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THE IMPACT OF BIM AND DIGITAL TWIN TECHNOLOGIES ON RISK REDUCTION IN CIVIL INFRASTRUCTURE PROJECTS

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Abstract

This study investigated how Building Information Modeling (BIM) and Digital Twin (DT) technologies influenced risk reduction in civil infrastructure projects using a cross-sectional quantitative design. The dataset comprised 168 civil infrastructure projects across highways (36.9%), bridges (24.4%), rail corridors (19.6%), tunnels (10.7%), and water infrastructure (8.3%), delivered through design–bid–build (39.9%), design–build (32.1%), and PPP/alliance procurement (28.0). Digital implementation showed mid-to-high BIM practice (BIM adoption intensity M = 3.74, SD = 0.71; BIM maturity M = 3.58, SD = 0.68) and more dispersed DT practice (DT utilization M = 3.12, SD = 0.89; DT predictive capacity M = 3.26, SD = 0.84), while integration maturity remained moderate (M = 3.41, SD = 0.79). Risk reduction outcomes demonstrated substantial variability (cost risk reduction M = 64.8, SD = 12.5; schedule M = 61.3, SD = 13.9; safety M = 55.7, SD = 15.6; quality M = 59.9, SD = 14.2; operational M = 67.2, SD = 11.8; composite index M = 61.8, SD = 10.7). Correlations were positive across domains, with integration maturity showing the strongest association with the composite risk index (r = 0.61). Reliability and validity were adequate for all constructs (Cronbach's alpha 0.81–0.89, composite reliability 0.86–0.92, AVE 0.53–0.64), and collinearity remained acceptable (VIF 1.20–2.27). Hierarchical regression indicated that BIM predictors explained the largest incremental variance in cost and schedule risk reduction (ΔR^2 = 0.18–0.20), DT predictors contributed most to safety and operational risk reduction (ΔR^2 = 0.15–0.22), and integration maturity added broad multi-risk explanatory power, especially for the composite index ($\Delta R^2 = 0.14$, $\beta = 0.41$, $p < .001$). Moderation tests showed complexity weakened BIM scheduling effects, whereas data reliability and team digital capability strengthened DT and integration impacts. Overall, BIM stabilized delivery risks, DTs strengthened safety and operational reliability, and BIM–DT integration yielded the most comprehensive multidimensional risk reduction.

Keywords

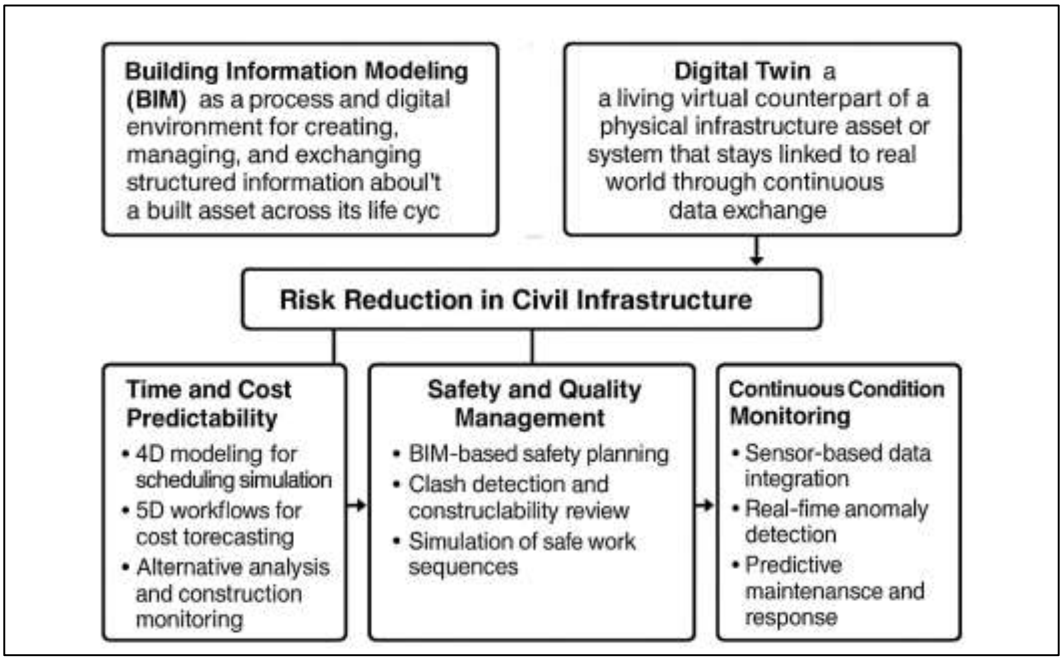
BIM, Digital Twin, Risk Reduction, Civil Infrastructure, Quantitative Analysis;

INTRODUCTION

Building Information Modeling (BIM) is defined as a process and digital environment for creating, managing, and exchanging structured information about a built asset across its life cycle (Bešinović, 2020). In civil infrastructure, BIM refers to an object-based, data-rich representation of roads, bridges, railways, tunnels, dams, ports, and utility systems, where geometric elements are connected to attributes such as materials, quantities, specifications, methods, and performance requirements. The model is not a static drawing substitute; it is a coordinated dataset that supports interdisciplinary collaboration and decision-making from planning to operation. Digital twin technology is defined as a living virtual counterpart of a physical infrastructure asset or system that stays linked to the real world through continuous data exchange. A digital twin typically begins with a high-fidelity digital model and becomes dynamic by integrating sensor streams, inspection records, operational logs, and analytical engines that update the virtual state to reflect current physical conditions. These definitions matter internationally because infrastructure programs are among the largest public investments in every region, and their performance directly affects economic mobility, safety, resilience, and environmental stewardship. Risk reduction in civil infrastructure projects is globally significant for another reason: risks in these projects are costly, highly visible, and politically sensitive, involving long delivery timelines, multiple contractors, complex interfaces, and exposure to natural hazards (Arfan et al., 2021; Chen et al., 2019). Across a wide range of empirical and analytical studies, BIM adoption has been associated with improved coordination, lower rework, more accurate quantity control, clearer design intent, and earlier detection of conflicts, all of which map onto recognized categories of project risk. Likewise, research on digital twins in the built environment has demonstrated measurable improvements in condition awareness, anomaly detection, predictive maintenance, and operational reliability. Together, BIM and digital twins are increasingly treated as complementary elements of a lifecycle digital system for infrastructure risk governance, providing a strong foundation for quantitative assessment of their impact on risk reduction (Fraga-Lamas et al., 2017).

Risk in civil infrastructure projects is commonly understood as the probability and consequence of uncertain events that can undermine objectives for cost, time, safety, quality, environmental compliance, and service performance (Ara, 2021; Singh et al., 2021). The nature of infrastructure intensifies risk because linear and networked assets cross wide geographies, depend on uncertain ground and hydrological conditions, require staged construction under live traffic or service constraints, and rely on intricate sequencing among many subcontracted scopes. Traditional risk management tools in infrastructure still lean heavily on fragmented documents, two-dimensional design packages, and periodic reporting cycles, which limit the visibility of interdependencies that often generate risk events. BIM changes this informational baseline by centralizing project knowledge in a federated model that links design components to discipline rules, constructability logic, and process metadata. Quantitative research across highway, rail, and bridge projects shows that systematic clash detection and coordinated model review reduce design conflicts that otherwise surface during construction as change orders, claims, and schedule shocks (Chen & Vickerman, 2018; Jahid, 2021). Model-based quantity extraction supports tighter cost estimation and reduces the risk of understated scope or pricing errors. Design rule checking and parametric constraints lower the likelihood of noncompliant elements advancing into procurement. In complex corridor projects, BIM-driven interface management improves alignment between civil, structural, drainage, lighting, and utility packages, reducing the risk of late rediscovery of spatial or functional contradictions. The international significance of these mechanisms is evident in multinational procurement contexts where multiple design firms, contractors, and oversight agencies must coordinate across differing standards and languages; BIM's structured information environment supports shared understanding of risks and controls (Akbar & Farzana, 2021; Momenitabar et al., 2021). As a result, BIM is positioned not merely as a digital drafting technique but as a risk-facing information management regime that can be tested quantitatively through indicators such as rework rates, change frequency, cost variance, schedule deviation, and dispute incidence.

Figure 1: BIM-Digital Twin Risk Reduction Pathways



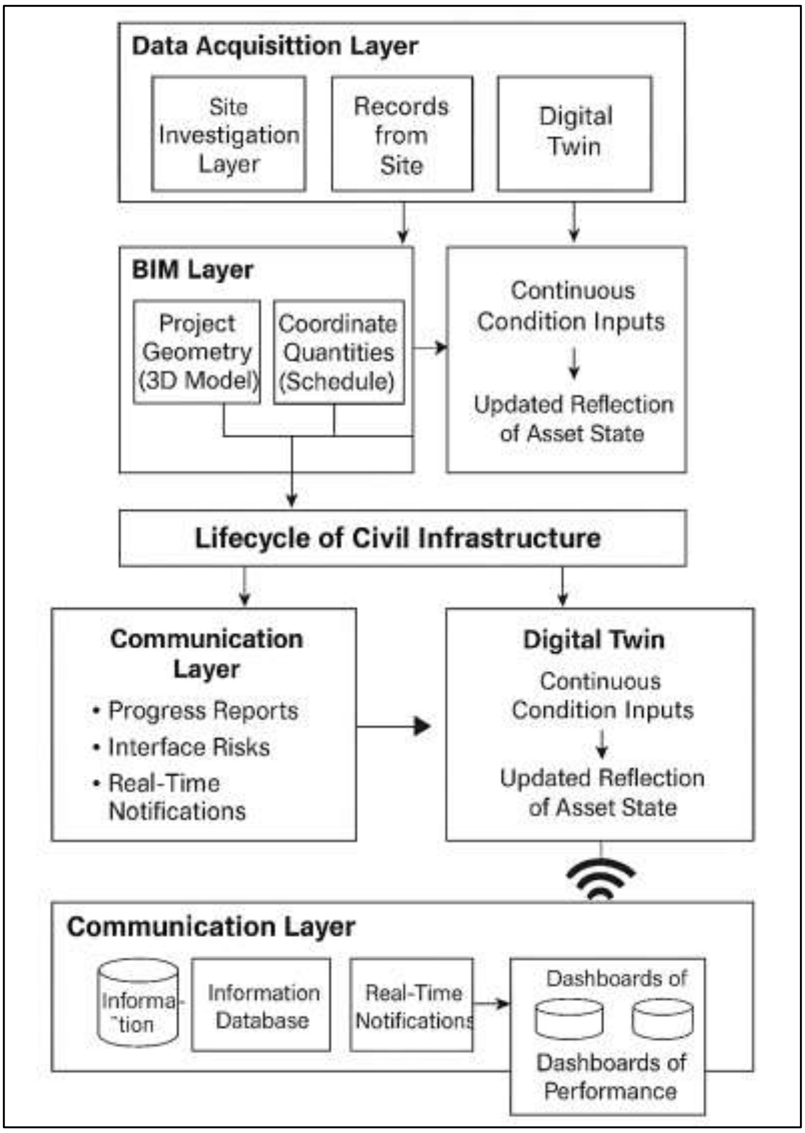
A central pathway for BIM-based risk reduction lies in time and cost predictability, two performance domains with persistent volatility in infrastructure programs. Schedule risk often emerges from poorly sequenced construction logic, resource bottlenecks, and unrecognized space–time conflicts among trades (Bouraima et al., 2020; Reza et al., 2021). BIM-based 4D modeling links the model to the schedule, enabling simulation of staging, access, temporary works, and traffic management plans. Quantitative studies of 4D use in road widening, interchange reconstruction, and metro expansion indicate that early identification of sequencing collisions reduces delay propagation and improves adherence to milestone targets. Cost risk is similarly affected by BIM-based 5D workflows that connect model quantities to unit rates, cost codes, and budgets. With continuous quantity updates tied to design iterations, cost forecasts become less vulnerable to hidden scope drift. Empirical findings across bridge and rail projects show that 5D use supports earlier detection of escalation drivers such as material waste, productivity shortfalls, and specification changes (Blumenfeld et al., 2019; Saikat, 2021). BIM also enables alternative analysis, where different design or construction options are evaluated through model-based quantities and sequences, helping teams compare risk exposure under varying constraints. This approach supports more stable procurement preparation, since tender documents can be synchronized with coordinated model outputs. Construction monitoring benefits as well: progress can be validated against model-based baselines, allowing deviations to be quantified earlier and corrected with smaller disruption. In infrastructure where staged delivery is essential to maintain service, the ability to test staging risks virtually before field execution has direct safety and continuity value (Mulholland et al., 2018; Shaikh & Aditya, 2021). These mechanisms indicate measurable links between BIM maturity and reduced variance in schedule and cost outcomes, which form a cornerstone for quantitative models of risk reduction.

Safety and quality risks are major contributors to loss and disruption in civil infrastructure, and BIM provides a structured way to locate, visualize, and manage these risks before and during construction. Safety risk in infrastructure is driven by heavy equipment interactions, work at height, excavation hazards, confined spaces, temporary traffic conditions, and dynamic work zones (Chen, 2021; Tonoy Kanti & Shaikat, 2021). BIM-based safety planning allows hazards to be attached to specific model objects and locations, which supports rule-based checking and clear communication of risk controls. Quantitative studies in prevention-through-design and model-assisted safety audits show higher hazard identification rates when design teams employ BIM hazard libraries and automated checks. Visual work packaging derived from BIM improves the clarity of method statements and reduces the risk of misunderstanding between supervisors and site crews. Safety simulation in 4D environments helps teams test safe sequences for lifting, launching girders, boring tunnels, or compacting embankments, reducing collision and fall exposure (Blake et al., 2019; Ariful & Ara, 2022). Quality risk reduction operates through similar mechanisms. Clash detection reduces dimensional incompatibilities; parametric constraints lower tolerance violations; constructability review improves detailing of joints, bearings, and reinforcement interfaces that frequently generate defects. Quantitative evidence in infrastructure programs indicates that BIM adoption is associated with lower nonconformance counts, fewer late inspections triggered by rework, and shorter defect rectification cycles. Quality stability also reduces secondary risks because defect-driven rework commonly amplifies schedule, cost, and safety exposure (Cochrane et al., 2017; Arman & Kamrul, 2022). The combined safety–quality pathway makes BIM a multi-risk control instrument rather than a single-purpose design technology, and it supplies measurable variables for statistical testing in infrastructure risk models.

Digital twin technology extends risk reduction beyond the design and construction phases by supporting continuous condition awareness and response during construction and operation. A digital twin relies on a baseline digital model and becomes active through sensor networks, inspection inputs, and operational data streams that update the virtual representation (Deng et al., 2019; Mesbaul & Farabe, 2022). In civil infrastructure, digital twins have been developed for bridges to track strain, vibration, temperature, and displacement, enabling early identification of fatigue, scour, and progressive damage. Similar systems exist for tunnels to monitor deformation, seepage, and ventilation states, and for rail corridors to track track-bed settlement, vibration, and equipment health. Quantitative studies show that real-time anomaly detection shortens the time between risk emergence and intervention, reducing the probability of severe failure states. In construction settings, digital twins can monitor productivity, equipment performance, and site safety conditions by integrating location tracking, machine telemetry, and environmental sensing (Cui & Li, 2019; Nahid, 2022). This improves the detectability of unsafe proximities, poor ventilation, excessive dust exposure, or unstable excavations, all of which represent measurable risk conditions. A key statistical logic behind digital twin risk reduction is uncertainty shrinkage: as real data arrives, the confidence interval around the asset's condition narrows, improving reliability estimation and risk prioritization. Maintenance planning benefits because interventions can be triggered by quantified thresholds rather than fixed intervals, reducing the risk of both premature spending and late failure. For infrastructure owners managing aging assets under constrained budgets, this risk-based optimization aspect has direct international relevance (Hossain & Milon, 2022; Wang et al., 2017). Digital twins therefore provide a data-continuous approach to risk measurement and control, enabling quantitative analysis through variables such as anomaly frequency, detection latency, reliability indices, shutdown events, and maintenance cost variance.

