



AI-Driven Quality Assurance Framework for Transportation Infrastructure Using BIM, Digital Twins, and ISO 19650

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Abstract

This study has examined how artificial intelligence, when embedded within Building Information Modelling (BIM), digital twins, and the information-management requirements of the ISO 19650 series, affects the effectiveness of quality assurance in transportation infrastructure, and it has developed and tested a framework for AI-driven quality assurance across the delivery and operational phases of highway, bridge, and rail assets. The central problem has been that quality assurance in transportation infrastructure remains largely document-centric, sample-based, and retrospective, so that nonconformances in geometry, materials, workmanship, and asset information are frequently discovered late, after cover-up, handover, or the onset of service, when correction is most costly and least reversible, and that the digital models and sensor streams now routinely produced on such projects are seldom converted into continuous, auditable quality evidence. Guided by five research questions, concerning how AI-driven BIM and digital twin integration affects quality assurance performance, which nonconformance categories are most effectively detected, which AI and sensing techniques are most effective, what risks document-centric manual regimes carry, and how ISO 19650 compliance and common data environment governance improve reliability, the study has proposed a framework comprising five contributing constructs: BIM model maturity and information standardisation; digital twin integration and real-time asset sensing; AI-based defect detection and predictive analytics; ISO 19650 compliance and common data environment governance; and data quality, interoperability and workflow integration, with quality assurance effectiveness as the outcome. A quantitative, cross-sectional design supplemented by a prototype pipeline evaluation has been used, and data have been collected from BIM and information managers, quality assurance and quality control engineers, digital twin and data engineers, asset and maintenance managers, and project directors. Out of 292 distributed questionnaires, 249 valid responses have been retained, producing an 85.3% valid response rate. The analysis has included descriptive statistics, reliability testing, correlation analysis, multiple regression, hypothesis testing, and a prototype evaluation of detection performance, discovery latency, and information-compliance conformance across the asset lifecycle. The findings have shown that all five constructs were significantly and positively associated with quality assurance effectiveness, that the regression model was significant, $F(5, 243) = 58.63$, $p < .001$, explaining 54.7% of the variance, and that AI-based defect detection and predictive analytics and BIM model maturity and information standardisation were the strongest predictors. The prototype evaluation showed that document-centric manual regimes discovered the largest share of nonconformances after cover-up or handover, while multimodal AI detection coupled with scan-versus-model geometric checking and rule-based information checking moved discovery decisively upstream.

Keywords

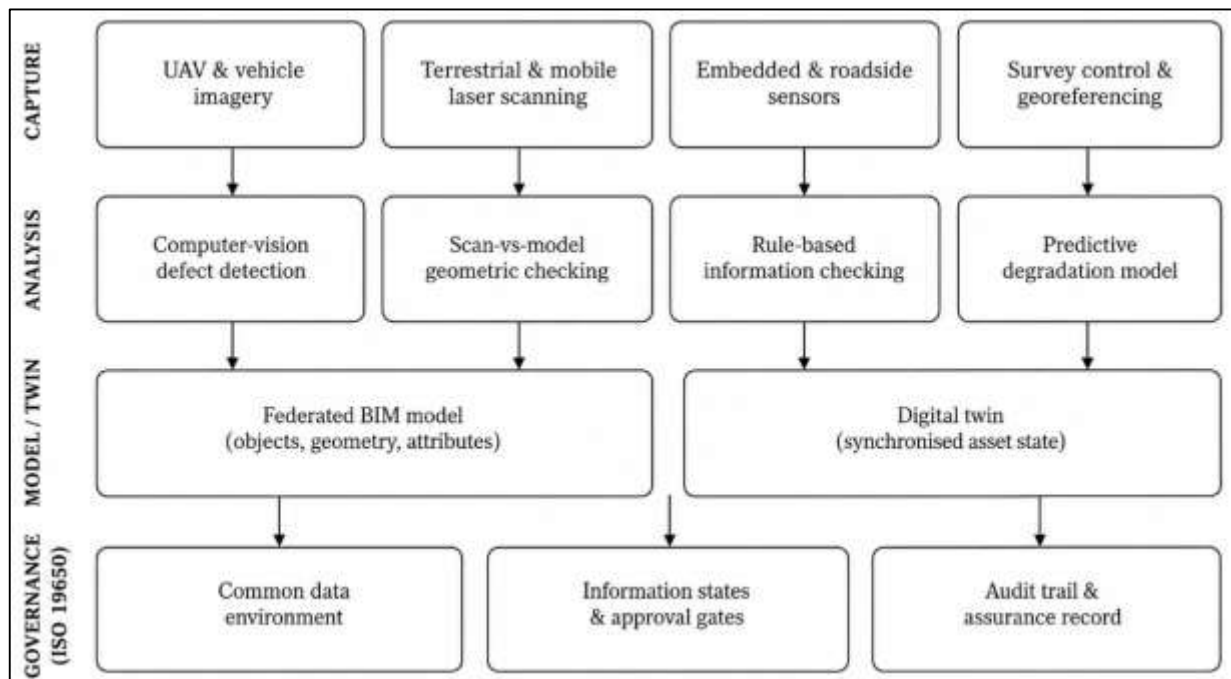
Quality Assurance; Building Information Modelling; Digital Twin; ISO 19650; Transportation Infrastructure; Defect Detection; Common Data Environment; Information Management.

INTRODUCTION

Quality assurance in transportation infrastructure is one of the most consequential and least automated processes in the built environment, because it must confirm that a physically large, geometrically complex, and long-lived asset has been constructed in conformity with a design intent expressed across thousands of drawings, specifications, and data records, and it must do so under schedule pressure, in adverse field conditions, and with only partial physical access. Building Information Modelling has become the principal medium in which that design intent is expressed, and its established methods and technologies have demonstrated substantial potential in the transportation sector (Costin et al., 2018; Bradley et al., 2016). Yet a structural feature of infrastructure assurance distinguishes it from most model-based workflows and undermines the assumption on which the value of those models rests: the model describes what should be built, whereas quality assurance concerns what was in fact built, and the two are connected in current practice only by manual, sampled, document-mediated inspection. This gap between the modelled asset and the constructed asset, and the delay with which it is closed, is the central challenge this study addresses.

The consequence of that gap is that nonconformances are discovered late. A dimensional deviation in a bridge bearing seat, a compaction or surface defect in a pavement layer, a reinforcement cover shortfall, or a missing asset attribute in a handover dataset may all remain undetected until they are covered by subsequent work, until commissioning, or until the asset has entered service, at which point correction requires demolition, closure, or an expensive service-life concession (Volk et al., 2014). This latency is especially damaging in transportation infrastructure because the assets are linear and continuously constructed, so that the interval between the creation of a defect and the completion of the work that conceals it is often measured in hours, while the interval between the defect and its discovery under a sampled, document-centric regime is measured in weeks or months. The premise of this study is that quality assurance can therefore not be improved by tightening documentary audit, but requires systems that observe the physical asset continuously, compare that observation automatically against the model and the specification, and manage the resulting evidence under a formal information-management standard.

Figure 1: AI-Driven Quality Assurance Architecture for Transportation Infrastructure



The stakes of this problem are large and growing. Transportation networks constitute a substantial share of public capital, much of it now beyond its original design life, and the cost of quality failure is borne not only in rework but in disruption to a network on which economic activity depends (Spencer et al., 2019). At the same time, the technical means to close the gap have matured rapidly and in parallel. Computer-vision methods now detect surface defects on concrete and asphalt with accuracies that approach or exceed trained human inspectors on comparable tasks (Cha et al., 2017; Zhang et al., 2017); digital twin architectures now support the continuous synchronisation of a physical asset with its information model (Sacks et al., 2020; Jiang et al., 2021); and the ISO 19650 series has established an internationally recognised process for managing the information itself, including the specification of information requirements, the operation of a common data environment, and the control of information states and approvals (ISO, 2018a; ISO, 2018b). What has not been established is how these three developments combine, and whether their combination in fact improves quality assurance rather than merely instrumenting it. That is the gap this study seeks to close.

Research on the individual components is substantial. The computer-vision literature has produced increasingly capable defect detectors for pavements, concrete surfaces, and structural components (Gopalakrishnan et al., 2017; Gao & Mosalam, 2018; Liu et al., 2019); the digital twin literature has moved from conceptual definition toward implemented civil-engineering applications (Boje et al., 2020; Opoku et al., 2021); and the automated-compliance-checking literature has demonstrated rule-based verification of models against codified requirements (Eastman et al., 2009; Solihin & Eastman, 2015). These streams, however, have developed largely in isolation, and their integration into the specific, regulated, contractually governed context of transportation infrastructure assurance remains incomplete (Md Mostafizur, 2025; Md Syeedur & Sharmin, 2025; Muhammad Zahidul, 2024). In particular, the interaction between automated detection and the information-management requirements that determine whether a detection becomes admissible quality evidence has been underexplored, even though those requirements shape what assurance is contractually recognised. This study addresses that gap by developing a framework that integrates AI-based detection and digital twin monitoring with ISO 19650 information governance, and by testing it against the perceptions of practitioners and a prototype pipeline evaluation (Debasish, 2021; Md Mesbaul, 2025; Mukut Kanti, 2025).

