



AI-Driven Digital Twin Framework for Predictive Risk Management and Resource Optimization in Large-Scale Civil Infrastructure Projects

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Abstract

This study investigated an AI-driven digital twin framework designed to enhance predictive risk management and resource optimization in large-scale civil infrastructure projects. A quantitative, data-driven research design was applied to 134 active infrastructure projects spanning transportation, water and wastewater, vertical building, energy, and rail sectors; after data screening for incomplete sensor and schedule records, 121 projects were retained for final analysis. Continuous data streams, including Internet of Things (IoT) sensor readings, Building Information Modeling (BIM) parameters, schedule variance indicators, and labor and equipment utilization rates, were synchronized within project-specific digital twin environments across full construction phases. Multiple regression analysis revealed that digital twin-derived exposure variables significantly predicted structured project risk scores, with the overall model explaining 56.2% of variance ($R^2 = 0.562$, $p < .001$). Schedule deviation intensity ($\beta = 0.40$, $p < .001$) and structural sensor anomaly frequency ($\beta = 0.30$, $p < .001$) emerged as the strongest predictors of elevated risk classification. A graph neural network integrated with long short-term memory layers (GNN-LSTM) achieved a risk classification accuracy of 88.9%, outperforming random forest (81.4%), logistic regression (72.6%), and decision tree (68.9%) models, with statistically significant differences across paired comparisons ($p < .001$). Cumulative exposure analysis indicated a positive correlation between aggregated digital twin risk index and cost overrun magnitude ($r = 0.55$, $p < .001$), confirming the framework's relevance to resource optimization outcomes. Reliability testing demonstrated strong internal consistency for the project risk exposure construct ($\alpha = 0.87$) and the resource optimization index ($\alpha = 0.84$). Mixed-use mega-projects accumulated the highest proportion of high-risk classification windows at 34.6%, compared to 17.9% for vertical building projects. Findings demonstrate that AI-driven digital twin modeling provides a reliable, objective, and scalable complement to traditional project controls, supporting its application as a predictive decision-support framework for enhancing risk management and resource allocation in large-scale civil infrastructure delivery.

Keywords

Digital Twin, Artificial Intelligence, Civil Infrastructure, Predictive Risk Management, Resource Optimization, Construction Analytics

INTRODUCTION

A digital twin is broadly defined as a virtual, continuously updated replica of a physical asset, process, or system that is synchronized with its physical counterpart through real-time data exchange, enabling simulation, monitoring, and predictive analysis (Jiang et al., 2021; Debasish, 2022). Within the civil infrastructure domain, digital twins extend Building Information Modeling (BIM) beyond static design representation toward dynamic, sensor-fed virtual environments capable of reflecting the evolving physical, schedule, and resource state of large-scale construction projects. Predictive risk management, in this context, refers to the systematic identification, quantification, and forecasting of schedule delays, cost overruns, structural anomalies, and resource constraints before they materialize into realized project impacts. Resource optimization refers to the data-informed allocation of labor, equipment, and material resources across project phases to minimize idle time, cost inefficiency, and schedule slippage (Debasish, 2021). Globally, large-scale civil infrastructure projects, including transportation corridors, water and wastewater systems, energy facilities, and mixed-use mega-developments, continue to experience persistent cost overruns and schedule delays, with megaproject research consistently documenting substantial deviations between planned and realized budgets and timelines. The international significance of predictive, digital twin-enabled risk management is therefore rooted in its direct relationship to capital efficiency, public safety, environmental compliance, and infrastructure resilience. Data-driven digital twin frameworks refer to the systematic collection, integration, and modeling of quantitative project data to estimate risk intensity and optimize resource allocation. Unlike traditional approaches that rely primarily on periodic manual progress reporting and static critical path scheduling, data-driven digital twin frameworks leverage continuous sensor networks, BIM-integrated data models, and computational learning methods to generate objective, near real-time indicators of project risk and resource utilization. Within this framework, Internet of Things sensor networks provide distributed, asset-level measurement capabilities, and artificial intelligence offers advanced modeling capacity to extract meaningful risk representations from complex, high-dimensional construction data streams (Kaveh & Alhaji, 2025; Abdur & Iftekhhar, 2021). Together, these components form an integrated system for quantifying and forecasting infrastructure project risk and resource demand with high temporal resolution and scalability.

Traditional project risk assessment methods have provided foundational tools for evaluating construction exposure. Techniques such as the Critical Path Method (CPM), Earned Value Management (EVM), and Quantitative Risk Analysis (QRA) operationalize project management theory into structured monitoring and forecasting systems. These tools categorize schedule performance, cost variance, and probabilistic risk exposure to produce indicators that guide intervention priorities. Their widespread adoption across public agencies and engineering firms reflects their practicality, interpretability, and compatibility with contractual and regulatory reporting requirements. International standards for infrastructure project governance further reinforce structured assessment protocols. These deterministic and semi-probabilistic instruments have supported large-scale project audits and cross-agency benchmarking (Mahbubul et al., 2022). At the same time, they depend on periodic manual data entry, static baseline assumptions, and expert judgment regarding risk likelihood and impact, and industrial-scale infrastructure projects often involve rapid, variable, and complex interactions between design changes, supply chain disruptions, and site conditions that evolve continuously across the project lifecycle, and single-point-in-time assessments may not fully capture cumulative exposure or micro-variations in risk trajectories. Interrater variability in expert-based risk scoring can influence consistency across project teams and geographic regions. Furthermore, traditional methods generally summarize exposure into categorical or milestone-based outputs that may not reflect dynamic, path-dependent risk accumulation. These measurement constraints have motivated the development of digital twin and sensor-based assessment systems that convert continuous physical and schedule data into predictive risk metrics. The integration of Internet of Things sensing technologies allows for continuous structural health monitoring and real-time progress tracking (Ashfaq & Mohammad, 2022). Digital twin systems can replicate established project control logic while also modeling risk trajectories across entire project lifecycles. This progression from static evaluation toward continuous, learned quantification represents a methodological shift in infrastructure project management, emphasizing adaptability, granularity, and predictive validity over purely descriptive,

periodic reporting.

