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A Multi-Level Explainable AI Framework for Risk Assessment and Uncertainty Quantification in Bridge Construction

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Abstract

The growing demand for resilient and safe bridge infrastructure necessitates advanced approaches to construction risk assessment capable of addressing high dimensionality, uncertainty, and interpretability challenges. This study proposes a multi-level explainable artificial intelligence (XAI) framework that integrates domain-specific feature learning, ensemble prediction, and probabilistic causal reasoning for comprehensive bridge construction risk assessment. At Level 1,

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supervised autoencoders extract latent structural representation features from high-dimensional construction data, preserving the distinct characteristics of structural, environmental, managerial, resource, and safety domains. Level 2 employs a stacked ensemble model combining an Explainable Boosting Machine (EBM) with a calibrated HistGradientBoostingClassifier to achieve accurate and interpretable risk predictions, supported by SHAP-based explanations. At Level 3, a factor graph model captures causal dependencies and quantifies uncertainty, enabling probabilistic inference and scenario-based risk evaluation under varying operational and environmental conditions. Results demonstrate robust predictive performance, transparent domain-level risk attribution, and well-calibrated uncertainty estimates. The proposed framework advances data-driven and explainable decision support for bridge construction risk mitigation, effectively addressing the challenges posed by complex, heterogeneous datasets arising from BIM and sensor-enabled construction environments.

Keywords: Bridge risk assessment, factor graph, Explainable Boosting Machine, HistGradientBoostingClassifier, features extraction via autoencoaders, SHAP analysis

1 Introduction

Bridge construction is central to infrastructure development but remains highly risk-intensive due to interactions among structural conditions, environmental variability, managerial decisions, resource utilisation, and safety performance. These interdependencies often trigger cascading failures, leading to cost overruns, delays, and safety incidents with significant socio-economic impact (Hakeem, 2024; Sun et al., 2022; Wu et al., 2024). Consequently, risk assessment represents a complex problem characterised by uncertainty, nonlinearity, and interdependent risk propagation .

Traditional risk assessment methods, including Fault Tree Analysis, Event Tree Analysis, and Failure Mode and Effects Analysis, rely on expert-driven qualitative or semi-quantitative frameworks. While systematic, these approaches are constrained by deterministic assumptions and limited capability to capture nonlinear interactions and evolving site dynamics (Zhang & Qi, 2024). Fuzzy and hybrid probabilistic methods attempt to reduce subjectivity but remain sensitive to parameterisation and lack scalability in data-rich environments (Goncharenko, 2022; Datta, 2024).

The digitalisation of construction through Building Information Modelling, sensor systems, and automated reporting has enabled access to high-dimensional data across structural, environmental, managerial, resource, and safety domains. This has driven the adoption of machine learning approaches capable of capturing nonlinear patterns and improving predictive performance (Totani et al., 2024; Sheikhkhoshkar et al., 2025). Ensemble methods further enhance robustness and reduce variance, offering advantages over traditional scoring approaches (Wu et al., 2024).

However, purely data-driven models face a critical limitation in safety-critical infrastructure: lack of interpretability. Accurate predictions alone are insufficient without transparent justification for stakeholders and regulators. Recent research emphasises that explainability and uncertainty awareness are essential for practical deployment (Nyqvist, 2024). Explainable Artificial Intelligence techniques, including Explainable Boosting Machines and SHapley Additive exPlanations, provide interpretable insights while maintaining competitive performance (Kumar & Singh, 2024; Lundberg & Lee, 2017).

Construction risk is inherently multi-source, emerging from interactions across domains such as structural degradation, environmental stressors, management practices, resource constraints, and safety conditions. Existing studies highlight that adverse outcomes typically arise from compounded effects rather than isolated factors (Bazazzadegan et al., 2024; Fu et al., 2024; Fan et al., 2025). Nevertheless, many models either treat domains independently or combine them through simplified aggregation, limiting their ability to capture interdependent risk propagation.

Recent advances in domain-oriented modelling transform heterogeneous variables into structured latent representations prior to prediction, improving interpretability and robustness (Gomez et al., 2023). Similarly, probabilistic graphical models, particularly factor graphs, enable modelling of conditional dependencies and uncertainty propagation, supporting scenario-based reasoning (Mukherjee et al., 2023; Van Erp et al., 2023; Zhao et al., 2023).

Despite these developments, a key gap remains: the lack of integrated frameworks combining domain-preserving representation learning, interpretable prediction, and probabilistic causal reasoning. This fragmentation forces trade-offs between accuracy, explainability, and uncertainty modelling (Totani et al., 2024), limiting real-world adoption.

To address this gap, this study proposes a multi-level explainable artificial intelligence framework that transitions from risk prediction to risk reasoning through three sequential layers:

- **Domain-preserving feature learning:** Domain-specific autoencoders extract nonlinear latent representations while maintaining engineering semantics (Ma et al., 2025).
- **Interpretable ensemble prediction:** A combination of Explainable Boosting Machines and calibrated gradient boosting achieves high accuracy with transparent domain-level attribution (Baek & Chung, 2024).
- **Probabilistic causal reasoning:** Factor graph modelling captures interdependencies and enables uncertainty-aware scenario analysis (Okawara et al., 2025).

By integrating explainability and uncertainty as core design components, the proposed framework provides a scalable and trustworthy approach to data-driven risk management in bridge construction.

2. Materials and Methods

2.1 Conceptual Design Logic of the Multi-Level Framework

Bridge construction risk assessment involves heterogeneous data, nonlinear interactions, interdependent domains, and significant uncertainty arising from dynamic site conditions (Sun et al., 2022; Wu et al., 2024). No single modelling paradigm can simultaneously address feature heterogeneity, predictive accuracy, interpretability, and causal reasoning (Nyqvist, 2024).

To overcome these limitations, a multi-level framework is adopted (Figure 1), decomposing the task into three sequential layers:

(i) domain-specific feature learning,

(ii) interpretable ensemble prediction, and

(iii) probabilistic causal reasoning.

