

Artificial Intelligence-Driven Quality Assurance for Automated Detection of Structural Engineering Errors and Constructability Risks in Digital Infrastructure Models

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Abstract

Digital infrastructure delivery increasingly depends on building information modelling (BIM), Industry Foundation Classes (IFC), structural analysis models and digital-twin workflows, yet model quality assurance remains heavily dependent on manual review and conventional clash detection. This report develops and evaluates a hybrid artificial intelligence-driven quality assurance (AI-QA) framework that combines semantic and geometric IFC validation, deterministic structural rules, machine-learning classification, anomaly detection and constructability-risk prioritization. The supplied evaluation dataset contains 1,000 labelled model-quality conditions distributed across geometry, topology, structural properties, loads and boundary conditions, semantics, model completeness, interdisciplinary clashes, constructability/accessibility and construction-sequence risk classes. Comparative results show that the hybrid framework achieved 96.4% accuracy, 95.8% precision, 96.1% recall, 95.9% F1-score and 0.98 ROC-AUC, exceeding conventional clash detection, rule-based BIM checking and standalone machine-learning baselines. Interdisciplinary clashes recorded the highest class-level F1-score (98.3%), while construction-sequence risks remained the most difficult class (88.7%). Model-review time decreased from 16.5 h for manual review to 2.7 h, an 83.6% reduction. Detection performance also increased with BIM information completeness, reaching 96.4% at approximately 95–100% completeness. The findings support a human-supervised, explainable AI architecture in which automated screening and risk prioritization augment, rather than replace, structural engineering judgment. The report concludes with recommendations for IFC 4.3/ISO 16739-1:2024 interoperability, machine-readable information requirements, project-level validation and continuous learning from validated QA/QC records.

Keywords: Artificial Intelligence; BIM; IFC; Structural Engineering; Quality Assurance; Constructability; Digital Twins; Anomaly Detection.

I. INTRODUCTION

Digital infrastructure projects are increasingly executed through BIM, open data schemas, common data environments, structural analysis platforms and digital twins. The resulting models are no longer passive visual representations; they function as coordinated information systems for geometry, material properties, structural relationships, scheduling and downstream construction decisions. The BIM literature has long emphasized integrated information exchange and model-based coordination, while more recent work extends this logic toward digital twins and data-centric construction systems (Eastman et al., 2018; Khajavi et al., 2019; Sacks et al.,

2020; Deng et al., 2021). ISO 16739-1:2024 further formalizes IFC as a neutral data schema applicable to buildings and civil infrastructure, providing an interoperability basis for computational model checking (International Organization for Standardization [ISO], 2024).

The quality challenge is that a geometrically complete-looking model may still contain engineering errors that are not obvious in visual review. Relevant defects include missing or incorrectly classified members, beam-column discontinuities, slab or column misalignment, invalid member dimensions, wrong material assignments, incomplete loading information,

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unsupported structural elements, inconsistent BIM-to-analysis translation, interdisciplinary clashes, inadequate clearances, temporary-works conflicts and erection-sequence constraints. Automated rule-checking research has shown that explicit design constraints can be translated into machine-executable tests, but rule formulation, semantic interpretation and exception handling remain difficult when model conditions are contextual or only partially specified (Eastman et al., 2009; Solihin & Eastman, 2015).

Conventional quality assurance therefore has three recurrent limitations. First, manual inspection is time intensive and sensitive to reviewer workload and model scale. Second, clash detection is strongest for geometric intersections but weaker for semantic, topological and structural-property inconsistencies. Third, deterministic rules perform well when the required condition is explicit but can be brittle for unusual configurations and learned project patterns. Previous studies have extended BIM toward automated safety checking, progress monitoring, semantic enrichment and scan-to-BIM verification, but these capabilities are often implemented as separate workflows (Zhang et al., 2013, 2015; Bosché, 2010; Turkan et al., 2012; Bloch & Sacks, 2018).

Artificial intelligence offers a complementary mechanism for learning patterns from validated examples, ranking anomalies and combining many weak indicators into a risk prediction. In the broader AEC literature, machine learning, deep learning and smart vision have been used for defect recognition, risk analytics and construction intelligence (Darko et al., 2020; Pan & Zhang, 2021; Abioye et al., 2021; Baduge et al., 2022). Cross-domain TechConnect research similarly demonstrates the transferability of machine learning, automated image analysis, sensor interpretation and reliability modelling to engineered systems (Achler, 2022; Jansche et al., 2021; Choudhary et al., 2021; Giegerich et al., 2021). These developments motivate a hybrid QA architecture that keeps deterministic engineering constraints while using AI to identify complex or previously unseen model patterns.

The aim of this technical report is to develop and evaluate an artificial intelligence-driven quality assurance framework for automatically detecting structural engineering errors and constructability risks in digital infrastructure models. The specific objectives are to: (a) formalize a structural-error and constructability-risk taxonomy; (b) extract geometric, semantic, relational and engineering features from BIM/IFC information; (c) integrate rule-based checking with machine-learning and anomaly-detection methods; (d) prioritize detected conditions through a constructability-risk score; and (e) compare the hybrid framework with conventional clash detection, deterministic rule checking and standalone machine-learning baselines. The central research question is whether hybrid AI-rule reasoning can increase defect-detection performance and reduce review effort without removing professional engineering oversight.