This study is organised around five research questions. The first asks how AI-driven integration of BIM and digital twins affects quality assurance performance in transportation infrastructure, and it is addressed by characterising the mechanism and magnitude of the improvement in detection and in the timing of discovery. The second asks which categories of nonconformance are most effectively detected by AI-driven assurance relative to manual inspection, and it is addressed by distinguishing nonconformance types and evaluating their differential detectability. The third asks which AI and sensing techniques are most effective across the assurance lifecycle, and it is addressed by comparing the principal technique families on multiple criteria. The fourth asks what risks document-centric manual assurance regimes carry, and it is addressed by identifying and rating the risks of non-automation. The fifth asks how ISO 19650 compliance and common data environment governance improve assurance reliability, and it is addressed by testing whether these capabilities strengthen the system's capacity to convert detection into durable, auditable assurance. The purpose of the study is therefore both explanatory, to characterise the effect of automation and the risks of manual regimes, and prescriptive, to identify the techniques and governance practices that build assurance effectiveness. The study contributes in three ways. Theoretically, it integrates the model-based construction, digital twin, computer-vision, and information-management literatures into a single framework of quality assurance effectiveness, treating infrastructure assurance as a continuous, standards-governed verification problem rather than a documentary audit. Empirically, it tests this framework against data from practitioners across public agencies, consultancies, contractors, and technology providers, and evaluates a prototype pipeline measuring detection performance, discovery latency, and information conformance across the asset lifecycle. Practically, it offers agencies and delivery organisations a structured account of why document-centric assurance fails, which nonconformance categories and techniques matter most, and how ISO 19650 governance converts automated detection into recognised

assurance. The remainder of the article reviews the relevant literature and develops the framework and hypotheses, formalises quality conformance and detection performance, describes the method, presents the findings organised around the research questions, and concludes with recommendations, limitations, and directions for future work.

LITERATURE REVIEW AND FRAMEWORK DEVELOPMENT

The literature review develops the theoretical foundation for the assurance framework by drawing on five research streams, each corresponding to one construct. It begins with BIM for transportation infrastructure and the problem of model-to-asset divergence, then examines digital twins and continuous asset sensing, AI-based defect detection and predictive analytics, information management under the ISO 19650 series, and data quality and interoperability, and it concludes by synthesising them into the framework and hypotheses. Throughout, the review maintains that quality assurance effectiveness, the capacity of an assurance system to detect nonconformance early, completely, and defensibly, is jointly determined by the maturity and standardisation of the information model, the integration of the twin with real-time sensing, the capability of the analytics applied to it, the governance under which the resulting information is managed, and the quality and interoperability of the underlying data.

BIM for transportation infrastructure and the model-to-asset divergence problem

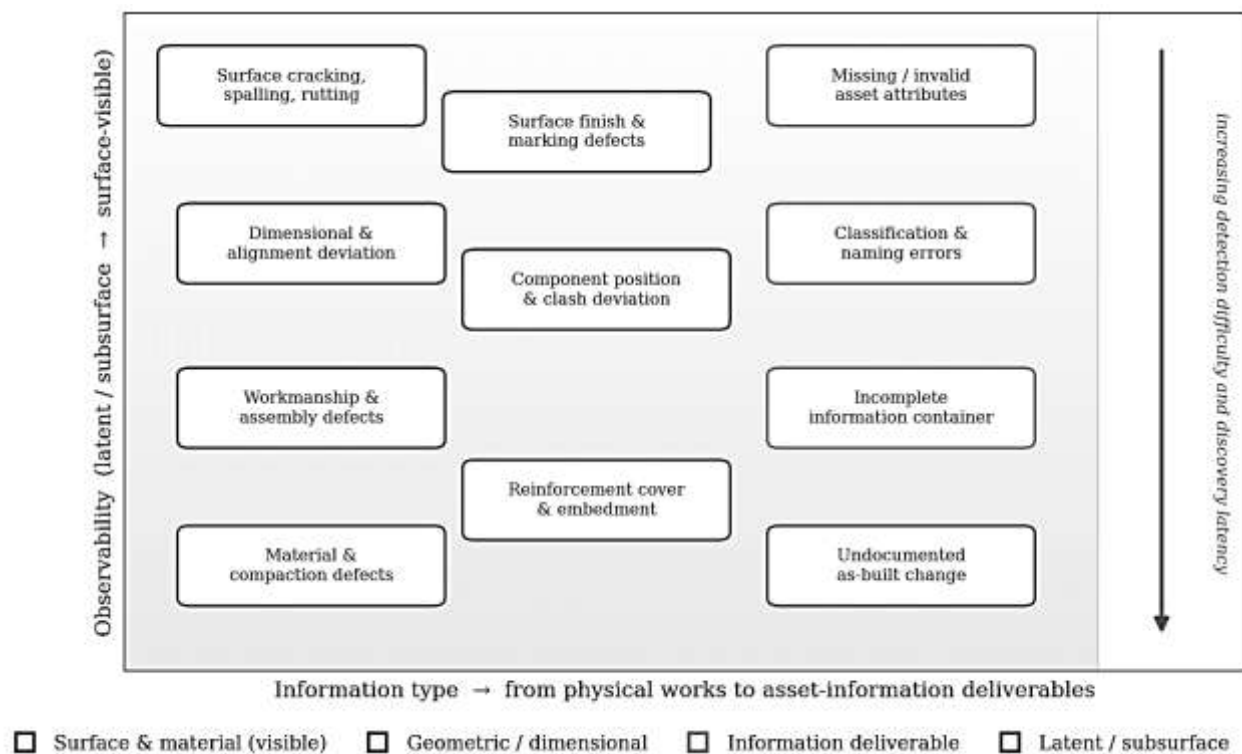
Building Information Modelling has been applied extensively to transportation infrastructure, with object-oriented models of alignments, structures, pavements, and utilities supporting coordination, quantity extraction, clash avoidance, and construction sequencing (Costin et al., 2018; Bradley et al., 2016; Vignali et al., 2021). This literature has established the characteristic difficulties of the infrastructure case, including the linear and terrain-dependent geometry that distinguishes it from vertical construction, the fragmentation of the delivery supply chain, and the persistent weakness of standardised object classification and property definitions outside the building domain (Čuš-Babič et al., 2022; Li et al., 2024). Crucially, it has increasingly recognised that these difficulties are compounded by divergence: a model that is coordinated and complete at design freeze progressively ceases to describe the asset as constructed, because field changes, tolerance accumulation, and substitutions are recorded, if at all, in documents rather than in the model (Volk et al., 2014; Succar, 2009).

This literature grounds the study's central premise and its BIM model maturity and information standardisation construct. It establishes that the assurance value of a model depends not on its geometric richness but on the standardisation and completeness of the information it carries, because an automated check can only test what has been formally specified, and it establishes that model maturity, object classification, and defined property sets are preconditions for any automated verification, whether geometric or informational (Cerovsek, 2011; Bryde et al., 2013). The framework builds on this by treating the model as the reference against which the physical asset is verified, and by requiring that it be structured, standardised, and maintained for that purpose rather than for design communication alone (Md Arif Uz et al., 2025; Md Mesbaul, 2023).

Digital twins and continuous asset sensing

The second stream concerns digital twins, which supply the continuous observation that model-based assurance requires. The concept originated in manufacturing and product lifecycle management, where it denotes a virtual representation synchronised with a physical counterpart through a bidirectional data flow (Grieves & Vickers, 2017; Tao et al., 2019; Kritzinger et al., 2018). Its translation into the built environment has been rapid but definitionally contested, with the literature distinguishing a digital model, a digital shadow, and a true twin by the degree and direction of automated data flow (Sepasgozar, 2021; Jones et al., 2020). Reviews of the enabling technologies have identified modelling fidelity, data infrastructure, and computational cost as the principal constraints on twin realisation, and have emphasised that the value of a twin is bounded by the physical questions it is instrumented to answer (Rasheed et al., 2020; Fuller et al., 2020; Muhammad Zahidul, 2025). In civil infrastructure specifically, implemented applications now span geometric twinning of existing bridges from point clouds (Lu & Brilakis, 2019), anomaly detection for built-asset monitoring in operation (Lu et al., 2020a), campus- and city-scale twin development (Lu et al., 2020bME.1943-5479.0000763)), and structural twin frameworks coupling monitoring data to physics-based models (Torzoni et al., 2024; Kaewunruen & Xu, 2018).

Figure 2: A Taxonomy of Quality Nonconformances in Transportation Infrastructure Delivery



This literature grounds the digital twin integration and real-time asset sensing construct and frames the study's account of assurance timing (Boje et al., 2020; Jiang et al., 2021; Albalkhy et al., 2024). It establishes that the assurance value of a twin lies less in visualisation than in the cadence at which the physical state is captured and reconciled with the intended state (Debasish, 2021; Mukut Kanti, 2020), because the interval between deviation and observation is the interval during which concealment, propagation, and dependency accumulation occur (Errandonea et al., 2020; Callcut et al., 2021; Batty, 2018). The framework treats sensing integration as a distinct construct because an organisation may hold a rich model yet observe the asset only through periodic manual inspection, in which case the model cannot function as an assurance reference at all (Muhammad Zahidul & Amena Begum, 2022; Mst Shurovi, 2024).