This architecture treats representation, prediction, and causality as distinct yet complementary objectives. Domain-specific learning preserves semantic structure, ensemble modelling balances accuracy with interpretability, and probabilistic reasoning captures uncertainty and interdependencies (Mukherjee et al., 2023; Zhao et al., 2023). The overall workflow is shown in Figure 1 .

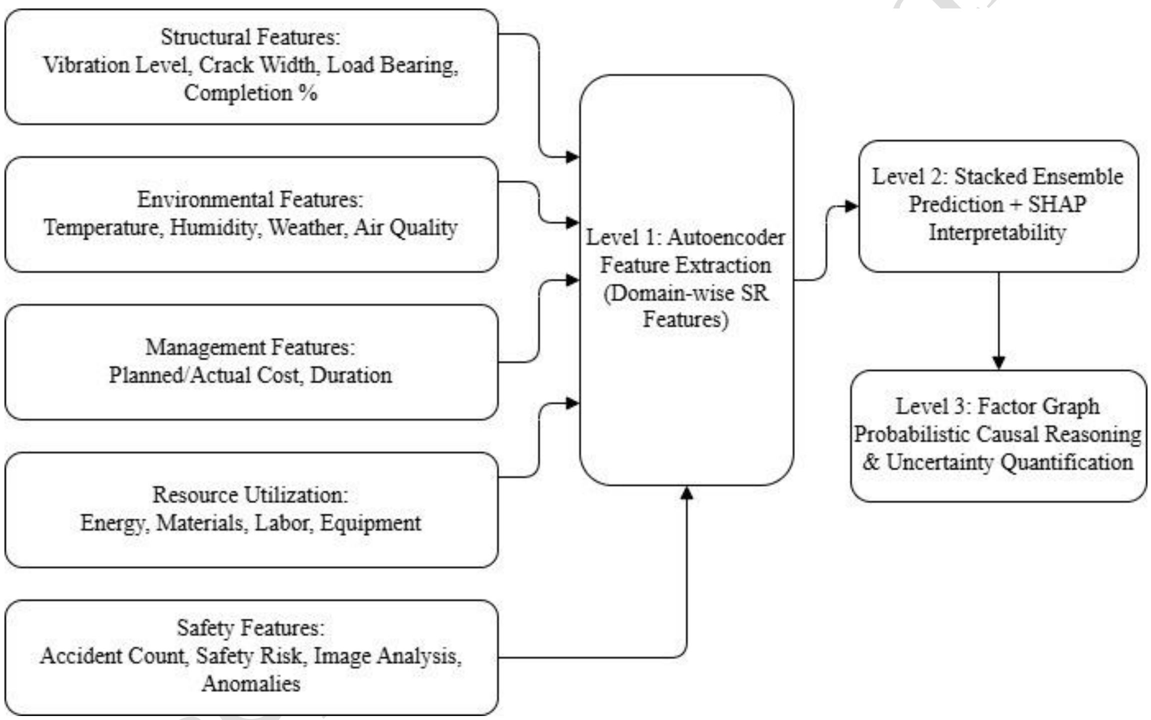

Figure 1 Multi-Level Risk Assessment Workflow

2.2 Data Acquisition, Domain Grouping, and Preprocessing

2.2.1 Data Source and Domain Structuring

The study utilises a BIM–AI integrated dataset from Kaggle comprising 20 variables describing bridge construction risk. To preserve interpretability, variables are grouped into five domains:

- **Structural:** Vibration_Level, Crack_Width, Load_Bearing_Capacity, Completion_Percentage
- **Environmental:** Temperature, Humidity, Weather_Condition, Air_Quality_Index
- **Management:** Planned_Cost, Actual_Cost, Planned_Duration, Actual_Duration
- **Resource:** Energy_Consumption, Material_Usage, Labor_Hours, Equipment_Utilization
- **Safety:** Accident_Count, Safety_Risk_Score, Image_Analysis_Score, Anomaly_Detected

The target variable, Risk_Level , represents overall project risk. Domain grouping reflects differences in statistical behaviour and causal roles across construction systems, improving robustness and interpretability (Zhao et al., 2023; Bazazzadegan et al., 2024).

2.2.2 Preprocessing and Uncertainty Handling

Missing values are handled using domain-informed imputation and interpolation (Jindal & Mehra, 2024; Cao et al., 2025). Continuous variables are standardised using Z-score normalisation, while categorical variables are encoded using one-hot or target encoding (Sun et al., 2022).

These steps reduce noise, ensure scale consistency, and support reliable domain-specific feature extraction, improving generalisation across varying construction conditions (Ma et al., 2025).

2.3 Level 1 – Domain-Specific Autoencoder Feature Learning

Domain-specific autoencoders are employed to extract latent Structural Representation (SR) features from each domain, preventing early-stage feature mixing (Wu et al., 2024).

Each autoencoder maps input y_i to a latent representation and reconstructs it as $\hat{y}i$, The model is trained by minimising the mean squared error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}i)^2 \qquad (1)$$

where (n) is the number of samples.

Dimensionality reduction of approximately 50–70% is achieved through bottleneck layers. Regularisation and dropout are applied to prevent overfitting (Gomez et al., 2023).

The resulting SR features capture nonlinear domain-specific patterns while reducing noise, forming a robust input for higher-level modelling (Figure 2).