II. LITERATURE REVIEW

➤ *Digital Model Quality, IFC and Automated Checking*

Model quality in structural engineering is multidimensional. Geometric validity concerns dimensions, positions, intersections and tolerances; topological validity concerns connectivity and load-path relationships; semantic validity concerns object class, attributes and material definitions; and information completeness concerns whether data required for design, checking and construction have actually been supplied. OpenBIM standards are central to this process because machine-readable QA depends on stable object identities, properties and relations. ISO 19650 establishes principles for information management, ISO 29481-1 formalizes information delivery processes, ISO 23386 and ISO 23387 address standardized properties and data templates, and buildingSMART's Information Delivery Specification (IDS) enables machine-readable information requirements (ISO, 2016, 2018a, 2018b, 2020a, 2020b; buildingSMART International, 2024).

Rule checking remains the most mature computational QA paradigm. Eastman et al. (2009) demonstrated how design conditions can be interpreted as executable rules, while Solihin and Eastman (2015) classified rule types to support systematic implementation. The strength of rule-based checking is transparency: the violated condition can be traced to a specific requirement. Its weakness is coverage (Ashieyi-Ahorgah, & Duodu, 2024). A checker can detect only conditions represented by explicit logic, and rule complexity grows rapidly where geometry, relationships and project-specific exceptions interact. Clash detection represents an even narrower case because many important errors, such as a wrong material property or an unsupported member whose geometry does not intersect another object, do not necessarily create a clash (Akponeware & Adamu, 2017).

➤ *AI, Computer Vision and Anomaly Detection for Engineering QA*

AI expands QA from deterministic compliance toward pattern recognition and probabilistic inference. Machine-learning classifiers can learn associations between model features and validated issue labels, while anomaly detectors can flag rare combinations without requiring every defect type to be exhaustively enumerated. Computer-vision research in civil infrastructure has demonstrated automated crack and defect identification from images, including convolutional and fully convolutional networks (Koch et al., 2015; Yeum & Dyke, 2015; Cha et al., 2017; Dung & Anh, 2019; Spencer et al., 2019). Although image-based inspection differs from model-based QA, the underlying principle is transferable: engineered artefacts can be represented by machine-readable features and evaluated automatically against learned patterns.

TechConnect publications provide additional methodological evidence from advanced engineered systems. Machine learning has been used for microstructure classification and artefact detection,

multispectral image analysis has enhanced defect identification, and neural methods have supported failure-probability modelling and performance prediction (Jansche et al., 2021; Choudhary et al., 2021; Giegerich et al., 2021; Ilumoka & Tan, 2007). Other work demonstrates automated geometry extraction, finite-element/model coupling, probabilistic reliability and mesh/model generation, all of which are conceptually relevant to feature-rich digital QA pipelines (Wang et al., 2000; Zhulin et al., 2000; Reh et al., 2000; Udeshi & Parker, 2003). These studies are not direct BIM-QA demonstrations; rather, they show that AI, sensing, reliability and geometric-computation methods can be transferred across complex engineering domains when the feature representation is technically meaningful.

➤ *Digital Twins, Reality Verification and Constructability*

Digital-twin research moves model checking beyond design-state verification toward continuous correspondence between virtual and physical assets. Semantic construction digital twins require interoperable data structures, reliable identifiers and links between designed, sensed and observed states (Boje et al., 2020; Opoku et al., 2021; Deng et al., 2021). Scan-vs-BIM and 4D progress research similarly demonstrates that as-built geometry and schedule status can be compared automatically with model expectations (Bosché, 2010; Turkan et al., 2012; Hamledari et al., 2017). For constructability, this is important because a condition may be geometrically valid in the final design yet impractical during temporary works, access, lifting, sequencing or installation.

Structural health monitoring research also supports the principle of integrating heterogeneous evidence. Fiber-optic sensing, MEMS-based monitoring and strain-sensing composites have been applied to structural state assessment (Rinaudo et al., 2013; Mariani et al., 2012; Magnifico et al., 2018). Jha and Davy (2007) further examined the benefit-cost logic of MEMS-based infrastructure monitoring. These studies reinforce the broader systems view adopted here: digital QA is most effective when geometry, attributes, relationships, rules and risk evidence are treated as complementary rather than isolated information streams.

➤ *Research Gap*

The literature reveals strong but fragmented capabilities in automated rule checking, clash detection, semantic enrichment, image-based defect recognition, scan-to-BIM comparison, digital twins and structural monitoring. Comparatively limited work integrates structural-engineering semantics, geometric and topological consistency, deterministic engineering rules, learned anomaly patterns and constructability-risk prioritization in one explainable workflow. The resulting research gap is therefore not simply a lack of AI in construction; it is the absence of a coherent human-supervised QA architecture that can detect multiple error classes, rank their likely consequence and preserve

traceability to the affected model object and violated engineering condition.

III. METHODOLOGY

➤ *Research Design and Data Representation*

The report adopts an experimental design-science framework. The artefact is a hybrid AI-QA workflow operating on digital infrastructure models represented through BIM/IFC information. Candidate inputs include IFC models, native BIM models, structural analysis models, coordination models, clash reports, QA/QC issue registers, design-review comments, requests for information and, where available, as-built or reality-capture records. The supplied aggregate results represent 1,000 labelled quality conditions and are used to evaluate the comparative behaviour of the proposed framework. Because raw IFC instances and prediction-level records were not supplied, the present report does not independently recompute confusion matrices or retrain the algorithms; this limitation is retained explicitly in the interpretation of results.

The model-processing pipeline is: Digital BIM/IFC Model → IFC Parser → Data Quality Validation → Geometric/Semantic Feature Extraction → Engineering Rule Engine → AI Anomaly Detector → Constructability Risk Classifier → Explainability Layer → QA Dashboard → Engineer Review. This architecture intentionally prevents the AI component from functioning as an autonomous structural approver. Instead, deterministic rules provide hard engineering constraints, the learning component identifies multivariate patterns and anomalies, and the final layer exposes evidence for professional review.