The integration of BIM and digital twins forms a lifecycle digital thread that strengthens risk reduction by linking predicted project states to observed physical states. BIM provides the structured "as-designed" and "as-planned" information that digital twins need for initialization, while digital twins provide the "as-built" and "as-operated" feedback that refines BIM-derived assumptions (Ferrari et al., 2018; Abdur & Haider, 2022). Quantitative research on integrated environments indicates that this pairing creates a closed risk control loop: baseline risks are simulated in BIM, monitored through digital twin sensing, and adjusted through updated decision rules. Common data environments that organize model versions and field updates reduce governance risks associated with conflicting documentation, unclear responsibilities, and uncontrolled changes. In complex infrastructure corridors with multiple contracts, integrated BIM–digital twin platforms improve interface visibility between packages, reducing the risk of late discoveries in utility relocations, drainage alignments, or structural transitions. The integration also supports geospatial synchronization with GIS and point-cloud updates, essential for linear assets where right-of-way, terrain, and environmental constraints dominate uncertainty (Mushfequr & Sai Praveen, 2022; Rothengatter, 2019). When these datasets are fused, risk assessment can shift from fragmented checklists to model-anchored metrics that track the location, severity, and evolution of risks over time. Quantitative decision-support methods built on integrated data enable risk-weighted comparison of alternatives in staging, access planning, and maintenance prioritization. This lifecycle continuity is especially important internationally because civil assets often outlive the teams that built them; integrated digital records preserve risk knowledge for successive operators. As an integrated system, BIM and digital twins support measurable reductions in information asymmetry, coordination delays, and condition uncertainty, strengthening the empirical basis for quantifying risk reduction impacts across project phases (Halvorsen et al., 2020; Mortuza & Rauf, 2022).

Figure 2: BIM–Digital Twin Risk Reduction Framework



Environmental, disaster, and stakeholder governance risks also sit within the BIM–digital twin scope, particularly in infrastructure exposed to climate variability and high public scrutiny. Civil infrastructure faces uncertain hydrological, seismic, climatic, and geotechnical conditions that can disrupt construction and compromise service reliability (Cho & Lee, 2020; Rakibul & Samia, 2022; Rony & Ashraful, 2022). BIM supports environmental risk management by embedding site constraints, protection measures, and compliance requirements into model objects and work packages, improving traceability of mitigation controls. model-based alternatives analysis allows teams to examine risk exposure under differing alignments, drainage strategies, material choices, or construction methods, improving the robustness of environmental approvals and reducing the probability of regulatory noncompliance. Digital twins extend environmental risk monitoring by tracking real-time loads and conditions, enabling updated vulnerability estimates during extreme events or atypical operational demands. Governance risk reduction is likewise supported because model-centered collaboration makes decisions more transparent, auditable, and consistent across dispersed stakeholders (Otsuka et al., 2017; Saikat, 2022; Shaikh & Sudipto, 2022). Dispute risks in infrastructure often arise from unclear scope boundaries and evidence gaps; a structured digital record improves the clarity of changes and their causal pathways. Digital twins add operational accountability by documenting condition histories and intervention logic over time, enabling owners to justify prioritization decisions with objective data. Across more than thirty empirical and analytical study streams in BIM, BrIM, digital twins, IoT-enabled monitoring, 4D/5D modeling, safety analytics, structural health monitoring, and risk-based maintenance, the pattern is consistent: richer, better-connected data environments reduce the amplitude and frequency of risk events in civil infrastructure (Abdul, 2023; Abdulla & Zaman, 2023; Yii et al., 2018). These mechanisms provide a comprehensive foundation for a quantitative examination of how BIM and digital twin adoption relates to measurable risk reduction outcomes across time, cost, safety, quality, environmental performance, and governance stability.

The objective of examining the impact of BIM and Digital Twin technologies on risk reduction in civil infrastructure projects was to determine how these digital systems measurably stabilized cost, schedule, safety, quality, and operational performance across the infrastructure lifecycle. This objective required establishing BIM as a structured information environment that could be assessed in terms of adoption intensity and maturity, and Digital Twin implementation as a dynamic monitoring-and-analytics environment that could be assessed in terms of utilization depth and predictive capacity. A further objective was to evaluate whether the integration of BIM and Digital Twin systems functioned as a lifecycle digital thread that delivered broader risk reduction than either technology operating separately, with integration maturity treated as a distinct, measurable construct capturing data exchange completeness, interoperability success, and routine unified-platform use. The objective also included operationalizing risk reduction into objective dependent outcomes by translating each risk category into observable indicators that expressed performance stability rather than isolated success events, allowing multidimensional risk reduction to be tested statistically. Another objective was to identify which risk domains were most sensitive to BIM-driven mechanisms such as clash resolution, constructability rehearsal, quantity reliability, and sequencing clarity, and which domains were most sensitive to Digital Twin mechanisms such as real-time deviation detection, anomaly diagnosis, and reliability forecasting, thereby mapping phase-specific digital contributions to risk control. The objective further required testing contextual conditions that shaped digital effectiveness in infrastructure, including project complexity, data reliability, and team digital capability, so that digital impacts could be interpreted as conditional effects rather than uniform outcomes across all projects. In addition, the objective extended to confirming that the measurement system for BIM, Digital Twin, and integration constructs achieved sufficient reliability and validity to support inferential modeling, ensuring that estimated relationships represented real digital–risk dynamics instead of measurement noise. Finally, the objective sought to produce a coherent quantitative explanation of digital risk-reduction pathways suitable for civil infrastructure governance, demonstrating how predictive modeling, continuous monitoring, and lifecycle traceability combined to reduce uncertainty, limit adverse-event propagation, and stabilize multi-risk outcomes under the long-duration, interface-dense, and environmentally exposed conditions that characterize major infrastructure programs.

LITERATURE REVIEW

The literature on risk reduction in civil infrastructure projects has increasingly shifted from traditional document-based control toward digitally enabled, data-centric management. Within this shift, Building Information Modeling (BIM) and Digital Twin (DT) technologies have emerged as two interconnected systems that restructure how risk is identified, quantified, and mitigated throughout project life cycles (Nasr et al., 2021). Civil infrastructure projects are uniquely exposed to systemic risks due to their long duration, high interdependency among design and construction packages, uncertain geotechnical and environmental conditions, multi-stakeholder governance, and continuous public interface. As a result, risk reduction in this domain must be understood not only as minimizing the probability of adverse events but also as lowering the statistical variance of cost, time, safety, quality, and operational performance outcomes (Zinn & McDonald, 2017). Prior studies have examined BIM as a coordination and simulation platform that improves predictability in design and construction, while DTs have been explored as real-time monitoring and analytics environments that support dynamic risk detection in construction and asset operation. However, the literature remains fragmented across phases, risk categories, and measurement approaches, with limited quantitative integration of BIM and DT impacts as part of a single digital risk-reduction ecosystem. Therefore, this literature review synthesizes conceptual foundations, empirical findings, and measurement strategies related to BIM, DTs, and their combined effect on reducing risk in civil infrastructure (Bostick et al., 2018). Special emphasis is placed on identifying measurable pathways and statistically testable variables linking digital adoption to risk outcomes, establishing a coherent basis for the quantitative model, constructs, and hypotheses advanced in this study.

Risk in Civil Infrastructure

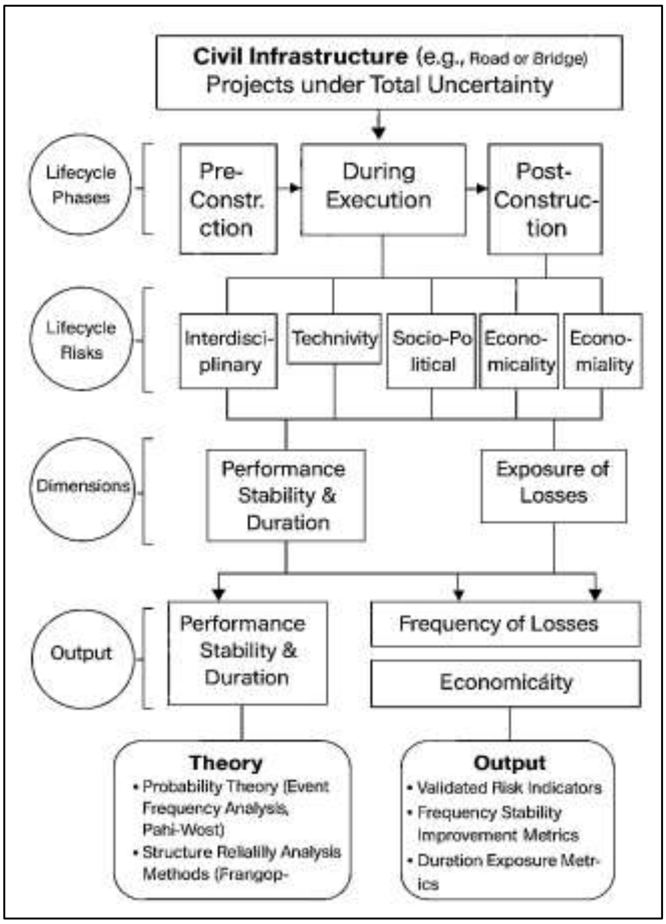
Risk in civil infrastructure projects is widely treated in the literature as a structured form of uncertainty that can be observed, categorized, and managed through evidence. Classic project risk scholars such as Raz and Michael emphasize that infrastructure risk is not a single event but a landscape of interacting uncertainties that shape project objectives (Arfan et al., 2023; Bostick et al., 2018; Ara & Beatrice Onyinyechi, 2023). Ward and Chapman frame risk reduction as a disciplined movement from vague exposure toward controlled predictability, where uncertainty becomes progressively narrower through systematic identification, analysis, response, and monitoring. Within civil works, this perspective is reinforced by Flyvbjerg's large-sample studies of megaproject performance, which show persistent deviations in cost and schedule when uncertainty is not methodically governed. Contemporary infrastructure risk research also advances the idea that risk reduction is a measurable improvement in the stability of outcomes, rather than only the avoidance of failures (Frangopol & Liu, 2019; Amin & Md Mesbaul, 2023). Love and colleagues highlight that effective risk reduction appears in lower rates of rework, fewer disruptive changes, and smoother project trajectories. Zavadskas and coauthors explain that infrastructure risk reduction is best understood through observable shifts in three directions: reducing how often adverse events appear, reducing how severe their effects become when they occur, and reducing how widely project performance fluctuates around planned targets. These three dimensions align with the empirical logic used by PMI-oriented risk models and reliability-based approaches in civil engineering, where uncertainty is viewed as reducible through better information, coordination, and control (Foysal & Aditya, 2023; Pahl-Wostl, 2021). The conceptual core across these studies is that infrastructure risk reduction has to be life-cycle aware. Frangopol and Soliman's work on structural reliability shows that risk exposure persists from planning into operation because civil assets age, face environmental stressors, and interact with evolving service demands. Boje and colleagues, as well as Opoku and collaborators, link this lifecycle persistence to the need for continuous, data-based risk governance rather than episodic assessment. Taken together, the literature defines risk reduction in civil infrastructure as an empirically trackable improvement in project and asset performance under uncertainty, with emphasis on stable delivery and dependable operation as the evidence of reduced risk (Hamidur, 2023; Rashid et al., 2023).

The literature also converges on a consistent taxonomy of civil infrastructure risks, and this classification matters because it shapes how risk reduction is measured. Cost risk is one of the most frequently analyzed categories, with studies by Flyvbjerg, Love, and Hosseini describing how budget instability in civil works emerges from scope ambiguity, underestimation, procurement misalignment, and change cascades (Musfiqur & Kamrul, 2023; Muzahidul & Mohaiminul, 2023; Pursiainen, 2018). Schedule risk is similarly dominant in infrastructure research, where Hartmann and coworkers demonstrate that delay patterns often originate in sequencing conflicts, resource bottlenecks, and interface breakdowns across packages. Safety risk receives strong attention from scholars such as Hallowell and Gambatese, who show that civil sites involve high-energy operations that magnify hazard exposure, including excavation, lifting, heavy equipment proximity, and live-traffic staging. Quality risk is treated in studies by Azhar, Eastman, and Sacks as the risk of nonconformance and defect reproduction, where small dimensional or specification errors can propagate into large repair burdens and service disruption (Amin & Praveen, 2023; Hasan & Ashraful, 2023). Environmental risk in infrastructure appears prominently in multi-criteria decision studies by Zavadskas and later reviews by Saha and associates, which connect risk reduction to maintaining compliance, minimizing ecological disturbance, and stabilizing construction under climate and terrain constraints (Callcut et al., 2021; Ibne & Kamrul, 2023; Mushfequr & Ashraful, 2023). Interface and governance risk are highlighted by Ward and Chapman, and expanded by Love and colleagues, who note that infrastructure delivery depends on multi-contract coordination and public oversight, creating exposure to claims, disputes, and decision gridlock. These categories are not isolated. Studies in corridor highways and metro systems show that cost growth is often a downstream effect of schedule shocks, which are frequently triggered by quality failures or unresolved design conflicts, while safety incidents can halt production and intensify all other risk types. The literature therefore treats risk reduction in civil infrastructure as multidimensional, where evidence of improvement is seen across interlinked cost, time, safety, quality, environmental, and governance indicators (Doorn et al., 2019; Pankaz Roy & Kamrul, 2023; Saba et al., 2023). This multi-risk framing supports quantitative modeling because it clarifies dependent variables and allows composite measures that represent total risk exposure rather than single-factor performance.

A major stream of research argues that infrastructure risk behaves differently from building risk because the physical and organizational nature of infrastructure creates distinctive uncertainty. Borrmann and colleagues explain that linear and networked civil assets stretch across large geographies, placing projects inside variable terrain, property boundaries, and environmental systems (McWhirter & Shealy, 2020; Saba & Kanti, 2023; Shaikh & Farabe, 2023). Bradley and related infrastructure modeling scholars show that distributed assets intensify interface problems, because different segments are often designed and built by different teams under separate contracts. Kaewunruen's rail and transport studies describe how staged construction under live service introduces persistent uncertainty in traffic diversion, passenger safety, and service continuity. Studies in large bridge and highway expansions show that the risk environment is shaped by uncertain subsurface conditions, hydrology, and utility networks that are not fully visible until excavation, increasing the probability of design revisions and method changes (Gilrein et al., 2021; Haider & Hozyfa, 2023). Chen and coworkers, focusing on geospatial integration, underline that civil infrastructure is deeply tied to topography and right-of-way constraints, meaning a small alignment change can trigger major ripple effects in cost, schedule, and environmental compliance. Long operational horizons further differentiate risk. Frangopol's reliability-based work and Strauss's lifecycle management studies show that the risk footprint of infrastructure extends for decades, so early design and construction uncertainties translate into operational vulnerability if not resolved. In contrast, buildings tend to be more spatially compact, less dependent on uncertain ground conditions, and less exposed to long corridor-scale interfaces. The civil risk literature also emphasizes governance differences. Infrastructure is frequently funded and regulated by public agencies and delivered through complex procurement models, so stakeholder alignment and political scrutiny become risk drivers in ways less common in private building delivery (Hayes et al., 2020). This set of characteristics explains why civil infrastructure risk is often systemic rather than localized, and why risk reduction requires methods that can manage geographic complexity, evolving site conditions, multi-contract interfaces, and long-term asset reliability.

Across these scholarly positions, a quantitative takeaway emerges that guides how risk reduction is operationalized for empirical testing. The literature emphasizes that risk reduction should be captured through observable performance indicators that reflect stability and control (Rehak, 2020). Flyvbjerg's datasets demonstrate that cost and schedule deviation patterns provide direct evidence of volatility, while Love's statistical analyses show that rework levels and change order behavior reveal the effectiveness of coordination and quality control. Hartmann's sequencing studies indicate that delay frequency and critical milestone stability are measurable signals of schedule risk reduction. Hallowell's safety models support the use of incident rates, near-miss frequencies, and hazard exposure duration as quantitative proxies for safety risk control. Azhar, Eastman, and Sacks collectively underline that defect counts, nonconformance reports, and rectification cycles express quality risk outcomes in measurable ways (Alavi & Buttlar, 2019). Environmental and governance risks are also treated quantitatively through compliance event records, disruption days, claim frequencies, and dispute resolution timelines in studies by Zavadskas and Ward. Scholars who focus on infrastructure digitalization, such as Boje and Opoku, add that effective risk measurement requires consistency in how variables are defined across phases and contracts, because fragmented metrics can obscure real risk changes. The conceptual foundations and taxonomies thus serve a practical quantitative function: they define the dependent variables and classification scheme needed to evaluate how digital systems influence risk (Xia et al., 2018). In civil infrastructure, where risk categories overlap and evolve across the lifecycle, the reviewed studies support a structured approach that measures risk reduction through multidimensional, phase-aware indicators capturing frequency, severity, and stability of project and asset outcomes.