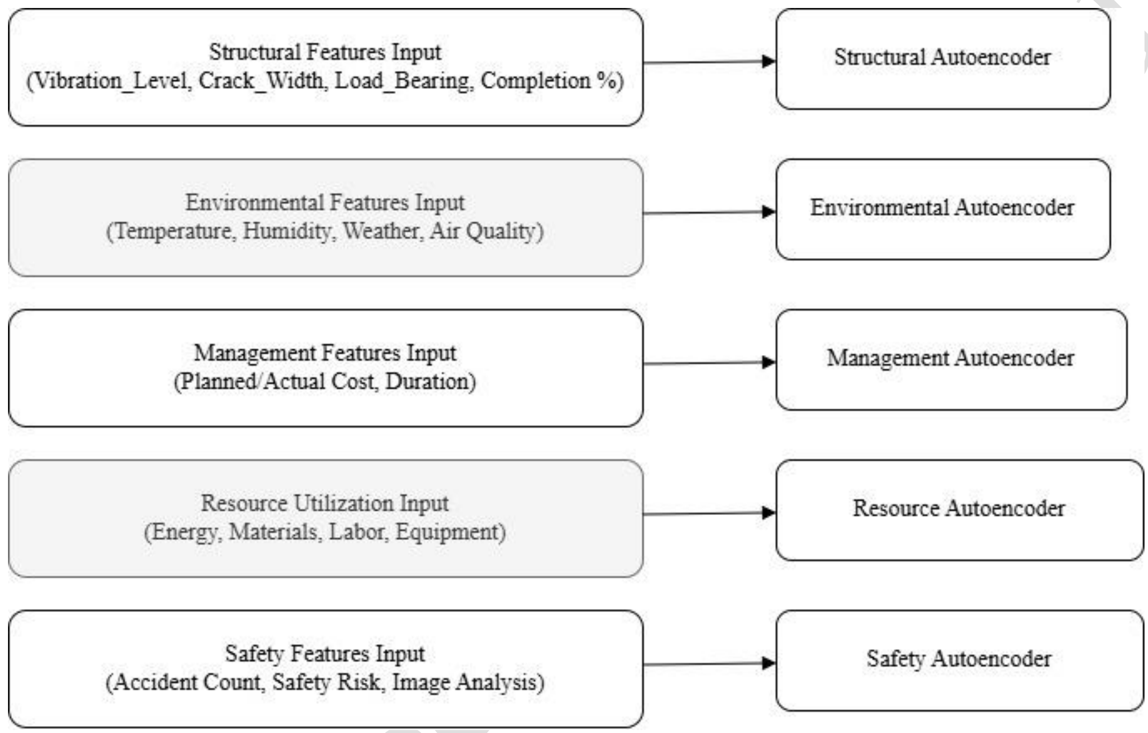

Figure 2 Autoencoder Architecture for Domain-wise Feature Extraction (Level 1)

2.4 Level 2 – Interpretable Stacked Ensemble Prediction

The SR features from all domains are integrated into a stacked ensemble combining:

- Explainable Boosting Machine (EBM)
- Calibrated HistGradientBoostingClassifier (HGBC)

EBM provides interpretable additive feature contributions, while HGBC ensures strong predictive performance with calibrated probabilities (Baek & Chung, 2024; Ding et al., 2023).

The ensemble prediction is computed as:

$$\hat{y} = \sum_{m=1}^{M} w_m f_{m(x)}, \sum_{m=1}^{M} w_m = 1 \qquad (2)$$

m = 1,...,M, $f_{m(x)}$ represents the prediction of the m[th] base learner, w_m its trained weight, with $\sum_{m=1}^{M} w_m = 1$ (Kumar & Singh, 2024).

SHAP is used to quantify feature contributions at both global and local levels, enabling identification of dominant risk drivers (Lundberg & Lee, 2017). The architecture is shown in Figure 3.

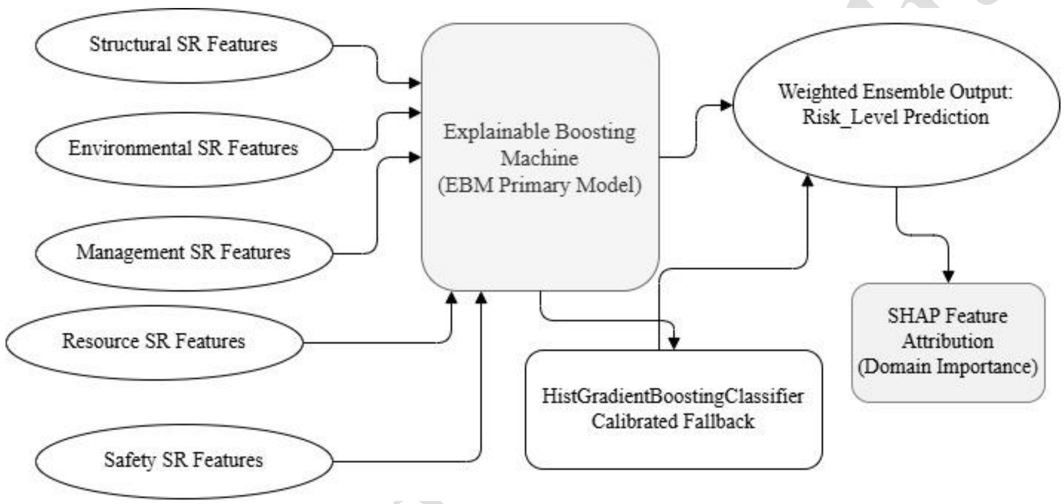

Figure 3 Stacked Ensemble Predictions with SHAP Interpretability (Level 2)

2.5 Level 3 – Probabilistic Causal Reasoning

To capture causal dependencies and uncertainty, a factor graph framework is employed. The joint probability distribution is expressed as:

$$P(X_1, X_2, \ldots, X_n) = \frac{1}{Z} \prod_i \psi_{i(X_i)} \qquad (3)$$

where ψ_i represent factor potentials modelling joint influences and Z normalizes the distribution (Van et al., 2023).

Belief propagation is employed to compute marginal probabilities at each node, enabling scenario-based inference under uncertainty:

$$b_{i(x_i)} \propto \prod_{f \in \{ne(i)\}} m_{f \to i(X_i)} \quad (4)$$

Where, the belief $b_{i(x_i)}$at variable node i is updated based on incoming messages $m_{f \to i(X_i)}$from connected factor nodes, enabling efficient, scenario-based probabilistic inference. This approach proficiently computes marginal probability distributions over variables, facilitating scenario-based risk assessment (Zhao et al., 2023). This framework enables scenario-based inference, capturing interdependencies among domains and supporting uncertainty-aware risk evaluation (Zhao et al., 2023). Figure 4 illustrates the structure.