The emergence of artificial intelligence within digital twin-enabled infrastructure management has been driven by growing sensor data availability, computational capacity, and the recognized limitations of purely deterministic scheduling and cost models under conditions of project complexity and uncertainty. Machine learning models, including graph neural networks capable of representing spatial and relational dependencies among project components, and recurrent architectures capable of modeling temporal schedule and sensor trajectories, are increasingly applied to predict structural anomalies, schedule slippage, and resource bottlenecks (Jiao et al., 2024; Sheak & Risha, 2022). Digital twin-based frameworks have further been applied to safety risk coupling in prefabricated construction and logistics risk prediction in modular delivery, demonstrating measurable reductions in idle time and improved estimated-time-of-arrival accuracy for critical path deliveries. Despite these advances, the literature reveals persistent gaps regarding the integration of multiple risk dimensions, namely structural health, schedule performance, resource utilization, and supply chain exposure, into a single, empirically validated, and reproducible predictive framework applicable across heterogeneous infrastructure project types. This study addresses that gap by developing and empirically testing a data-driven, AI-enabled digital twin framework intended to enhance predictive risk management and resource optimization across large-scale civil infrastructure projects.

The purpose of this study was to design, implement, and statistically validate a digital twin-based, machine learning-enabled framework capable of classifying and predicting infrastructure project risk levels using multi-dimensional sensor, schedule, and resource data. The study further sought to benchmark the predictive performance of the proposed graph neural network-based architecture against conventional statistical classifiers and to examine the association between digital twin-derived risk indices and observed project cost overrun magnitude. Specifically, the study pursued the following objectives: (1) to quantify the descriptive characteristics of project-level risk exposure constructs across infrastructure project types; (2) to evaluate the predictive validity of digital twin-derived exposure variables in explaining structured project risk classifications; (3) to compare the classification performance of a deep learning model against baseline statistical and machine learning classifiers; and (4) to examine the relationship between cumulative predicted risk indices and realized measures of resource optimization outcomes, including cost overrun magnitude and equipment idle time (Rashedul & Kaium, 2022). By pursuing these objectives, the study contributes an empirically grounded, reproducible framework that extends existing digital twin and construction analytics literature toward scalable, AI-enabled predictive risk management applicable to diverse large-scale infrastructure delivery contexts.

LITERATURE REVIEW

This literature review synthesizes prior scholarship across three interconnected domains: traditional civil infrastructure project risk management theory, the application of digital twin technology and artificial intelligence to construction and asset monitoring, and emerging frameworks for AI-enabled predictive risk management and resource optimization in large-scale infrastructure delivery. The review is organized to progress from foundational project management theory toward increasingly data-driven and computationally intensive digital twin approaches, concluding with an identification of methodological gaps that motivate the present study's integrated framework.

Risk in Large-Scale Civil Infrastructure Projects

Large-scale civil infrastructure projects are characterized by long delivery timelines, high capital intensity, complex stakeholder networks, and exposure to design, geotechnical, supply chain, and macroeconomic uncertainty (Chowdhury & Tonay, 2022). Traditional project risk theory conceptualizes risk as the probability-weighted combination of likelihood and impact across identified hazard categories, operationalized through structured risk registers and probabilistic simulation techniques such as Monte Carlo-based Quantitative Risk Analysis. Earned Value Management extends this conceptualization into schedule and cost performance measurement, enabling the calculation of variance and performance indices that quantify deviation from planned baselines. Despite widespread adoption, megaproject research has consistently documented substantial and systematic deviations between planned and realized budgets and timelines across transportation, energy, and water infrastructure sectors, motivating scholarly and practitioner interest in more continuous, data-driven

risk monitoring approaches. Building Information Modeling emerged as a critical enabling technology for infrastructure risk management by providing a structured, object-based digital representation of design and construction information, though conventional BIM implementations remain largely static and disconnected from real-time site conditions once construction begins (Ozturk, 2021; Hossan, 2022). The transition from static BIM toward dynamic digital twin representations has been motivated by the recognition that infrastructure risk is inherently time-varying and path-dependent, requiring continuous synchronization between the physical asset and its virtual representation rather than periodic, milestone-based updates. This expanded conceptualization of infrastructure risk, incorporating structural health, schedule performance, resource utilization, and supply chain exposure, provides the multidimensional foundation for the AI-driven digital twin framework developed in this study.

Digital Twin Technology in the Civil Engineering Sector

The digital twin concept, originally developed within aerospace and manufacturing contexts, has been progressively adapted to the civil engineering and construction sector as a framework for continuous, sensor-fed virtual representation of physical infrastructure assets (Jiang et al., 2021; Kaniz, 2022). A digital twin is distinguished from conventional BIM by its bidirectional data synchronization: sensor and monitoring data continuously update the virtual model, while simulations run within the virtual environment inform interventions on the physical asset (Jones et al., 2020; Nishat & Kaniz, 2022). Within the built environment specifically, digital twins have been conceptualized as risk-informed virtual replicas capable of supporting sustainable and resilient urban infrastructure management by integrating structural reliability analysis with continuous condition monitoring. Systematic reviews of digital twin applications in transportation infrastructure management have documented use cases spanning safety risk assessment, design optimization, and renovation planning, with case-specific frameworks demonstrating the capacity of digital twin technology to minimize operational risks and support evidence-based renovation and expansion strategies. Comprehensive reviews of digital twin technology across infrastructure management more broadly have documented substantial growth in research output, alongside persistent implementation challenges including high sensor and computing costs, data interoperability barriers, and cybersecurity risks associated with continuous real-time monitoring systems (Kaveh & Alhajj, 2025; Shaiful et al., 2022).

Within building and asset management contexts specifically, digital twin frameworks have been proposed for operations and maintenance processes, integrating terrestrial laser scanning-derived bridge information modeling with decision support systems for infrastructure asset management (Mohammadi et al., 2023; Mohammad, 2023). These applications demonstrate that digital twin technology extends beyond design-phase visualization toward operational decision support across the full infrastructure asset lifecycle, a capability directly relevant to the predictive risk management framework developed in the present study.