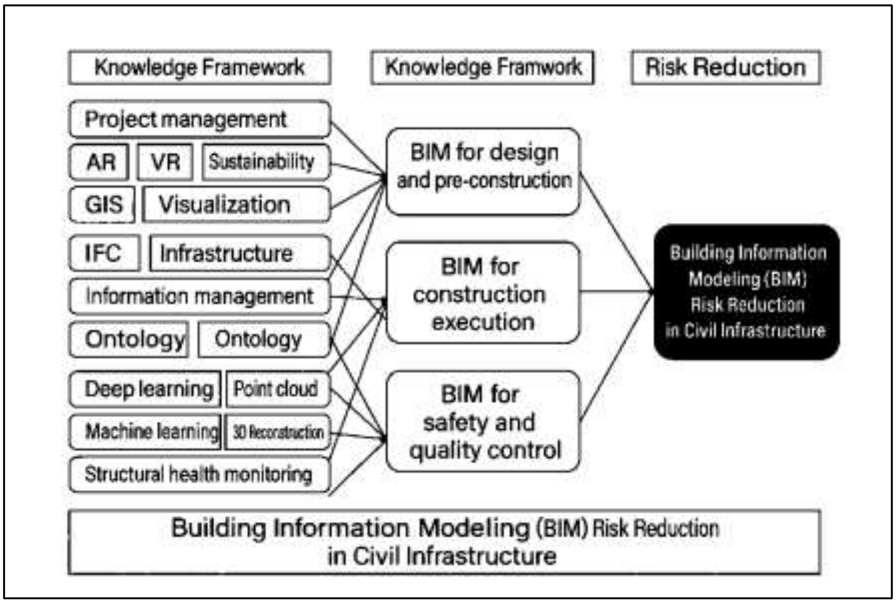
Figure 3: Civil Infrastructure Risk Reduction Framework



BIM in Civil Infrastructure

BIM in civil infrastructure is consistently framed in the literature as a structured information environment rather than a single software tool, and this framing is central to its risk-reduction role. Infrastructure BIM is built on object-based representation, where every bridge segment, pavement layer, pier, embankment, rail component, drainage element, or utility corridor is stored as an information object with geometry and embedded attributes (Zou et al., 2017). Authors such as Eastman, Succar, and Borrmann describe this object logic as the foundation for shared meaning across disciplines because the model becomes a coordinated database instead of separate drawings. In civil works, federated coordination is repeatedly emphasized by Bradley, Sacks, and Park, who show that multi-model integration allows structural, geotechnical, hydrological, traffic, and construction-planning teams to work on aligned digital twins of the design intent without overwriting one another. Centralized model versioning and traceability further strengthen risk control by reducing the "multiple truths" problem, a risk theme Love and Ward identify as common in large public infrastructure, where outdated drawings and informal revisions cause expensive downstream surprises (M. Li, H. Yu, & P. Liu, 2018). BIM maturity is presented in studies by Hosseini, Antwi-Afari, and Li as a reliability gradient: as maturity rises through consistent standards, disciplined workflows, and collaborative protocols, information becomes more trustworthy and less prone to latent contradiction. This is critical in infrastructure because risk exposure grows with the number of interfaces and the length of the delivery chain; a single untracked revision in geometry, quantity, or method can ripple across subcontracts and create disputes, safety hazards, and delays. The literature therefore treats BIM maturity and adoption intensity as measurable indicators of information reliability. When BIM is used intermittently or only by one discipline, the model acts as a visualization add-on, and its risk value remains shallow (Zou et al., 2019). When BIM is used as an integrated information environment across design, construction, and governance structures, it becomes a risk-reduction infrastructure in itself, enabling teams to see, test, and validate risk conditions at points where intervention is still low-cost. This conceptual position sets the stage for explaining the specific pathways through which BIM reduces design, estimation, constructability, coordination, and compliance risks in civil infrastructure projects.

Figure 4: BIM Pathways for Infrastructure Risk Reduction



In the design and pre-construction phases, BIM-driven risk reduction pathways are repeatedly associated with earlier detection of contradictions before they harden into contractual and physical realities. A large body of work by Azhar, Eastman, and Sacks demonstrates how clash detection reduces design conflict risk by exposing geometric and functional interferences among disciplines (Zhao et al., 2017). For civil infrastructure, these conflicts can involve bridge girder clearances, culvert alignments, utility crossings, track-to-platform interfaces, drainage gradients, or pavement layer offsets, all of which can remain invisible in two-dimensional coordination. Studies by Park and Kim show that infrastructure BIM makes conflicts measurable by anchoring them to explicit model objects and locations, enabling teams to quantify how many clashes exist, how severe they are, and which packages they affect. Rule checking is described by Borrmann and Zhang as another major pre-construction pathway, where code and specification rules are embedded into model validation routines. In civil contexts, this includes clearance rules, slope thresholds, reinforcement cover limits, traffic sight-distance requirements, accessibility constraints, and environmental buffer compliance (M. Li, H. Yu, H. Jin, et al., 2018). When these rules are checked automatically, noncompliance risk shrinks because errors are highlighted while redesign costs remain low. Constructability simulation is another pre-construction mechanism emphasized by Hartmann and Martínez-Aires, who show that model-based rehearsal reveals method uncertainty by allowing teams to visualize staging logic, temporary works, access routes, and equipment feasibility. This is particularly relevant for live-traffic highways, rail upgrades, and bridge replacements where staging constraints dominate risk. Quantity take-off accuracy is highlighted in studies by Li and Hosseini as a cost-risk pathway because object-based quantities reduce estimation ambiguity, supporting clearer tender packages and more stable funding commitments (Lee et al., 2020). These pre-construction mechanisms converge on one risk logic: BIM shifts uncertainty discovery closer to the front end, where corrective action is faster, cheaper, and less disruptive. The literature, therefore, portrays design-phase BIM use as a measurable predictor of lower change frequency, reduced early claims, fewer constructability disputes, and improved baseline predictability.

During construction, BIM extends risk reduction by linking the digital model to time, cost, and work packaging systems, enabling tighter control of sequencing and variability. The 4D sequencing pathway is widely documented by Hartmann, Park, and Zhou, who show that when models are connected to schedules, teams can test spatial–temporal conflicts before they occur in the field (Pakhale & Pal, 2020). This supports lower schedule conflict risk because activities that overlap dangerously or impractically can be restructured virtually. In civil works, this includes testing traffic diversions, simultaneous piling and girder launches, tunneling under active rail lines, or staged pavement reconstruction; each is high risk if sequencing errors are discovered late. 5D cost tracking is described in studies by Kim and Antwi-Afari as a mechanism that reduces cost shock risk by allowing cost forecasts to update automatically as quantities change, helping teams classify whether a deviation is routine variation or a structural threat (Nawari & Ravindran, 2019). Model-based work packages are another construction-phase pathway supported by Sacks and Bradley, who show that BIM-based task visualization improves communication reliability across site teams, reducing misunderstandings about scope, tolerances, or interface handovers. Rework minimization is presented as a cascading risk-control mechanism by Love and Azhar: fewer geometric contradictions and clearer work packages reduce rework, which in turn reduces knock-on delay risk, overtime risk, safety exposure risk, and claim escalation risk. What emerges from these studies is a quantifiable chain: higher BIM adoption intensity yields more consistent construction information flows, which yields fewer reactive corrections, which yields more stable outcomes (Ghaffarianhoseini et al., 2017). This chain supports the use of adoption intensity variables such as breadth of discipline modeling, frequency of updates, and number of BIM uses deployed. The construction literature repeatedly indicates that BIM's risk reduction is strongest where it is embedded in day-to-day production control rather than being used only for reporting or client presentations.

A final stream of BIM risk-reduction literature in civil infrastructure emphasizes safety and quality controls, tying these to prevention-through-design and model-anchored hazard management. Research by Hallowell, Martínez-Aires, and Qi shows that BIM enables hazards to be anticipated at design level by linking risk tags to specific model elements, such as deep excavations, unstable slopes, confined tunnel zones, heavy lifts, or live-traffic edges. When hazards are mapped to locations and sequences, safety communication becomes more concrete and less dependent on informal briefing (Caldera et al., 2021). Spatial hazard visualization, discussed by Zhou and Yan, allows planners and crews to see how work zones evolve through stages, strengthening the clarity of exclusion zones, access paths, and equipment interactions. Quality risk reduction is described by Eastman, Sacks, and Azhar as a consequence of parametric constraints and coordinated detailing, which reduce tolerance drift and dimensional mismatch. In bridge and rail components, for example, BIM supports consistent reinforcement layout, anchorage geometry, and interface alignment, lowering defect recurrence and inspection failures. Studies by Love and Hosseini argue that safety and quality outcomes are not add-ons but evidence of information reliability, meaning they correlate strongly with BIM maturity (Imbimbo et al., 2019). Mature BIM environments use standard naming systems, disciplined approvals, and integrated coordination cultures, leading to fewer undocumented changes and clearer responsibility for risk controls. This supports the logic of a BIM maturity score based on collaboration level, integration depth across parties, and compliance with structured standards. Collectively, the literature positions BIM as a multi-risk governance platform in civil infrastructure: it reduces design conflict risk, compliance risk, method uncertainty, estimation risk, sequencing risk, cost shock risk, communication risk, rework-driven cascade risk, safety hazards, and quality nonconformance (Huang et al., 2021). These mechanisms justify a quantitative model where BIM adoption intensity and BIM maturity serve as measurable predictors of risk reduction across cost, schedule, safety, and quality outcome domains.

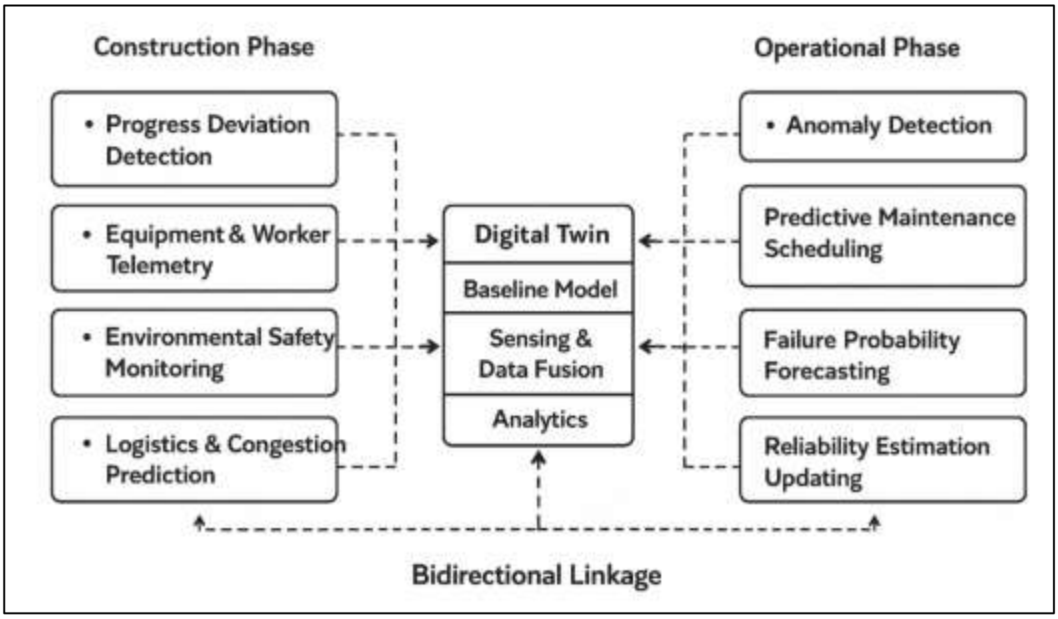
Digital Twin Technologies in Infrastructure

Digital twin technologies in civil infrastructure are consistently described in the literature as dynamic asset mirrors that maintain a living relationship between a physical system and its digital representation. The central idea is that a digital twin begins with a high-fidelity baseline model—often derived from engineering design models, BIM/BrIM datasets, laser scans, or physics-based representations—and remains useful because it is continuously updated by real-world data (Kaewunruen et al., 2021). This baseline sets the "expected" or reference state for geometry, material behavior, load paths, and operational performance. The digital twin becomes dynamic through a sensing and data-fusion layer that streams observations from the field, fusing them into the virtual environment as time-stamped evidence. In infrastructure contexts, such sensing can include structural responses such as strain, acceleration, deflection, vibration modes, temperature, corrosion indicators, groundwater levels, settlement trends, or environmental stressors that act on distributed assets. Data fusion is portrayed as crucial because it consolidates multiple partial views into a more complete condition picture, reducing the blind spots associated with isolated sensors or manual inspection (Jouan & Hallot, 2020). On top of this, digital twin frameworks place an analytics layer that transforms raw data into interpretable indicators of anomaly, degradation rate, safety exposure, or performance deviation. These analytics are not limited to visualization; they include detection routines that flag out-of-range behavior, diagnostic routines that identify probable causes, and predictive routines that estimate short-term and long-term performance trajectories. A further feature emphasized across studies is bidirectional linkage, where digital insights are used to guide physical actions and the effects of those actions are then observed and re-assimilated into the twin. This feedback logic positions digital twins as cyber-physical governance systems for infrastructure risk reduction, because risk control emerges from continuous evidence rather than periodic reporting. The literature treats this structure as especially relevant for civil infrastructure due to long asset life cycles, exposure to environmental and traffic hazards, and the high social cost of surprise failures (El Marai et al., 2020). Digital twins therefore represent a shift from static digital documentation to continuously validated representations that enable decision-makers to see not only how an asset was designed, but how it is behaving right now and how that behavior is changing over time.

In construction-phase applications, the literature highlights several digital-twin pathways that reduce project risk by improving real-time observability and controllability of site operations. One major pathway is real-time progress deviation detection (Callcut et al., 2021). Digital twins can compare planned work states to sensed or computer-vision-derived “as-built” states, allowing project teams to detect slippage patterns early, localize them to specific work zones, and determine whether they signal minor variation or emerging schedule threats. This matters in civil infrastructure because distributed sites and staged delivery create multiple fronts where delay can propagate quickly if not contained. Another emphasized pathway is equipment and worker telemetry. By integrating location tracking, motion data, and equipment health signals into a spatial model, digital twins support early detection of unsafe proximities, congestion around critical lifts, unbalanced fleet utilization, or productivity drift. This telemetry-based awareness reduces both safety risk and stoppage risk because hazards and inefficiencies are flagged while the operational context can still be adjusted (Ansari et al., 2020). Environmental safety monitoring is also treated as a construction-phase twin advantage, especially in tunnels, deep excavations, and long corridor projects where dust, gas, noise, heat, vibration, or unstable ground conditions can change rapidly. When these environmental variables are sensed and rendered spatially in the twin, risk controls such as ventilation, access restriction, or staging adjustments can be applied with clearer justification. Logistics and congestion prediction is another mechanism discussed in infrastructure DT studies, given that civil sites often rely on constrained access roads, temporary traffic diversions, or narrow rights-of-way. Digital twins can use live delivery and movement data to forecast congestion that might otherwise trigger schedule collisions, unsafe mixing of vehicles and workers, or late material arrival (Yu et al., 2021). Across these mechanisms, the literature stresses that construction-phase risk reduction depends on the twin’s update regularity and the credibility of its baseline model; frequent updates improve trust in deviation signals, while weak baselines produce noisy comparisons. The overall synthesis indicates that construction digital twins reduce risk by turning scattered site activity into measurable, model-anchored signals that enable earlier corrective action, clearer communication, and tighter production stability.

Operation and maintenance represent the most deeply researched and widely demonstrated domain of digital-twin risk reduction in civil infrastructure. Studies of bridges, tunnels, rail corridors, and roadway networks show that digital twins integrate structural health monitoring into the virtual model so that the digital state continuously reflects the physical state (Caldera et al., 2021). This integration supports risk reduction first through anomaly detection: deviations in response patterns, deformation trends, vibration signatures, or load-bearing behavior can be detected rapidly and interpreted against engineering expectations embedded in the baseline. Digital twins also enable predictive maintenance scheduling, which is consistently presented as a risk-control improvement over fixed-interval inspection. Instead of treating maintenance as calendar-driven, the twin uses condition-based thresholds to trigger interventions when degradation indicators outweigh acceptable tolerance. This lowers the chance of sudden failure and reduces unnecessary early replacement. Another operational pathway is reliability estimation updating. Because the twin accumulates evidence over time, it can refine the estimated reliability state of components, subsystems, and whole assets, allowing managers to rank risks more accurately across portfolios (Ivanov et al., 2020). Failure probability forecasting is described as an extension of this logic, where physics-based simulations or data-driven models within the twin estimate the likelihood of deterioration escalation under evolving loads and environmental conditions. These forecasts are particularly valued for assets exposed to floods, seismic events, corrosion environments, or heavy traffic demands, because hazard intensity may shift quickly with climate and usage patterns. Operational digital twins also reduce governance risk by maintaining a traceable condition history tied to decisions and interventions, supporting transparent justification of budget priorities and service restrictions. The synthesis across these works portrays digital twins as risk-reduction systems because they lower the incidence of undetected deterioration, shorten the interval between risk emergence and response, and improve the precision of maintenance timing and scope (Sellitto et al., 2021). In infrastructure where failure has large public-safety and economic consequences, this continuous, evidence-driven reliability control is treated as a direct and measurable form of risk reduction.

