured variables to ensure a consistent and transparent evaluation.

Feature relevance was assessed using correlation analysis, statistical tests, and tree-based ensemble feature importance methods. Random Forest and Extreme Gradient Boosting (XGBoost) are used as diagnostic tools to identify influential tender evaluation criteria and reduce redundancy across predictors (Oo et al., 2025; Coffie and Cudjoe, 2024; Gredell et al., 2019). Machine learning techniques facilitate the identification of cost, time, technical capability, and project performance determinants while preserving the interpretability requirements necessary for the subsequent analysis of explainability. When dimensionality or multicollinearity poses analytical challenges, dimensionality reduction methods such as principal component analysis (PCA) may be applied cautiously to simplify the feature space without compromising decision interpretability (Bachmann, 2025).

3.2.2 Model training and predictive evaluation

Supervised machine learning, particularly tree-based ensemble models such as Random Forest and XGBoost, are used as primary predictive techniques for tender evaluation and ranking because of their robustness in handling heterogeneous tender and procurement datasets, nonlinear data relationships, and mixed numerical and categorical variables while maintaining compatibility with explainability methods (Alazawy et al., 2025; Oo et al., 2025). RF and XGBoost are suitable for classification tasks (e.g., technical compliance categories and risk classes) and regression tasks (e.g., predicted cost performance and contractor scoring) (Coffie and Cudjoe, 2024). Tree-based ensemble models, such as Random Forest and XGBoost, are particularly suitable for dynamic procurement environments due to their robustness in managing evolving data distributions, heterogeneous feature sets, and real-time incremental dataset expansion (ForouzeshNejad et al., 2024). Furthermore, the ensemble architecture allows retraining with newly accumulated tender data without requiring a complete model redesign (Oo et al., 2025), thereby supporting adaptive learning across procurement cycles. Neural network models may be explored as complementary predictive tools where more complex nonlinear interactions between tender variables are expected.

Model training is conducted on preprocessed datasets using stratified k-fold cross validation to improve generalizability and reduce the risk of overfitting. This approach ensures that the proposed XAI model remains adaptable across procurement contexts and project types. Model performance is conceptually evaluated using metrics aligned with the specific prediction task before explainability technique integration. Regression outputs (e.g., cost, time, or performance predictions) are assessed using mean absolute error (MAE), mean squared error (MSE), and coefficient of determination (R^2), whereas classification outcomes (e.g., contractor risk categories or compliance screening) are evaluated using accuracy, precision, recall, and F1-score (Shekhar et al., 2023). This structured modeling process establishes a robust analytical foundation for the subsequent evaluation of explainable contractors.

3.2.3 Integration of the Explainability Techniques

Explainability mechanisms are embedded within the predictive modeling pipeline to ensure transparency, auditability, and alignment of governance in automated tender evaluation. Shapley Additive Explanations (SHAP) serve as the primary interpretability technique in this model due to its strong theoretical grounding in cooperative game theory and compatibility with the proposed tree-based ensemble models (Li et al., 2024). SHAP enables global and local interpretability, allowing institutional and decision-level transparency to be maintained (Alazawy et al., 2025).

Global interpretability refers to understanding the overall behavior of the model across the procurement dataset (Ahmed et al., 2023). SHAP summary plots and aggregated feature importance values reveal the relative influence of tender evaluation criteria on tender ranking outcomes, such as bid price, technical capability, past performance, and project risk indicators. This enables the project evaluation committee to verify that the model behavior aligns with the established tender evaluation priorities and project governance requirements (Burkart and Huber, 2021). Local interpretability explains individual contractor predictions by quantifying how specific attributes increase or decrease the predicted scores (Alazawy et al., 2025). SHAP values provide traceable explanations that can be presented through annotated scorecards, dashboards, or narrative summaries to support defensible decision-making and audit review.