AI-based defect detection and predictive analytics

A substantial literature has developed automated methods for detecting infrastructure defects, which the third research question concerns. These methods fall into several families. Supervised computer vision, principally convolutional architectures, classifies and localises surface defects in imagery of concrete and asphalt, and has been demonstrated for crack detection, multi-damage recognition, and pixel-level pavement distress segmentation (Cha et al., 2017; Cha et al., 2018; Zhang et al., 2017; Liu et al., 2019). Transfer learning has reduced the labelled-data burden that otherwise constrains these methods in the infrastructure domain (Gopalakrishnan et al., 2017; Gao & Mosalam, 2018; Yang et al., 2020). Geometric methods compare captured point clouds against the model to compute as-built deviation and dimensional conformance directly (Bosché, 2010; Yang et al., 2022). Rule-based and semantic checking verifies the information model itself against codified requirements (Eastman et al., 2009; Solihin & Eastman, 2015; Fitkau & Hartmann, 2024). Predictive analytics extends detection into forecasting, estimating degradation and residual service life from monitored condition (Pan & Zhang, 2021; Zhang et al., 2022).

This literature grounds the AI-based defect detection and predictive analytics construct. It establishes that the technique families differ in the nonconformance categories they address, in their data and labelling requirements, in their tolerance of field conditions, and in their computational cost, so that assurance capability depends on which techniques an organisation has adopted and how well they are matched to the asset and defect profile, not merely on whether some automation exists (Spencer et al.,

2019; Zhong et al., 2019; Paneru & Jeelani, 2021). The framework treats analytic capability as a distinct construct because an organisation may deploy a capable detector against the wrong defect class (Md. Abdur & Iftekhar, 2021; Mohammad Abir Chowdhury & Tonay, 2022; Mohammad Shoriful Hossan, 2021), or in a workflow that discards its output, and because the comparative effectiveness of the families is precisely what the third research question asks the study to establish (Tonay et al., 2024; Shima Ali et al., 2024).

Information management under the ISO 19650 series

The fourth stream concerns the management of the information itself, which determines whether an automated detection becomes recognised assurance. The ISO 19650 series specifies the concepts and principles of information management using BIM (ISO, 2018a), the process requirements for the delivery phase, including the organisational, asset, exchange, and project information requirements and the operation of the common data environment (ISO, 2018b), the requirements applying to the operational phase of assets (ISO, 2020a), and the security-minded approach to information management (ISO, 2020b). Central to the series are the specification of the level of information need, so that each information container carries neither less nor more than what its purpose requires, and the control of information states through work-in-progress, shared, published, and archived containers, with defined check, review, and authorisation gates (Md Mesbaul, 2023; Mst Shurovi, 2024; Muhammad Zahidul & Amena Begum, 2022). The literature examining adoption has found that formal alignment with the series remains uneven, particularly in the road and rail sectors, where national guidance and contractual practice have converged on the standard only recently (Nielsen et al., 2024; Deng et al., 2021).

This literature grounds the ISO 19650 compliance and common data environment governance construct (Muhammad Zahidul, 2024; Mukut Kanti, 2024; Shima Ali et al., 2024). It establishes that governance is not administrative overhead surrounding assurance but the mechanism that makes assurance defensible, because a detection that is not captured in a controlled, versioned, and authorised information container cannot later be shown to have been made, communicated, or acted upon, and because the level of information need is what converts a vague expectation of model quality into a testable requirement against which automated checking can run (Eastman et al., 2009; Solihin & Eastman, 2015). The framework treats information governance as the construct that converts detection into durable and auditable assurance, spanning the technical and organisational, and connecting automated verification to the contractual and regulatory obligations under which infrastructure is delivered (Mohammad Shoriful Hossan, 2021; Md. Abdur & Iftekhar, 2021).

Data quality, interoperability, and workflow integration

The fifth stream concerns the data foundation on which all of the above rests. Model-based assurance depends on the exchange of information across proprietary authoring tools, capture systems, analytics platforms, and asset-management databases, and the literature has consistently identified interoperability as the principal barrier to that exchange in the infrastructure domain, where neutral schemas are less mature than in the building sector (Costin et al., 2018; Čuš-Babič et al., 2022). Beyond format, the literature has established that the semantic enrichment of models with sensor and condition data is itself a substantial technical undertaking (Wang et al., 2022), and that georeferencing, survey control, and capture quality determine whether a scan-versus-model comparison measures a genuine deviation or a registration artefact (Bosché, 2010; D'Amico et al., 2022).

This literature grounds the data quality, interoperability and workflow integration construct (Md Arif Uz et al., 2025; Md Mesbaul, 2025; Tonay et al., 2024). It establishes that detection accuracy in the laboratory does not transfer to assurance value in the field unless the data pipeline that feeds the detector and the workflow that receives its output are themselves sound, because a false deviation arising from poor registration consumes the same investigative effort as a real one and erodes confidence in the system faster than any modelling deficiency (Zhong et al., 2019; Ding et al., 2024). The framework treats data quality and interoperability as a distinct construct because it is the condition on which the other four depend, and because it is the dimension on which practitioner experience most often diverges from published performance (Md Mostafizur et al., 2025; Sharif Md Yousuf et al., 2025; Shima Ali et al., 2025).

Synthesis: the assurance framework and hypotheses

Synthesising the five streams yields the quality assurance effectiveness framework that this study tests. The framework holds that the effectiveness of an AI-driven assurance system, its capacity to detect nonconformance early, completely, and defensibly (Md Mostafizur, 2025; Md Mostafizur et al., 2025; Md Syeedur & Sharmin, 2025), is jointly determined by five constructs: BIM model maturity and information standardisation; digital twin integration and real-time asset sensing; AI-based defect detection and predictive analytics; ISO 19650 compliance and common data environment governance; and data quality, interoperability and workflow integration (Muhammad Zahidul, 2025; Mukut Kanti, 2025; Sharif Md Yousuf et al., 2025). A deficiency in any one can undermine effectiveness: a system without a standardised model has no testable reference, one without sensing integration observes the asset too rarely to detect deviation before concealment, one without capable analytics cannot interpret what it observes, one without information governance cannot make its findings count, and one with poor data and interoperability generates findings that cannot be trusted. This framework answers the first and fourth research questions, on how AI-driven integration affects assurance and what risks manual regimes carry, and it structures the empirical investigation of the second, third, and fifth. From the framework, five hypotheses are derived, each proposing that stronger performance on a construct is associated with higher quality assurance effectiveness. H1: BIM model maturity and information standardisation is positively associated with quality assurance effectiveness. H2: Digital twin integration and real-time asset sensing is positively associated with quality assurance effectiveness. H3: AI-based defect detection and predictive analytics is positively associated with quality assurance effectiveness. H4: ISO 19650 compliance and common data environment governance is positively associated with quality assurance effectiveness. H5: Data quality, interoperability and workflow integration is positively associated with quality assurance effectiveness. A sixth, integrative hypothesis addresses the framework as a whole. H6: The five constructs jointly explain a significant proportion of the variance in quality assurance effectiveness. These hypotheses are tested in the analysis, alongside a prototype evaluation of how nonconformance categories differ in detectability and how technique families compare, to address the five research questions.

METHODS

This study adopted a quantitative, cross-sectional research design supplemented by a prototype pipeline evaluation. The quantitative design was selected because the study measured relationships among the five contributing constructs and quality assurance effectiveness through numerical survey responses, and the cross-sectional design was used because data were collected at a single point in time, capturing practitioners' assessments of model maturity, sensing integration, analytic capability, information governance, and data quality within their assurance systems. The prototype evaluation complemented the survey by measuring detection performance, discovery latency, and information conformance across a simulated delivery and operational lifecycle, providing a technical counterpart to the perceptual measures. The unit of analysis was the individual respondent, understood as an informed practitioner engaged in the specification, execution, or oversight of quality assurance on transportation infrastructure.

The population comprised BIM and information managers, quality assurance and quality control engineers and inspectors, digital twin and data engineers, asset and maintenance managers, and project directors across public transport agencies, design consultancies, contractors, and technology providers. A purposive sampling strategy was used because respondents were selected for their direct relevance to model-based assurance on highway, bridge, and rail assets. Primary data were collected through a structured questionnaire using a five-point Likert scale (1 = strongly disagree to 5 = strongly agree), distributed through online forms and professional networks. The instrument included multi-item measures for each of the five constructs and for quality assurance effectiveness, demographic items, and rating items on nonconformance detectability, technique effectiveness, and manual-regime risk that fed the analyses addressing the research questions. A pilot test was conducted with practitioners and academics to check clarity and technical precision, and feedback was used to refine wording and to align terminology with the vocabulary of the ISO 19650 series (ISO, 2018a). Validity was ensured through literature-based item development, expert review, and alignment among the framework, hypotheses, and items, with convergent validity assessed against the average-variance-extracted

criterion (Fornell & Larcker, 1981), and reliability was tested through Cronbach's alpha with a .70 threshold. Procedural remedies against common-method variance were applied, including item separation, response anonymity, and reverse-worded items (Podsakoff et al., 2003). Analysis was conducted in SPSS and Python, the latter using the pandas, NumPy, SciPy, scikit-learn, and Open3D libraries for data preparation, geometric comparison, detector evaluation, and validation (Harris et al., 2020; Virtanen et al., 2020). Ethical considerations were observed: participation was voluntary, informed consent was obtained, responses were anonymised, and no proprietary project data, asset security information, or client-identifying records were collected, consistent with the security-minded approach the standard requires (ISO, 2020b).