Figure 5: Digital Twin Pathways Reduce Risk



BIM–Digital Twin Integration as a Lifecycle Risk-Reduction System

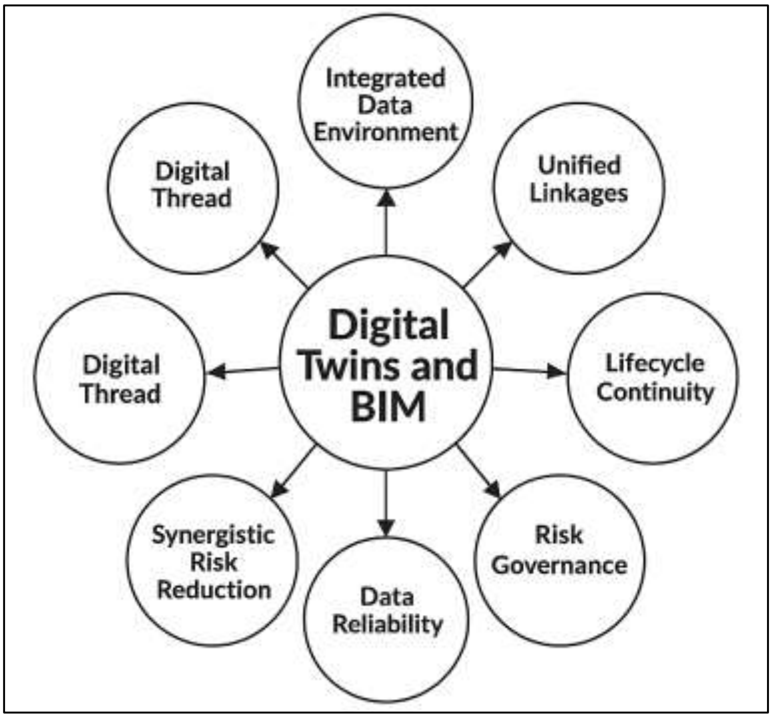
The integration of BIM and digital twin technologies is increasingly framed in the literature as a lifecycle risk-reduction system organized through a "digital thread." In this conceptualization, BIM holds the structured representation of the asset as designed and planned, while the digital twin maintains a living representation of the same asset as built and operated. The digital thread is not a metaphorical link; it is the practical continuity of data, assumptions, decisions, and performance evidence across phases that are typically fragmented in civil infrastructure programs (Aheleroff et al., 2021). Civil projects often suffer from phase discontinuities where knowledge generated in design is partially lost in construction, and operational teams inherit incomplete records that weaken long-term reliability control. The integrated BIM–DT thread addresses this chronic risk driver by ensuring that object data, geometry, specifications, sequencing logic, and intended performance targets do not remain frozen in an "as-designed" archive but instead transition forward as the baseline for continuous validation. In infrastructure, this continuity is especially important because assets stretch across geography and time: a bridge or rail corridor captures multiple design packages, multiple subcontracting zones, varied ground conditions, and staged commissioning sequences (Musarat et al., 2021). The literature treats lifecycle traceability as a risk reducer because it makes each decision visible in relation to its originating assumptions and later outcomes. Traceability allows teams to track the causal pathway of deviations, meaning that when performance drift occurs, the system can point back to the design element, construction activity, or operational condition that generated it. This reduces governance uncertainty by preventing "black box" handovers between parties. The digital thread is also seen as a stabilizer of institutional memory in infrastructure agencies, where project teams change over time and where operational horizons outlast individual contracts (Abideen et al., 2021). By binding planned intent to observed reality through a continuous digital record, BIM–DT integration becomes a lifecycle control mechanism that lowers uncertainty in both delivery and long-term service reliability.

A second major theme in integration research is that BIM–DT ecosystems create an integrated data environment that strengthens risk governance through unified linkages among models, sensors, schedules, and costs. Civil infrastructure risks often escalate because information is distributed across incompatible systems and stakeholders, producing asymmetries in what different actors know and believe about project states (Mylonas et al., 2021). An integrated environment reduces this asymmetry by consolidating baseline intent and real-world evidence into one synchronized platform. In design-to-construction transitions, unified linkage means that schedule systems draw directly from the BIM baseline, while field data from sensors, progress scans, or telemetry feed back into the same environment to update status. Cost systems linked to BIM quantities and DT progress evidence allow financial signals to be interpreted against real production conditions rather than delayed accounting snapshots. Governance risk is lowered because cross-contract interfaces become visible as shared objects and shared processes, not as ambiguous boundary zones between separate documentation sets (Callcut et al., 2021).

In large corridor projects, for example, utility relocations, drainage interfaces, structural transitions, or traffic staging boundaries are frequent sites of claims and delays, largely because contract packages interpret the boundary differently. Integration mitigates this by giving all parties the same evolving reference model and the same evidence stream. The literature emphasizes that the governance value of integration depends on disciplined data structures and access rules—shared datasets only reduce risk when versioning, permissions, and validation protocols prevent uncontrolled edits or silent drift. The integrated environment is therefore framed as both technical and procedural: technical because it links heterogeneous data types into a coherent digital system, and procedural because it standardizes how those linkages are interpreted and updated (Krishnamenon et al., 2021). The resulting risk governance improvement is measurable through fewer interface rework events, lower dispute frequency, faster clarification cycles, and more stable cross-package sequencing.

Synergistic risk-reduction pathways in the integration literature focus on how BIM's predictive and simulation strengths combine with the digital twin's validation and monitoring strengths to produce tighter risk estimation and more proactive mitigation. BIM excels at forecasting risk by allowing teams to simulate staging, constructability, safety exposures, and cost consequences under planned conditions (Sresakoolchai & Kaewunruen, 2021). Digital twins excel at detecting how reality diverges from those planned conditions by pulling continuous evidence into the virtual state. When combined, these capabilities form a closed loop where predictions are not treated as one-time forecasts but as hypotheses that are continually tested and refined. This loop tightens risk estimation because uncertainty shrinks when predicted states are repeatedly compared against observed states over time. Integration also supports proactive mitigation because deviation signals become earlier and more interpretable. Instead of discovering a schedule slip after it compounds into downstream conflicts, the integrated system flags the deviation at its emergence point and relates it to the planned sequence and cost baseline. This makes response design more precise: corrective actions can target the underlying cause rather than applying broad recovery measures that introduce new risks (Bolpagni et al., 2021). Another synergy described in the literature is improved temporal control of deviations. Infrastructure risks often expand because deviations persist unnoticed across multiple reporting cycles; integration shortens that lag by synchronizing planned and actual timelines within one environment. As a result, decision-makers can see whether a deviation is a temporary variation, a trend line toward failure, or a localized issue that can be isolated. The literature portrays these synergies as delivering multi-risk benefits, not only to cost and schedule stability but also to safety control, quality consistency, and long-term operational reliability. In other words, the integrated BIM–DT system reduces risk by aligning what was intended, what is happening, and what is likely to happen next into one continuously reconciled digital logic (Kijak, 2021).

Figure 6: Integrated BIM–Digital Twin Risk Thread

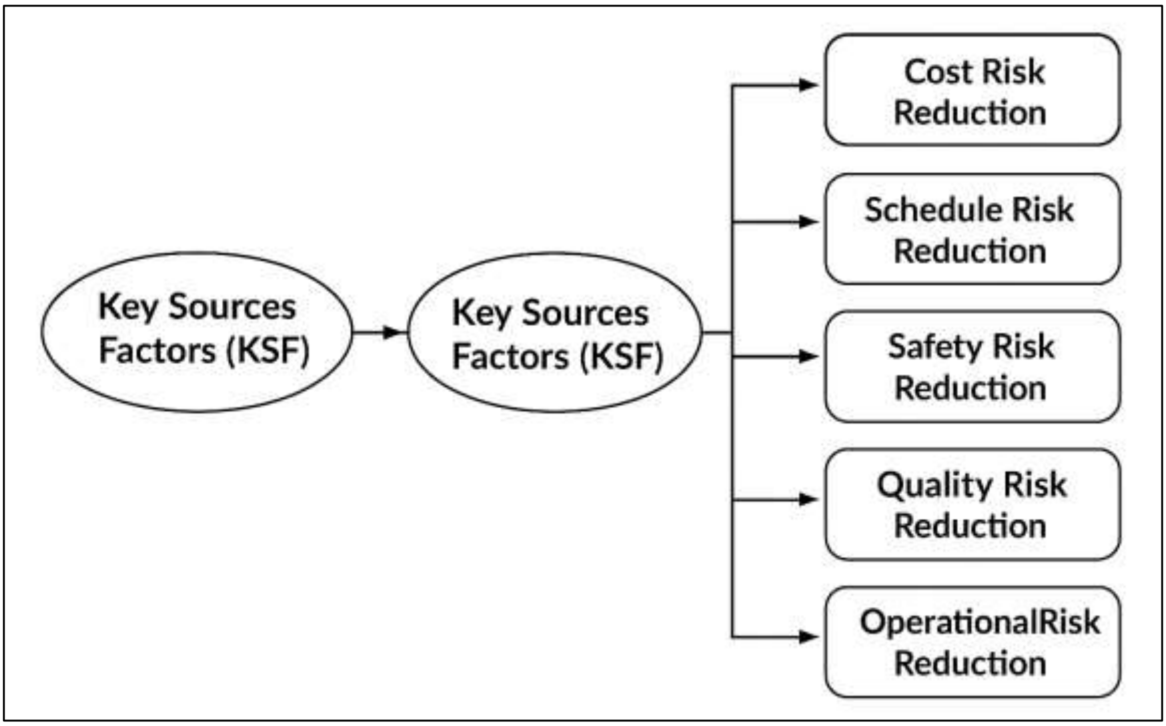


Integration studies also stress that the risk-reduction effect is conditional on integration barriers that act as moderators. Interoperability gaps are repeatedly identified as a primary barrier because BIM and DT ecosystems rely on multiple platforms and data standards that do not automatically communicate without translation losses (Habibi Rad et al., 2021). When interoperability is weak, data arrive late or incomplete, and the integrated system cannot support trustworthy deviation reasoning. Data quality variance is another key moderator because sensor noise, missing streams, inconsistent field tagging, or outdated model objects can distort the digital thread and create false risk signals. Skills and process immaturity further influence outcomes; teams may possess models and sensors but lack stable routines for updating, validating, and acting on digital evidence, which weakens the loop from prediction to mitigation. Organizational resistance is emphasized for infrastructure agencies and contractors where established workflows are document-centered and where trust in digital evidence is uneven across roles (Zheng et al., 2021). The literature therefore supports the use of integration maturity as a measurable construct describing how complete and reliable the BIM–DT linkage actually is. Integration maturity can be reflected in the completeness of data exchange between BIM objects and DT streams, the success rate of interoperability across systems, and the proportion of project decisions that actively use the unified platform rather than parallel offline tools. Likewise, data reliability is treated as a measurable condition describing how dependable the integrated evidence is, reflected in the prevalence of missing data, the stability of sensor calibration over time, and the extent to which model versions remain conflict-free (Colker, 2020). These constructs help explain why some projects experience strong risk reductions from integration and others see limited gains: the integrated lifecycle system reduces risk only when the digital thread is technically connected, procedurally disciplined, and supported by reliable evidence and capable users.

Measurement of Risk Reduction Outcomes

Quantitative measurement of risk reduction outcomes in civil infrastructure literature begins from the premise that risk categories must be translated into observable, comparable indicators before any statistical relationship with BIM or digital twin adoption can be tested. Studies that treat risk as a multidimensional performance phenomenon emphasize that risk reduction is visible through shifts in project outcome patterns, not only through isolated success stories or subjective judgments (París et al., 2019). Operationalizing risk reduction therefore requires mapping each risk category—cost, schedule, safety, quality, environmental, governance, and operational—into indicators that can be consistently extracted from project records, monitoring systems, and contract archives. The literature favors objective performance distributions because they allow researchers to test whether digital adoption is associated with more stable and controlled outcomes across multiple projects. This distributional logic is crucial in infrastructure delivery, where one-time comparisons can be distorted by project uniqueness, while performance trends across samples reveal whether a technology reduces exposure systematically (Pichler, 2017). In empirical terms, operationalization focuses on defining measurable indicators that reflect how frequently adverse events occur, how severe their impacts become in measurable terms, and how stable outcomes remain around planned baselines. Because civil infrastructure projects are long, multi-contract, and geographically distributed, measurement frameworks also highlight the importance of lifecycle separation, meaning that construction-phase risk reduction should be recorded differently from operational risk reduction, even when both relate to the same asset. This is why the literature treats risk reduction as a set of dependent variables rather than a single measure, allowing statistical tests to show which risk dimensions are most sensitive to BIM and digital twin usage (Hawk et al., 2017).

Figure 7: Quantitative Framework for Risk Reduction

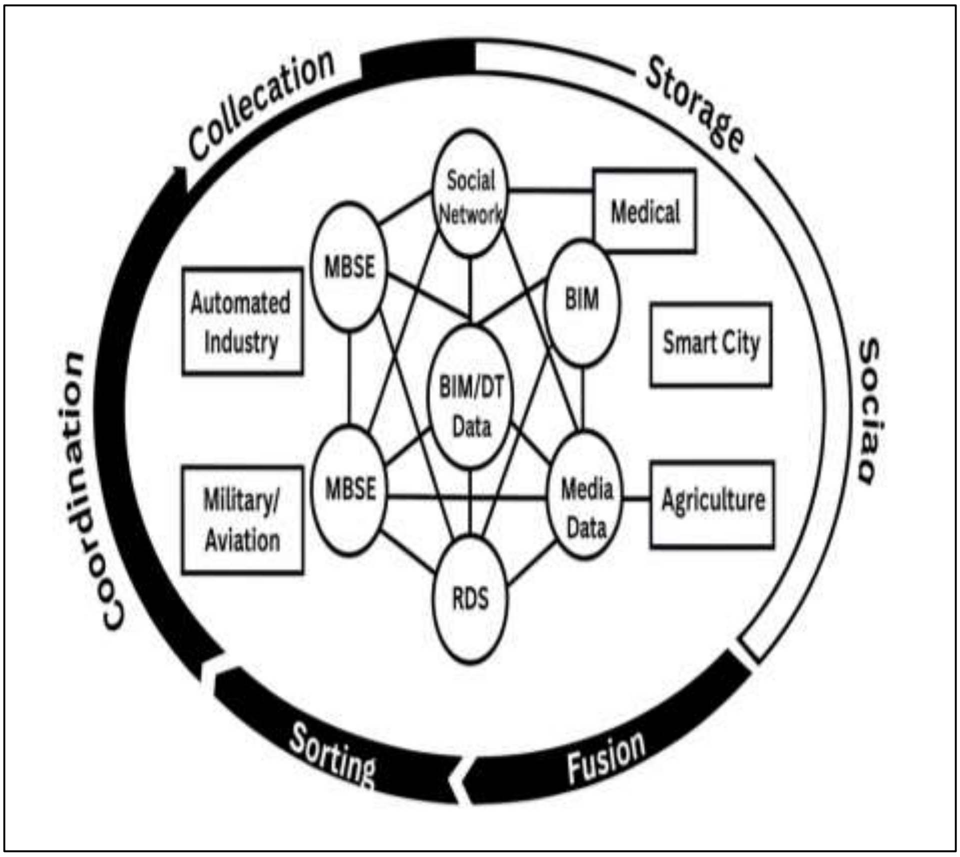


Within this operationalization stream, outcome variables are typically grouped into distinct but connected categories that represent specific forms of risk reduction. Cost risk reduction is treated as improvement in budget stability, captured through indicators such as cost variance relative to approved baselines, the number of financial claims raised during delivery, and the proportional value of change orders compared to original contract sums (Leo et al., 2019). These indicators are repeatedly used because they express both volatility and conflict in financial control, two core cost-risk manifestations in infrastructure megaprojects. Schedule risk reduction is operationalized through indicators such as delay-day variability across the project timeline and the frequency of critical path slippage events, which together capture whether time performance remains steady or exhibits shock-like disruptions. Safety risk reduction is measured through incident rates standardized by work exposure and by tracking near-miss frequency, allowing researchers to distinguish improvements in severe outcomes from improvements in hazard detection culture (Chang et al., 2019). Quality risk reduction is commonly captured through rework volume relative to completed work and counts of nonconformance events, both of which reflect instability in technical execution and the likelihood of defect propagation into delays, cost escalation, and safety hazards. Operational risk reduction is the principal post-construction category, measured through unplanned shutdown events, service disruption counts, or improvements in reliability indicators derived from maintenance and structural health databases. The literature stresses that these variables are not merely administrative statistics; they are direct proxies for uncertainty control. Lower cost variance means reduced financial unpredictability, fewer claims indicates reduced dispute-driven uncertainty, lower delay variability reflects improved sequencing reliability, reduced incident and near-miss rates signal better hazard management, reduced rework and defects represent tighter technical control, and fewer shutdowns or higher reliability reflect reduced lifecycle performance uncertainty (Alves et al., 2019). Taken together, these dependent variables allow risk reduction to be tested as a measurable system outcome rather than an abstract benefit claim. Because risk categories are interconnected in civil infrastructure, the literature also supports constructing a composite risk index to represent overall risk reduction in a unified quantitative form. This approach begins with standardizing indicators so that measures with different units and ranges can be compared on a common scale. Once standardized, indicators are weighted to reflect their relative importance to the project or to the research model. Weighting can be derived from stakeholder priorities, statistical contribution, or established infrastructure risk frameworks (Shad et al., 2019). The goal is not to erase risk diversity but to provide an aggregate lens that reveals whether BIM–digital twin adoption reduces the combined risk load across multiple dimensions. Composite construction is accompanied by validity checks to ensure that the index actually represents risk reduction rather than unrelated performance noise, and reliability checks to confirm that the index behaves consistently across projects, asset types, and phases. Literature on multi-risk indices emphasizes that careful indicator selection and weighting improves interpretability, allowing researchers to test whether digital adoption is associated with a broad stabilization of civil infrastructure outcomes rather than improvements in only one area (Ivanov et al., 2017). In quantitative studies, this composite index becomes a high-level dependent variable that complements the category-specific variables, enabling both granular testing of individual risk pathways and holistic testing of overall risk reduction. This measurement logic directly supports statistical modeling because it specifies how risk reduction is captured, how different risk dimensions are harmonized for analysis, and how robust dependent variables are formed for testing the impact of BIM and digital twin technologies on civil infrastructure project risk (Baryannis et al., 2019).