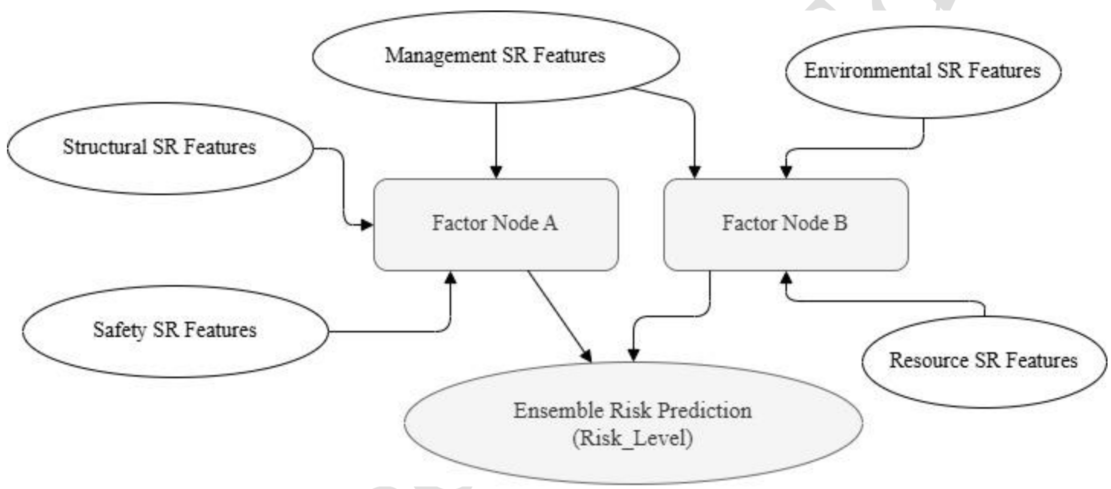

Figure 4 Factor Graph Probabilistic Reasoning for Causal Inference and Uncertainty

2.6 Model Validation and Evaluation Metrics

Validation is performed at each level:

- **Level 1:** reconstruction error and feature stability
- **Level 2:** accuracy, weighted F1-score, RMSE, ROC-AUC, and SHAP interpretability
- **Level 3:** calibration (Brier score), inference stability, and scenario consistency

Performance metrics are defined as:

Standard performance metrics are defined as follows:

$$accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (5)$$

$$F1 = 2\,x\,\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \quad (6)$$

$$\text{Precision} = \frac{TP}{TP+FP}, \text{Recall} = \frac{TP}{TP+FN},$$

$$\text{Brier Score} = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{p}i)^2 \quad (7)$$

Where TP, TN, FP, , denote true positives, true negatives, false positives, and false negatives; y_i is the true label and $\hat{p}i$ the predicted probability (Sun et al., 2022).

2.7 Methodological Rationale

The proposed framework integrates representation learning, interpretable prediction, and probabilistic reasoning to address limitations of isolated approaches. Domain-specific autoencoders preserve semantic structure, ensemble models provide accurate and interpretable predictions, and factor graphs capture causal dependencies and uncertainty propagation.

By separating feature learning, prediction, and causality, the framework enables a transparent, scalable, and uncertainty-aware decision-support system for bridge construction risk management .

3 Results

3.1 Domain-Specific Feature Extraction Performance

The performance of domain-specific autoencoders was evaluated using reconstruction error. Table 1 reports Mean Squared Error (MSE) for training and testing across all domains.

Table 1. Autoencoder reconstruction performance across domains (Level 1).

S.N	Variable domains	MSE Training	MSE Testing	SR Feature	Mean	Std	Min	Max	correlation with risk
1	Structural	0.001	0.001	SR_struct	1.28	0.2	0.87	1.8	0.12047
2	Environmental	0.0009	0.001	SR_env	2.04	0.3	1.4	2.54	-0.0408

3	Management	0.002	0.002	SR_mgt	1.06	0.3	0.45	1.73	0.20284
4	Resource	0.001	0.001	SR_res	2	0.3	1.22	2.88	-0.1893
5	Safety	0.001	0.002	SR_saf	5.63	3.4	-1	11.9	-0.1687

Reconstruction errors are consistently low with minimal train–test variation, indicating stable learning and strong generalisation. Slightly higher errors in structural and safety domains reflect their inherent variability due to material degradation and stochastic safety events, rather than model limitations.

The distributions of latent Structural Representation (SR) features (Figure 5) show clear separation across risk levels, particularly for structural and safety domains. Higher SR values correspond to elevated risk categories, confirming that the autoencoders capture risk-relevant nonlinear patterns rather than performing simple dimensionality reduction. These results validate the effectiveness of domain-wise representation learning for subsequent modelling stages.