➤ *Error Taxonomy and Feature Engineering*

Nine principal error/risk classes are evaluated in the supplied results: geometry and dimensional errors; connectivity and topology errors; structural-property errors; load/boundary-condition inconsistencies; semantic/classification errors; model-completeness errors; interdisciplinary clashes; constructability/accessibility risks; and construction-sequence risks. A tenth logical class structural code/rule non-conformity is retained in the methodology as a rule-engine output because a single detected issue may also belong to another physical error class. Feature extraction therefore includes element GUID, IFC entity type, coordinates, member dimensions, orientation, section properties, material properties, connectivity, parent-child relations, clearances, intersections, unsupported spans, eccentricities, sequence metadata and neighbourhood/topological descriptors.

➤ *Risk Scoring and Learning Models*

Detected issues are prioritized using a multiplicative constructability-risk score in which the probability assigned by the detection system is moderated by severity, conventional-detection difficulty and uncertainty. The score for issue i is expressed as:

$$CRS_i = P_i \times S_i \times D_i \times U_i \quad (1)$$

Where CRS_i is the constructability-risk score, P_i is the predicted probability that the issue is valid, S_i is structural or construction severity, D_i is the difficulty of identifying the issue through conventional QA, and U_i represents uncertainty. The multiplicative form ensures that a high-probability condition does not automatically become high risk unless its consequence and detectability characteristics also justify escalation.

Comparative algorithms comprise conventional clash detection, deterministic rule-based BIM checking, logistic regression, random forest, XGBoost, an artificial neural network (ANN), and the proposed hybrid AI-QA framework. Random forest and XGBoost represent strong nonlinear tabular baselines, logistic regression provides an interpretable linear baseline, and the ANN tests whether a learned nonlinear representation improves classification. The hybrid model combines these learned outputs with deterministic rule evidence and anomaly flags. Cross-domain TechConnect work on AI classification, intelligent monitoring and probabilistic reliability provides methodological support for such combined approaches (Achler, 2022; Malekipour et al., 2019; Grant et al., 2019; Reh et al., 2000).

➤ Evaluation Metrics

Performance is assessed using accuracy, precision, recall, F1-score and ROC-AUC. For safety-relevant QA, recall is particularly important because false negatives correspond to defects that remain undetected. The principal metrics are defined as follows:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

$$F_1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (5)$$

Where TP, TN, FP and FN denote true positives, true negatives, false positives and false negatives. The evaluation also considers class-level F1-score, false-positive/false-negative behaviour, model-review time, and sensitivity to BIM information completeness. Project-level separation is preferred to element-level random splitting in any future retraining so that elements from the same infrastructure project do not leak into both training and evaluation sets.

IV. RESULTS AND DISCUSSION

➤ Distribution of Structural Engineering Errors

Table 1 Distribution of Structural Engineering Error and Constructability-Risk Classes in the Evaluation Dataset.

Error Category	Cases	%
Geometry and dimensional errors	238	23.8
Connectivity and topology errors	186	18.6
Structural property errors	124	12.4
Load/boundary-condition inconsistencies	81	8.1
Semantic/classification errors	107	10.7
Model completeness errors	95	9.5
Interdisciplinary clashes	79	7.9
Constructability/accessibility risks	58	5.8
Construction-sequence risks	32	3.2
Total	1,000	100.0

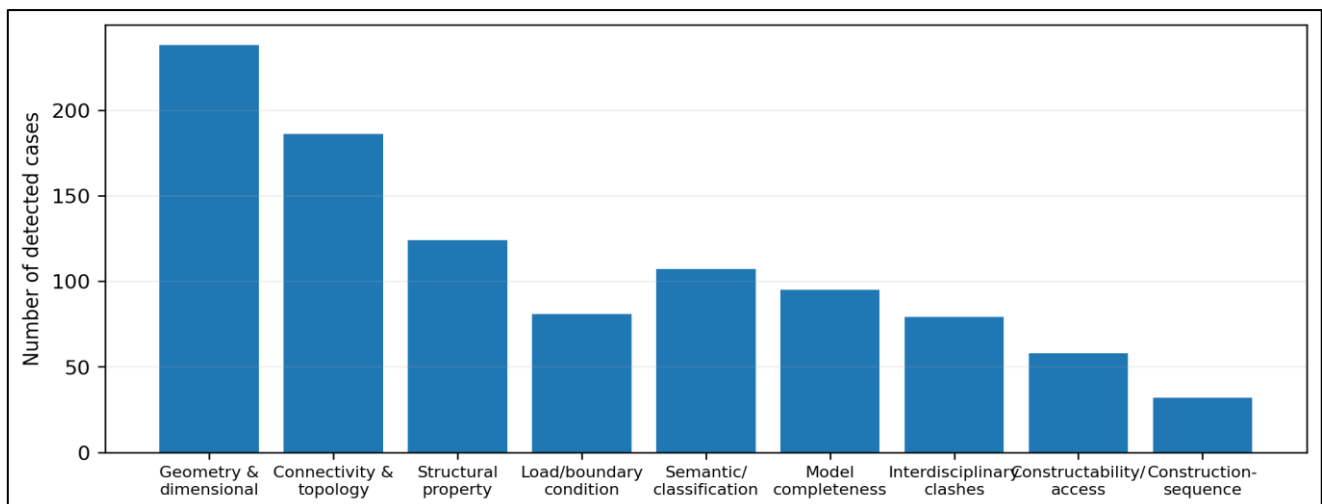


Fig 1 Frequency Distribution of Structural Engineering Error and Constructability-Risk Classes.