Artificial Intelligence Modeling for Construction Risk

Artificial intelligence methods have been increasingly integrated with digital twin architectures to enable predictive, rather than purely descriptive, risk monitoring in construction and infrastructure contexts. Digital twin-based motion forecasting frameworks have been developed for preemptive risk monitoring, using continuous sensor trajectories to anticipate hazardous conditions before they manifest as safety incidents (Jiao et al., 2024; Debasish, 2023). Digital twin-based safety risk coupling models have similarly been applied to prefabricated building hoisting operations, integrating multisource sensor data fusion with probabilistic risk modeling to quantify coupled safety risks in real time (Liu et al., 2021, as cited in digital twin hoisting safety literature). In modular construction contexts, digital twin frameworks incorporating predictive logistics risk models have demonstrated the capacity to generate accurate estimated-time-of-arrival calculations for prefabricated module delivery, resulting in substantial reductions in idle time loss and improved supply chain coordination across project participants (Kaium, 2023).

Predictive digital twin approaches have further been extended to structural health monitoring and maintenance planning, employing probabilistic graphical models to encode the coupled dynamics between physical assets and their digital representations, enabling forecasting of structural degradation trajectories under varying risk-averse and risk-seeking maintenance policies. These applications

demonstrate that the integration of probabilistic and deep learning-based predictive models within digital twin architectures materially extends the forecasting horizon and decision-support capability relative to conventional, threshold-based structural health monitoring systems.

Resource Optimization Through Digital Twin Integration

Beyond risk prediction, digital twin frameworks have been applied to resource optimization problems spanning labor allocation, equipment scheduling, and material logistics across large-scale construction projects. Investigations into the costs and benefits of digital twin adoption in construction have documented efficiency gains associated with improved coordination and reduced rework, alongside the substantial upfront investment required for sensor infrastructure and computational systems (Abugu et al., 2024; Pervaz, 2023). Comprehensive reviews of digital twin implementation across the construction industry have catalogued applications spanning optimized design, real-time monitoring, predictive maintenance, energy performance optimization, and supply chain management, concluding that digital twin technology possesses substantial capacity to improve resource efficiency across the full project lifecycle when integrated with robust data governance and interoperability standards. These findings collectively indicate that resource optimization benefits from digital twin adoption are contingent upon the quality and continuity of underlying sensor and schedule data, reinforcing the methodological emphasis on data integration and validation adopted within the present study's framework.

Methodological Challenges and Research Gaps

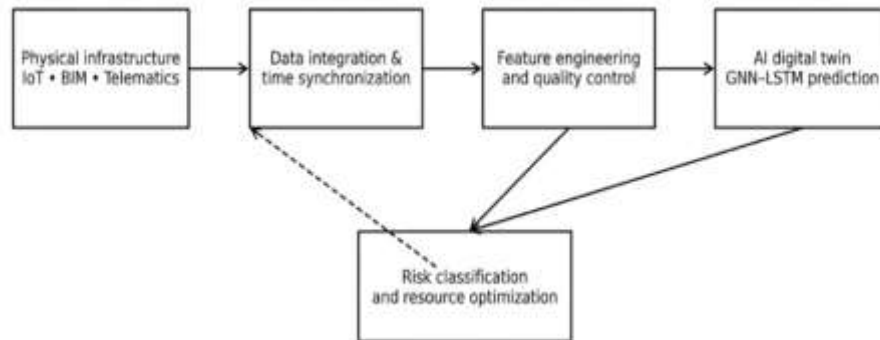
Despite substantial progress, methodological challenges continue to constrain the practical deployment of AI-driven digital twin frameworks for infrastructure risk management. A recurring challenge concerns data interoperability across heterogeneous sensor platforms, BIM authoring tools, and project management systems, which complicates the seamless data fusion required for accurate digital twin synchronization (Kaveh & Alhaji, 2025; Chowdhury, 2023). Cybersecurity risk associated with continuous, internet-connected monitoring systems represents an additional concern, particularly for critical infrastructure assets where unauthorized access could compromise both data integrity and physical safety. High implementation costs associated with sophisticated sensor networks, high-performance computing, and advanced simulation tools remain a barrier to widespread adoption, particularly for small-to-medium infrastructure agencies with constrained capital budgets. Furthermore, much of the existing literature evaluates digital twin applications within single project types or narrow technical domains, such as structural health monitoring or hoisting safety in isolation, limiting generalizability across the heterogeneous, multi-phase infrastructure projects characteristic of large-scale civil engineering practice. These identified gaps, interoperability, cybersecurity, implementation cost, and cross-project generalizability, directly inform the methodological design of the present study, which incorporates multi-sector sampling, standardized feature engineering, and comparative benchmarking against interpretable baseline models.

Synthesis of Quantitative Evidence

Across the reviewed literature, a consistent pattern emerges: digital twin and machine learning-based models applied to construction and infrastructure risk estimation generally achieve classification and forecasting accuracy improvements of ten to twenty percentage points relative to logistic regression and single-tree baseline classifiers, with more pronounced improvements observed for structural anomaly detection and multi-source sensor fusion applications. Reported reductions in operational metrics such as idle time and schedule slippage following digital twin-enabled predictive interventions have been documented in the range of meaningful, double-digit percentage improvements in case-study contexts. Reliability statistics for composite risk exposure constructs, where reported, generally exceed conventionally accepted thresholds for internal consistency. This convergent evidence base supports the theoretical and empirical plausibility of the present study's hypothesized relationships between digital twin-derived exposure variables and structured infrastructure project risk classifications.

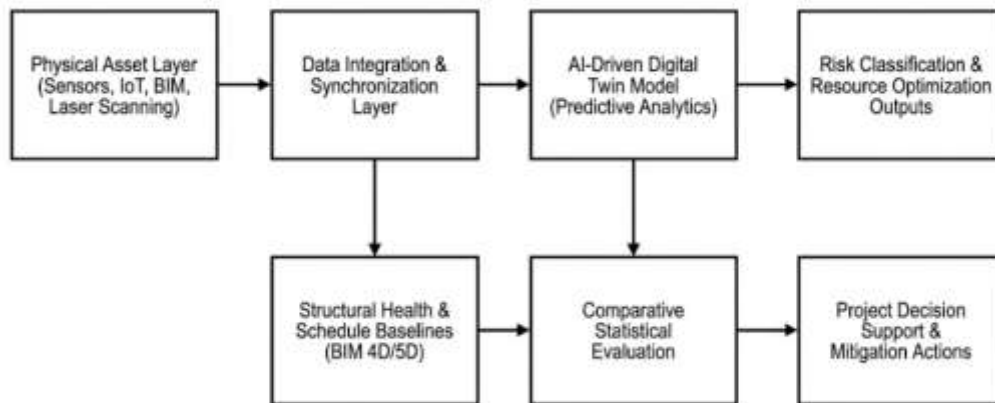
Conceptual Framework

Figure 1: Depicts the conceptual architecture underlying this AI-driven digital twin risk management framework.