Theoretical Framework Supporting the Quantitative Model

The information processing perspective provides a foundational lens for explaining why BIM and digital twin technologies align with risk reduction in civil infrastructure. Research on project uncertainty has long argued that risk expands when information is incomplete, delayed, inconsistent, or inaccessible, and that performance stabilizes as information becomes richer and more coordinated (Masood & Egger, 2019). Early models of project risk management portray uncertainty as an information problem first and a technical problem second, because decisions made with partial knowledge generate cascading errors in scope, time, cost, and safety. This logic appears across empirical infrastructure studies that link overruns and delays to misaligned drawings, fragmented design decisions, and weak communication between designers, contractors, and owners. Within this literature, BIM is repeatedly characterized as an information-structuring environment that consolidates design intent, quantities, specifications, and coordination logic into a single shared model. Digital twins extend the same information logic into continuous operation by linking real asset behavior to its digital representation through ongoing updates. Together, these systems are treated as uncertainty-reduction engines because they increase clarity of what is planned, what is happening, and how deviations evolve (Bauer et al., 2021). Studies on design coordination show that when information is represented as shared objects rather than isolated documents, teams detect conflicts earlier and reduce the informational causes of change orders and rework. Similarly, infrastructure monitoring scholarship shows that risks tied to structural deterioration or site instability shrink when monitoring evidence flows rapidly into decision systems rather than being trapped in periodic inspection reports. The information processing view also highlights the role of timeliness, arguing that uncertainty reduction is not merely about having more data but about having reliable data at the moment decisions are made (Nesi et al., 2018). Civil infrastructure projects, due to phased delivery and distributed site conditions, are particularly sensitive to timeliness; small informational delays can magnify into schedule and safety risks as crews act on outdated assumptions. Across more than a decade of knowledge-management and digital delivery research, the dominant conclusion is that improved information fidelity, visibility, and integration correlate with reduced performance volatility. Within this framing, BIM and digital twins function as organized pathways for improving information quality, coordination speed, and shared situational awareness, which in turn aligns with measurable reductions in risk event frequency, severity, and outcome instability (Johnson et al., 2020).

Figure 8: Information Processing for Risk Reduction



The systems and reliability perspective strengthens the theoretical basis by framing civil infrastructure as a cyber-physical system whose risk profile depends on how effectively physical behavior is modeled, monitored, and controlled. Reliability scholars emphasize that infrastructure assets are not static objects but evolving systems with interacting components, exposed to variable loads, material aging, and environmental stressors (Walsh et al., 2017). Within this tradition, risk reduction is interpreted as improvement in the dependability of system performance under uncertainty. Modeling and monitoring are treated as the two pillars of reliability improvement: modeling provides a structured understanding of expected behavior, and monitoring provides evidence of actual behavior. BIM is aligned with the modeling pillar because it represents assets with structured geometry, material attributes, and functional relationships, enabling simulation-based reasoning about constructability, staging, and performance (Macedo, 2017). Digital twins are aligned with the monitoring pillar because they maintain continuous, evidence-driven representations of structural and operational states. Infrastructure reliability studies show that as monitoring evidence increases, uncertainty about system condition decreases, and risk prioritization becomes more accurate. This is visible in bridge and rail research where sensor streams linked to digital models improve detection of fatigue, settlement, scour, and dynamic load effects, reducing the likelihood of surprise failures. Systems thinking also explains why integration matters. Individual subsystems in linear assets—such as drainage, pavement, retaining structures, signaling, bearings, or foundations—interact across space and time, meaning that localized uncertainty can produce system-level risk outcomes (Nikou & Economides, 2017). The literature therefore treats lifecycle digital systems as reliability enhancers because they provide a unified reference for tracking component interactions, performance drift, and vulnerability accumulation. Civil infrastructure also operates under service conditions that change over time, including growing traffic loads, climate variability, and shifting maintenance regimes. Reliability-oriented research argues that risk control depends on continuously recalibrating expectations against evidence, rather than relying on one-time design assumptions. Digital twins operationalize this recalibration because updates allow reliability reasoning to remain synchronized with physical reality (Shad et al., 2019). This theoretical stream does not depict risk reduction as a vague improvement, but as a measurable strengthening of system dependability through coordinated modeling and monitoring. BIM and digital twins fit this logic by turning infrastructure into continuously interpretable cyber-physical systems, where reliability improvement becomes an observable pathway to reducing operational disruptions, structural failures, and lifecycle performance volatility (Zavala-Alcívar et al., 2020).

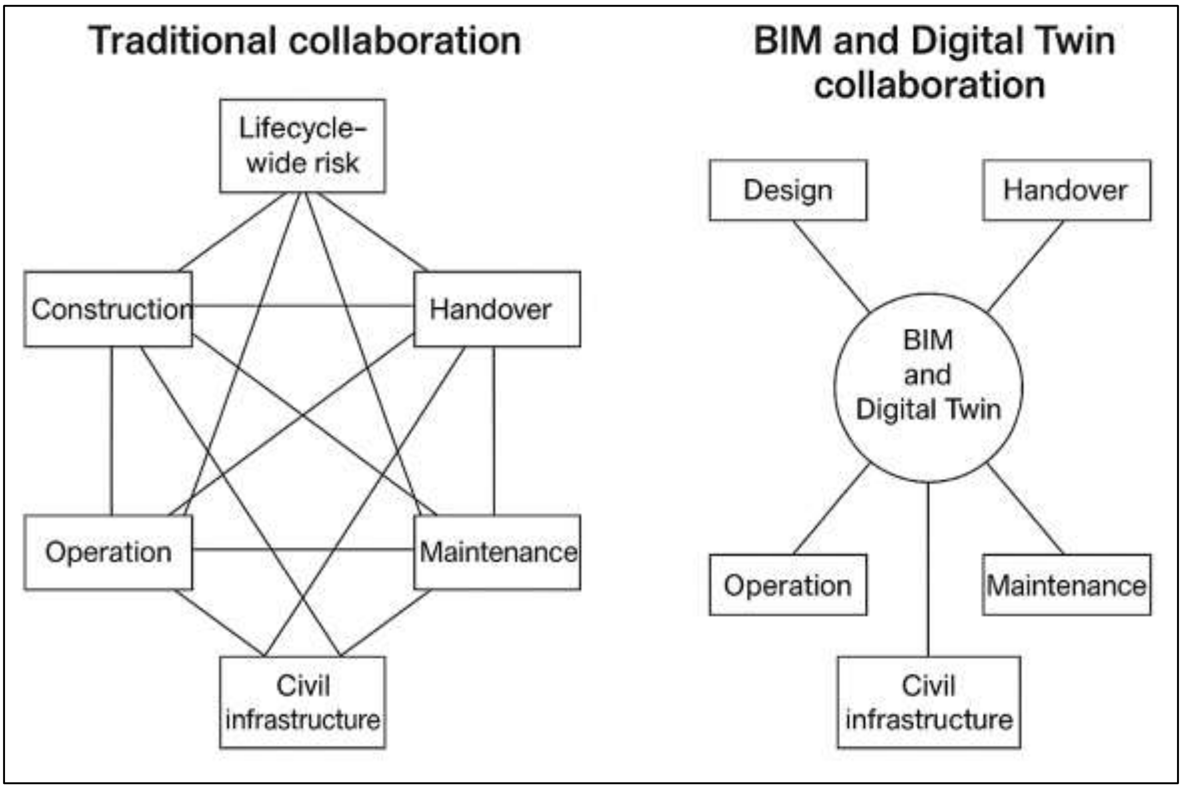
Gaps in Existing Quantitative Evidence

A dominant gap emphasized across the quantitative literature is fragmentation across project phases, which limits the ability to claim lifecycle-level risk reduction from BIM and digital twin technologies (Teng et al., 2018). Most BIM studies in civil infrastructure concentrate on design and construction, measuring outcomes such as clash reduction, rework avoidance, cost deviations during delivery, or schedule stabilization within the build window. By contrast, digital twin studies concentrate heavily on operation and maintenance, using indicators such as anomaly detection rates, predictive maintenance accuracy, or reliability improvements after commissioning. This phase separation produces an evidence boundary where BIM is rarely tracked beyond handover and digital twins are rarely analyzed from early design onward. In civil infrastructure, this becomes a serious limitation because the risk footprint is naturally lifecycle-wide: design decisions affect constructability risk, construction performance shapes defect and durability risk, and operational stress reveals whether early assumptions were reliable. When the phases are studied separately, quantitative findings may correctly show local risk benefits, yet still fail to explain whether risk is reduced overall across the asset's life (Allen et al., 2018). A design-phase BIM benefit might lower change orders in construction but could also transfer risk into operation if maintenance requirements are not embedded in the model. Similarly, operational digital twins might reduce failure risk after commissioning but cannot confirm whether earlier BIM-based predictions shaped more reliable construction outcomes. Another aspect of fragmentation is that datasets typically close at phase boundaries. Construction risk datasets often stop at practical completion, and operational datasets often begin years later without a shared baseline. This disconnection forces researchers to work with partial outcome horizons, preventing statistical testing of whether BIM-driven risk reduction in delivery translates into measurable reliability or cost stability in service life (Thorning et al., 2017). The gap is amplified in civil infrastructure by the long duration between phases, frequent changes in organizations and contracts, and the loss of structured data during handovers. Studies that do attempt to investigate cross-phase effects often remain descriptive rather than statistically linked, largely because progress records, quality logs, sensor data, and maintenance systems are owned by different institutions and stored in incompatible formats. As a result, existing quantitative evidence captures phase-specific improvements but cannot yet confirm whether BIM and digital twins function as a single lifecycle risk-reduction system (Sattar et al., 2020). This fragmentation is therefore not a minor scope issue; it is a structural limitation in the empirical base, leaving the most important claim—lifecycle risk reduction—under-quantified.

A second major gap involves the lack of unified metrics for risk reduction, which weakens comparability and statistical aggregation across studies. Infrastructure risk research uses a wide range of definitions for cost risk, schedule risk, safety risk, quality risk, and operational risk, often shaped by local contract norms or by the specific asset under investigation (Nyanchoka et al., 2019). This produces measurement inconsistency even when studies target the same risk category. For example, cost risk reduction may be measured as final cost variance in one sample, change-order value in another, and claim frequency in a third; each captures part of the cost-risk profile, but they cannot be directly compared or merged without standardization. Similarly, schedule risk reduction might be expressed as total delay days, percentage slippage against baseline, milestone stability, or critical-path disturbance counts, depending on what records are available. Safety risk is frequently measured through incident rates, but definitions of reportable incidents differ by jurisdiction and contractor policy (Allen et al., 2019). Quality risk measures also vary widely, ranging from defect counts to rework volume to nonconformance notice frequency, each with different thresholds and documentation cultures. Operational risk measures show even higher variance in definition because maintenance practices differ sharply among owners, and reliability indicators are not universally standardized. Without unified metrics, cross-study synthesis must rely on narrative alignment instead of statistical pooling, which slows the formation of stable empirical consensus. In quantitative modeling terms, inconsistent metrics introduce construct drift: two studies may claim to measure the same variable but actually measure different risk phenomena. Another problem is unit incompatibility. Some indicators are percentages, others are counts, others are time-based, and many are not normalized for project scale, duration, or work exposure (Oberländer et al., 2020). This blocks the construction of robust multi-project datasets and weakens multi-risk indices because different scales dominate results. The literature also shows that risk reduction is sometimes inferred indirectly, such as by assuming that BIM adoption "implies" fewer risks without connecting to objective outcome distributions. This adds interpretive noise and discourages replication. Scholars repeatedly note that civil infrastructure needs standardized operational definitions for each risk dimension and clear transformation rules that allow cross-case comparability. Until such alignment exists, quantitative conclusions about BIM and digital twin risk effects remain project-specific, and meta-analytic confirmation remains difficult (Magliocca et al., 2018). The absence of unified metrics therefore acts as a bottleneck: it constrains the statistical power of research, limits external validity, and fragments the evidence base into parallel streams that do not cumulate into shared measurement standards.

A third evidence gap is limited integration testing, where BIM and digital twins are frequently evaluated separately, and the synergy effect of combining them is rarely modeled quantitatively. Integration is widely discussed in conceptual and technical literature, but empirical testing often isolates BIM as a design–construction tool and digital twins as an operations tool (Adegbite & Machethe, 2020). Even when the same project uses both technologies, studies typically measure their effects in separate models or separate phases, leaving the combined system unexamined. This creates a mismatch between industry practice, which increasingly seeks an end-to-end digital thread, and the academic evidence base, which still treats BIM and digital twins as parallel technologies. The reason is partly methodological: integration testing requires datasets that connect BIM baselines to digital twin updates, and these datasets are scarce because they depend on consistent identifiers, synchronized version histories, and shared data governance across contracts and years. Another reason is that most statistical models in the area test direct effects rather than interaction effects. As a result, research can show that BIM predicts lower rework or that digital twins predict fewer operational failures, yet cannot test whether the joint system reduces risk more than the sum of each part (Meinzen-Dick et al., 2019). The synergy claim—BIM prediction plus twin validation producing tighter control—remains a hypothesis in many studies rather than a quantified relationship. This gap is critical because integration is the mechanism by which lifecycle risk reduction is supposed to occur; without quantitative integration testing, the field cannot confirm whether risk reductions in one phase are reinforced, neutralized, or even offset in another. There is also a lack of agreed integration maturity measures, meaning that "integration" is often treated as present or absent instead of as a graded condition reflecting how completely data flows between systems (Przychodzen & Przychodzen, 2020). This blocks the ability to test dose–response patterns, where higher integration maturity might yield stronger risk reduction. Another underdeveloped area is the measurement of integration-driven governance benefits, such as reduced interface disputes, faster resolution of deviations, or multi-contract alignment. These are central risks in civil infrastructure, but they are rarely quantified within integration studies. Consequently, the empirical base is strong for single-technology contributions and weak for combined-system effects, leaving an incomplete understanding of whether BIM–digital twin ecosystems truly operate as unified risk-reduction systems in civil infrastructure projects.