SHAP is selected over alternative explainability techniques such as Local Interpretable Model-agnostic Explanations (LIME) and rule-based explainers due to its consistency and unified interpretability capabilities. LIME produces local approximations that may vary across runs (Gunes, 2024). The SHAP provides stable and theoretically consistent feature attribution. Compared with rule-based techniques, which require manual rule specification and may oversimplify complex relationships, SHAP accommodates nonlinear interactions within heterogeneous procurement datasets while preserving interpretability (Ahmed et al., 2023). The compatibility of SHAP with tree-based ensemble models further supports the coherent integration between the prediction and explanation layers (Sepiolo and Ligęza, 2022). The SHAP explanation layers embedded within the tender evaluation workflow enable project stakeholders to trace the relationships between input data, model logic, and AI insight recommendations. This further strengthens confidence in AI-assisted tender evaluation for strategic contractor selection, supports tendering decision justification, and facilitates institutional learning across procurement cycles (Saldiran et al., 2023). Explainability functions not only as a transparency mechanism but also as a decision support layer that allows evaluators to interpret model outputs, detect potential bias or misclassification, and make informed final award decisions.

3.3 Phase 3: Automated model improvement

A structured implementation strategy embeds the XAI model within existing procurement workflows and establishes feedback loops for automated model refinement and explanation enhancement. The initial model outputs are continuously evaluated against key performance indicators, with deviations triggering automated retraining using newly acquired tender data (Handfield et al., 2019). Simultaneously, procurement experts validate the clarity and relevance of generated explanations, providing targeted feedback that guides iterative adjustments to explanation algorithms to improve the fidelity and granularity of the XAI model rationale. This dual process of automated recalibration and expert validation ensures that predictive accuracy and explainability mature in tandem over successive cycles. The XAI model offers data-driven decision-making insights in the form of interactive dashboards, annotated scorecards, and narrative explanations that synthesize contractor scores and rankings into actionable recommendations for technical teams. These insights incorporate transparent, human-readable justifications of the criteria, empowering stakeholders to confidently defend award decisions (Saldiran et al., 2023; Wang et al., 2023). Figure 2 presents the XAI conceptual tender evaluation model, which is structured into three sequential phases.

4. Explainable Decision Logic in Project Tender Evaluation

Explainable Artificial Intelligence (XAI) in tender evaluation and procurement operates within an inherently high-stakes project management decision environment requiring a robust governance process. Contractor selection decisions influence project cost certainty, delivery reliability, and schedule risk exposure across the project lifecycle, particularly in public procurement settings subject to audit and regulatory scrutiny (Almuhannadi and Ghareeb, 2024; Demetracopoulou et al., 2024). Conventional tender evaluation mechanisms make assessment criteria explicit but offer limited visibility into how cost, technical capability, and risk interact to shape outcomes (Van Der Meer et al., 2015; Ballesteros-Pérez et al., 2015). Machine learning models can capture these interdependencies across large and heterogeneous datasets, yet the underlying decision logic often remains insufficiently transparent (Badhon et al., 2025). The central issue addressed in this study concerns how predictive modeling can be integrated with structured explainability to support the evaluation of transparent, auditable, and defensible contractors.

The proposed conceptual XAI tender evaluation model embeds explanation mechanisms within the predictive modelling pipeline to allow model outputs to remain linked to identifiable evaluation variables throughout training, validation, and deployment. XAI integration enables systematic decision documentation of how contractor rankings are derived from structured tender data, including bid price, technical competence, past performance, and project risk indicators. Figures 3-5 visualise illustrative representations of the expected analytical outputs for the proposed XAI model. At the dataset level, global feature attribution (Figure 3) provides aggregated insight into the evaluation criteria that consistently influence ranking outcomes, allowing the project evaluation team to verify the alignment between the model behavior and the established institutional procurement criteria. At the decision level, local explanations

(Figure 4) quantify the contribution of individual contractor attributes to predicted scores, enabling structured deliberation and defensible tender award justification. Figure 5 consolidates AI insights in contractor evaluation by linking explainability functions to decision transparency, accountability, and reliability.