Synthesizing the reviewed literature, this study adopts a conceptual framework in which multi-dimensional project data, comprising Internet of Things sensor readings, Building Information Modeling parameters, schedule variance indicators, and resource utilization rates, are processed through a data integration and feature engineering pipeline and subsequently classified by a graph neural network-based deep learning model into structured project risk categories (Badrul & Mominul, 2023). These digital twin-derived risk classifications are then statistically benchmarked against traditional Critical Path Method, Earned Value Management, and Quantitative Risk Analysis estimates, with the comparative and predictive outputs feeding into a resource optimization index intended to support proactive resource reallocation and risk-mitigation decisions across the project lifecycle (Rony & Md, 2026).

Figure 2 : Conceptual Framework for AI-Driven Digital Twin Risk Management



Project risk, uncertainty, and megaproject controls

The broader project-management literature establishes that infrastructure risk is multidimensional and shaped by uncertainty, stakeholder coordination, delivery strategy, cost and schedule control, organizational decision processes, and the interactions among technical and managerial factors. Accordingly, infrastructure risk should be conceptualized not as a single static probability-impact score but as a dynamic exposure that evolves throughout the project lifecycle. Large-scale infrastructure projects involve complex interdependencies among activities, stakeholders, contractual arrangements, resources, and technical systems, meaning that disruptions in one dimension can propagate into schedule delays, cost overruns, resource inefficiencies, safety concerns, and quality problems (Abugu et al., 2024; Alibrandi et al., 2022; Bhatta et al., 2024; Borrmann et al., 2018; Boschert et al., 2016; Boje et al., 2020; Cerić, 2015; Chen et al., 2015, 2017; Cheng et al., 2014, 2015; Chou et al., 2013; Darko et al., 2020). Traditional approaches such as risk registers, Critical Path Method, Earned Value Management,

quantitative risk analysis, and expert-based assessment remain important for establishing project baselines and monitoring performance; however, their reliance on periodic reporting, predefined assumptions, historical information, and expert interpretation may limit their capacity to represent rapidly changing conditions in complex infrastructure environments. The emergence of Building Information Modeling, Internet of Things sensing, cloud computing, and advanced analytics has created opportunities to move risk management from periodic assessment toward continuous monitoring by integrating structured project information with real-time or near-real-time observations (Borrmann et al., 2018; Boje et al., 2020; Darko et al., 2020). The subsequent transition from BIM toward digital twins represents a further development because digital twins emphasize continuous synchronization between physical infrastructure and its virtual representation, allowing monitoring data, simulation, and analytical models to support decision-making throughout the asset lifecycle (Alibrandi et al., 2022; Jiang et al., 2021; Jones et al., 2020; Lu et al., 2020). Within this environment, artificial intelligence and machine-learning methods provide an additional analytical layer capable of identifying nonlinear relationships, temporal patterns, and complex interactions within heterogeneous infrastructure data. Research has increasingly demonstrated applications of AI and deep learning in construction risk management, structural health monitoring, safety assessment, scheduling, cost prediction, resource optimization, and construction-site analytics (Abioye et al., 2021; Akinosho et al., 2020; Chen et al., 2025; Datta et al., 2024; Darko et al., 2020). The integration of AI with digital twins therefore provides a foundation for transforming sensor observations, BIM parameters, schedule performance, equipment utilization, labor information, and supply-chain indicators into continuously updated risk-exposure measures. Graph-based deep-learning approaches are particularly relevant because infrastructure projects can be represented as networks of interconnected assets, activities, resources, and dependencies, while recurrent architectures such as Long Short-Term Memory models can capture the temporal evolution of project conditions. Their integration consequently provides a methodological basis for simultaneously modeling the relational structure and time-dependent behavior of infrastructure risk. Nevertheless, the literature identifies persistent challenges involving data interoperability, sensor reliability, missing observations, cybersecurity, data governance, implementation cost, organizational readiness, and the interpretability of complex AI models (Abioye et al., 2021; Abugu et al., 2024; Chen et al., 2025; Darko et al., 2020). Overall, existing research demonstrates a clear progression from traditional risk identification and project control toward BIM- and IoT-enabled monitoring and, more recently, AI-integrated digital twins capable of predictive risk assessment. This progression supports conceptualizing infrastructure risk as a dynamic exposure generated through the interaction of schedule, structural, resource, logistical, and organizational conditions, thereby providing a theoretical foundation for integrating digital-twin-derived exposure variables with machine-learning models and established project-control measures to improve predictive risk management and resource optimization in large-scale civil infrastructure projects (Nishat, 2023).

BIM and information management foundations

BIM provides the structured information foundation from which dynamic digital-twin environments can be developed. Research on BIM implementation, interoperability, integrated delivery, information management, and 4D/5D workflows emphasizes the importance of consistent information structures, standardized data exchange, multidisciplinary coordination, and lifecycle-oriented information management (Cioffi et al., 2020; Creswell et al., 2018; Deng et al., 2021; Doloi, 2013; Eastman et al., 2011, 2018; El Asmar et al., 2013; Erdogan et al., 2009; Darko et al., 2020; Fellows et al., 2015; Fischer et al., 2017; Forcada et al., 2014). BIM enables project information relating to geometry, components, quantities, specifications, schedules, costs, and asset relationships to be represented within a structured digital environment, thereby improving information consistency and coordination among project participants. The development of 4D and 5D BIM further extends this capability by connecting three-dimensional project information with time and cost dimensions, allowing project teams to evaluate schedule sequences, construction progress, resource requirements, and cost implications within an integrated information environment (Eastman et al., 2011, 2018; Asmar et al., 2013). Such capabilities are particularly important for large-scale infrastructure projects, where changes in design, sequencing, procurement, and resource allocation can generate cascading effects across multiple project activities