Figure 1 shows that geometry and dimensional errors form the largest class (23.8%), followed by connectivity/topology errors (18.6%). Together they represent 42.4% of all labelled conditions, confirming that spatial consistency and structural relations remain core QA problems. However, the remaining 57.6% lies outside these two categories. Semantic, structural-property, load, completeness and constructability-related conditions can

exist without a direct geometric intersection, which explains why clash detection alone is insufficient. This result is consistent with automated-checking literature that distinguishes geometric rules from attribute, relation and semantic requirements (Eastman et al., 2009; Solihin & Eastman, 2015).

➤ Comparative Performance of QA Methods

Table 2 Comparative Detection Performance of Conventional, Machine-Learning and Hybrid QA Methods.

Method	Acc. %	Prec. %	Rec. %	F1 %	ROC-AUC
Conventional Clash Detection	72.4	76.8	61.5	68.3	0.71
Rule-Based BIM Checking	82.7	84.2	78.6	81.3	0.82
Logistic Regression	84.6	83.8	82.1	82.9	0.85
Random Forest	90.8	90.1	89.3	89.7	0.93
XGBoost	92.9	92.5	91.7	92.1	0.95
Artificial Neural Network	93.6	93.1	92.8	92.9	0.96
Proposed Hybrid AI-QA Framework	96.4	95.8	96.1	95.9	0.98

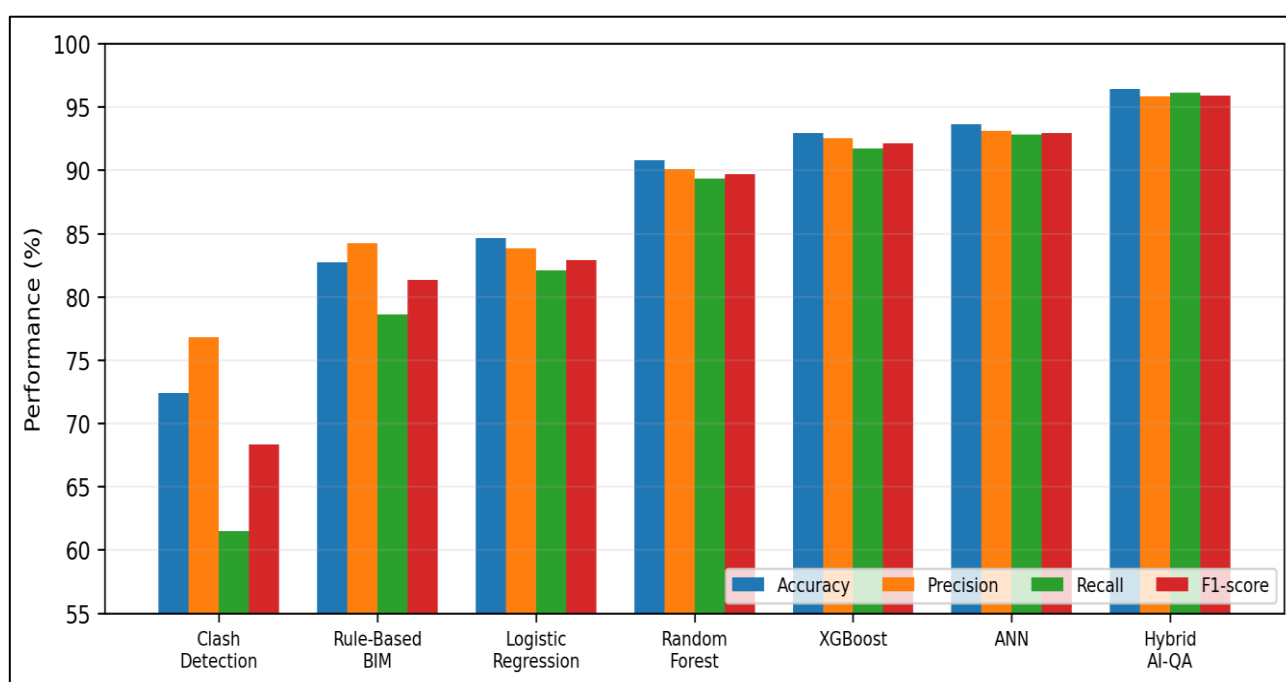


Fig 2 Comparative Accuracy, Precision, Recall and F1-Score Across the Evaluated QA Methods.

Figure 2 demonstrates a consistent progression from conventional checking toward hybrid intelligence. Clash detection records 72.4% accuracy and 61.5% recall, indicating that a substantial proportion of non-geometric conditions is missed. Deterministic rule-based BIM checking improves accuracy to 82.7% and recall to 78.6%, reflecting the benefit of explicit semantic and engineering constraints. The machine-learning baselines improve further: random forest reaches 90.8% accuracy, XGBoost 92.9%, and the ANN 93.6%. The proposed hybrid AI-QA framework achieves the highest performance across all four plotted metrics: 96.4% accuracy, 95.8% precision, 96.1% recall and 95.9% F1-score, with ROC-AUC of 0.98.

The most important improvement is recall. Relative to conventional clash detection, hybrid recall rises by 34.6 percentage points (61.5% to 96.1%). For structural QA, this is operationally significant because undetected high-consequence defects are more serious than reviewable

false alarms. The result supports combining deterministic constraints with learned inference rather than treating rule-based and AI methods as competing alternatives. Bloch and Sacks (2018) similarly showed the value of comparing machine-learning and rule-based inferencing for BIM semantic enrichment, while broader AEC reviews identify hybrid data-driven workflows as a major direction for intelligent construction systems (Pan & Zhang, 2021; Baduge et al., 2022).