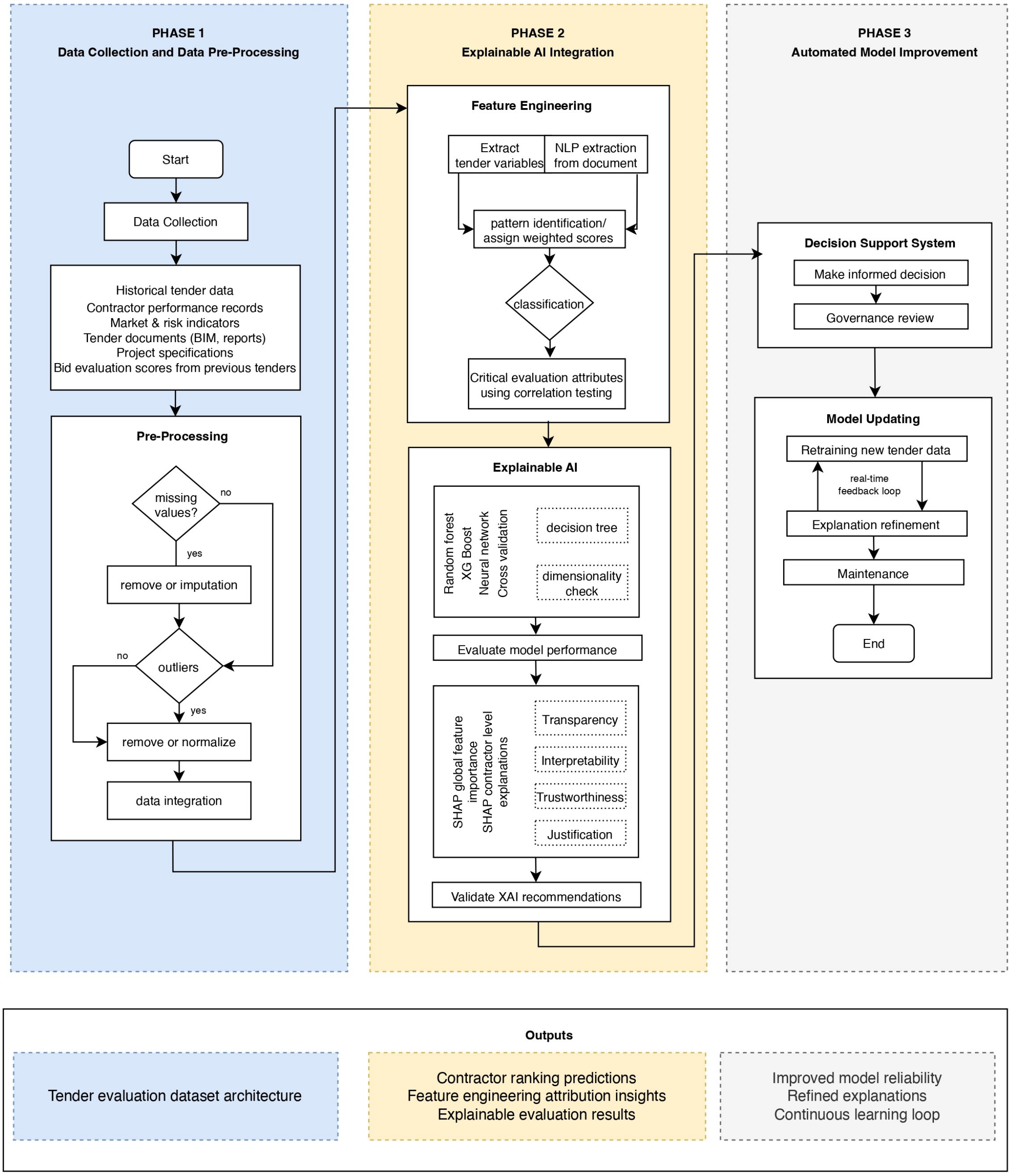

Figure 2 Conceptual model for XAI tender evaluation in construction projects

This model addresses the limitations of conventional tender scoring systems and opaque predictive models. Conventional tender evaluation matrices disclose criteria weightings but do not reveal interaction logic among variables (El Korany et al., 2025; Jaskowski et al., 2010), whereas AI black-box models learn relationships without exposure to scrutiny (Hassija et al., 2024; Von Eschenbach, 2021). In conventional tender evaluation processes, the aggregation of weighted scores often obscures the interaction dynamics among the evaluation criteria. Although individual weightings are formally disclosed, the interaction between cost competitiveness and technical quality, performance history, or project risk factors typically remains implicit within project team deliberations and spreadsheet calculations. Tender evaluation outcomes are reported as composite scores without analytical visibility into which variables substantively drove ranking differences between competing contractors (Cheaitou et al., 2019; Padhi and Mohapatra, 2010). This restricts the ability of stakeholders to trace how specific bid attributes offset or amplify one another in shaping final award decisions. The integration of feature engineering attributes within the proposed XAI model renders decision interaction effects explicit, enabling the project team to move beyond aggregated scoring toward structured and inspectable decision logic, which supports clearer interpretability and justification during and after tender evaluation.