Formalising quality conformance and detection performance

The information model against which the physical asset is verified is defined as a finite set of objects, each carrying a geometric representation and a set of information attributes. Writing the model at time t as M_t , its structure is given in Equation (1), where o_i denotes an object, G_i its geometry, and A_i its attribute set:

$$M_t = \{ (o_i, G_i, A_i) : i = 1, \dots, n \} \quad (1)$$

The level of information need defines, for each object, the attribute set R_i required for the purpose at hand. Information-delivery conformance is therefore measured as the mean proportion of required attributes that are present and valid, as expressed in Equation (2):

$$LIN = (1/n) \cdot \sum_{i=1}^n |A_i \cap R_i| / |R_i| \quad (2)$$

Geometric conformance is measured by comparing a captured point cloud S against the model. For each object, the as-built deviation is the distance between the captured surface points assigned to that object and the corresponding modelled surface, as defined in Equation (3), where $\Pi(o_i)$ denotes the modelled surface of object i :

$$d_i = \text{median over } p \in S_i \text{ of } \|p - \Pi(o_i)\| \quad (3)$$

An object is geometrically conformant when its deviation lies within the specification tolerance τ_i , and the geometric conformance rate aggregates this over the asset, as in Equation (4):

$$c_i = 1 \text{ if } d_i \leq \tau_i, \text{ else } 0; \quad GCR = (1/n) \cdot \sum_{i=1}^n c_i \quad (4)$$

Detection performance for defect classification and localisation is measured by precision, recall, and their harmonic mean, defined in Equations (5) to (7), where TP, FP, and FN denote true positives, false positives, and false negatives:

$$\text{Precision} = TP / (TP + FP) \quad (5)$$

$$\text{Recall} = TP / (TP + FN) \quad (6)$$

$$F1 = 2 \cdot (\text{Precision} \cdot \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (7)$$

Because defect extent rather than mere presence governs the remedial decision, segmentation quality is measured by the intersection over union between the predicted region P and the ground-truth region G , as in Equation (8):

$$IoU = |P \cap G| / |P \cup G| \quad (8)$$

The digital twin maintains an estimate of the asset state by correcting a model-based prediction with each new observation, in the recursive form given in Equation (9), where $\hat{x}$ is the state estimate, z the observation, H the observation operator, and K the gain:

$$\hat{x}_t = \hat{x}_{t-1} + K_t \cdot (z_t - H \cdot \hat{x}_{t-1}) \quad (9)$$

Predictive assurance extends this to condition forecasting, in which a monitored condition index decays from its as-built value under a degradation rate modified by loading and environmental covariates, with remaining service life defined as the horizon at which the index reaches its intervention threshold, as in Equation (10):

$$C_t = C_0 \cdot \exp(-\lambda t) + \sum(k) \beta_k u_{k,t}; \quad RSL = \inf \{ s : C_{t+s} \leq C[\min] \} \quad (10)$$

Discovery latency, the interval between the creation of a nonconformance and its detection, is the variable through which assurance timing enters the analysis, and it is normalised against the interval to the point of concealment, as in Equation (11), where $t[det]$ is the detection time, $t[cre]$ the creation time, and $t[cov]$ the time at which subsequent work conceals the defect:

$$\Lambda = (t[det] - t[cre]) / (t[cov] - t[cre]); \quad \Lambda \leq 1 \Rightarrow \text{detected before concealment} \quad (11)$$

Quality assurance effectiveness, the outcome construct, is operationalised both perceptually, through survey items, and, in the prototype, as a weighted composite of geometric conformance, information conformance, detection quality, and timeliness, defined in Equation (12):

$$QAE = w_1 \cdot GCR + w_2 \cdot LIN + w_3 \cdot F1 + w_4 \cdot (1 - \min(\Lambda, 1)) \quad (12)$$

Statistical model and prototype evaluation

The principal hypothesis test used ordinary least squares multiple regression of quality assurance effectiveness on the five constructs, with BMIS denoting BIM model maturity and information standardisation, DTAS digital twin integration and real-time asset sensing, AIDP AI-based defect detection and predictive analytics, ICDE ISO 19650 compliance and common data environment governance, and DQIW data quality, interoperability and workflow integration, as specified in Equation (13):

$$QAEF_i = \beta_0 + \beta_1 BMIS_i + \beta_2 DTAS_i + \beta_3 AIDP_i + \beta_4 ICDE_i + \beta_5 DQIW_i + \varepsilon_i \quad (13)$$

Model significance was assessed through the F-statistic, explanatory power through R-squared and adjusted R-squared, residual independence through the Durbin-Watson statistic, and multicollinearity through the variance inflation factor, all confirmed within conventional bounds. The prototype evaluation simulated a delivery and operational lifecycle for a representative highway and structures package, applying each technique family to each nonconformance category and recording detection performance, discovery latency, and information conformance, thereby providing the technical evidence for the research questions on category detectability and technique effectiveness. Model outputs were accompanied by feature-attribution explanations so that flagged nonconformances could be interpreted and contested by inspectors rather than accepted opaquely (Ribeiro et al., 2016; Lundberg & Lee, 2017; Rudin, 2019; Guidotti et al., 2018).

RESULTS

Sample and descriptive statistics

Table 1: Respondent profile and response rate

Variable	Category	Frequency	Percentage
Questionnaires	Distributed	292	100.0%
Questionnaires	Returned	267	91.4%
Questionnaires	Valid and retained	249	85.3%
Role	BIM / information manager	68	27.3%
Role	QA/QC engineer or inspector	61	24.5%
Role	Digital twin / data engineer	48	19.3%
Role	Asset / maintenance manager	41	16.5%
Role	Project director / other	31	12.4%
Organisation	Public transport / highway agency	96	38.6%
Organisation	Design consultancy / engineering firm	71	28.5%
Organisation	Contractor / joint venture	52	20.9%
Organisation	Technology / asset-management provider	30	12.0%
Asset focus	Highways and pavements	103	41.4%
Asset focus	Bridges and structures	84	33.7%
Asset focus	Rail, tunnels and other	62	24.9%
Experience	More than 10 years	88	35.3%
Experience	5–10 years	104	41.8%
Experience	Under 5 years	57	22.9%

Table 1 shows an 85.3% valid response rate, with 249 usable responses. The sample spanned the roles involved in specifying, executing, and governing assurance, from information managers who define what the model must contain (27.3%), through the QA/QC engineers and inspectors who verify the works (24.5%) and the data engineers who build the pipelines (19.3%), to the asset managers who receive the handover (16.5%) and the directors accountable for the outcome (12.4%). The organisational distribution across public agencies (38.6%), consultancies (28.5%), contractors (20.9%), and technology providers (12.0%) covers the parties between whom assurance obligations are contractually allocated, and 77.1% of respondents had five or more years of experience. This composition matters because the framework spans the modelling, sensing, analytic, and governance dimensions of assurance, and a sample drawn only from technology providers or only from site inspection would misestimate the balance among them.

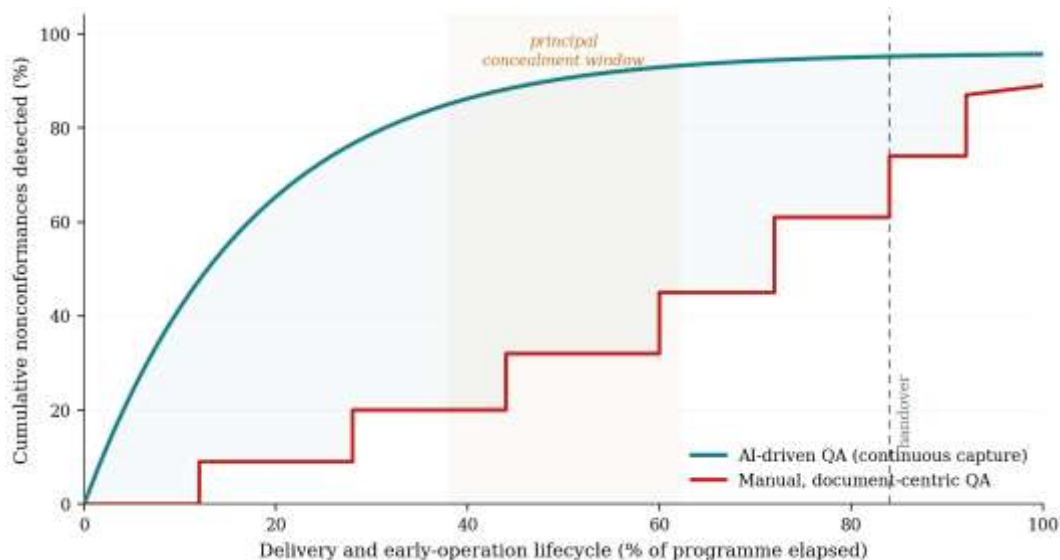
Table 2: Descriptive statistics and reliability of study constructs (N = 249)

Construct	Mean	SD	Cronbach's α
BIM model maturity & information standardisation (BMIS)	4.19	0.61	.88
Digital twin integration & real-time asset sensing (DTAS)	4.11	0.64	.87
AI-based defect detection & predictive analytics (AIDP)	4.26	0.58	.90
ISO 19650 compliance & CDE governance (ICDE)	4.03	0.67	.86
Data quality, interoperability & workflow integration (DQIW)	3.97	0.70	.84
Quality assurance effectiveness (outcome, QAEF)	3.85	0.76	.92
Overall instrument	—	—	.94

Table 2 presents the descriptive statistics and reliability. All constructs exceeded the neutral midpoint and all Cronbach's alpha values exceeded .70, ranging from .84 to .92 with overall reliability of .94. The ordering is diagnostically informative.