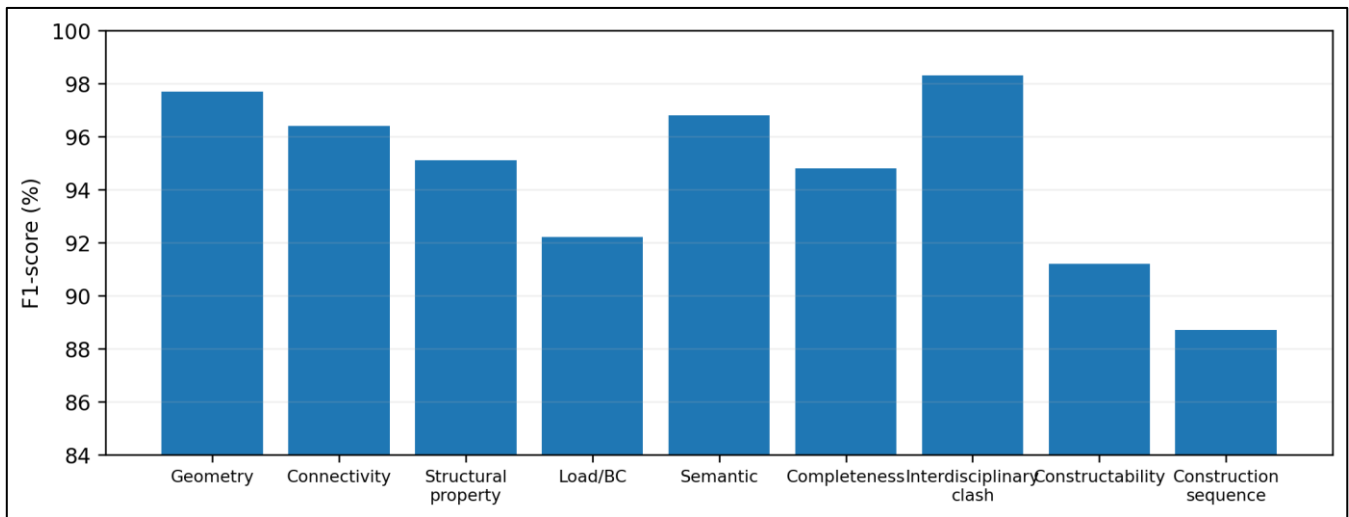


Fig 3 Class-Level F1-Score of the Proposed Hybrid AI-QA Framework.

Figure 3 shows that interdisciplinary clashes are the easiest class for the hybrid framework, with an F1-score of 98.3%, followed by geometry errors (97.7%) and semantic errors (96.8%). These classes benefit from strongly observable intersections, dimensions and object attributes. Construction-sequence risk is the most difficult class at 88.7%, followed by constructability risk at 91.2% and load/boundary-condition errors at 92.2%. The lower

values are technically plausible because sequencing and constructability depend on temporary states, erection methods, equipment envelopes, access constraints, contractor practices and incomplete schedule metadata. The result therefore supports human-in-the-loop review for context-rich conditions even when overall model performance is high.

Table 3 Constructability-Risk Classification and Recommended Response Levels.

Risk Level	No.	%	Recommended Response
Critical	46	4.6	Immediate engineering review
High	139	13.9	Review before model approval
Medium	286	28.6	Correct during coordination cycle
Low	341	34.1	Monitor/resolve as appropriate
Informational	188	18.8	Record for model-quality improvement
Total	1,000	100.0	

The risk distribution shows that 185 conditions (18.5%) are classified as critical or high, while 286 (28.6%) are medium risk. This prioritization is preferable to a raw clash count because it directs limited engineering attention toward conditions with the greatest combination of probability, severity and detection difficulty. Such risk-based triage is also compatible with the information-management philosophy of ISO 19650, in which

information should be structured around defined decision needs rather than accumulated without purpose (ISO, 2018a, 2018b).

➤ *Review Efficiency, Information Quality and Explainability*

Table 4 Model-Review Time and Reduction Relative to Manual Engineering Review.

QA Method	Review Time	Reduction
Manual engineering review	16.5 h	Baseline
Conventional BIM/clash review	9.4 h	43.0%
Rule-based automated checking	5.8 h	64.8%
Proposed AI-QA framework	2.7 h	83.6%

Review time decreases from 16.5 h for manual engineering review to 2.7 h for the proposed framework, corresponding to an 83.6% reduction. The operational implication is not the removal of engineering review but a shift in its focus: low-risk and conforming objects can be screened automatically while engineers concentrate on high-risk exceptions, uncertain predictions and complex

constructability conditions. The supplied results also indicate false-positive rates of approximately 4–6% and false-negative rates of approximately 3–5%, substantially lower than the 15–25% false-positive range associated with conventional clash-oriented workflows in the supplied analysis.