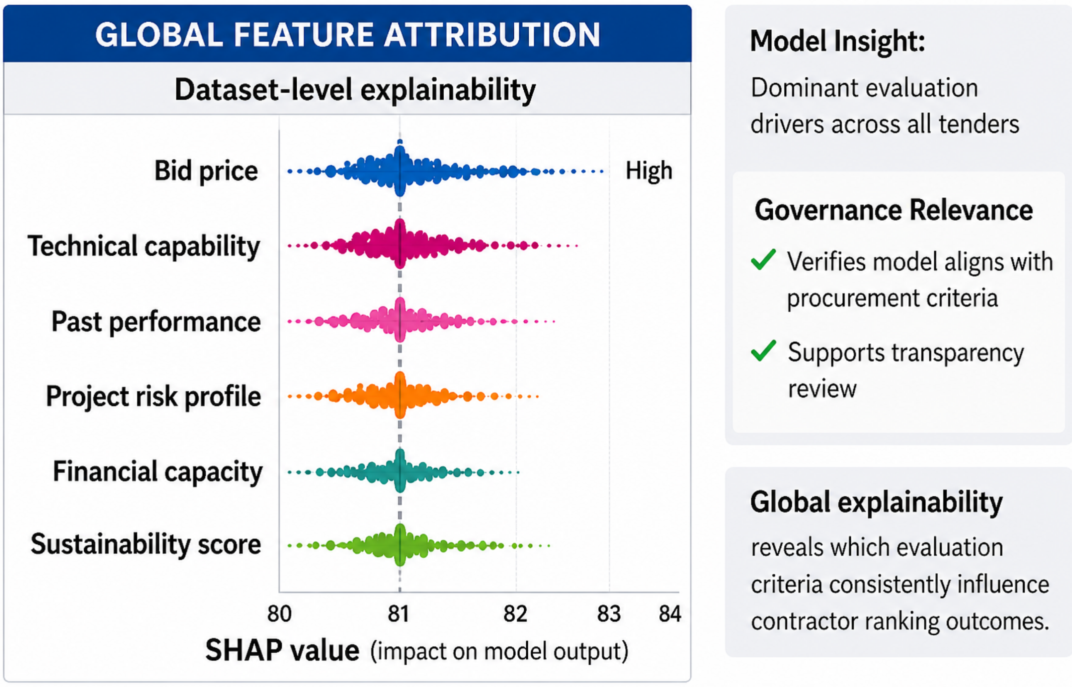

Figure 3 Simulated global feature evaluation for tender evaluation criteria

The credibility of these explanations is contingent on the quality and governance of project data (Shehadeh and Abuaddous, 2025; Zhan et al., 2024). Fragmented, inconsistent, or incomplete tender datasets can distort predictive outputs and attribution results, indicating that reliable data preprocessing, validation, integration, and secure handling are prerequisites for trustworthy XAI deployment in construction project environments (Chamola et al., 2023). Therefore, robust data governance underpins the interpretability and reliability of explanation outputs, ensuring that revealed decision relationships reflect actual contractor performance and project conditions.

Existing XAI exploration in the construction engineering sector mainly focuses on delay prediction, safety monitoring, and operational risk analytics (Shehadeh and Abuaddous, 2025; Zhan et al., 2024; Chen and Mason, 2024; Love et al., 2023). This study extends explainable modeling to procurement stage contractor selection, where systematic alignment between predictive analytics and project governance remains underdeveloped. Contractor selection constitutes a consequential project management decision with downstream implications for delivery performance, coordination reliability, and risk allocation. The model supports closer alignment between procurement assessment and anticipated project engineering outcomes by linking predictive outputs to traceable evaluation variables. This allows cost engineers, project managers, and evaluation committees to interrogate model logic, examine trade-offs across evaluation dimensions, and confirm award decisions with clearer justification.