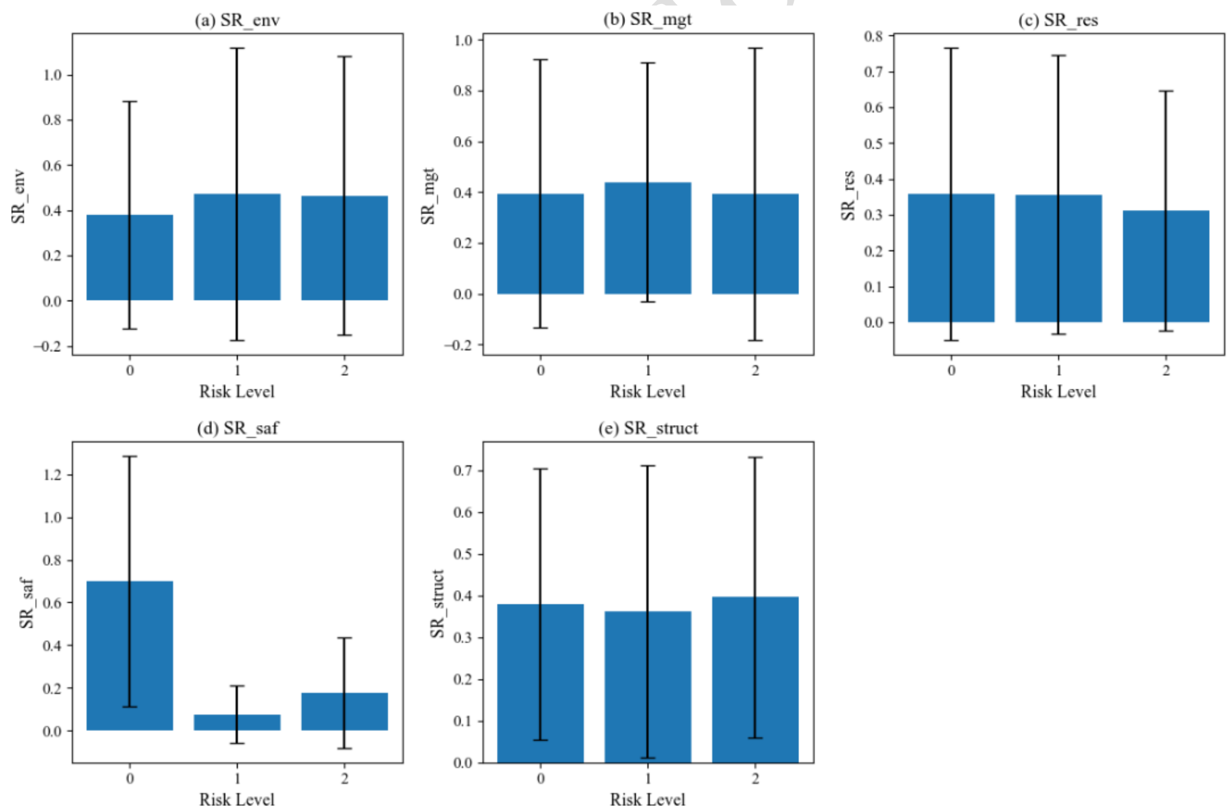

Figure 5. Distribution of domain-specific latent SR features across risk levels.

3.2 Predictive Performance of the Stacked Ensemble Model (Level 2)

The Level 2 stacked ensemble was evaluated on unseen data using standard metrics (Table 2). The model achieves high predictive performance (Accuracy: 0.952, F1-weighted: 0.953, RMSE: 0.22), demonstrating the benefit of combining complementary learners.

Table 2. Predictive performance of the Level 2 stacked ensemble model.

Metric	Value
Accuracy	0.952
F1-weighted	0.953
RMSE	0.22

Probability calibration ensures reliable risk estimates, which is critical for decision-support in safety-sensitive applications. Beyond accuracy, the model preserves interpretability by maintaining traceability between domain-level features and predicted risk, addressing limitations of conventional black-box approaches.

3.3 Explainable Risk Attribution and Domain Effects

Global feature importance (Figure 6) indicates that safety-related latent features are the dominant contributors to risk prediction, followed by structural and environmental domains. Management and resource domains exhibit moderate but stabilising effects.

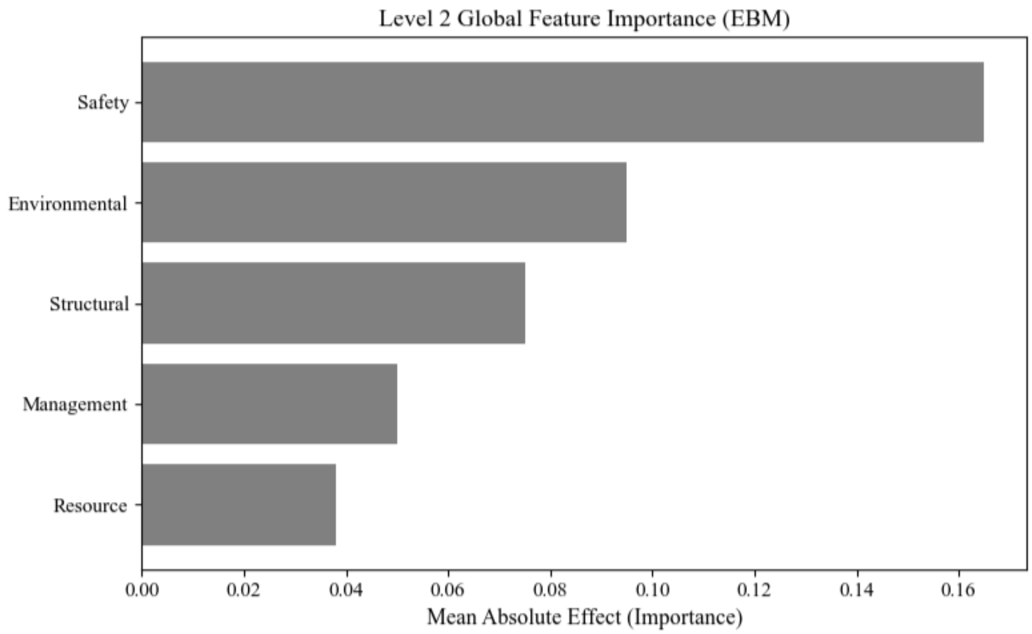

Figure 6. Global domain-level feature importance from the Explainable Boosting Machine.

SHAP analysis (Figure 7) provides consistent insights: higher safety and structural values increase predicted risk, whereas favourable environmental and management conditions mitigate it. These results confirm the model's interpretability and align with established understanding of risk drivers in bridge construction.