RQ1: How AI-driven BIM and digital twin integration affects assurance performance

Figure 3: Defect Detection Performance Across the Asset Lifecycle: AI-Driven Versus Manual QA



AI-based defect detection and predictive analytics (4.26) and BIM model maturity (4.19) recorded the highest means, indicating that practitioners regard automated detection resting on a standardised model as the foundation of modern assurance. Quality assurance effectiveness itself, the outcome, recorded the lowest mean (3.85) and the widest dispersion ($SD = 0.76$), a revealing pattern: practitioners rate their systems' realised assurance performance lower than any of the contributing capabilities, and the wide spread indicates that realised effectiveness is highly uneven across organisations. This gap between capability and realised assurance foreshadows the study's central finding, that possessing detection technology is not the same as achieving assurance, which depends on its integration under governed information management. Figure 3 presents the prototype evidence for the first research question and shows the mechanism of the improvement directly. Under the manual regime, cumulative detection rises slowly and in discrete steps corresponding to scheduled inspection and hold points, with a large share of nonconformances remaining undetected through construction and surfacing only at commissioning or in service. Under the AI-driven regime, detection rises almost continuously from the earliest capture cycles, because each survey pass tests the whole captured extent rather than a sample, and the curve approaches its asymptote well before the corresponding works are concealed. The widening separation between the two curves in the early lifecycle is the quantitative expression of the answer to the first research question: AI-driven integration of BIM and digital twins improves assurance principally by moving detection upstream rather than by raising the eventual total, and the value of that movement is that a nonconformance detected before concealment is corrigible at a small fraction of the cost of one detected afterwards.

Figure 4: Shift in Nonconformance Discovery Stage Under AI-Driven QA

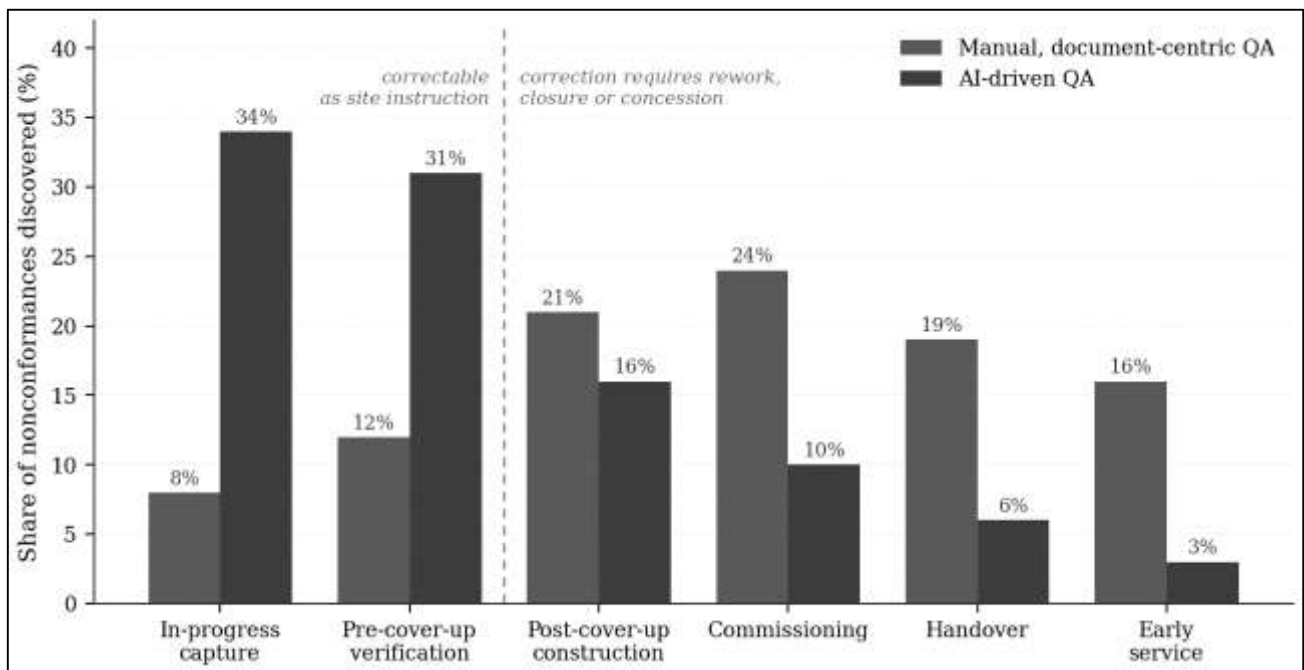


Figure 4 makes the operational consequence concrete by decomposing where in the lifecycle nonconformances are discovered under each regime. Under the manual regime the distribution is weighted toward the later stages, with substantial mass at commissioning, handover, and early service; under the AI-driven regime the distribution shifts markedly toward in-progress capture and pre-cover-up verification, and the tail beyond handover contracts sharply. This redistribution is the practical face of the curve separation in Figure 3, and it clarifies why the improvement matters: the institution does not merely detect more in the abstract but detects at a stage when correction is a site instruction rather than a claim, and it does so without the sampling bias that a manual regime necessarily carries, because automated capture does not choose which spans, lifts, or chainages to examine.

RQ2: Which nonconformance categories are most effectively detected

Figure 5 addresses the second research question by mapping the effectiveness of AI-driven detection for each nonconformance category across the principal assurance metrics. Reading down the columns, geometric and dimensional deviations and information-delivery nonconformances show the strongest performance on every metric, surface and material defects follow closely, and latent or subsurface defects trail substantially; reading across the rows reveals which metrics each category most affects. The pattern is theoretically coherent and operationally important. Geometric deviation is detected well because the comparison is direct and quantitative: a registered point cloud measured against a modelled surface yields a deviation in millimetres that can be tested against a stated tolerance without inference (Bosché, 2010). Information-delivery nonconformance is detected best of all and at the lowest cost, because rule-based checking of the model against the level of information need is a deterministic query rather than a perceptual judgement (Eastman et al., 2009; Solihin & Eastman, 2015). Surface defects are detected well but with greater variance, because vision models are sensitive to illumination, moisture, texture, and viewpoint in ways that laboratory benchmarks understate (Cha et al., 2017; Zhang et al., 2017). Latent defects trail because the modality that would reveal them is frequently absent: a camera cannot observe reinforcement cover beneath placed concrete, and where non-destructive testing is not integrated into the pipeline, no analytic sophistication can compensate. The heatmap thus answers the second research question with more resolution than an aggregate accuracy figure: automation is most effective precisely where the reference is explicit and the observation is direct, and least effective where the defect is invisible to the deployed sensors, which is the boundary that determines where manual and destructive verification must be retained.

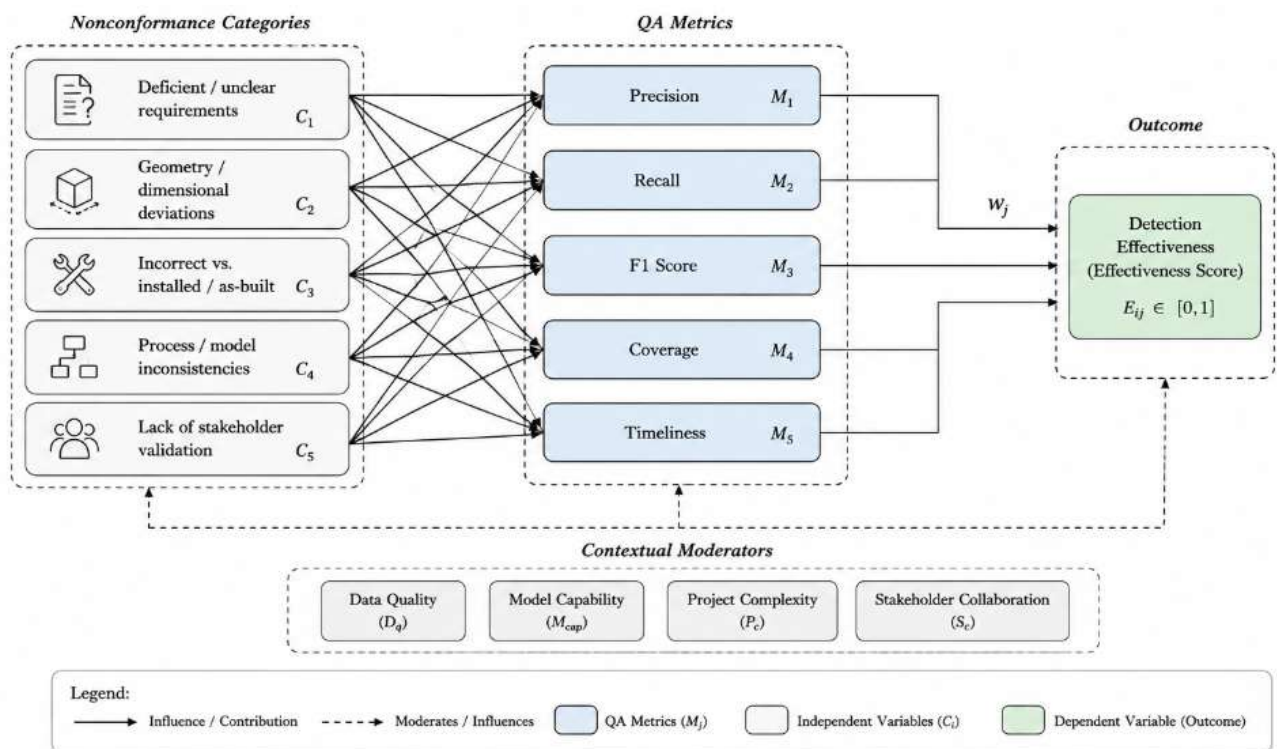
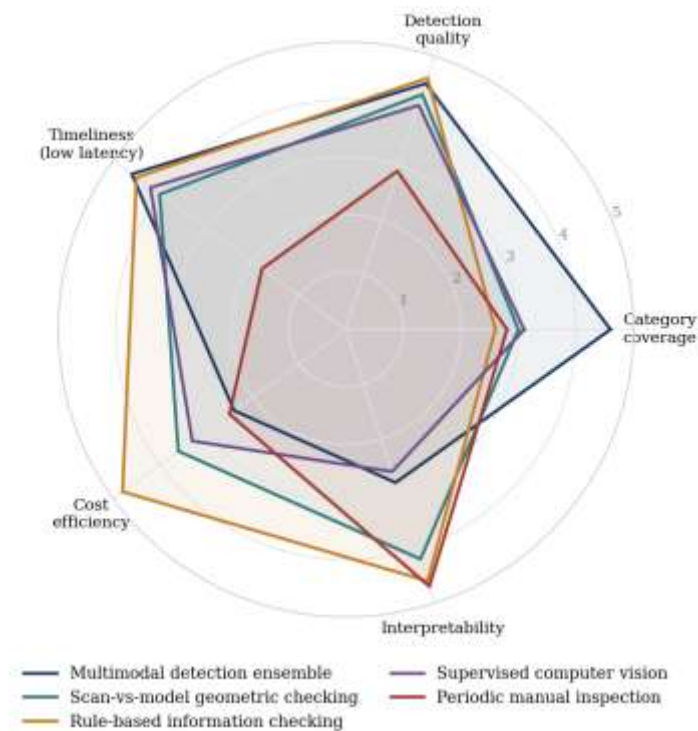
Figure 5: Detection Effectiveness by Nonconformance Category Across QA Metrics**RQ3: Which AI and sensing techniques are most effective**