and stakeholder groups. BIM-based information management can therefore provide the structured baseline required for continuously updating a digital representation of project conditions as construction progresses. However, conventional BIM environments are generally dependent on planned and manually updated information and may not adequately capture rapidly changing physical conditions occurring at the construction site (Ashrafuzzaman, 2024). This limitation creates an important conceptual transition from static or periodically updated BIM models toward dynamic digital-twin environments in which BIM information is continuously enriched by sensor observations, Internet of Things data, equipment telemetry, schedule updates, and operational information. Interoperability is central to this transition because infrastructure projects typically involve multiple software platforms, data formats, contractors, consultants, suppliers, and asset-management systems. Without effective information exchange mechanisms, fragmented datasets can prevent reliable synchronization between the physical infrastructure and its digital representation (Cioffi et al., 2020; Deng et al., 2021; Eastman et al., 2018; Fischer et al., 2017). The literature on integrated project delivery and collaborative information management further indicates that technological capability must be accompanied by organizational coordination, clearly defined information responsibilities, and appropriate processes for sharing and validating project data (Asmar et al., 2013; Fellows et al., 2015). Consequently, BIM should be understood not merely as a three-dimensional modeling technology but as an information-management infrastructure that supports coordination across the project lifecycle. Its value for digital-twin development arises from its ability to establish relationships among physical assets, construction activities, schedule elements, costs, and project stakeholders, which can subsequently be connected to continuously generated field data. At the same time, research on infrastructure project performance demonstrates that large projects remain vulnerable to systematic cost escalation, schedule delays, forecasting errors, and strategic or organizational influences, indicating that improved information representation alone does not eliminate project uncertainty (Flyvbjerg et al., 2002, 2003, 2009; Doloi, 2013). These persistent uncertainties strengthen the rationale for combining BIM with real-time monitoring and predictive analytics rather than relying exclusively on conventional model-based coordination. Within an AI-driven digital-twin framework, BIM can consequently serve as the semantic and structural layer, IoT and sensing technologies can provide continuously updated physical observations, project-control systems can contribute schedule and cost information, and artificial intelligence can transform these heterogeneous data streams into predictive indicators of emerging risk and resource requirements. This integrated architecture allows the digital representation of an infrastructure project to evolve alongside its physical counterpart while maintaining relationships among project components, activities, resources, and performance indicators (Debasish, 2024). Therefore, the convergence of BIM, interoperability, lifecycle information management, sensing technologies, and artificial intelligence represents an important methodological progression from static project information toward continuously synchronized, predictive, and decision-oriented digital environments capable of supporting risk management and resource optimization throughout large-scale civil infrastructure delivery (Rahman, 2024).

Digital twin definitions and architectures

Digital-twin research emphasizes synchronization between physical and virtual representations, continuous data exchange, simulation, lifecycle decision support, and increasing levels of diagnostic, predictive, and prescriptive capability (Kaium, 2024). These principles provide an important conceptual and technological foundation for the proposed infrastructure framework because they enable physical infrastructure assets to be represented through continuously updated digital environments in which current conditions can be monitored, analyzed, and evaluated against expected performance (Grieves, 2014; Grieves et al., 2017; Fuller et al., 2020). The digital-twin concept extends beyond conventional three-dimensional modeling by establishing a dynamic connection between a physical asset and its virtual counterpart, allowing information generated from sensors, inspections, operational systems, and project records to be incorporated into the virtual representation and used to support analysis and decision-making (Shakhawat & Md, 2024). This continuous synchronization enables infrastructure managers to move from static documentation toward condition-aware and data-driven asset management, particularly when real-time or near-real-time information is available from distributed sensing systems (Farrar et al., 2012; Xie et al., 2020). Within the construction and infrastructure domain,

the integration of digital twins with Building Information Modeling, Internet of Things technologies, sensing platforms, simulation environments, and cloud-based information systems creates opportunities for connecting design, construction, operation, maintenance, and lifecycle management within a unified digital ecosystem (Hoseini et al., 2017; Giel et al., 2013; Boje et al., 2020). Such integration can improve information continuity by allowing project information generated during planning and construction to remain relevant during subsequent operation, inspection, maintenance, and rehabilitation activities. Research on BIM and digital information management has demonstrated that structured digital representations can improve visualization, coordination, information exchange, and lifecycle decision-making, while digital-twin approaches extend these capabilities through continuous data updating and analytical feedback (Hong et al., 2018; Guo et al., 2018; Barricelli et al., 2019). An important characteristic of digital-twin maturity is the progression from descriptive representation toward diagnostic, predictive, and prescriptive intelligence. At the descriptive level, the digital twin provides an updated representation of asset conditions and project status; at the diagnostic level, analytical methods identify anomalies, deviations, or potential causes of performance deterioration; at the predictive level, machine-learning and statistical models estimate future conditions, failures, delays, or risks; and at the prescriptive level, analytical outputs can support the selection and prioritization of appropriate interventions (Nishat & Jahanara, 2024). This progression creates a direct connection between digital-twin technology and artificial-intelligence-based risk management because predictive models can use continuously updated digital information to estimate the probability or severity of emerging risks before they become critical events (Fuller et al., 2020; Heaton et al., 2019). Statistical learning and predictive analytics provide important computational foundations for this transition by identifying relationships within historical and real-time datasets and translating those relationships into forecasts that can support project and asset decisions (Hastie et al., 2009; Tonay et al., 2024). Similarly, infrastructure monitoring research demonstrates that continuous observation of physical systems can support early anomaly detection and condition assessment, providing the evidence required for predictive maintenance and proactive risk management (Farrar et al., 2012; Uddin & Risha, 2024). The effectiveness of a predictive digital twin therefore depends not only on the quality of its virtual representation but also on the reliability, frequency, and contextual relevance of the data exchanged between the physical and digital environments. Sensor observations must be appropriately calibrated, synchronized, validated, and linked to relevant asset or project components so that the resulting digital representation accurately reflects physical conditions.