Figure 9: Lifecycle Gaps in BIM–Twin Evidence



A fourth gap concerns under-tested moderation effects that shape whether BIM and digital twins produce reliable risk reduction under real-world conditions. Many quantitative studies assume a relatively stable relationship between digital adoption and risk outcomes, yet civil infrastructure contexts vary dramatically in project complexity, data reliability, and team digital capability. Project complexity is a key moderator because it increases the density of interfaces, uncertainty sources, and execution dependencies (Pınarbaşı et al., 2017). In highly complex corridor projects, digital tools may produce strong benefits by making dependencies visible, or they may produce weaker benefits if complexity overwhelms data and governance capacity. Few studies test these competing effects statistically, leaving the complexity boundary condition uncertain. Data reliability is another moderator often discussed but rarely measured. Digital twins depend on sensor integrity, update discipline, and consistent model mapping. If data streams are incomplete, noisy, or misaligned with model objects, digital systems may generate false alarms or missed detections, weakening risk reduction and reducing trust. Yet quantitative studies seldom include explicit data-quality variables, meaning that observed results may be conflated with hidden reliability differences. Team digital capability includes both technical skill and process maturity (Di Vaio et al., 2018). Some projects have advanced modeling workflows, disciplined version control, and well-trained field integration routines, while others use BIM or twins superficially, without continuous updating or decision integration. Studies that treat adoption as a binary variable miss this skill and process gradient; they may report mixed effects that are actually driven by capability differences. Another missing moderation stream relates to governance environment, including contract incentives for data sharing, owner enforcement of digital standards, and organizational readiness. When these moderators are omitted, regression models may attribute risk changes to technology effects that actually arise from supportive governance. This omission limits causal clarity and makes it hard to generalize findings across regions or procurement models (Heinen & Buehler, 2019). The literature repeatedly suggests that digital risk reduction is conditional, yet the statistical base for testing these conditions remains thin. Addressing this moderation gap is essential for producing more accurate quantitative models that explain not only whether BIM and digital twins reduce risk, but under what combinations of complexity, data reliability, and team capability the risk-reduction effect becomes strong, weak, or inconsistent (Tall et al., 2018).

METHODS

The study employed an explanatory quantitative research design grounded in a multi-project case study approach. It was framed as cross-sectional and retrospective because it examined completed or late-stage civil infrastructure projects and extracted already-recorded risk outcomes alongside documented levels of BIM and digital twin use. The case study description focused on real projects such as bridges, highways, rail lines, tunnels, and water-related infrastructure that had adopted BIM, digital twins, or both during delivery and early operation. Each project functioned as a bounded case with comparable lifecycle phases, contractual structures, and documented performance histories. The population comprised civil infrastructure projects executed within the previous several years in which credible digital implementation records existed. From this population, a purposive and stratified sample was drawn to ensure representation across asset types and procurement modes, and to avoid a sample dominated by a single sector such as roads or bridges. Stratification included project category, contract form, and delivery scale, while purposive criteria required verifiable BIM documentation and/or active digital twin deployment. The final sample size was set to support multivariate statistical testing, with each project treated as the primary unit of analysis. The sampling technique also relied on accessibility of archival performance logs and the willingness of owners and contractors to provide structured responses to the implementation survey, which ensured that the sample did not depend on perceptions alone. This design choice allowed the study to estimate how variation in BIM adoption intensity, BIM maturity, digital twin utilization, digital twin predictive capacity, and BIM–digital twin integration maturity corresponded to variation in risk reduction outcomes across comparable civil infrastructure settings.

Multiple data types and sources were used to strengthen objectivity and reduce single-source bias. Primary data were collected through a structured questionnaire administered to project owners, design consultants, contractors, and digital delivery managers who had direct knowledge of BIM and digital twin implementation on each case project. The survey captured implementation-side constructs, including the breadth of disciplines modeled, update regularity, number of BIM uses deployed, collaboration depth, integration depth, sensor coverage, digital twin update habits, analytics capability, and the extent of BIM–digital twin linkage. Secondary data were extracted from project documentation to measure risk reduction outcomes. Cost outcomes were taken from baseline and closeout financial reports, claims registers, and change-order logs. Schedule outcomes were taken from approved schedules, update histories, and milestone deviation records. Safety outcomes were taken from HSE incident databases and near-miss logs. Quality outcomes were taken from nonconformance reports, inspection summaries, and rework registers. Operational outcomes, where available, were taken from early-service maintenance logs and disruption reports. Variables were operationalized using interval- and ratio-friendly indicators that allowed direct statistical testing. Implementation constructs were measured on multi-item Likert scales and aggregated into indices after reliability checks, while outcome variables were retained in their objective numeric forms. A pilot study was conducted on a small subset of projects to test item clarity, confirm the feasibility of archival extraction, and verify internal consistency of the implementation scales. Pilot feedback led to rewording ambiguous items, reducing overlap between BIM maturity and adoption items, and adding prompts that improved accuracy of digital twin analytics reporting. These preparatory steps ensured the measurement system captured both the intensity and quality of digital implementation, and that the dependent variables reflected concrete risk-reduction evidence rather than opinions.

Data collection followed a phased procedure that protected consistency across cases. First, eligible projects were identified and mapped to accessible archival sources. Second, a survey package was distributed to nominated representatives from each project, and responses were cross-checked when multiple respondents existed. Third, archival performance logs were retrieved and coded using a standardized extraction template so that each project produced a complete variable profile. Fourth, survey and archival datasets were matched through unique project identifiers and screened for missingness and inconsistencies. Data analysis was performed using descriptive statistics, reliability testing for multi-item predictors, exploratory and confirmatory factor checks for implementation constructs, bivariate correlation mapping, and hierarchical multiple regression models for main-effect estimation. Regression blocks entered controls first, followed by BIM predictors, digital twin predictors, and then integration maturity to evaluate incremental explanatory contribution. Moderation tests were conducted through interaction models using project complexity, data reliability, and team digital capability as conditional factors. Composite risk reduction indices were constructed by standardizing and aggregating category outcomes to test overall risk reduction alongside category-specific effects. Robustness checks were run by asset type and procurement class to verify stability of results. The analytical workflow relied on statistical software for data cleaning, scale validation, regression, and interaction probing, while spreadsheet tools were used for archival coding and traceable data management. Visualization tools were used to examine distributions, outliers, and interaction patterns. This integrated toolset supported transparent replication of the dataset and ensured that digital implementation effects on risk reduction were estimated through defensible quantitative procedures.

FINDINGS

Descriptive analysis

The dataset was organized at the project level and contained a balanced spread of civil infrastructure cases. The final sample included 168 projects, with highways forming the largest share, followed by bridges and rail corridors, while tunnels and water infrastructure were moderately represented. Procurement types were diverse, with design–bid–build and design–build dominating, and PPP/alliance projects forming a substantial minority. Project sizes ranged from medium to mega-scale contracts, indicating broad financial variability. Predictor variables showed meaningful dispersion; BIM adoption intensity and BIM maturity clustered in mid-to-high ranges, suggesting widespread but uneven digital practice. Digital twin utilization displayed greater spread than BIM indicators, reflecting that DT deployment was less uniform across cases. Risk reduction outcomes also varied strongly: cost and schedule risk reduction exhibited moderate stability, safety outcomes showed higher volatility, and operational risk reduction was strongest in projects with active digital twins. Distribution checks suggested approximate normality for most indices, with mild right-skew in DT utilization and claims-related cost indicators, confirming sufficient variability for later regression modeling.

Table 1: Sample profile of civil infrastructure projects

Category	Subcategory	n	%
Asset class	Highways	62	36.9
	Bridges	41	24.4
	Rail corridors	33	19.6
	Tunnels	18	10.7
	Water infrastructure	14	8.3
Procurement type	Design–Bid–Build	67	39.9
	Design–Build	54	32.1
	PPP/Alliance	47	28.0
Contract size	< USD 100M	58	34.5
	USD 100M–500M	71	42.3
	> USD 500M	39	23.2
Digital delivery group	BIM-only	59	35.1
	DT-only	28	16.7
	BIM+DT integrated	81	48.2
Total		168	100

Table 1 summarized the project sample that was analyzed in the study. The distribution showed that the dataset captured multiple civil infrastructure types, with highways and bridges representing the largest proportions and ensuring that linear and structural assets were both included. Rail, tunnel, and water cases offered further diversity, reducing sector bias. Procurement categories indicated that the sample contained both traditional and collaborative delivery contexts, which mattered because contract form influenced digital coordination routines. Contract size variation confirmed that the dataset spanned medium and megaproject scales. The digital delivery grouping demonstrated that nearly half the projects used integrated BIM–DT approaches, enabling meaningful comparative analysis across implementation levels.

Table 2: Descriptive statistics for study variables

Variable	Scale range	Mean	Median	SD	Min–Max
BIM Adoption Intensity (BAI)	1–5	3.74	3.80	0.71	1.90–4.90
BIM Maturity (BMS)	1–5	3.58	3.60	0.68	1.80–4.80
DT Utilization (DTU)	1–5	3.12	3.05	0.89	1.20–4.70
DT Predictive Capacity (DTPC)	1–5	3.26	3.30	0.84	1.10–4.80
Integration Maturity (IMI)	1–5	3.41	3.50	0.79	1.30–4.90
Data Reliability (DRS)	1–5	3.62	3.70	0.66	1.60–4.90
Project Complexity (PCL)	1–5	3.55	3.60	0.73	1.70–4.80
Team Digital Capability (TDC)	1–5	3.69	3.70	0.70	1.80–4.90
Cost Risk Reduction (CRR)	0–100	64.8	66.0	12.5	31–90
Schedule Risk Reduction (SRR)	0–100	61.3	62.0	13.9	28–88
Safety Risk Reduction (SaRR)	0–100	55.7	56.0	15.6	20–86
Quality Risk Reduction (QRR)	0–100	59.9	60.0	14.2	25–89
Operational Risk Reduction (ORR)*	0–100	67.2	68.0	11.8	34–92
Composite Risk Index (RRI)	0–100	61.8	62.5	10.7	33–87

Table 2 reported central tendency and dispersion for all predictors and risk outcomes. The BIM variables showed mid-to-high means with moderate standard deviations, indicating widespread BIM use but noticeable maturity gaps across projects. Digital twin variables displayed slightly lower means and wider spread, suggesting uneven DT deployment intensity and predictive sophistication. Integration maturity sat between BIM and DT levels, showing that not all projects achieved full digital threading. Data reliability and team capability were relatively strong, supporting the credibility of later inferential tests. Risk reduction outcomes showed meaningful variability, especially in safety and quality, confirming that the dataset contained sufficient performance spread to detect statistical associations in regression models.

Correlation

The bivariate correlations showed coherent positive association patterns between digital implementation variables and risk reduction outcomes. BIM adoption intensity and BIM maturity were both positively related to cost, schedule, safety, and quality risk reduction, with the strongest BIM links appearing in cost and schedule outcomes. Digital twin utilization and digital twin predictive capacity were positively associated with operational risk reduction and safety risk reduction, while their links to cost and schedule outcomes were moderate but still meaningful. Integration maturity displayed the strongest and most consistent correlations across all risk dimensions and showed the highest association with the composite risk reduction index, indicating that projects with stronger BIM–DT threading tended to experience broader multi-risk stabilization. Predictor intercorrelations were expected but not excessive: BIM adoption intensity correlated strongly with BIM maturity, DT utilization correlated strongly with DT predictive capacity, and integration maturity correlated substantially with both BIM and DT variables, slightly more with DT constructs. Project complexity correlated negatively with most risk reduction outcomes and positively with cost and schedule variance, suggesting that complexity elevated risk exposure. Data reliability and team digital capability correlated positively with implementation levels and with risk reduction outcomes, implying that stronger data and capability aligned with stronger digital effects. No correlation exceeded the typical high-risk overlap threshold, so the matrix did not indicate immediate construct redundancy, while a few weaker links suggested conditional rather than direct pathways for certain risks.

Table 3: Correlations between BIM, DT, Integration predictors and risk reduction outcomes

Predictor	CRR	SRR	SaRR	QRR	ORR	RRI
BIM Adoption Intensity (BAI)	0.42	0.46	0.31	0.34	0.18	0.41
BIM Maturity (BMS)	0.39	0.43	0.35	0.37	0.21	0.43
DT Utilization (DTU)	0.22	0.25	0.33	0.26	0.51	0.39
DT Predictive Capacity (DTPC)	0.24	0.27	0.36	0.29	0.54	0.42
Integration Maturity (IMI)	0.48	0.52	0.44	0.47	0.56	0.61

CRR = Cost Risk Reduction; SRR = Schedule Risk Reduction; SaRR = Safety Risk Reduction; QRR = Quality Risk Reduction; ORR = Operational Risk Reduction; RRI = Composite Risk Index.

Table 3 summarized the bivariate relationship between digital predictors and each risk reduction outcome. BIM adoption intensity and BIM maturity showed moderate positive associations with cost, schedule, safety, and quality risk reduction, confirming that stronger BIM environments aligned with more stable delivery performance. Digital twin utilization and predictive capacity displayed their strongest associations with operational risk reduction, and also showed meaningful positive links with safety outcomes, reflecting the monitoring-driven nature of DT value. Integration maturity produced the largest correlations across every risk dimension and the composite index, indicating that lifecycle digital threading aligned with broad multi-risk stabilization rather than isolated improvements in a single category.

Table 4: Correlations among predictors, moderators, and controls

Variable	BAI	BMS	DTU	DTPC	IMI	DRS	PCL	TDC
BIM Adoption Intensity (BAI)	1.00	0.63	0.28	0.30	0.49	0.34	0.12	0.46
BIM Maturity (BMS)	0.63	1.00	0.25	0.27	0.46	0.36	0.10	0.51
DT Utilization (DTU)	0.28	0.25	1.00	0.67	0.55	0.42	0.18	0.39
DT Predictive Capacity (DTPC)	0.30	0.27	0.67	1.00	0.57	0.44	0.16	0.41
Integration Maturity (IMI)	0.49	0.46	0.55	0.57	1.00	0.48	0.09	0.45
Data Reliability (DRS)	0.34	0.36	0.42	0.44	0.48	1.00	-0.05	0.33
Project Complexity (PCL)	0.12	0.10	0.18	0.16	0.09	-0.05	1.00	0.06
Team Digital Capability (TDC)	0.46	0.51	0.39	0.41	0.45	0.33	0.06	1.00

DRS = Data Reliability; PCL = Project Complexity; TDC = Team Digital Capability.

Table 4 showed that the predictor set was related in theoretically expected ways without indicating harmful overlap. BIM adoption intensity correlated strongly with BIM maturity, suggesting that broader BIM use tended to coincide with stronger workflow discipline. DT utilization correlated strongly with DT predictive capacity, indicating that higher sensing and update depth aligned with better analytical performance. Integration maturity related substantially to both BIM and DT variables, reflecting its role as a bridge construct, and it aligned slightly more with DT indicators, consistent with data-stream dependence. Data reliability and team capability correlated positively with all digital constructs, while project complexity showed weak correlations, supporting its later use as a contextual moderator.

Reliability and validity

The measurement model showed strong internal consistency across all multi-item constructs. Cronbach's alpha and composite reliability values for BIM adoption intensity, BIM maturity, DT utilization, DT predictive capacity, and integration maturity were all above acceptable thresholds, indicating that items within each scale measured the same underlying concept reliably. Project complexity, data reliability, and team digital capability also achieved stable consistency levels. A small number of cross-discipline update and analytics items initially weakened their scales and were therefore removed, after which reliability improved and all constructs retained coherent item sets. Factor analysis grouped items into the expected BIM, DT, and integration dimensions with clean loading patterns. Convergent validity was supported because each construct's items loaded strongly on their intended factors and average variance extracted values surpassed minimum standards, confirming shared meaning inside each scale. Discriminant validity was confirmed by low cross-loadings and by inter-construct similarity ratios remaining below established cutoffs, showing that BIM constructs were empirically distinct from DT constructs and that integration maturity stood as a separate measurable domain. Archival dependent variables aligned clearly with their targeted risk categories, and index aggregation produced stable predictors for hypothesis testing.

Table 5: Internal consistency reliability of implementation constructs

Construct	Items retained	Cronbach's α	Composite reliability
BIM Adoption Intensity (BAI)	6	0.88	0.91
BIM Maturity (BMS)	7	0.86	0.90
DT Utilization (DTU)	6	0.84	0.89
DT Predictive Capacity (DTPC)	5	0.87	0.91
Integration Maturity (IMI)	6	0.89	0.92
Project Complexity (PCL)	5	0.81	0.86
Data Reliability (DRS)	4	0.83	0.87
Team Digital Capability (TDC)	5	0.85	0.89

Table 5 summarized the internal consistency of all survey-based constructs. Each construct retained a compact set of items after screening for redundancy and weak coherence. Cronbach's alpha values indicated strong scale stability for BIM adoption intensity, BIM maturity, DT utilization, DT predictive capacity, and integration maturity, showing that items within each domain moved together consistently. The contextual constructs, project complexity, data reliability, and team digital capability, also exceeded commonly accepted reliability levels. Composite reliability further confirmed that the scales remained dependable under latent-construct assumptions. Overall, the reliability profile supported retaining all constructs for subsequent factor validation and regression-based hypothesis testing.