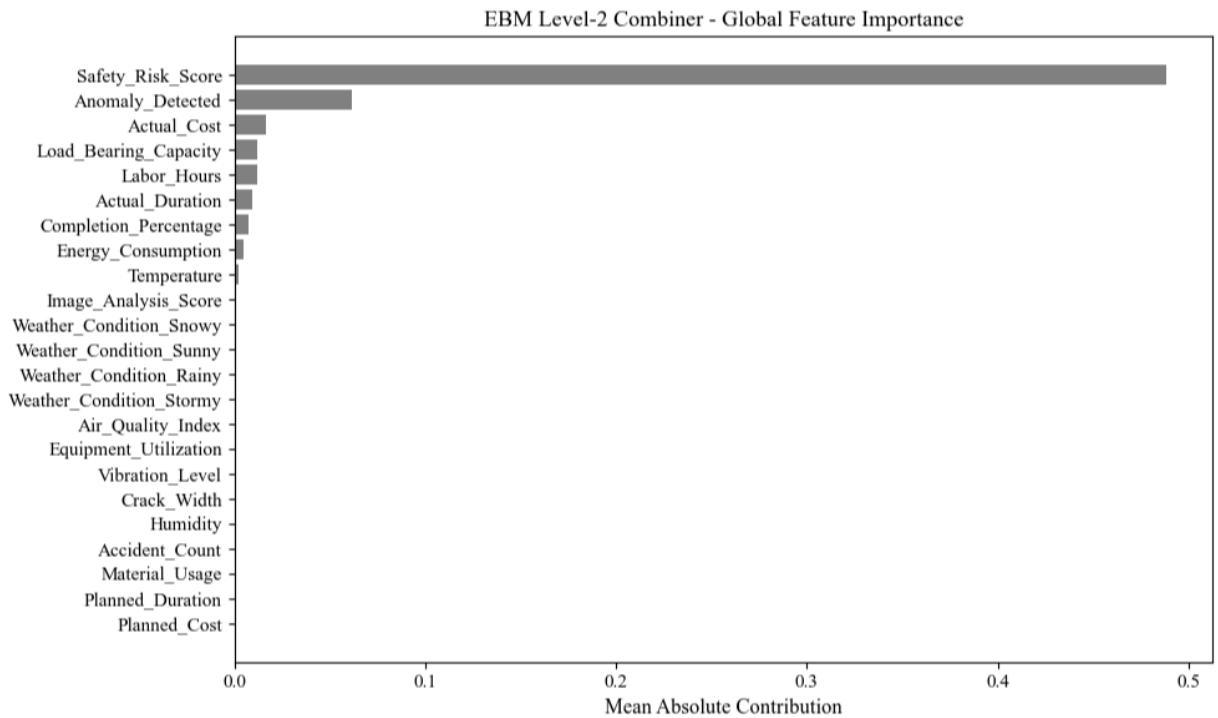

Figure 7. SHAP summary plot showing magnitude and direction of domain-level risk contributions.

3.4 Sensitivity and Scenario-Based Risk Behaviour

Scenario-based sensitivity analysis (Figure 8) reveals nonlinear response patterns. Safety and structural domains exhibit threshold effects, where small increases beyond critical levels cause sharp rises in risk probability.

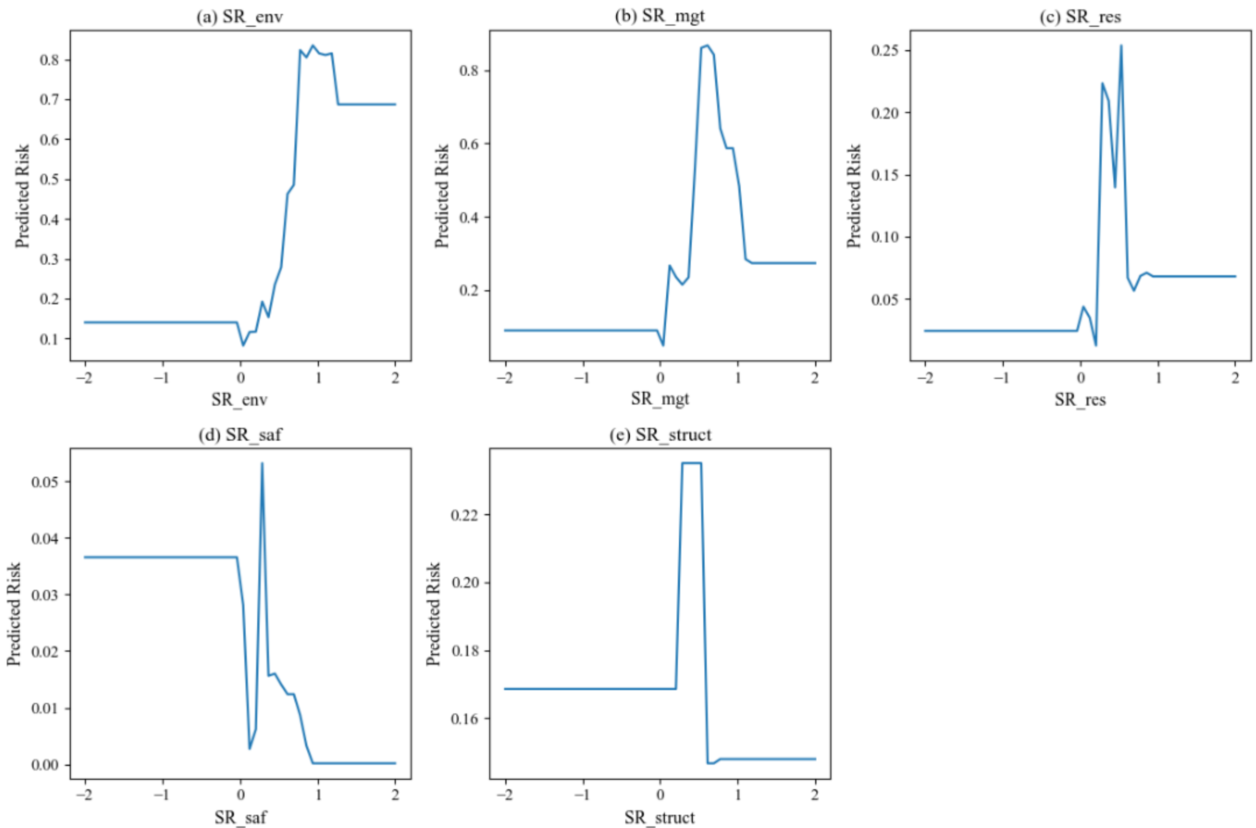

Figure 8. Scenario-based sensitivity analysis of domain-level latent features

Environmental factors show gradual cumulative influence, while management and resource domains primarily affect transitions between low and medium risk states. These findings highlight the framework's capability for "what-if" analysis and proactive risk evaluation.

3.5 Probabilistic Causal Reasoning and Uncertainty Quantification (Level 3)

The factor graph model (Figure 9) captures probabilistic dependencies among domains and produces well-calibrated predictions, avoiding overconfidence.