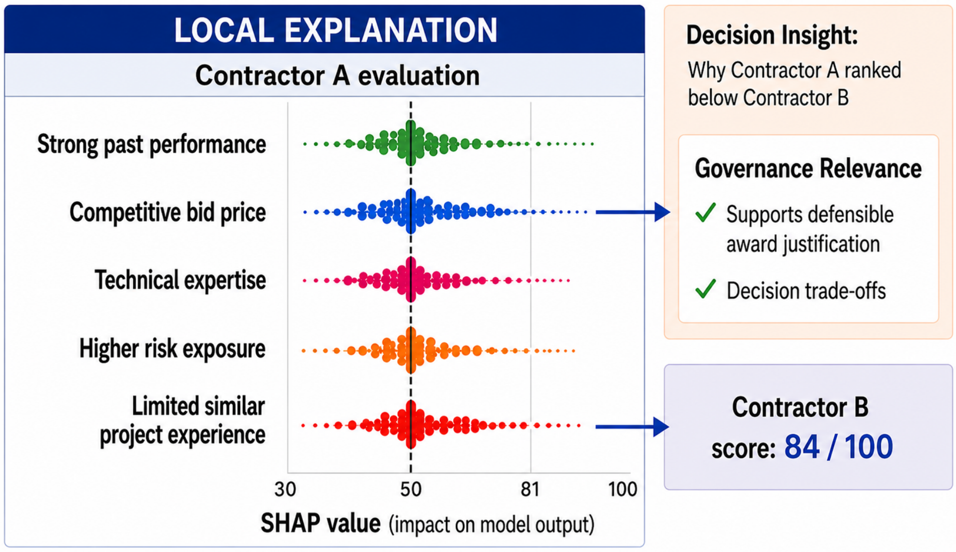

Figure 4 Simulated contractor-level explanation of the ranking outcome

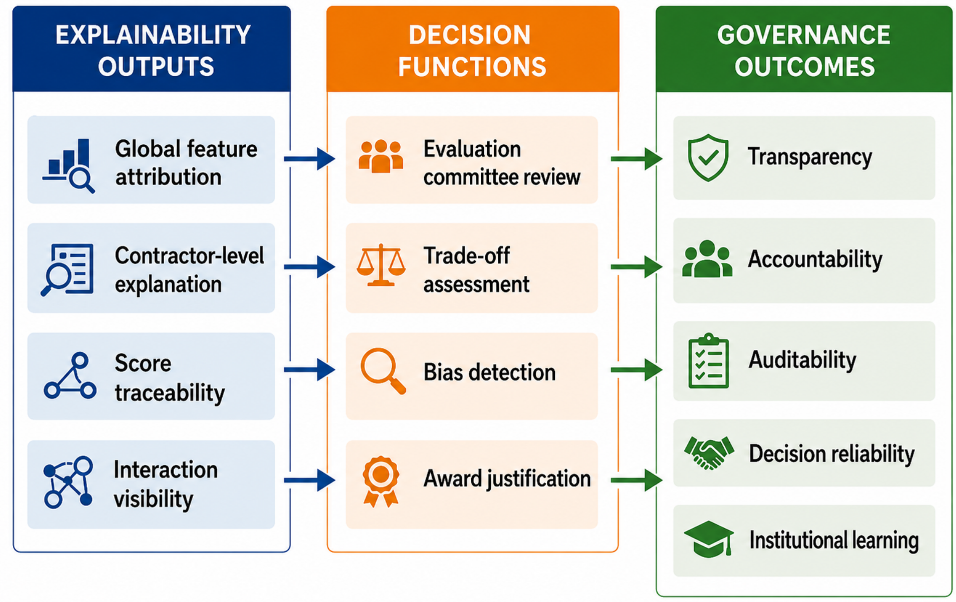

Figure 5 Conceptual decision linkages in the XAI tender evaluation model

Overall, this study specifies how explainable analytics can be structured as a decision workflow aligned with project procurement governance requirements for contractor evaluation. The model integrates predictive modelling, structured tender datasets, and feature attribution outputs to allow the contractor rankings to remain traceable to defined evaluation criteria and can be examined against established procurement priorities. This integration enables the project team decision committee to verify model recommendations, evaluate trade-offs among competing attributes, and document defensible rationales for tender award decisions. Therefore, predictive capability is aligned with transparency, interpretability, trustworthiness, and justification requirements. This study outlines a structured pathway for embedding explainable AI within construction tender evaluation in a manner that strengthens accountability, supports institutional learning across procurement cycles, and improves coherence between contractor selection decisions and anticipated project delivery performance by emphasizing data governance and preparation as prerequisites for credible explanation outputs.