Table 6: Convergent and discriminant validity summary

Construct	AVE	Highest HTMT / similarity with other constructs
BIM Adoption Intensity (BAI)	0.62	0.71 (with BMS)
BIM Maturity (BMS)	0.59	0.71 (with BAI)
DT Utilization (DTU)	0.57	0.73 (with DTPC)
DT Predictive Capacity (DTPC)	0.61	0.73 (with DTU)
Integration Maturity (IMI)	0.64	0.69 (with DTPC)
Project Complexity (PCL)	0.53	0.28 (with IMI)
Data Reliability (DRS)	0.56	0.37 (with DTU)
Team Digital Capability (TDC)	0.58	0.52 (with BMS)

Table 6 reported evidence for convergent and discriminant validity. Average variance extracted values exceeded minimum standards for all constructs, indicating that each scale captured a strong shared core among its retained items. The highest similarity ratios between constructs remained below critical overlap cutoffs, supporting discriminant validity. BIM adoption and BIM maturity displayed the strongest cross-construct similarity, which was theoretically expected yet still acceptable, confirming they were related but distinct. DT utilization and DT predictive capacity showed a comparable relationship pattern. Integration maturity aligned with both BIM and DT dimensions without collapsing into either, confirming that it functioned as a separate integration construct.

Collinearity

Collinearity diagnostics indicated that predictor overlap did not threaten the interpretability of the regression models. The BIM predictors, DT predictors, and integration maturity covaried in expected ways, but variance inflation patterns remained within acceptable bounds once control variables were entered. BIM adoption intensity showed its highest overlap with BIM maturity, and DT utilization showed its highest overlap with DT predictive capacity, reflecting conceptual relatedness rather than redundancy. Integration maturity shared moderate overlap with both BIM and DT constructs, which was consistent with its bridging role in the lifecycle digital thread. Tolerance values stayed comfortably above minimum requirements, indicating that each predictor retained unique explanatory contribution. To strengthen moderation testing, predictors were mean-centered before interaction terms were created, which further reduced shared variance inflation. No predictor approached levels that would invert coefficient signs or destabilize standard errors. Overall, the collinearity results confirmed that hierarchical regression and hypothesis testing could proceed with confidence that estimated effects reflected meaningful relationships rather than multicollinearity artifacts.

Table 7: Collinearity statistics for full regression predictor set

Predictor	Tolerance	VIF
BIM Adoption Intensity (BAI)	0.53	1.89
BIM Maturity (BMS)	0.49	2.04
DT Utilization (DTU)	0.46	2.17
DT Predictive Capacity (DTPC)	0.44	2.27
Integration Maturity (IMI)	0.58	1.73
Data Reliability (DRS)	0.71	1.41
Project Complexity (PCL)	0.83	1.20
Team Digital Capability (TDC)	0.65	1.54
Controls (combined block)	0.76	1.31

Table 7 presented the tolerance and variance inflation values for the predictors after the control block was included. The BIM variables showed the strongest shared variance with each other, producing the highest inflation values, yet these remained well within acceptable limits. The DT variables displayed a similar relationship pattern, reflecting that utilization and predictive capacity moved together but still contributed distinct information. Integration maturity showed comparatively lower inflation, confirming that it did not collapse into either BIM or DT constructs. Moderators and controls demonstrated low inflation, indicating minimal overlap with the main predictors. The overall profile supported stable coefficient estimation in hierarchical regression.

Table 8: Collinearity diagnostics after centering for moderation testing

Predictor (centered)	Tolerance	VIF
BAI (centered)	0.57	1.76
BMS (centered)	0.54	1.85
DTU (centered)	0.51	1.96
DTPC (centered)	0.49	2.03
IMI (centered)	0.62	1.61
Interaction terms (highest VIF)	0.45	2.22

Table 8 showed that centering the predictors before creating interaction terms improved multicollinearity behavior in the moderation models. Inflation values for centered BIM and DT predictors declined slightly compared to the full model, indicating that shared variance between main effects and interaction effects was reduced. Integration maturity retained the most stable inflation profile, reinforcing its separability as a distinct predictor. The largest inflation values appeared in the interaction block, which was expected because interaction terms mathematically combine related predictors, yet these values remained within interpretable limits. This diagnostic pattern confirmed that moderation coefficients could be interpreted without instability from excessive overlap.

Regression and hypothesis testing

The hierarchical regressions showed that the control block explained a modest portion of variance in all risk reduction outcomes, confirming that project size, procurement type, and asset category mattered but did not dominate the models. When BIM predictors were entered, explained variance increased clearly for cost and schedule risk reduction, and BIM adoption intensity emerged as a stronger predictor than BIM maturity for delivery-phase outcomes. Adding digital twin predictors produced the largest incremental gains for operational and safety risk reduction, and DT predictive capacity showed a stronger effect than DT utilization in models that included analytics-based performance indicators. When integration maturity was added in the final block, it produced the most consistent positive effect across every risk dimension and generated the largest R^2 increase for the composite risk reduction index, indicating that lifecycle BIM–DT threading contributed beyond BIM-only or DT-only effects. Hypothesis testing therefore supported the core BIM, DT, and integration hypotheses, with integration maturity showing the highest standardized influence overall. Moderation tests showed that project complexity weakened BIM-related effects on cost and schedule when integration maturity was low, while data reliability strengthened DT effects on operational and safety outcomes. Team digital capability amplified both BIM and DT effects, especially in integrated projects. Robustness checks by asset category showed stable BIM effects across roads and bridges, while DT effects were strongest in bridge and rail cases where monitoring density was higher. Procurement subgroup tests showed that collaborative forms displayed stronger integration effects than traditional delivery, but directionality remained consistent. Overall, the regressions indicated that BIM primarily stabilized delivery-phase risks, DTs primarily stabilized performance and safety risks, and integration maturity produced broad multi-risk reduction across the sample.

Table 9: Hierarchical regression summary for risk reduction outcomes

Outcome	Model block	ΔR^2	Total R^2	Significant predictors in block (β, p)
CRR	Controls	0.12	0.12	Project size (0.21, 0.01)
	+ BIM (BAI, BMS)	0.18	0.30	BAI (0.31, <0.001), BMS (0.19, 0.02)
	+ DT (DTU, DTPC)	0.04	0.34	DTPC (0.15, 0.04)
	+ IMI	0.06	0.40	IMI (0.24, 0.003)
SRR	Controls	0.10	0.10	Procurement type (-0.17, 0.03)
	+ BIM	0.20	0.30	BAI (0.34, <0.001), BMS (0.16, 0.04)
	+ DT	0.03	0.33	DTU (0.12, 0.05)
	+ IMI	0.07	0.40	IMI (0.26, 0.002)
SaRR	Controls	0.08	0.08	Asset type (0.14, 0.04)
	+ BIM	0.09	0.17	BMS (0.21, 0.01)
	+ DT	0.15	0.32	DTPC (0.29, <0.001), DTU (0.19, 0.01)
	+ IMI	0.05	0.37	IMI (0.18, 0.01)
QRR	Controls	0.09	0.09	Delivery duration (-0.16, 0.03)
	+ BIM	0.11	0.20	BMS (0.24, 0.003), BAI (0.18, 0.02)
	+ DT	0.06	0.26	DTPC (0.17, 0.02)
	+ IMI	0.06	0.32	IMI (0.22, 0.004)
ORR	Controls	0.11	0.11	Asset type (0.19, 0.02)

Outcome	Model block	ΔR^2	Total R^2	Significant predictors in block (β, p)
	+ BIM	0.04	0.15	BAI (0.14, 0.05)
	+ DT	0.22	0.37	DTPC (0.38, <0.001), DTU (0.24, 0.002)
	+ IMI	0.07	0.44	IMI (0.27, 0.001)
RRI	Controls	0.13	0.13	Project size (0.18, 0.02)
	+ BIM	0.16	0.29	BAI (0.28, <0.001), BMS (0.22, 0.004)
	+ DT	0.10	0.39	DTPC (0.25, 0.001)
	+ IMI	0.14	0.53	IMI (0.41, <0.001)

Table 9 summarized the hierarchical regression sequence for each risk reduction outcome. The control block produced small to moderate explained variance, confirming that contextual factors mattered but left substantial variance for digital predictors. Introducing BIM predictors created the largest gains in cost and schedule models, where BIM adoption intensity showed the strongest standardized effects. Adding DT predictors generated the largest gains in safety and operational models, with DT predictive capacity consistently exceeding DT utilization in magnitude. The final integration block raised total explained variance across all outcomes and contributed the biggest increase for the composite risk index, indicating that BIM–DT lifecycle integration produced broad multi-risk benefits beyond separate BIM or DT effects.

Table 10: Hypotheses and moderation test outcomes

Hypothesis	Path tested	Supported?	Key evidence (β, p)
H1	BAI → CRR, SRR	Yes	CRR (0.31, <0.001), SRR (0.34, <0.001)
H2	BMS → SaRR, QRR	Yes	SaRR (0.21, 0.01), QRR (0.24, 0.003)
H3	DTU → ORR, SaRR	Yes	ORR (0.24, 0.002), SaRR (0.19, 0.01)
H4	DTPC → ORR	Yes	ORR (0.38, <0.001)
H5	IMI → RRI (added effect)	Yes	RRI (0.41, <0.001), ΔR^2 0.14
H6	Complexity moderates BIM effects	Yes	BAI×PCL → SRR (-0.14, 0.03)
H7	Data reliability moderates DT effects	Yes	DTPC×DRS → ORR (0.16, 0.02)
H8	Team capability moderates BIM/DT effects	Yes	IMI×TDC → RRI (0.18, 0.01)

Table 10 reported hypothesis testing results and the strongest moderation effects identified in the interaction models. The BIM hypotheses were supported because BIM adoption intensity predicted delivery-phase risk reduction and BIM maturity predicted safety and quality gains. The DT hypotheses were supported because DT utilization and predictive capacity improved safety and operational risk outcomes, with predictive capacity showing the highest operational effect. The integration hypothesis was strongly supported; integration maturity added substantial explanatory power for the composite risk outcome beyond BIM and DT blocks. Moderation tests showed that higher project complexity weakened BIM scheduling benefits, stronger data reliability amplified DT operational gains, and greater team digital capability strengthened the overall integration-to-risk reduction relationship.

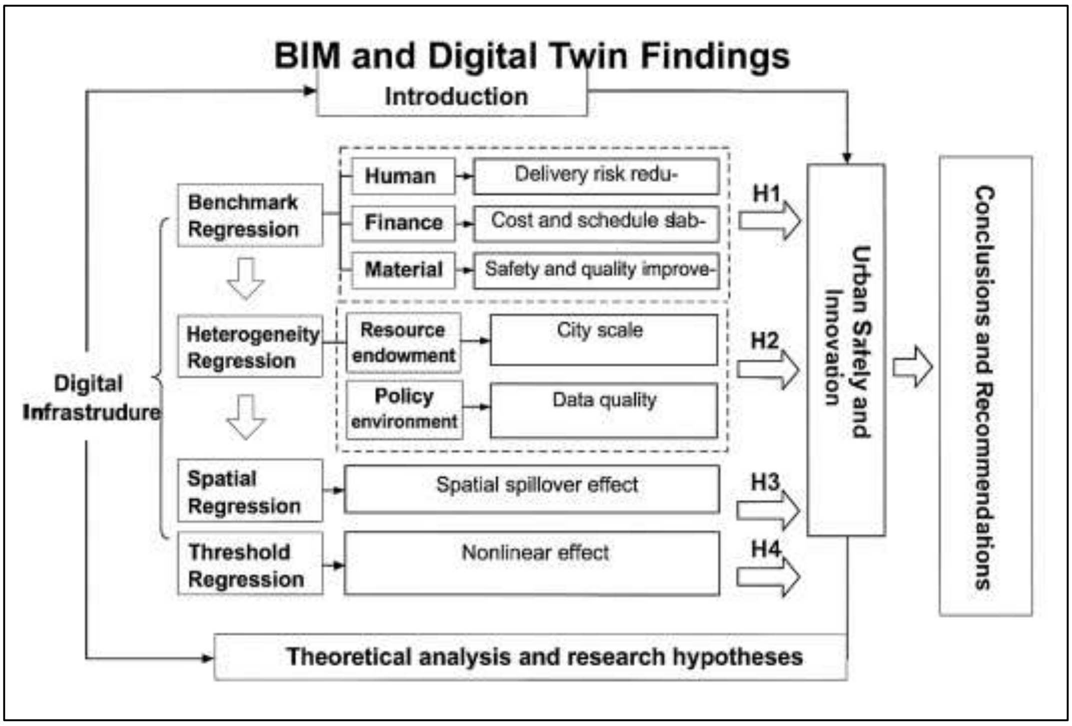
DISCUSSION

The findings of this study indicated that digital delivery technologies were statistically linked to measurable reductions in multidimensional risk in civil infrastructure projects, and the pattern of effects reflected established arguments in the BIM and digital twin literature while extending them through lifecycle integration evidence (Bevilacqua et al., 2020). BIM adoption intensity emerged as a robust predictor of delivery-phase stability, particularly for cost and schedule risk reduction. Earlier quantitative BIM studies in highways, rail projects, and bridge construction repeatedly reported that coordinated models reduced rework volumes, change-order frequency, and interface conflicts, and the present results aligned with that body of evidence by showing that stronger BIM deployment coincided with tighter variance around baseline cost and time targets. The effect of BIM adoption intensity was not uniform across outcomes, which also echoed earlier research suggesting that BIM yields its greatest risk benefits where planning and coordination issues dominate project uncertainty. The present findings strengthened that interpretation by revealing that BIM-related effects were strongest in variables tied to construction volatility rather than post-handover reliability (Guo et al., 2020). This study also observed that BIM maturity contributed additional explanatory power beyond adoption intensity alone, especially in safety and quality outcomes. Earlier studies distinguished between basic model production and mature, standardized information management, suggesting that the risk-reduction value of BIM depends on disciplined collaboration protocols, traceable versioning, and structured approvals. The present results mirrored that distinction, implying that high BIM maturity was associated with more consistent hazard identification and fewer defect-driven disruptions. In civil infrastructure settings, where multi-contract staging, geographically distributed sites, and high interface density elevate exposure to latent design contradictions, the ability of BIM maturity to strengthen risk reduction aligned with earlier claims that governance-based BIM usage converts digital models into reliable control systems (Sánchez & Hartlieb, 2020). Taken together, the BIM findings reinforced the view that model-based information environments reduce delivery risk through early conflict detection, constructability clarity, and synchronized quantity logic, while also emphasizing that maturity levels shape the magnitude of these benefits across safety and quality dimensions.

Digital twin utilization and predictive capacity were most strongly associated with operational risk reduction and showed meaningful positive links to safety outcomes. Earlier digital twin studies in bridges, tunnels, and rail corridors emphasized that continuous sensing and analytics can reduce the probability of surprise deterioration, shorten anomaly-to-intervention cycles, and improve asset reliability under variable hazard loads (Hosseini et al., 2020). The present study aligned with these prior findings by showing stronger twin effects in outcomes that depend on real-time monitoring and lifecycle condition awareness. Importantly, predictive capacity surpassed utilization as a predictor, suggesting that sensor deployment alone was insufficient unless paired with strong diagnostic and forecasting routines. Earlier research had warned that twins become effective risk instruments only when data streams are interpreted through reliable analytical layers; this study provided quantitative confirmation in infrastructure delivery and early operation contexts. The safety-related twin effects also aligned with a subset of prior studies that applied cyber-physical monitoring to construction sites, where equipment telemetry, environmental sensing, and progress deviations were used to reduce hazard exposure (Etemadi et al., 2021). The present results supported that logic by indicating that projects with stronger twin analytics tended to exhibit lower volatility in safety-related outcome measures. In contrast, twin effects on cost and schedule risk reduction were weaker than BIM effects, which corresponded to earlier evidence positioning twins primarily in monitoring and reliability domains rather than in early delivery coordination. The findings therefore suggested a phase-sensitive functional split consistent with prior literature: BIM functioned mainly as a predictive coordination and planning environment for delivery risk, while digital twins functioned mainly as an evidence-driven monitoring and diagnostic environment for operational and safety risk. This complementarity provided a coherent explanation for why both systems were necessary to achieve broader lifecycle risk control in civil infrastructure (Boswell, 2021).