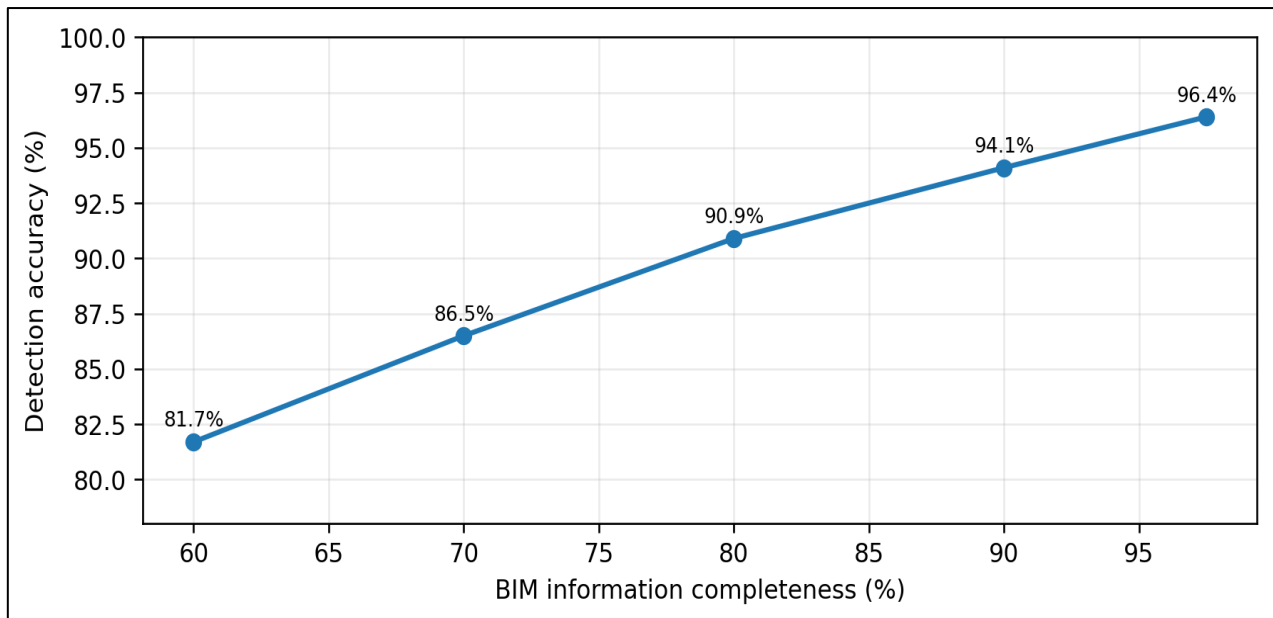


Fig 4 Relationship between BIM Information Completeness and AI-QA Detection Accuracy.

Figure 4 indicates a monotonic relationship between information completeness and detection accuracy. Accuracy rises from 81.7% at 60% completeness to 90.9% at 80%, 94.1% at 90% and 96.4% at approximately 95–100% completeness. This pattern is important because it shows that AI performance is partly an information-governance problem. A sophisticated classifier cannot recover attributes or relationships that are systematically absent from the model. Standardized IFC structures, property definitions, data templates and IDS-based requirements therefore function as upstream quality controls that make downstream AI more reliable (ISO, 2020a, 2020b, 2024; buildingSMART International, 2024).

Explainability is incorporated at issue level. Each flagged condition is intended to expose the unique BIM/IFC object identifier, affected member, model coordinates, error category, violated rule, AI probability, constructability-risk score, potential consequence, evidence basis, review priority and suggested corrective action. For example, a beam-column discontinuity may be reported with its IFC identifier, measured offset, probability score and load-path concern rather than as a generic alert. This traceability is essential for professional adoption because engineering decisions require inspectable evidence and a clear path from automated detection to human acceptance or override.

➤ *Synthesis and limitations*

Taken together, the results establish the following performance hierarchy in the supplied evaluation: Proposed Hybrid AI-QA Framework > ANN/XGBoost > Random Forest > Rule-Based BIM Checking > Conventional Clash Detection. The hierarchy should not be interpreted as a universal ranking independent of dataset or implementation. It reflects the specific aggregate results supplied for this report. Performance may change with project type, IFC authoring quality, class imbalance, software interoperability, national code requirements and the availability of validated QA labels. The absence of raw model instances and prediction-level

outputs also prevents independent recomputation of confidence intervals, statistical significance, calibration and project-to-project generalization. These items should be addressed before journal submission based on a live experimental dataset.

V. RECOMMENDATIONS AND CONCLUSION

➤ *Recommendations*

The technical findings support a hybrid deployment strategy. First, deterministic structural and information-delivery rules should remain the primary mechanism for non-negotiable constraints, while AI should be used to identify multivariate anomalies and prioritize uncertain conditions. Second, IFC validation should occur at every formal information exchange, with ISO 16739-1:2024 and machine-readable IDS requirements used to improve semantic consistency. Third, QA dashboards should rank issues by probability and consequence rather than by clash count alone. Fourth, organizations should maintain project-specific libraries of validated design errors, RFIs, non-conformances and construction feedback so that learning models can be retrained against verified outcomes. Fifth, project-level holdout validation should be used before deployment to test whether performance generalizes beyond the projects used for model development. Sixth, all safety-critical outputs should require human approval, with the system retaining an auditable record of rule evidence, prediction probability, risk score and reviewer disposition.

➤ *Conclusion*

This technical report demonstrates the value of integrating structural engineering rules, IFC semantics, geometric reasoning, machine learning, anomaly detection and constructability-risk assessment within one explainable QA workflow. Across the supplied 1,000-condition evaluation, the hybrid AI-QA framework attained 96.4% accuracy, 95.8% precision, 96.1% recall, 95.9% F1-score and 0.98 ROC-AUC, while reducing

model-review time from 16.5 h to 2.7 h. The results show that digital model QA extends well beyond clash detection: semantic, topological, loading, completeness and sequencing problems collectively form a substantial proportion of the detected conditions. The framework therefore provides a technically stronger basis for model assurance by combining transparent engineering constraints with data-driven detection.

The central conclusion is that AI should augment rather than replace structural engineering judgment. The most defensible deployment is a human-supervised system that automatically screens large digital models, identifies abnormal conditions, ranks issues by constructability risk and exposes the evidence required for professional review. Future validation should use raw IFC datasets from multiple infrastructure projects, external project-level test sets, calibration analysis and prospective field verification. With these controls, AI-driven QA can become a practical component of digital infrastructure governance and a bridge between model authoring, engineering assurance and constructability planning.