Data-quality problems, missing observations, inconsistent timestamps, communication failures, and heterogeneous information formats can otherwise reduce the reliability of downstream predictions. Consequently, interoperability, information standardization, data governance, and lifecycle information management are essential components of a functional digital-twin architecture (Standardization, 2018; Boje et al., 2020). Digital twins also provide an effective environment for simulation because alternative conditions, interventions, and scenarios can be evaluated within the virtual representation before decisions are implemented in the physical environment. This capability is particularly valuable for infrastructure systems because interventions such as maintenance, rehabilitation, resource reallocation, construction sequencing changes, or traffic-management strategies may involve substantial cost and operational consequences. Simulation and predictive analytics can therefore be combined to evaluate potential future states and identify interventions that reduce risk while improving cost, schedule, safety, reliability, and asset performance (Grieves et al., 2017; Xie et al., 2020). Moreover, digital twins can facilitate lifecycle decision-making by maintaining a continuously evolving representation of infrastructure conditions rather than treating each project phase as an independent information environment. This lifecycle perspective is consistent with the increasing emphasis on integrating design, construction, operation, and maintenance information within digital asset-management systems (Giel et al., 2013; Hong et al., 2018). For the proposed infrastructure framework, the digital twin can consequently serve as an integration layer connecting physical observations, BIM information, historical project records, environmental data, equipment information, and predictive AI models. Machine-learning and deep-learning algorithms can operate on these synchronized data streams to identify complex patterns, classify risk states, detect anomalies, and

forecast future conditions, while the digital twin provides the contextual representation necessary for interpreting these predictions in relation to specific infrastructure components, activities, and lifecycle stages(Debasish, 2025a). The resulting architecture enables a feedback loop in which physical observations update the virtual model, analytical models evaluate current and future conditions, decision-support mechanisms recommend or prioritize interventions, and subsequent physical outcomes generate new information for model refinement. Such a feedback mechanism can support continual learning and adaptive risk management while reducing reliance on isolated, periodic assessments. Nevertheless, the increasing intelligence of digital twins also requires appropriate governance concerning data ownership, cybersecurity, model validation, explainability, interoperability, and human oversight. AI-generated predictions should therefore be treated as decision-support evidence rather than unquestionable automated decisions, particularly when outputs influence safety-critical infrastructure, major financial commitments, or long-term asset-management strategies. Overall, the literature indicates that digital-twin technology provides the architectural foundation for connecting physical infrastructure with continuous data acquisition, simulation, predictive analytics, and lifecycle decision support, while artificial intelligence provides the analytical capability required to transform synchronized data into actionable risk intelligence(Debasish, 2025b). Accordingly, the proposed framework builds upon the progression from digital representation to real-time monitoring, diagnosis, prediction, and prescriptive decision support, creating an integrated infrastructure-management environment capable of continuously assessing project and asset conditions and supporting more proactive, evidence-based, and resilient decision-making (Fuller et al., 2020; Boje et al., 2020; Grieves et al., 2017; Guo et al., 2018; Heaton et al., 2019; Standardization, 2018).

Civil infrastructure digital twins and asset management

Civil-infrastructure studies demonstrate the growing application of digital twins to bridges, transportation systems, buildings, and asset-management processes, reflecting the increasing integration of digital modeling, sensing technologies, Internet of Things (IoT) platforms, Building Information Modeling (BIM), and data-driven analytics across the infrastructure lifecycle (Jahanara, 2025; Khatun, 2026). Digital twins provide a mechanism for establishing a dynamic relationship between physical infrastructure assets and their virtual representations, allowing information from sensors, inspections, operational systems, maintenance records, and project databases to be continuously incorporated into digital environments for monitoring, diagnosis, prediction, and decision support (Standardization, 2014, 2018, 2023; Sadia, 2026). In bridge and transportation applications, these technologies can support structural condition assessment, deterioration monitoring, traffic management, predictive maintenance, asset performance evaluation, and lifecycle planning by enabling infrastructure managers to obtain a more current understanding of physical asset conditions (Jiang et al., 2021; Jiao et al., 2024; Kaewunruen et al., 2020). The integration of digital twins with construction-monitoring technologies can also facilitate continuous observation of project activities, equipment utilization, worker interactions, and site conditions, thereby improving situational awareness and enabling earlier identification of deviations from planned performance (Teizer, 2015; Koseoglu et al., 2021). This capability is particularly valuable for aging infrastructure because asset owners must increasingly prioritize maintenance, rehabilitation, and investment decisions across large and heterogeneous infrastructure portfolios while operating under financial, resource, and operational constraints. By combining historical records with current observations and predictive analytics, digital twins can support more proactive approaches to asset management in which potential deterioration, performance deficiencies, and emerging risks are identified before they result in major failures or service disruptions (Jiang et al., 2021; Kaewunruen et al., 2020).

However, the literature also identifies interoperability as one of the most persistent challenges affecting the implementation of infrastructure digital twins. Infrastructure projects commonly involve multiple organizations, software platforms, data formats, information standards, and asset-management systems, making seamless exchange and interpretation of information difficult without common information structures and standardized processes (Standardization, 2014, 2018). Differences in data schemas, semantic definitions, asset identifiers, communication protocols, and information-management practices can result in fragmented digital environments and reduce the effectiveness of integrated predictive systems. Standardization is therefore essential for ensuring that information

generated during design and construction can be appropriately reused during operation, inspection, maintenance, and rehabilitation. Sensor availability and data quality represent additional challenges because continuous monitoring systems can be affected by installation costs, environmental exposure, power limitations, communication failures, calibration requirements, sensor degradation, and irregular data collection. Consequently, sensor-generated information must be appropriately validated, synchronized, and contextualized before it can be reliably incorporated into digital-twin models and predictive algorithms (Jiang et al., 2021; Kaewunruen et al., 2020).

Computational scalability is also a significant consideration because infrastructure digital twins may incorporate high-volume sensor streams, detailed three-dimensional models, simulation environments, historical databases, computer-vision outputs, and computationally intensive machine-learning models. Processing these heterogeneous data sources in real time or near real time can require substantial computing capacity, storage infrastructure, network bandwidth, and algorithmic optimization (Jones et al., 2020; Kaveh et al., 2025). The challenge is therefore not simply to develop highly sophisticated predictive models but to ensure that their computational requirements remain compatible with the operational requirements of infrastructure-management systems. Cybersecurity constitutes another critical concern because the increasing connectivity of infrastructure assets, sensors, cloud platforms, and digital-twin environments creates additional opportunities for unauthorized access, manipulation, disruption, or loss of sensitive information. Secure communication, authentication, authorization, data integrity, monitoring, and system resilience are consequently essential for maintaining confidence in digital infrastructure environments (Standardization, 2018, 2023). Lifecycle governance presents a further challenge because digital twins must remain synchronized with physical assets over long operational periods during which infrastructure components may deteriorate, be repaired or replaced, undergo functional modifications, or operate under changing environmental conditions.