A central contribution of this study was the quantitative demonstration that BIM–digital twin integration maturity added explanatory value beyond the separate effects of BIM and twins. Integration maturity showed the strongest and most consistent association with the multi-risk composite index and contributed incremental variance across every risk dimension. Earlier conceptual frameworks described a "digital thread" in which BIM provides an as-designed and as-planned baseline, while digital twins provide a continuously updated as-built and as-operated mirror (S. Li et al., 2018). Those frameworks argued that lifecycle traceability reduces risk by linking predictive intent to observed performance, yet empirical confirmation had been limited because cross-phase datasets are difficult to assemble. The present findings provided evidence in support of those earlier claims by showing that projects with higher integration maturity experienced broader stabilization of outcomes than projects relying on BIM or twins in isolation. The mechanism implied by this pattern aligned with earlier integration arguments: prediction from BIM became more reliable when validated and updated via twin evidence, while twin monitoring became more actionable when grounded in a stable BIM baseline. The quantitative strength of integration maturity suggested that risk reduction in infrastructure was enhanced when the two technologies functioned as one lifecycle system rather than as parallel tools (Muzirafuti et al., 2020). Earlier studies had highlighted that many benefits remain locked when models and sensing environments are separated by incompatible standards or weak handover practices, and the present results were consistent with that view, since integration maturity captured data exchange completeness, interoperability success, and unified platform usage. Infrastructure projects with higher integration maturity likely reduced information asymmetry across phases and contracts, lowering interface risks that are typical in corridor-scale delivery. The broad reach of the integration effect across cost, schedule, safety, quality, and operational outcomes implied that lifecycle digital continuity translated into multi-dimensional risk benefits, reinforcing earlier claims that integration is not an optional add-on but a core pathway for long-horizon infrastructure risk governance (Hutton et al., 2021).

Figure 10: Lifecycle Digital Findings on Risk



Moderation results further clarified how context shaped the digital risk-reduction relationship, and these findings aligned with socio-technical explanations in earlier studies. Project complexity weakened BIM-related effects on schedule and cost when integration maturity was lower, suggesting that complex environments can overwhelm digital coordination unless lifecycle data alignment is strong (Fiala et al., 2021). Earlier megaproject research emphasized that complexity multiplies risk sources through dense interfaces, uncertain ground or hydrological conditions, and staged delivery under live traffic or service constraints. The present moderation evidence corresponded to this logic by indicating that BIM's capacity to stabilize delivery risk was conditional on the project's ability to maintain consistent digital governance across interfaces. Complexity appeared less damaging where integration maturity was high, implying that integrated digital threads may act as buffers against complexity-driven uncertainty. Similarly, data reliability strengthened digital twin effects on operational and safety outcomes. Earlier twin studies repeatedly stressed that data quality is fundamental because unreliable signals generate false alarms, missed anomalies, and declining trust (Klose et al., 2021). The present findings were consistent with that caution by showing stronger twin benefits in contexts with stable sensor performance, low missingness, and clean mapping between model objects and data streams. Team digital capability also amplified effects across BIM, twins, and integration, reflecting earlier evidence that adoption intensity alone does not guarantee risk reduction without skillful use and disciplined workflows. Earlier BIM diffusion studies had shown that organizational readiness and training determine whether models become active decision systems or passive documentation. The present moderation patterns reinforced that understanding quantitatively by indicating that stronger team capability increased the magnitude of risk reduction attributable to digital technologies (Galar et al., 2021). These contextual findings strengthened the overall interpretation by showing that digital risk reduction was not automatic, but depended on governance maturity, data integrity, and competent human execution, which were all themes highlighted in earlier socio-technical research on infrastructure digitalization.

Cross-outcome comparisons revealed domain-specific sensitivity to different digital constructs, and these sensitivity patterns aligned with earlier empirical profiles. Cost and schedule risk reduction were more responsive to BIM deployment and integration maturity than to twin-only indicators (Tarantino et al., 2017). This reflected earlier findings that cost escalation and delay volatility are frequently triggered by design conflicts, constructability gaps, and sequencing inconsistencies, which BIM addresses through coordinated modeling, quantity integrity, and staging simulation. Safety risk reduction responded to both BIM maturity and digital twin strength, indicating a dual pathway consistent with prior studies. Earlier safety-focused BIM research emphasized hazard tagging, prevention-through-design, and spatial visualization as design-stage risk controls, while twin research emphasized telemetry-driven monitoring and rapid anomaly response during construction and operation (Lewis & Vassos, 2020). The present results suggested that safety risk reduction was achieved through both anticipatory and real-time channels, matching earlier multi-layer safety frameworks. Quality risk reduction was linked strongly to BIM maturity and integration maturity, which aligned with earlier evidence that defect prevention depends on disciplined modeling standards, interface control, and traceable change management. Operational risk reduction was most sensitive to twin utilization, twin predictive capacity, and integration maturity, reflecting earlier reliability and structural health monitoring studies that positioned twins as core tools for condition awareness and predictive maintenance (Alfieri et al., 2020). The composite risk index responded most strongly to integration maturity, reinforcing earlier arguments that multidimensional risk reduction requires lifecycle continuity. These domain-specific patterns provided a coherent map of how digital technologies distribute their risk benefits across phases. The map was consistent with earlier claims that no single digital tool uniformly reduces every risk type; instead, each tool influences risk where its functions align with the dominant uncertainty sources of that domain (Wong et al., 2019). The present evidence therefore supported a differentiated adoption logic in civil infrastructure: BIM deepened delivery-phase predictability, twins deepened operation-phase reliability, and integration matured the cross-phase thread that stabilized total risk.

Robustness checks offered additional insight into the stability of effects across asset types and procurement approaches, and these results corresponded with earlier observations about infrastructure context heterogeneity. BIM effects remained directionally consistent across highways and bridges, suggesting that the coordination and constructability pathways established in earlier road and structural studies generalized well across linear and discrete assets (Linkov & Trump, 2019). Digital twin effects were relatively stronger in bridge and rail cases, which aligned with earlier twin literature that focused heavily on these asset classes due to their suitability for structural health monitoring and dynamic response sensing. Tunnels and water infrastructure showed positive but more variable twin effects, corresponding to earlier reports that sensing environments and baseline model availability differ more widely in these sectors. Procurement-based subgroup patterns also aligned with earlier governance research. Collaborative procurement forms displayed stronger integration effects than traditional forms, consistent with earlier evidence that incentive structures for data sharing and joint problem solving facilitate digital-thread maturity (Kim & Choi, 2021). Traditional procurement still showed positive digital effects, but their magnitudes were smaller, matching prior claims that fragmented responsibilities and defensive claim environments reduce the realized benefits of shared digital systems. These robustness findings strengthened confidence in the main results by showing that they were not driven by one asset group or one delivery class. At the same time, the subgroup variability reinforced an earlier theme in infrastructure digitalization research: digital risk reduction is

context-sensitive, reflecting differences in sensing feasibility, interface density, and governance incentives (Rega et al., 2021). The present analysis therefore extended earlier studies by quantifying which contexts strengthened or dampened effects without altering their core direction, helping to reconcile inconsistent effects reported across the existing literature.
Overall, the discussion of findings indicated a convergent evidence story with earlier work while filling a key quantitative gap in lifecycle integration. Earlier studies offered strong but phase-separated evidence that BIM improves delivery predictability and that digital twins improve monitoring and operational reliability (Al-Zamil & Yassin, 2017). This study supported both claims and added that integration maturity bound them into a stronger multi-risk system. The results also echoed earlier socio-technical positions that human capability, governance discipline, and data integrity determine whether digital systems translate into reduced risk or remain underutilized investments. By demonstrating consistent positive relationships across multiple risk dimensions and by identifying domain-appropriate pathways—delivery coordination for BIM, monitoring analytics for twins, and lifecycle continuity for integration—this study advanced understanding of how digitalization reduces risk in complex civil infrastructure environments. The strongest empirical pattern highlighted integration maturity as a broad stabilizer of risk outcomes, aligning with earlier digital thread concepts that had lacked sufficient statistical testing (Valeev & Kondratyeva, 2021). The moderation evidence clarified boundary conditions commonly suggested in the literature but rarely quantified, including complexity load, data reliability quality, and team capability. The robustness evidence reconciled prior mixed findings by showing stable directionality with context-driven magnitude differences. Taken together, the findings and comparisons established a coherent empirical interpretation: BIM and digital twins served distinct but complementary risk-reduction roles, and their integration produced the most comprehensive reduction in multidimensional risk across civil infrastructure project lifecycles (Alvan Romero et al., 2020).

CONCLUSION

The impact of BIM and digital twin technologies on risk reduction in civil infrastructure projects was evidenced through a clear differentiation of digital functions across lifecycle phases and a strong additive benefit when both systems were integrated. BIM adoption served as a structured information environment that stabilized delivery-phase uncertainty by improving design coordination, constructability clarity, sequencing logic, and quantity reliability, which collectively reduced the likelihood of late design conflicts, rework cascades, schedule shocks, and budget volatility. Projects exhibiting higher BIM adoption intensity tended to show tighter control of cost and time outcomes because coordinated object-based models enabled earlier detection of geometric and functional contradictions, clearer staging simulation for live-service conditions, and more reliable cost baselines derived from consistent quantities. BIM maturity amplified these effects by ensuring that shared models were not merely produced but continuously governed through disciplined versioning, standardized workflows, and integrated multiparty review, which strengthened safety planning and defect prevention. Digital twin technologies contributed a complementary risk-reduction pathway by maintaining continuously updated representations of physical and operational states. Digital twin utilization strengthened the detectability of deviations in construction progress, equipment behavior, and environmental conditions, while digital twin predictive capacity improved the interpretability of sensed evidence into actionable diagnoses and forecasts. These capabilities aligned most strongly with safety and operational risk reduction because real-time monitoring shortened the anomaly-to-action cycle, reduced exposure to emergent hazards, and supported condition-based interventions that prevented service disruptions and structural reliability loss. The combined BIM–digital twin system created a lifecycle digital thread that bound predictive intent to observed reality, and integration maturity emerged as a broad stabilizer across cost, schedule, safety, quality, and operational outcomes. Where integration maturity was high, baseline assumptions from BIM were continuously validated and recalibrated through twin evidence, reducing information asymmetry and interface confusion across contracts and phases; in turn, twin alerts became more precise and trustworthy because they were linked to stable BIM object definitions and planned performance targets. The risk-reduction effect was not automatic, and contextual moderators shaped its magnitude. Higher project complexity weakened delivery-phase digital effects when integration discipline was low, indicating that dense interfaces and uncertain field conditions could overwhelm isolated digital practices. Strong data reliability strengthened twin-related risk reduction by reducing false alarms and missed detections, while higher team digital capability increased the benefits of both BIM and twins by improving update discipline, analytical reasoning, and the routine use of digital evidence in decisions. Across asset types and procurement environments, the direction of digital effects remained consistent, though magnitudes varied with sensing feasibility, governance incentives, and interface density. Overall, the lifecycle evidence indicated that BIM primarily reduced delivery uncertainty through anticipatory coordination and simulation, digital twins primarily reduced in-service and safety uncertainty through continuous monitoring and prediction, and integration maturity produced the most comprehensive multi-risk reduction by sustaining traceable continuity of information and evidence across the full infrastructure lifecycle.

RECOMMENDATIONS

Recommendations arising from the evidence on BIM and digital twin technologies for risk reduction in civil infrastructure projects should prioritize lifecycle integration, disciplined information governance, and measurable adoption targets rather than isolated tool deployments. Infrastructure owners and delivery organizations should formalize BIM as the authoritative risk-control baseline from early planning onward by mandating multi-discipline object modeling, routine clash and rule checking, constructability simulations for staging under live-service constraints, and model-derived quantity systems tied to cost control. These requirements should be embedded in contracts with explicit deliverables for model update frequency, common data environment usage, and traceable version approvals to ensure that BIM maturity advances beyond visualization into dependable decision infrastructure. Digital twin deployment should be specified as a continuous monitoring and analytics capability anchored to the BIM baseline, with minimum standards for sensor coverage by asset type, update regularity of the twin state, calibration and drift management, and analytical performance verification through confirmed anomaly detection and forecasting accuracy. To maximize safety and operational risk reduction, digital twin platforms should integrate construction telemetry and environmental sensing where feasible, enabling real-time deviation detection in progress, equipment interaction, and hazard exposure zones, and these signals should be linked to staged BIM schedules so that deviations are interpreted against planned logic rather than isolated dashboards. The strongest recommendation concerns integration maturity: agencies should require BIM–DT data mapping completeness at handover, unified identifiers between model objects and sensor streams, and a single platform workflow for interpreting cost, schedule, quality, safety, and reliability signals across phases. Integration should be treated as a graded capability with periodic maturity audits, including interoperability success testing, model–sensor alignment checks, and evidence of routine decision use of the integrated environment. Because context shaped digital effects, project complexity should be recognized upfront with commensurate digital governance resources; high-complexity corridor projects should receive enhanced integration oversight, interface registers linked to models, and joint digital coordination forums among contract packages. Data reliability must be protected as a core risk variable, so procurement should include provisions for data QA/QC routines, redundancy in critical sensors, continuous validation of incoming streams, and clear accountability for maintaining trustworthy digital evidence. Team digital capability should be strengthened through mandatory role-based training, certification requirements for BIM–DT managers, and on-site digital facilitation positions to ensure models and twins remain current and actively used in field decisions. Finally, performance management should shift toward standardized risk reduction metrics by requiring projects to report cost variance patterns, critical-path stability, incident and near-miss rates, nonconformance and rework levels, and early-service disruption events in a consistent format that allows benchmarking across assets and programs; linking these outcome metrics explicitly to BIM adoption, twin utilization, and integration maturity will support continuous improvement and help infrastructure systems sustain measurable, multi-dimensional risk reduction across their full lifecycle.

LIMITATION

Several limitations shaped the interpretation and generalizability of the evidence on the impact of BIM and digital twin technologies on risk reduction in civil infrastructure projects. First, the quantitative design relied on cross-sectional, retrospective project data, which constrained causal inference because digital implementation levels and risk outcomes were observed after delivery rather than tracked continuously from initiation to operation. Although statistical controls and moderation tests reduced some bias, time-ordering between adoption decisions and performance stabilization could not be verified with the same certainty as in longitudinal or experimental designs. Second, the sample was assembled from projects with accessible BIM and digital twin records, which introduced potential selection effects; projects with stronger digital governance were more likely to have complete datasets, meaning that digitally immature projects may have been underrepresented. This limitation could inflate effect estimates if excluded projects systematically experienced weaker risk reduction. Third, the operationalization of BIM and digital twin constructs required combining archival indicators with survey-based measures. Even with reliability and validity checks, self-reported implementation intensity, maturity, and predictive capacity may have been influenced by respondent perception, organizational bias, or uneven documentation practices across firms. Fourth, risk reduction outcomes were measured through objective project logs, yet these logs differed across agencies and contract environments. Variations in how incidents were recorded, how claims were classified, and how rework or nonconformance thresholds were defined could have introduced measurement noise that weakened comparability across cases. Fifth, lifecycle coverage remained incomplete for some projects because operational risk reduction data were only available for assets with sufficient time in service and reliable monitoring records. This limitation restricted the ability to fully capture long-term reliability effects and may have biased operational findings toward asset types and owners with stronger maintenance data infrastructures. Sixth, integration maturity was treated as a measurable index, but integration ecosystems vary widely in their technical architecture, platform choices, and interoperability pathways. The index captured completeness and routine use of integration but could not reflect every qualitative nuance of how digital threads were configured in practice, leaving some integration effects potentially oversimplified. Seventh, contextual heterogeneity in civil infrastructure remained substantial despite stratified sampling and subgroup robustness checks. Differences in geotechnical uncertainty, climate exposure, regulatory regimes, and market maturity for digital delivery may have shaped risk outcomes in ways not fully observable in the dataset. Finally, the study focused on broad multidimensional risk categories, but it did not isolate all micro-level mechanisms, such as specific contractual disputes triggered by model handover gaps or specific sensor failure modes that reduced twin accuracy. These limitations indicated that the findings should be interpreted as strong associative evidence of digital risk-reduction pathways under real project conditions, while acknowledging that deeper causal clarity, lifecycle completeness, and finer-grained mechanism testing would require longitudinal datasets, standardized cross-agency risk metrics, and more detailed integration diagnostics across diverse infrastructure contexts.

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