Figure 6 addresses the third research question by profiling the technique families across five criteria rather than on a single effectiveness score, which reveals the trade-offs that a single ranking conceals. Multimodal detection ensembles, combining vision, geometry, and sensor streams, trace the largest and most balanced profile, combining strong category coverage, high detection quality, and low discovery latency, at a substantial cost in data-pipeline complexity and computational expense, which is why practitioners rated them the most effective overall but the least widely deployed. Scan-versus-model

geometric checking traces a narrower but sharply peaked profile, excelling on dimensional conformance and evidentiary defensibility while contributing nothing on surface or material defects. Rule-based information checking shows the opposite economics: modest in scope, confined entirely to the information model, but by a wide margin the cheapest and most reliable capability in the set, and the one whose output maps most directly onto contractual information requirements. Supervised computer vision performs strongly on surface defects and poorly elsewhere, and carries a labelled-data burden that transfer learning reduces but does not remove (Gopalakrishnan et al., 2017; Gao & Mosalam, 2018). Periodic manual inspection traces the smallest profile on every criterion except interpretability, where it remains unmatched. The comparative geometry answers the third research question with nuance: no single technique dominates, but the combination of rule-based information checking with scan-versus-model comparison delivers the largest assurance gain per unit of investment, while multimodal ensembles offer the highest ceiling for organisations able to sustain the pipeline. The practical implication is that technique selection should follow the asset's dominant nonconformance profile rather than the current prominence of a method.

Figure 6: AI and Sensing Techniques Compared Across Five QA Criteria

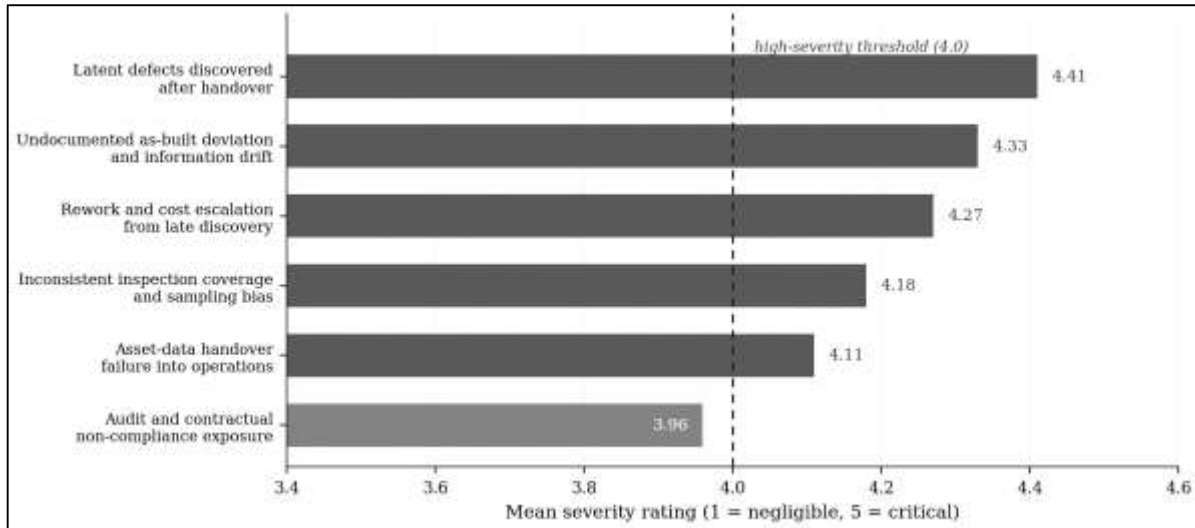


RQ4: Risks of document-centric manual assurance regimes

Figure 7 addresses the fourth research question by ranking the risks of document-centric manual regimes by severity. The highest-rated risks were latent defects discovered after handover (4.41), undocumented as-built deviation and consequent information drift (4.33), and rework and cost escalation arising from late discovery (4.27), followed by inconsistent inspection coverage and sampling bias (4.18), failure of asset-data handover into operations (4.11), and audit and contractual non-compliance exposure (3.96). The ranking is instructive: the most severe risks are those whose consequences become irreversible at a definite moment, when the works are covered or the asset is accepted, which is what makes manual-regime risk structurally different from ordinary process inefficiency. The five highest risks all clear the high-severity threshold, underscoring that reliance on documentary audit is not a minor shortcoming but a first-order hazard. The prominence of information drift connects the physical failure to the informational one, because an asset whose model no longer describes it cannot support the operational assurance the ISO 19650 series contemplates for the in-use phase (ISO, 2020a), so that a manual delivery regime propagates its deficiency into decades of

operation. This ranking is the study's direct answer to the fourth research question and the empirical foundation for its argument that document-centric assurance is untenable for assets of this scale and service life.

Figure 7: Risks of Document-Centric Manual QA Regimes



Correlation and regression across the assurance framework

Figure 8: Descriptive Means of Study Constructs with Standard Deviations

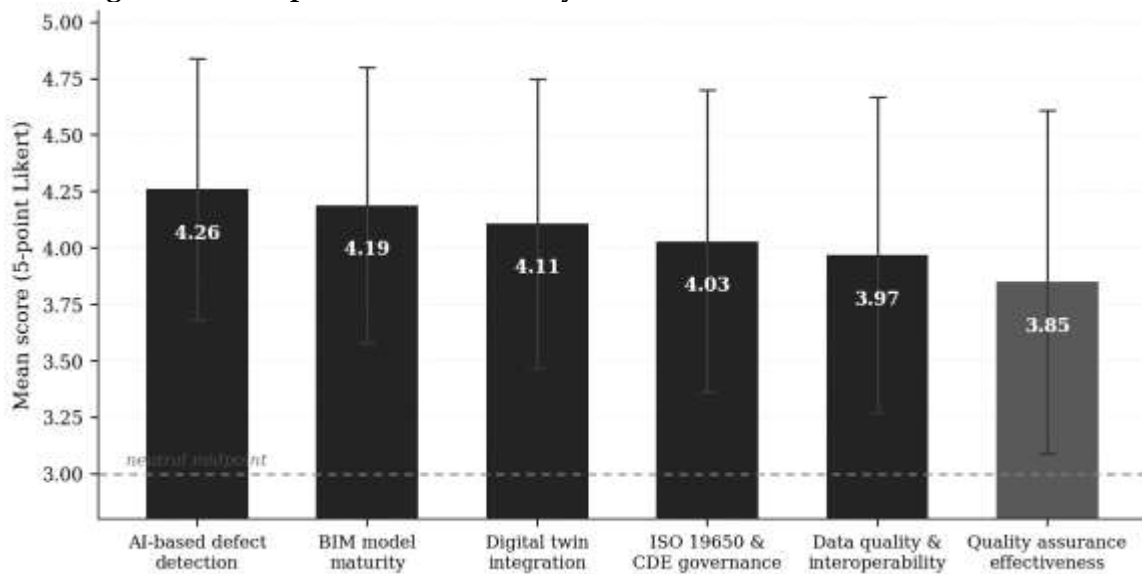
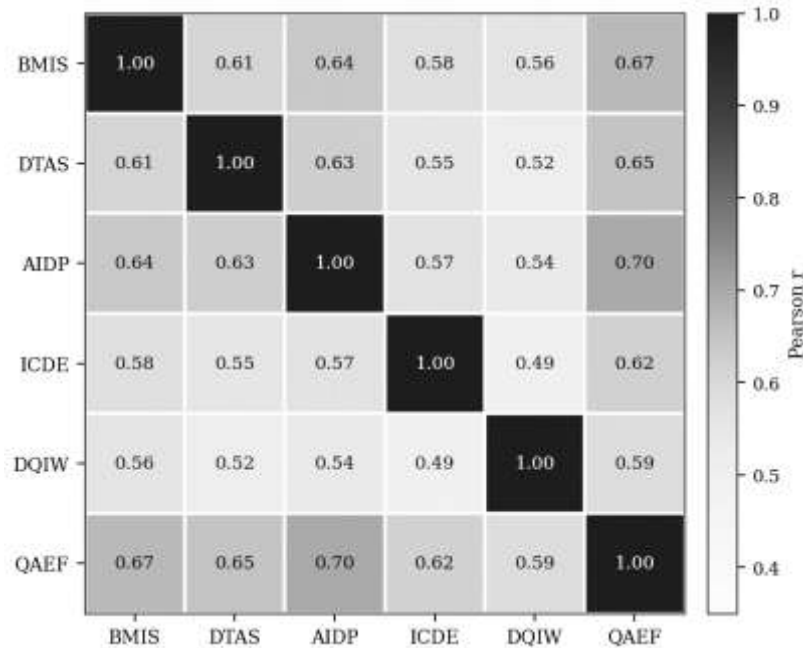