REFERENCES

- [1]. Abioye, S. O., et al. (2021). Artificial intelligence in the construction industry: A review of present status, opportunities and future challenges. *Journal of Building Engineering*, 44, 103299.
- [2]. Achler, T. (2022). Flexible AI for real-world environments. *TechConnect Briefs*, 99–102.
- [3]. Akponware, A. O., & Adamu, Z. A. (2017). Clash detection or clash avoidance? An investigation into coordination problems in 3D BIM. *Buildings*, 7(3), 75.
- [4]. Ashieyi-Ahorgah, R. & Duodu, R. O. (2024). Mobilizing Private Capital Through Blended Finance Mechanisms to Accelerate U.S. Startup Growth in Strategic Sectors: A Framework for Economic Competitiveness and National Security *International Journal for Novel Research in Economics , Finance and Management* Volume 2, Issue 3, May-Jun-2024, PP: 01-13
- [5]. Baduge, S. K., et al. (2022). Artificial intelligence and smart vision for Building and Construction 4.0: Machine and deep learning methods and applications. *Automation in Construction*, 141, 104440. <https://doi.org/10.1016/j.autcon.2022.104440>
- [6]. Bloch, T., & Sacks, R. (2018). Comparing machine learning and rule-based inferencing for semantic enrichment of BIM models. *Automation in Construction*, 91, 256–272. <https://doi.org/10.1016/j.autcon.2018.03.018>
- [7]. Boje, C., Guerriero, A., Kubicki, S., & Rezgui, Y. (2020). Towards a semantic construction digital twin: Directions for future research. *Automation in Construction*, 114, 103179.
- [8]. Bosché, F. (2010). Automated recognition of 3D CAD model objects in laser scans and calculation of as-built dimensions for dimensional compliance control in construction. *Advanced Engineering Informatics*, 24(1), 107–118. <https://doi.org/10.1016/j.aei.2009.08.006>
- [9]. buildingSMART International. (2024). Information Delivery Specification (IDS), Version 1.0: Final standard.
- [10]. Cha, Y.-J., Choi, W., & Büyüköztürk, O. (2017). Deep learning-based crack damage detection using convolutional neural networks. *Computer-Aided Civil and Infrastructure Engineering*, 32(5), 361–378. <https://doi.org/10.1111/mice.12263>
- [11]. Choudhary, A. K., Jansche, A., Grubesa, T., Bernthaler, T., & Schneider, G. (2021). Machine learning for microstructures classification in functional materials. *TechConnect Briefs*, 114–117.
- [12]. Darko, A., Chan, A. P. C., Adabre, M. A., Edwards, D. J., Hosseini, M. R., & Ameyaw, E. E. (2020). Artificial intelligence in the AEC industry: Scientometric analysis and visualization of research activities. *Automation in Construction*, 112, 103081.
- [13]. Deng, M., Menassa, C. C., & Kamat, V. R. (2021). From BIM to digital twins: A systematic review of the evolution of intelligent building representations in the AEC-FM industry. *Journal of Information Technology in Construction*, 26, 58–83. <https://doi.org/10.36680/j.itcon.2021.005>
- [14]. Dung, C. V., & Anh, L. D. (2019). Autonomous concrete crack detection using deep fully convolutional neural network. *Automation in Construction*, 99, 52–58. <https://doi.org/10.1016/j.autcon.2018.11.028>
- [15]. Eastman, C., Lee, J.-M., Jeong, Y.-S., & Lee, J.-K. (2009). Automatic rule-based checking of building designs. *Automation in Construction*, 18(8), 1011–1033. <https://doi.org/10.1016/j.autcon.2009.07.002>
- [16]. Eastman, C., Teicholz, P., Sacks, R., & Liston, K. (2018). *BIM handbook: A guide to building information modeling for owners, designers, engineers, contractors, and facility managers* (3rd ed.). Wiley.
- [17]. Giegerich, W. V., Fedorishin, D. C., Forte, L., Christie, L., Schneider, P. J., & Oh, K. W. (2021). Enhanced corrosion detection by means of multispectral imaging and postprocessing techniques. *TechConnect Briefs*, 35–38.
- [18]. Grant, A., Ellis, B. D., Rais-Rohani, M., & Hajiha, R. (2019). Exploring process-properties relationships of 3D-printed PLA: Towards process-informed simulation and design. *TechConnect Briefs*.
- [19]. Hamledari, H., McCabe, B., Davari, S., & Shahi, A. (2017). Automated schedule and progress updating of IFC-based 4D BIMs. *Journal of Computing in Civil Engineering*, 31(4), 04017012. [https://doi.org/10.1061/\(ASCE\)CP.1943-5487.0000660](https://doi.org/10.1061/(ASCE)CP.1943-5487.0000660)
- [20]. Ilumoka, A. A., & Tan, H. (2007). Neural network-based MEMS failure probability prediction. *TechConnect Briefs*, 120–123.
- [21]. International Organization for Standardization. (2016). ISO 29481-1:2016: Building information