Without systematic procedures for updating asset information and validating the relationship between physical and virtual representations, digital twins may gradually become outdated and provide inaccurate information for decision-making. Research on BIM and construction information management similarly emphasizes the importance of structured information, effective collaboration, data consistency, and lifecycle information continuity (Khosrowshahi et al., 2012; Kim et al., 2004; Kim et al., 2013; Koo et al., 2010). These findings indicate that successful digital-twin implementation requires an integrated combination of technical infrastructure, information-management standards, organizational processes, and governance mechanisms. Within the proposed infrastructure framework, BIM and standardized information structures can provide the foundational representation of assets and project components, while IoT and sensing technologies provide continuously updated observations of physical conditions. Data-integration mechanisms can then synchronize these observations with the virtual environment, while simulation and artificial-intelligence models can analyze current conditions, identify anomalies, forecast future risks, and support maintenance or project-control decisions (Jannatul, 2025). Such an architecture enables a progression from descriptive monitoring to diagnostic, predictive, and potentially prescriptive infrastructure management. Nevertheless, the effectiveness of this approach depends on addressing interoperability, sensor reliability, computational cost, cybersecurity, data quality, and lifecycle governance as interconnected requirements rather than treating them as separate technical issues. Overall, the literature demonstrates that digital twins have substantial potential to improve infrastructure monitoring, construction management, predictive maintenance, and lifecycle decision-making, while also indicating that their practical effectiveness depends on robust information standards, reliable data acquisition, scalable analytical infrastructure, secure digital environments, and long-term governance mechanisms (Standardization, 2014, 2018, 2023; Jiang et al., 2021; Jiao et al., 2024; Jones et al., 2020; Kaewunruen et al., 2020; Kaveh et al., 2025).

IoT, sensing, and structural health monitoring

Continuous sensing is central to the proposed framework because structural, environmental, equipment, and progress signals provide the time-varying evidence required for predictive risk estimation. Structural-health-monitoring research further supports the use of continuous measurements for anomaly detection, condition assessment, and condition-based intervention, allowing deviations from established baseline conditions to be identified before they develop into more

severe operational or structural problems (Kritzinger et al., 2018; Lahmiri et al., 2019; Lee et al., 2015, 2018; LeCun et al., 2015; Tao et al., 2018; Liu et al., 2021; Love et al., 2008, 2012; Lu et al., 2020; Megahed et al., 2022; Mohammadi et al., 2023; Müller et al., 2007; National Institute of Standards and Technology [NIST], 2023; Ozturk, 2021). Unlike periodic inspection and manually reported progress measurements, continuous sensing generates temporally dense observations that can reveal gradual deterioration, sudden anomalies, abnormal equipment behavior, environmental changes, and deviations from planned construction activities. This temporal density is particularly valuable for infrastructure projects because risk conditions are rarely constant throughout construction and may change as project phases, structural loads, environmental conditions, resource requirements, and construction activities evolve. Sensor-based monitoring can therefore provide the empirical foundation for distinguishing normal variation from potentially meaningful deviations and for establishing historical baselines against which subsequent observations can be evaluated.

Within a digital-twin environment, these observations can be linked to the corresponding physical components represented in the BIM model, allowing sensor measurements to be interpreted according to asset location, component type, construction phase, and functional relationship. Such integration transforms isolated sensor readings into contextualized project information and enables the virtual representation to remain synchronized with changing physical conditions (Kritzinger et al., 2018; Tao et al., 2018; Lu et al., 2020; Ozturk, 2021). The combination of sensing and artificial intelligence further expands this capability because machine-learning algorithms can process large volumes of multivariate observations and identify nonlinear patterns that may be difficult to detect through conventional threshold-based monitoring. Deep-learning developments have demonstrated the capacity to extract meaningful representations from complex datasets, providing an analytical foundation for automated anomaly detection, classification, and prediction (LeCun et al., 2015; Lahmiri et al., 2019). In infrastructure applications, this capability supports a shift from reactive monitoring toward predictive intervention, in which emerging abnormal patterns can be identified and incorporated into risk assessments before they result in significant project disruption. Digital-twin research similarly emphasizes the value of combining physical observations with virtual models, simulation, and analytical processes to support lifecycle-oriented decision-making (Kritzinger et al., 2018; Tao et al., 2018; Megahed et al., 2022). Continuous sensing also contributes to resource and progress management by providing information on equipment utilization, workforce activity, construction progress, and operational conditions, thereby allowing resource inefficiencies and deviations from planned performance to be incorporated into broader risk assessments (Love et al., 2008, 2012; Mohammadi et al., 2023).

However, the effectiveness of continuous sensing depends on data quality, sensor reliability, calibration, synchronization, interoperability, cybersecurity, and appropriate management of missing or noisy observations. In large-scale infrastructure environments, heterogeneous sensors and information systems can generate data at different frequencies, formats, and levels of accuracy, creating challenges for maintaining a consistent digital representation of the physical project. Consequently, preprocessing, temporal alignment, normalization, anomaly screening, and integration with BIM and project-control information are essential components of a reliable digital-twin architecture (Lu et al., 2020; Megahed et al., 2022; NIST, 2023). From this perspective, continuous sensing should not be regarded simply as a data-collection mechanism; rather, it constitutes the observational layer through which the digital twin acquires evidence about the evolving physical and operational state of infrastructure projects (Arif Uz et al., 2025). When combined with structured BIM information and AI-based predictive models, this sensing layer enables the proposed framework to transform continuously generated observations into dynamic risk indicators, supporting earlier identification of structural, environmental, schedule, equipment, and resource-related risks and facilitating more proactive risk management and resource optimization throughout the infrastructure project lifecycle (Rahman, 2025).