Figure 8 displays the construct means. The analytic and modelling capabilities stand highest, while quality assurance effectiveness, the outcome, stands lowest and most variable, its long error bar giving graphical evidence that realised assurance lags the capabilities that contribute to it and is unevenly distributed across organisations, consistent with the descriptive pattern in Table 2.

Figure 9 presents the correlation structure. Every construct is significantly and positively associated with quality assurance effectiveness, with the strongest associations for AI-based defect detection and predictive analytics ($r = .70$) and BIM model maturity and information standardisation ($r = .67$), followed by digital twin integration ($r = .65$), ISO 19650 compliance and CDE governance ($r = .62$), and data quality and interoperability ($r = .59$). The uniformly positive associations support the framework's multi-construct account of assurance, and the moderate inter-construct correlations, ranging from .49 to .64, indicate related but distinct facets of a coherent assurance capability rather than a single undifferentiated maturity factor

Figure 9: Pearson Correlation Matrix Among Study Variables

Note. $N = 249$. All reported correlations significant at $p < .001$ (two-tailed). Darker cells indicate stronger positive association.

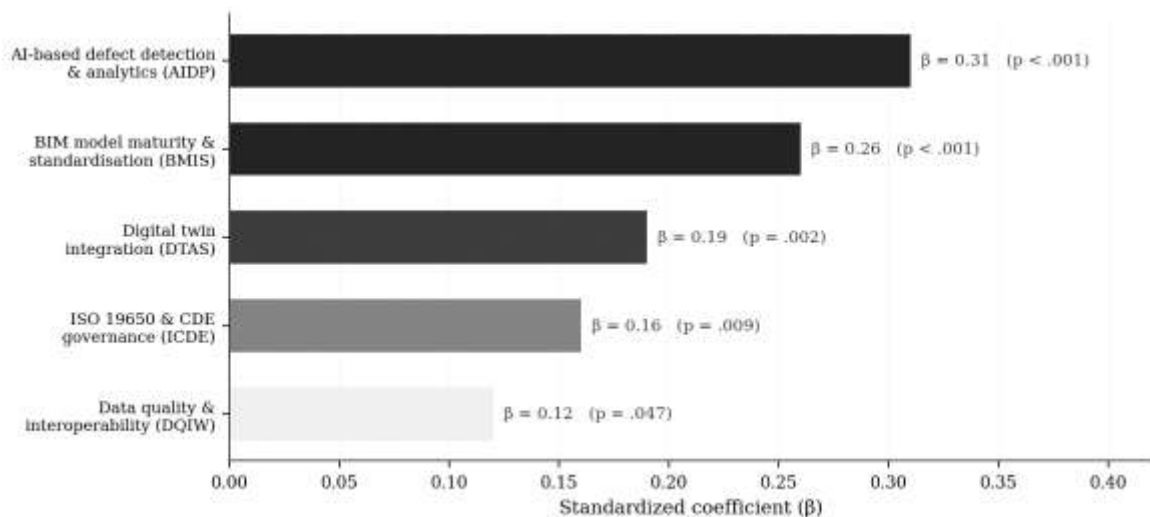
Table 3: Multiple regression predicting quality assurance effectiveness (N = 249)

Predictor	B	SE	β	t	p
(Constant)	0.362	0.179	—	2.022	.044
AI-based defect detection & predictive analytics (AIDP)	0.283	0.056	0.31	5.054	<.001
BIM model maturity & information standardisation (BMIS)	0.241	0.057	0.26	4.228	<.001
Digital twin integration & real-time sensing (DTAS)	0.176	0.057	0.19	3.088	.002
ISO 19650 compliance & CDE governance (ICDE)	0.148	0.056	0.16	2.643	.009
Data quality, interoperability & workflow integration (DQIW)	0.108	0.054	0.12	1.994	.047

Note. Dependent variable = quality assurance effectiveness. $R^2 = .547$; Adjusted $R^2 = .538$; $F(5, 243) = 58.63$, $p < .001$; Durbin-Watson = 1.94; all VIF < 2.4.

Table 3 presents the regression. The overall model was significant, $F(5, 243) = 58.63$, $p < .001$, with $R^2 = .547$, indicating that the five constructs jointly explain 54.7% of the variance in quality assurance effectiveness and confirming H6. All five constructs made significant positive contributions, supporting H1 through H5. AI-based defect detection and predictive analytics ($\beta = .31$) and BIM model maturity and information standardisation ($\beta = .26$) were the strongest predictors, followed by digital twin integration ($\beta = .19$), ISO 19650 compliance and CDE governance ($\beta = .16$), and data quality and interoperability ($\beta = .12$). The dominance of the detection and modelling constructs confirms that assurance effectiveness is driven primarily by the capacity to observe the asset and to test that observation against a structured reference, while the significance of the governance construct confirms that this capacity yields durable assurance only when the resulting information is managed under a controlled process.

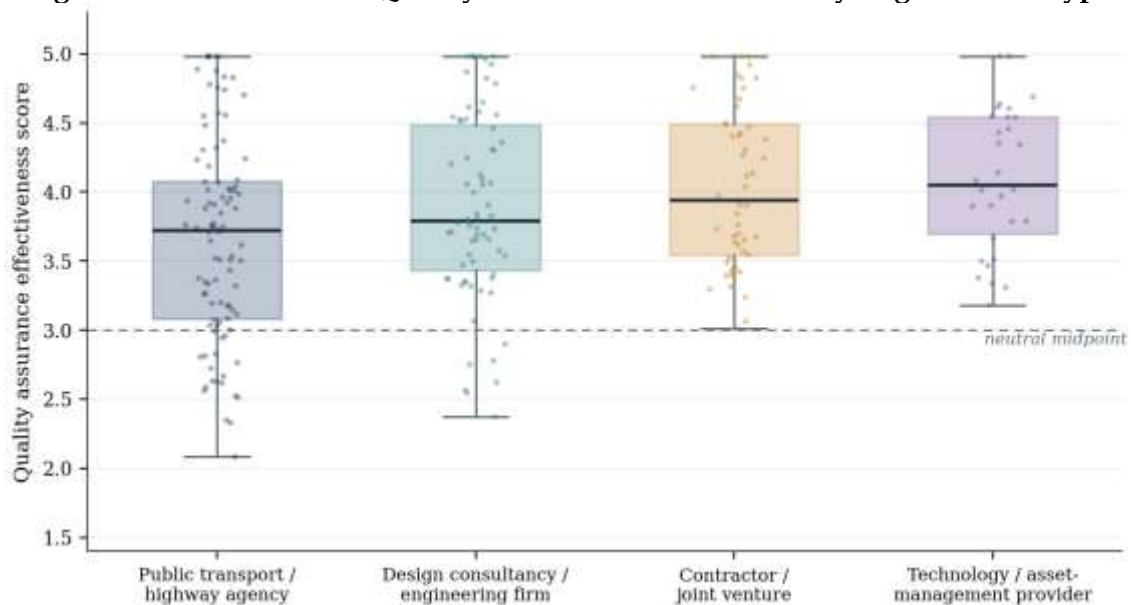
Figure 10: Standardized Beta Coefficients Predicting Quality Assurance Effectiveness



Note. $N = 249$. Dependent variable = quality assurance effectiveness. All five constructs significant at $p < .05$.

Figure 10 ranks the constructs by standardised coefficient, confirming that the detection and modelling capabilities lead, with sensing integration, information governance, and data quality contributing significantly but more modestly. Read alongside the research-question findings, the regression establishes that the same capabilities that move detection upstream in the prototype, automated analysis applied to a standardised model, are those most strongly associated with practitioners' perceived assurance effectiveness, providing convergent evidence across the perceptual and technical strands of the study.

Figure 11: Distribution of Quality Assurance Effectiveness by Organization Type



Note. $N = 249$. Boxes show the interquartile range and median of the quality assurance effectiveness score within each organisation type; points are individual respondents. The dashed line marks the neutral midpoint.