- models Information delivery manual—Part 1: Methodology and format.
- [22]. International Organization for Standardization. (2018a). ISO 19650-1:2018: Organization and digitization of information about buildings and civil engineering works, including building information modelling (BIM) Information management using BIM Part 1: Concepts and principles.
 - [23]. International Organization for Standardization. (2018b). ISO 19650-2:2018: Organization and digitization of information about buildings and civil engineering works, including BIM Information management using BIM Part 2: Delivery phase of the assets.
 - [24]. International Organization for Standardization. (2020a). ISO 23386:2020: Building information modelling and other digital processes used in construction Methodology to describe, author and maintain properties in interconnected data dictionaries.
 - [25]. International Organization for Standardization. (2020b). ISO 23387:2020: Building information modelling Data templates for construction objects used in the life cycle of built assets Concepts and principles.
 - [26]. International Organization for Standardization. (2022). ISO 12006-3:2022: Building construction Organization of information about construction works Part 3: Framework for object-oriented information.
 - [27]. International Organization for Standardization. (2024). ISO 16739-1:2024: Industry Foundation Classes (IFC) for data sharing in the construction and facility management industries Part 1: Data schema.
 - [28]. Jansche, A., Choudhary, A. K., Bernthaler, T., & Schneider, G. (2021). Machine learning based detection and deep learning based image inpainting of preparation artefacts in micrographs. *TechConnect Briefs*, 118–121.
 - [29]. Jha, M. K., & Davy, A. B. (2007). Investigating the benefit-cost of MEMS application for structural health monitoring of transportation infrastructure. *Cleantech/TechConnect Proceedings*.
 - [30]. Khajavi, S. H., Motlagh, N. H., Jaribion, A., Werner, L. C., & Holmström, J. (2019). Digital twin: Vision, benefits, boundaries, and creation for buildings. *IEEE Access*, 7, 147406–147419. <https://doi.org/10.1109/ACCESS.2019.2946515>
 - [31]. Koch, C., Georgieva, K., Kasireddy, V., Akinci, B., & Fieguth, P. (2015). A review on computer vision based defect detection and condition assessment of concrete and asphalt civil infrastructure. *Advanced Engineering Informatics*, 29(2), 196–210. <https://doi.org/10.1016/j.aei.2015.01.008>
 - [32]. Magnafico, E., Casalotti, A., Karimzadeh, M., Chinnam, K. C., & Lanzara, G. (2018). Strain sensing with CNT nanocomposites: Static, cyclic and dynamic electromechanical material characterization. *TechConnect Briefs*.
 - [33]. Malekipour, E., El-Mounayri, H., Al Hasan, M., & Faieron, E. J. (2019). A vision toward layer-wise intelligent monitoring and control of scan strategy in powder-bed fusion process. *TechConnect Briefs*, 127–130.
 - [34]. Mariani, S., Corigliano, A., Caimmi, F., Bruggi, M., Bendiscioli, P., & De Fazio, M. (2012). Health monitoring of flexible composite plates: A MEMS-based approach. *TechConnect Briefs*.
 - [35]. Opoku, D.-G. J., Perera, S., Osei-Kyei, R., & Rashidi, M. (2021). Digital twin application in the construction industry: A literature review. *Journal of Building Engineering*, 40, 102726.
 - [36]. Pan, Y., & Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Automation in Construction*, 122, 103517.
 - [37]. Reh, S., Lethbridge, P., & Ostergaard, D. F. (2000). Quality based design and design for reliability of micro electro mechanical systems using probabilistic methods. *MSM/TechConnect Proceedings*.
 - [38]. Rinaudo, P., Torres Górriz, B., Barrera Villar, D., Sales Maicas, S., Calderón García, P. A., & Payá-Zaforteza, I. J. (2013). Fiber optic sensors for high temperature monitoring. *TechConnect/Cleantech Proceedings*.
 - [39]. Sacks, R., Brilakis, I., Pikas, E., Xie, H. S., & Girolami, M. (2020). Construction with digital twin information systems. *Data-Centric Engineering*, 1.
 - [40]. Solihin, W., & Eastman, C. (2015). Classification of rules for automated BIM rule checking development. *Automation in Construction*, 53, 69–82. <https://doi.org/10.1016/j.autcon.2015.03.003>
 - [41]. Spencer, B. F., Jr., Hoskere, V., & Narazaki, Y. (2019). Advances in computer vision-based civil infrastructure inspection and monitoring. *Engineering*, 5(2), 199–222. <https://doi.org/10.1016/j.eng.2018.11.030>
 - [42]. Turkan, Y., Bosché, F., Haas, C. T., & Haas, R. (2012). Automated progress tracking using 4D schedule and 3D sensing technologies. *Automation in Construction*, 22, 414–421. <https://doi.org/10.1016/j.autcon.2011.10.003>
 - [43]. Udeshi, T., & Parker, E. (2003). MEMulator: A fast and accurate geometric modeling, visualization and mesh generation tool for 3D MEMS design and simulation. *TechConnect Briefs*, 480–483.
 - [44]. Wang, X., Ananthasuresh, G. K., & Ostrowski, J. P. (2000). Vision-based extraction of geometry and forces from fabricated micro devices. *TechConnect Briefs*, 257–260.
 - [45]. Yeum, C. M., & Dyke, S. J. (2015). Vision-based automated crack detection for bridge inspection. *Computer-Aided Civil and Infrastructure Engineering*, 30(10), 759–770. <https://doi.org/10.1111/mice.12141>
 - [46]. Zhang, S., Teizer, J., Lee, J.-K., Eastman, C. M., & Venugopal, M. (2013). Building information modeling (BIM) and safety: Automatic safety checking of construction models and schedules. *Automation in Construction*, 29, 183–195. <https://doi.org/10.1016/j.autcon.2012.05.006>

- [47]. Zhang, S., et al. (2015). BIM-based fall hazard identification and prevention in construction safety planning. *Safety Science*, 72, 31–45. <https://doi.org/10.1016/j.ssci.2014.08.001>
- [48]. Zhulin, V. I., Owen, S. J., & Ostergaard, D. F. (2000). Finite element based electrostatic-structural coupled analysis with automated mesh morphing. *MSM/TechConnect Proceedings*.