5. Exploratory Stakeholder Validation of the Proposed XAI Tender Evaluation Model

A pilot study was undertaken with ten experts from the Malaysian construction sector to examine the relevance of the proposed XAI tender evaluation in the conceptual model of construction projects. The pilot is an expert appraisal conducted through semi-structured interviews with 10 experts representing quantity surveying consultants, developers, contractors, local authorities, and academia, selected based on a minimum of eight to ten years of professional or academic experience in construction procurement, tender evaluation, project management, quantity surveying, or analytics decision support to ensure credible evaluation of the XAI model from technical, governance, and end-user perspectives. Experts' feedback was used to assess the clarity, relevance, and practical applicability of the proposed XAI elements across tender evaluation stages. Table 2 summarizes the expert perspectives on conventional, AI-driven, and XAI tender evaluation across tender evaluation decision contexts, focusing on strengths, limitations, and decision support implications.

Experts consistently viewed conventional tender evaluation as retaining an important project governance role because it preserves procedural transparency, institutional legitimacy, and accountable professional judgment. Procedural strengths in conventional tender evaluation are associated with prequalification screening, structured deliberation, and tender award stages, where formal documentation and human oversight remain central. Concurrently, conventional practice has persistent limitations, including fragmented data, labor-intensive processing, limited scalability, and weak analytical visibility into how competing evaluation criteria interact to shape final tender ranking outcomes. In this respect, expert judgment remains central to interpretation, but its reasoning is not always fully visible in tender scoring outputs.

In comparison, experts perceived XAI as a complementary decision support, particularly when tender evaluation moves beyond rule-based screening toward comparative ranking, structured deliberation, and defensible tender award justification. Participants recognized that conventional evaluation has limited decision trade-off visibility among tender bid price, technical capability, past performance, and risk, whereas AI-driven evaluation improves speed and scalability without sufficiently exposing decision logic. For this reason, experts did not view AI as replacing professional judgement, but black box outputs weaken the visibility of interpretive reasoning needed by quantity surveyors, project managers, and clients as decision-makers. The pilot study indicates that the proposed XAI elements add practical decision support value by making ranking logic more interpretable. In particular, the experts emphasized the relevance of global feature attribution for identifying the evaluation variables that most strongly influence ranking outcomes and contractor-level local explanations for clarifying how individual bid attributes contribute to predicted scores. When communicated through annotated scorecards, dashboards, and narrative summaries, XAI explainability outputs improve tender ranking clarity with supporting evidence for evaluation criteria trade-offs and strengthening contractor selection justification before final award decisions.

The pilot study further indicates that XAI explainability needs are stakeholder-specific and stage-dependent. Tender committees, clients, quantity surveyors, and project management consultants were perceived to require concise summaries of tender evaluation criteria trade-offs to support deliberation and recommendation, whereas auditors and local authorities were perceived to require transparent and traceable explanations for audit review and post decision defensibility. Experts further highlighted the governance roles of the XAI model in deliberation, justification, auditability, and institutional learning. However, experts consistently emphasized the role of the XAI model in supporting, rather than replacing, professional tender evaluators. Professional judgment is essential for interpreting ambiguity, assessing contextual relevance, and retaining accountability for final tender award recommendations. Hence, the value of XAI lies in strengthening the clarity, traceability, and defensibility of expert judgment while also supporting continuous model refinement across procurement cycles.

Table 2 Comparative expert appraisal on conventional, AI-driven, and XAI tender evaluation across tender evaluation decision stages