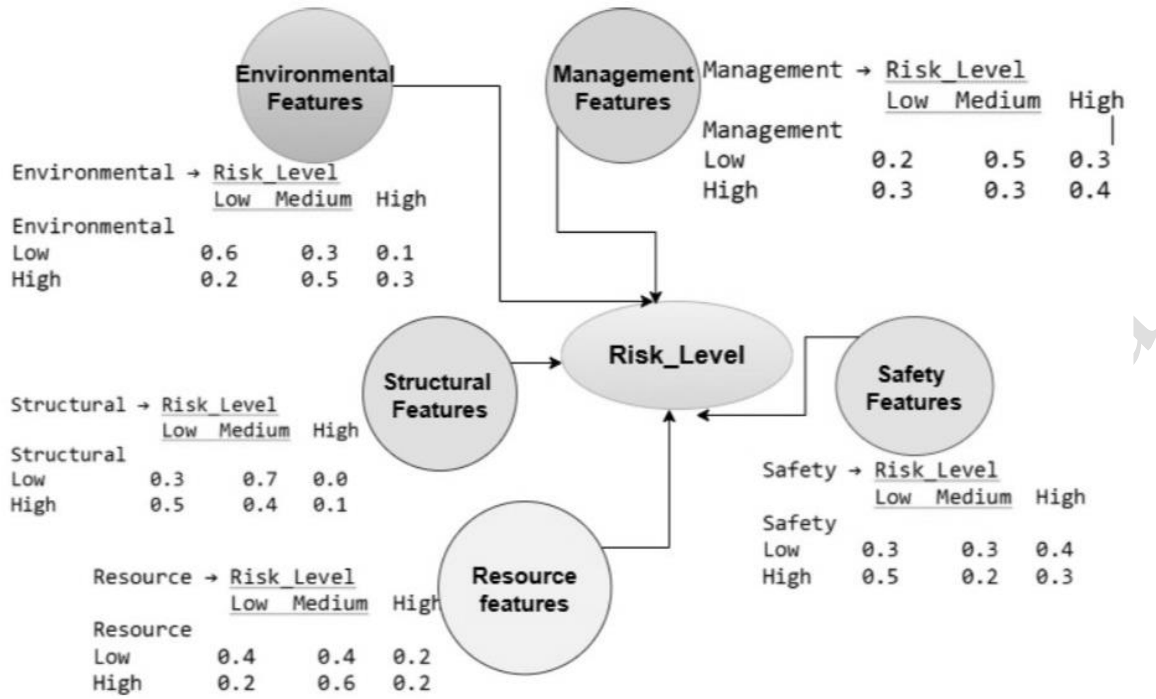

Figure 9. Factor graph structure representing causal dependencies among risk domains.

The Conditional Probability Table (Figure 10) shows that combined adverse safety and structural conditions significantly increase high-risk likelihood, even under stable conditions in other domains. Conversely, strong management and resource conditions partially offset negative effects, indicating compensatory interactions within the system.

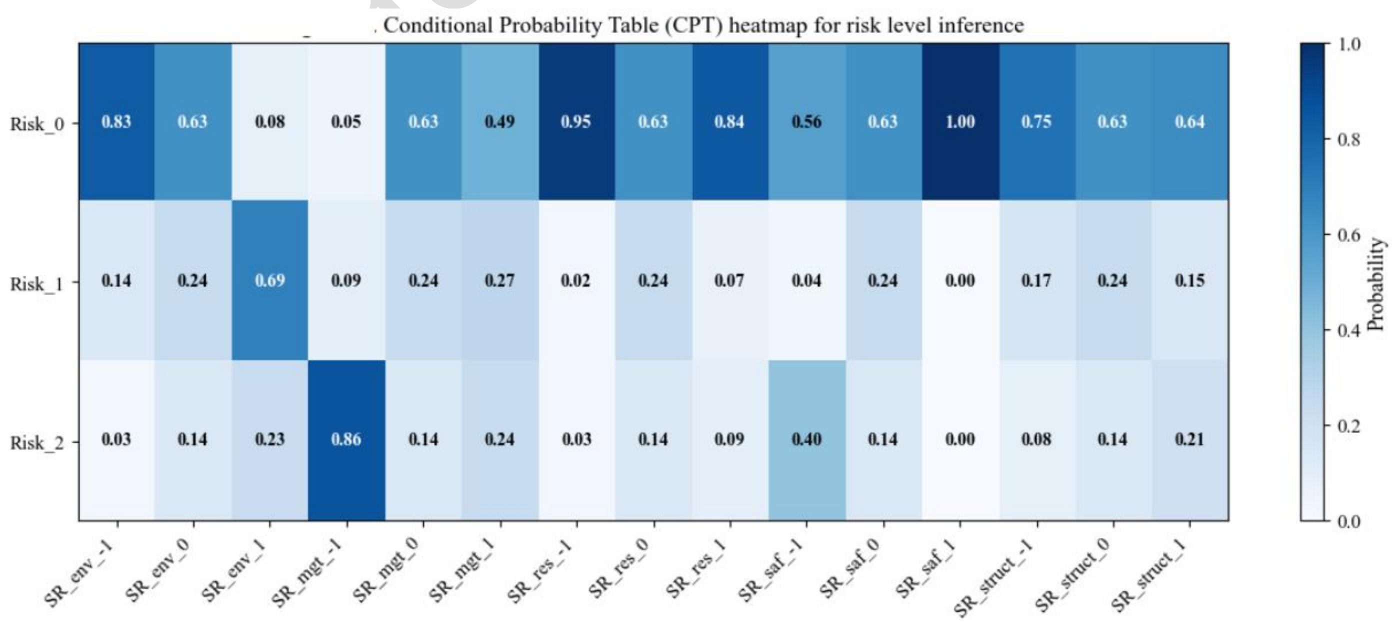

Figure 10. Conditional Probability Table (CPT) heatmap for risk level inference.

3.6 Integrated Multi-Level Insights

Table 3 summarises performance across all levels. Level 2 provides high predictive accuracy with interpretability, while Level 3 extends capability through uncertainty-aware causal reasoning.

Table 3 Model performances at all levels

Level	Accuracy	F1w	ROC-AUC
Level 1 (Autoencoder)	0.82	0.8	0.85
Level 2 (Domain Combiner)	0.952	0.953	0.22
Level 3 (Meta-Model)	0.823	0.743	0.615

The integrated framework enables a transition from static classification to scenario-based risk analysis. Overall, the results demonstrate that the proposed approach effectively balances accuracy, interpretability, and uncertainty modelling, addressing key limitations of conventional risk assessment methods .