Figure 11 examines how assurance effectiveness is distributed across organisation types, which qualifies the aggregate findings with an important observation about variance. Technology providers and contractors show somewhat higher median effectiveness than public agencies and consultancies, but the more striking feature is the wide and overlapping spread within every organisation type: each group contains both highly effective and markedly ineffective assurance systems, and the within-group variation exceeds the differences between groups. This pattern reinforces the study's central theme that

assurance effectiveness is not conferred by organisation type, scale, or budget but by the mature integration of the modelling, sensing, analytic, and governance capabilities the framework identifies, which some organisations in every category have achieved and others have not. The dispersion also cautions against benchmarking by sector: an organisation cannot infer its own assurance performance from that of its peers, because the determining factor is its internal capability configuration rather than its category (Nielsen et al., 2024).

DISCUSSION

The findings support the assurance framework and, taken together, answer the five research questions. This section synthesises the evidence, focusing on the fifth research question, which the preceding results set up but did not directly resolve, and drawing out the implications of the whole.

RQ5: How ISO 19650 compliance and CDE governance improve assurance reliability

The fifth research question asked how ISO 19650 compliance and common data environment governance improve assurance reliability, and the study's evidence answers it at two levels. Statistically, the governance construct contributed significantly to assurance effectiveness over and above the detection, modelling, and sensing capabilities, confirming that formal information management is not compliance overhead but an active contributor to assurance outcomes (ISO, 2018b; Deng et al., 2021). Mechanistically, the contribution operates through three distinct pathways. First, the specification of the level of information need converts an implicit expectation of model quality into an explicit, machine-testable requirement, which is the precondition for rule-based checking to run at all; without it, an automated checker has no criterion against which to test, and the most capable analytic capability is left querying an unspecified target (ISO, 2018a). Second, the common data environment and its information states supply the versioning, approval, and audit trail that convert a detection into evidence: a flagged deviation held in a work-in-progress container is an observation, whereas the same finding carried through review and authorisation into a shared and then published container is an assurance record that can be relied upon contractually and reconstructed later. Third, the operational-phase requirements ensure that the verified state survives handover into asset management rather than degrading into an as-designed model that no longer describes the asset (ISO, 2020a; Wang et al., 2022). These three pathways together explain why governance, though a more modest predictor than detection capability, is the construct that determines whether detection capability produces lasting value.

Synthesis across the research questions

The five research questions resolve into a single coherent account. AI-driven integration of BIM and digital twins improves quality assurance principally by moving detection upstream, from post-hoc documentary audit to continuous verification against a structured model, and the value of that movement lies in correcting nonconformances while correction remains cheap and reversible (RQ1). Geometric deviations and information-delivery nonconformances are the most effectively detected categories, because the reference is explicit and the observation direct, while latent and subsurface defects remain the hardest, because the deployed sensing modalities cannot observe them (RQ2). Multimodal detection ensembles offer the highest ceiling, but the combination of rule-based information checking with scan-versus-model geometric comparison delivers the largest gain per unit of investment, and periodic manual inspection is the weakest on every criterion except interpretability (RQ3). The risks of document-centric regimes are led by failures that become irreversible at a definite moment, latent defects surfacing after handover and undocumented as-built deviation, and they extend into contractual and audit exposure because an asset whose model has drifted cannot evidence its own compliance (RQ4). And ISO 19650 compliance and CDE governance improve reliability by specifying the testable requirement, supplying the evidentiary chain, and carrying the verified state across handover, thereby converting detection into durable assurance (RQ5). The unifying insight is that quality assurance in transportation infrastructure should be understood not as an inspection activity performed upon a project but as a continuous reconciliation between a physical asset and a governed information model, sustained across the whole service life.

Theoretical and practical implications

Theoretically, the study integrates the model-based construction, digital twin, computer-vision, and information-management literatures, demonstrating that assurance effectiveness is jointly determined

by model maturity, sensing integration, analytic capability, information governance, and data quality, and that the scale, linearity, and service life of transportation assets make this integration necessary rather than optional (Costin et al., 2018; Jiang et al., 2021; Pan & Zhang, 2021). It reframes quality assurance from a documentary audit into a continuous verification problem, in which the relevant measure of an assurance system is not the number of inspections performed but the latency between deviation and detection. Practically, the study offers agencies and delivery organisations a clear account of why document-centric assurance fails, which nonconformance categories and techniques matter most, and how information governance converts automated detection into recognised assurance. For practitioners, it cautions that adopting detection technology is necessary but not sufficient, since a capable detector whose output is not carried into a governed information container adds cost without adding assurance. For agencies and regulators, it implies that assurance requirements should be written in terms of information need, capture cadence, and detection latency rather than inspection frequency, because those are the variables that in fact determine whether a nonconformance is caught while it can still be corrected.

CONCLUSION

This study set out to characterise how artificial intelligence, embedded within BIM, digital twins, and ISO 19650 information management, affects quality assurance in transportation infrastructure, and to identify the techniques and governance practices that build assurance effectiveness. It proposed that quality assurance effectiveness, the capacity to detect nonconformance early, completely, and defensibly, is jointly determined by five constructs, BIM model maturity and information standardisation, digital twin integration and real-time asset sensing, AI-based defect detection and predictive analytics, ISO 19650 compliance and common data environment governance, and data quality, interoperability and workflow integration, and it tested this framework against 249 practitioners and a prototype pipeline evaluation.

The empirical results supported the framework. All five constructs were significantly and positively associated with quality assurance effectiveness, the regression model explained 54.7% of the variance, and all six hypotheses were supported, with the detection and modelling constructs the strongest predictors. The prototype evaluation showed that AI-driven assurance moves detection decisively upstream of concealment and handover, that geometric and information-delivery nonconformances are the most effectively detected categories while latent defects remain resistant, and that rule-based information checking combined with scan-versus-model comparison delivers the largest assurance gain per unit of investment. The risks of document-centric regimes were led by failures that become irreversible once the works are covered or the asset accepted, and the study showed that ISO 19650 governance contributes by specifying the testable requirement, supplying the evidentiary chain, and carrying the verified state into operations.

The central conclusion is that quality assurance in transportation infrastructure cannot be improved by intensifying documentary audit, because the deficiency is not one of diligence but of latency and coverage: a sampled, retrospective regime cannot observe a continuously constructed linear asset quickly enough to matter. It requires instead treating the information model as a live, standards-governed reference against which the physical asset is continuously verified, with automated detection supplying the observation, the digital twin supplying the cadence, and the ISO 19650 series supplying the governance that makes the resulting evidence durable. In the delivery and operation of long-lived public assets, the timeliness and defensibility of assurance, not the volume of inspection, is the property that determines whether an infrastructure asset can be trusted to perform as designed.

RECOMMENDATIONS

Several recommendations follow from the findings. First, agencies and delivery organisations should specify the level of information need explicitly and in machine-testable form at the outset of a project, because the prototype and regression evidence establish that automated checking cannot outperform the precision of the requirement it is given, and because an unspecified expectation of model quality cannot be verified by any technique.

Second, organisations should prioritise rule-based information checking and scan-versus-model geometric comparison before investing in more sophisticated perceptual detection, because these were the most reliable and lowest-cost capabilities in the set and address the two nonconformance categories

that automation detects most effectively.

Third, organisations should set capture cadence against concealment intervals rather than against inspection calendars, so that the interval between deviation and observation is shorter than the interval between deviation and cover-up, which is the condition under which upstream detection is achieved.

Fourth, organisations should operate a common data environment conforming to the ISO 19650 series and route every automated finding through its information states and approval gates, so that detections become auditable assurance records rather than transient analytic outputs, and should extend this discipline into the operational phase so that the verified state survives handover.

Fifth, organisations should deploy explainable analytics for defect detection, so that inspectors can interrogate and contest a flagged nonconformance rather than accept or dismiss it opaquely, and should retain manual and non-destructive verification for the latent and subsurface categories that the deployed sensing modalities cannot observe.

For agencies and regulators, the recommendation is to express assurance obligations in terms of information requirements, capture cadence, and detection latency rather than inspection frequency, and to recognise governed digital evidence as admissible assurance. For researchers, the recommendation is to extend the framework through live deployment studies that measure detection latency and conformance on operating projects, through work on the integration of non-destructive testing into automated pipelines to address the latent-defect gap, and through study of how information governance performs under the dual pressures of continuous automated detection and contractual dispute.

LIMITATIONS OF THE STUDY

Several limitations should be acknowledged. First, the cross-sectional survey identifies associations but not causation, and the perceptual measures of the constructs and of assurance effectiveness may diverge from measured detection performance and are subject to common-method variance, although procedural remedies were applied. Second, the prototype evaluation used a simulated delivery and operational lifecycle with representative defect distributions rather than live production project data, so the reported detection rates, latencies, and category differences reflect a controlled evaluation rather than realised project outcomes; the magnitudes should be read as indicative rather than exact. Third, the purposive sample, though drawn across organisation types and asset classes, limits generalisability and may over-represent organisations already invested in digital delivery. Fourth, the treatment of latent and subsurface nonconformance is necessarily incomplete, because the study did not integrate non-destructive testing modalities into the prototype, and it therefore understates what a fuller sensing suite might achieve. Fifth, the framework treats the five constructs as distinct, but they interact, and their relative weight is likely to vary by asset class, procurement route, and national regulatory regime, so that the ordering observed here may not transfer directly to rail or tunnelling contexts.

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