Tender Evaluation Stages	Decision-Making Roles and Responsibility	Conventional tender evaluation	AI-driven tender evaluation	XAI-Tender Evaluation
Prequalification screening	Quantity surveyor/consultant and client procurement team to verify tender documents and project qualification admissibility	Clear and auditable but rigid pass/fail screening may mask differences among compliant bidders.	Fast document screening and missing item detection; however, ambiguous submission data may be misread.	Makes explicit why a bid is flagged as non-responsive, improving traceability beyond automated screening outputs.
Integration and preprocessing of tender data	Quantity surveyor/consultant, client procurement team to consolidate current and historical tender records, project specifications, market conditions, and contractor performance as well as tender data preparation and standardization for evaluation	• Fragmented data across different files and formats • Manual checking allows contextual correction but it is slow, inconsistent, and has issues with version control	• Improves extraction and integration of heterogeneous datasets • Weak source data may distort downstream evaluation • Improves speed and consistency in standardization, but hidden automated assumptions remain	Preprocessing assumptions and variable changes are traceable, clarifying how integrated inputs influence later ranking logic, although weak source data governance remains unresolved.
Feature-Based Contractor Evaluation	Quantity surveyor/consultant, project management consultant, BIM engineers, and consultant engineers to compare bidders across tender bid price, technical capability, past performance, and risk indicators.	Supports multi-criteria evaluation and expert judgment; however, trade-offs remain implicit and ranking logic is limited in transparency.	Improves scalability and pattern detection across large and heterogeneous tender bid data, but weakens defensibility due to black-box ranking.	Reveals global feature influence, contractor-level attribution, and criterion trade-offs, making ranking logic inspectable rather than merely predictive.
Structured deliberation and tender awarding	Tender committee, client, quantity surveyor, and project management consultant make recommendations and justification for the preferred contractor.	Preserves accountability and engages in technical discussion; however, reasons for preferring one contractor may remain dispersed across reports and deliberations.	Prompt contractor ranking summary; however, opaque outputs are difficult for committees to challenge or defend.	Provides annotated scorecards and explanations of criteria that make ranking drivers contestable, discussable, and more defensible during tender deliberation.
Audit review and learning	Auditors and local authorities to examine transparency, consistency, and post-decision defensibility.	Produces formal records but often weakly documents how variable interactions shape the outcome.	Preservation of process history, but black-box reasoning remains difficult to audit.	Provides post-decision traceability of how ranking outcomes were produced, supporting audit review, accountability, and institutional learning across procurement cycles.

6. Conclusion and Future Research Directions

Construction project tender evaluation constitutes a high-stakes decision process in which contractor selection must remain transparent, auditable, and defensible. While AI enhances analytical scalability and predictive capability, its current application in tender evaluation remains constrained by limited interpretability and automated insights' limited justification. Conventional tender evaluation supports explicit assessment based on robust multi-criteria decision-making but offers limited analytical visibility into how cost, technical capability, past performance, and risk interact to shape final tender ranking outcomes, whereas black box AI models capture criteria interdependencies without adequately exposing decision logic. This study addressed the decision gap by developing a conceptual Explainable Artificial Intelligence (XAI) tender evaluation model that integrates data preprocessing, predictive modeling, and explanation mechanisms within a structured decision workflow. The proposed model demonstrates how tender rankings can remain traceable to identifiable evaluation variables through global feature attribution, contractor-level explanations, and project governance explainability, thereby supporting tender evaluation deliberation, award justification, and auditability, while highlighting strong data governance as a foundation for credible explanations and trustworthy decision support. An exploratory pilot study with Malaysian construction experts further indicates that the proposed XAI elements are relevant across tender evaluation stages, with XAI valued as a complementary mechanism that strengthens transparency, interpretability, and defensibility. More importantly, the XAI strongly preserves the central role of professional judgement in final tender award decisions. Future research should prioritize empirical implementation in live tender evaluation settings and advance sectoral standards for explainability and data governance in construction procurement.

Author Contributions

Dr. Zafira Nadia Maaz conceptualized the study, led the overall Explainable Artificial Intelligence (XAI) tender evaluation model, integrated XAI principles into the proposed model, and drafted the original manuscript. She also coordinated collaboration among co-authors and finalized the manuscript for submission. Dr. Umi Kalsum Zolkafli @ Zulkifly and Dr. Norhanim Zakaria contributed to the research design and model refinement from the perspective of construction procurement, ensuring alignment with professional tender evaluation practices. Dr. Chia Kuang Lee contributed to the development of the AI explainability components' analytical structure. Dr. Shamsulhadi Bandi provided construction management expertise and reviewed the practical applicability of the model to real-world tender evaluation processes. Dr. Chai Chang Saar provided interdisciplinary input from architectural and design perspectives and reviewed the model's conceptual coherence across built environment domains. Dr. Anis Sazira Bakri and Dr. Siti Norazniza Ahmad Sekak contributed to ensuring the mode's relevance to professional quantity surveying practice and public sector procurement.

Conflict of Interest

The authors have no conflicts of interest to declare.

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