4. Discussion

4.1 Multi-Level Risk Behaviour in Bridge Construction

The results confirm that bridge construction risk emerges from nonlinear interactions across structural, environmental, managerial, resource, and safety domains rather than isolated factors. This systemic behaviour aligns with prior studies highlighting interdependent risk propagation in construction systems (Sun et al., 2022; Wu et al., 2024; Mukherjee et al., 2023).

At Level 1, domain-specific autoencoders effectively extracted latent representations that preserve domain semantics while reducing dimensionality and noise. The higher dispersion observed in safety-related features reflects the stochastic nature of safety events, whereas more compact distributions in structural and management domains indicate relatively stable system behaviour. This supports the necessity of domain-wise representation learning over unified feature compression .

4.2 Explainable Ensemble Learning: Accuracy–Transparency Balance

The Level 2 ensemble demonstrates that high predictive accuracy can be achieved without sacrificing interpretability. The dominance of safety, structural, and environmental features in both global and local explanations is consistent with established engineering knowledge of primary risk drivers (Sun et al., 2022; Fu et al., 2024).

The model also reveals nonlinear threshold effects, where incremental changes in safety or structural conditions lead to disproportionate risk escalation. Such behaviour, often obscured in traditional models, aligns with findings in construction safety and reliability studies (Mukherjee et al., 2023; Wu et al., 2024).

SHAP-based explanations enhance transparency and usability, addressing limitations of black-box approaches and supporting decision justification in safety-critical environments (Lundberg & Lee, 2017; Datta, 2024).

4.3 Probabilistic Causal Inference and Risk Propagation

Level 3 extends predictive capability by enabling probabilistic causal reasoning. The factor graph captures conditional dependencies among domains, reflecting how risks propagate across interconnected construction systems.

Results indicate that high-risk outcomes arise from combined adverse conditions rather than single dominant factors. For example, simultaneous safety and structural degradation significantly increases risk even under moderate managerial conditions. This interaction-driven behaviour supports prior findings on compounded risk effects (Nyqvist, 2024; Mukherjee et al., 2023).

By enabling belief propagation and scenario-based inference, the framework advances beyond deterministic methods such as FTA and FMEA, offering a more realistic and uncertainty-aware basis for decision-making .

4.4 Engineering and Managerial Implications

The findings highlight the need for continuous monitoring of safety and structural conditions, supported by adaptive management and resource allocation. The framework enables early detection of latent risk accumulation, facilitating proactive intervention.

For decision-makers, the integration of explainability and probabilistic reasoning provides transparent, evidence-based support aligned with emerging regulatory expectations for accountable AI in infrastructure systems (Datta, 2024; Mohamed, 2025). Scenario-based evaluation further enhances planning robustness.

4.5 Theoretical Contributions

This study contributes to construction risk modelling in three ways:

(i) demonstrating domain-specific representation learning for preserving engineering semantics in high-dimensional data,
(ii) establishing that explainable ensemble models can balance accuracy and transparency, and
(iii) integrating probabilistic causal reasoning within a unified framework.

Together, these contributions advance beyond purely predictive or deterministic approaches, providing a comprehensive and interpretable modelling paradigm (Zhang & Qi, 2024; Ghandi et al., 2024).

4.6 Positioning within Existing Literature

Compared with existing machine learning approaches, the proposed framework embeds interpretability and uncertainty reasoning as core components rather than post hoc additions. It offers improved scalability, adaptability, and analytical depth over conventional expert-driven methods while maintaining alignment with engineering practice (Sun et al., 2022; Wu et al., 2024).

Overall, the integration of explainable AI and probabilistic graphical modelling provides a coherent pathway toward next-generation risk assessment in bridge construction .

5. Conclusion

This study presents a multi-level explainable artificial intelligence framework for risk assessment and uncertainty quantification in bridge construction. By integrating domain-specific representation learning, explainable ensemble prediction, and probabilistic causal inference, the framework addresses key limitations of existing approaches in handling high-dimensional data, interpretability, and uncertainty propagation.

The results show that domain-specific autoencoders effectively transform heterogeneous construction data into compact latent representations while preserving engineering semantics. The explainable ensemble model achieves strong predictive performance with transparent domain-level attribution, and the probabilistic layer enables causal reasoning and scenario-based risk estimation under uncertainty. Together, these components support interpretable and reliable decision-making across structural, environmental, managerial, resource, and safety domains.

By embedding explainability and uncertainty as core design principles, the framework provides a scalable and theoretically grounded alternative to conventional deterministic or black-box models in bridge construction risk assessment.

While validated on a BIM–AI dataset, further evaluation using real-time and project-specific data is required to confirm operational robustness. Future work should focus on dynamic risk monitoring, integration of real-time sensor data, and validation across diverse bridge types and construction environments.

Overall, the proposed framework advances interpretable, uncertainty-aware, and data-driven risk management for modern infrastructure systems.

Abbreviations

AE Autoencoder

ANN Artificial Neural Network

EBM Explainable Boosting Machine

FTA Fault Tree Analysis

ETA Event Tree Analysis

F1 F1-Score (harmonic mean of precision and recall)

FMEA Failure Mode and Effects Analysis

FN False Negatives

FP False Positives

HGBC HistGradientBoostingClassifier

IQR Interquartile Range

MSE Mean Squared Error

ML Machine Learning

SHAP SHapley Additive exPlanations

SR Structural Representation

ROC-AUC Receiver Operating Characteristic - Area Under Curve

RMSE Root Mean Squared Error

TP True Positives

TN True Negatives

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Declaration of interest

The authors have no conflicts of interest to declare. All co-authors have observed and affirmed the contents of the paper and there is no financial interest to report

Data availability

The data used in the current study are available from [https://www.kaggle.com/datasets/ziya07/bim-ai-integrated-dataset]

Declaration of use of generative artificial intelligence

This work was prepared without the assistance of any generative artificial intelligence (GenAI) tools or services. All aspects of the manuscript were developed solely by the authors, who take full responsibility for the content of this publication.

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