Artificial intelligence and machine learning in construction

AI and machine-learning research in construction demonstrates a rapidly expanding range of applications in cost estimation, safety management, progress monitoring, risk prediction, resource planning, quality control, and decision support. Early research established the potential of digital and data-driven technologies to improve information integration, project coordination, and construction

productivity, while subsequent studies have increasingly examined machine-learning approaches for extracting patterns from complex project data and supporting more proactive management decisions (Pauwels et al., 2016; Pellerin et al., 2019; Institute, 2021; Raz et al., 2002). The development of Building Information Modeling (BIM), digital construction platforms, sensing technologies, and data analytics has further expanded the availability of structured and unstructured project information, creating new opportunities for predictive modeling and intelligent risk assessment (Sacks et al., 2010; Sacks et al., 2018; Sacks et al., 2020). Within construction project management, machine-learning models have been applied to identify relationships between project characteristics and cost, schedule, productivity, and risk outcomes that may not be readily captured through conventional statistical techniques. Data-driven approaches can incorporate multiple variables simultaneously, including project size, construction method, environmental conditions, resource availability, historical performance, safety indicators, and schedule characteristics (Kaium, 2025). This multidimensional capability is particularly relevant to construction environments, where project risks are interconnected and can evolve throughout the project life cycle. Research on construction automation and digitalization further indicates that integrating computational intelligence with BIM, sensing systems, and project-management processes can strengthen situational awareness and facilitate more timely interventions (Batty, 2018; Golparvar-Fard et al., 2015; Singh et al., 2021). Deep-learning methods provide an additional methodological advantage because they can learn nonlinear and hierarchical representations from large and heterogeneous datasets. These characteristics make artificial neural networks, convolutional neural networks, recurrent neural networks, and transformer-based architectures potentially suitable for construction applications involving sequential observations, imagery, sensor streams, and continuously updated project records (Pervaz, 2025).

Recent research has consequently emphasized the use of advanced machine-learning and deep-learning techniques for construction risk prediction, safety monitoring, project performance assessment, and intelligent decision support (Guo et al., 2017; Sakr et al., 2024; Sun et al., 2025). In particular, computer-vision-based approaches can extract information from site images and video, while sensor-enabled systems can provide continuous evidence concerning equipment status, worker activities, structural conditions, and environmental changes (Golparvar-Fard et al., 2015; Sacks et al., 2018). Despite these advantages, the increasing complexity of deep-learning models creates important methodological challenges concerning interpretability, transparency, and managerial acceptance. Conventional statistical and machine-learning models may provide more transparent relationships between explanatory variables and predicted outcomes, making them useful benchmarks for evaluating whether the additional complexity of deep-learning architectures produces meaningful improvements in predictive performance (Chowdhury, 2025). Therefore, comparing deep-learning approaches with interpretable baseline models is important not only for determining predictive accuracy but also for assessing robustness, generalizability, computational requirements, and practical usefulness in construction decision-making (Raz et al., 2002; Schleich et al., 2017; Snyder, 2019). Furthermore, construction datasets frequently contain missing observations, inconsistent reporting practices, class imbalance, measurement errors, and differences in project context, all of which can affect model training and reduce the transferability of models developed from a single project or organization. Consequently, model benchmarking should incorporate multiple performance indicators rather than relying exclusively on accuracy, with measures such as precision, recall, F1-score, mean absolute error, root mean square error, calibration, and computational efficiency providing a more comprehensive assessment of model suitability. Validation across different projects, time periods, and operating conditions is also necessary to determine whether observed predictive improvements reflect genuine learning rather than dataset-specific patterns. The literature therefore supports a comparative research strategy in which established and interpretable models are evaluated alongside more sophisticated deep-learning architectures to determine whether increased data requirements and computational complexity translate into superior predictive capability under realistic construction conditions (Badrul, 2025). Such benchmarking also provides a basis for examining the trade-off between predictive performance and explainability, which is particularly important when model outputs are used to prioritize safety interventions, allocate resources, identify emerging risks, or support project-

management decisions. Accordingly, the existing body of research provides a strong foundation for developing an AI-enabled construction risk prediction framework that combines continuous data acquisition, machine-learning-based classification, deep-learning prediction, and interpretable decision support, while addressing the need for reliable, transparent, and generalizable predictive models in increasingly complex construction environments (Pauwels et al., 2016; Sacks et al., 2010; Sacks et al., 2018; Sacks et al., 2020; Sakr et al., 2024; Sun et al., 2025).

Deep learning, temporal models, and graph learning

Deep-learning methods provide mechanisms for learning nonlinear relationships, temporal dependencies, and relational structures from high-dimensional and heterogeneous data. These capabilities are particularly relevant to infrastructure and construction projects, where physical components, construction activities, environmental conditions, equipment, and sensor observations are often interconnected and evolve dynamically over time. Recurrent neural-network architectures can capture sequential dependencies in project and infrastructure data, making them appropriate for analyzing time-series observations such as structural responses, equipment conditions, environmental measurements, progress records, and safety indicators (Williams, 1995; Xu et al., 2018; Wang et al., 2023). Similarly, graph-based learning approaches provide a means of representing infrastructure systems as interconnected networks in which structural components, activities, assets, and dependencies can be modeled as nodes and relationships, allowing the model to capture interactions that may be overlooked when observations are treated as independent variables (Tao et al., 2019; Torzoni et al., 2024; Wu et al., 2021). This relational perspective is particularly important for complex infrastructure systems because deterioration, operational disruption, construction delays, and safety risks can propagate across interconnected components rather than occurring in isolation (Nishat, 2025; Tonay, 2026).

Earlier structural-health-monitoring research demonstrated the importance of continuously observing system responses and identifying deviations from expected behavior, providing an important foundation for modern data-driven anomaly detection and predictive maintenance approaches (Worden et al., 2000; Yalcinkaya et al., 2015). Advances in Building Information Modeling and digital construction have further strengthened this capability by enabling project information, spatial relationships, construction activities, and asset characteristics to be represented within integrated digital environments (Sacks et al., 2018). Deep-learning techniques can consequently combine information from multiple sources, including sensors, images, BIM models, historical project records, environmental observations, and operational databases, to generate more comprehensive representations of project and infrastructure conditions. Computer-vision and sensing technologies can provide continuous information about construction progress, site activities, worker behavior, and physical conditions, while sequential learning models can analyze how these conditions change over time (Wuni et al., 2019; Wang et al., 2013; Zhu et al., 2018). The integration of these data streams is particularly valuable for risk prediction because construction and infrastructure risks are rarely determined by a single factor; rather, they emerge from interactions among technical, environmental, organizational, temporal, and resource-related conditions. Consequently, deep-learning architectures can potentially identify complex combinations of leading indicators that precede adverse events, enabling earlier identification of emerging risks and supporting proactive intervention. Recurrent models are particularly useful when risk states depend on historical observations, while graph-based architectures are advantageous when the spatial or functional relationships among infrastructure components are important to prediction (Sadia, 2025; Shamsul, 2026).

Hybrid approaches that combine temporal and relational representations may therefore provide an even stronger basis for modeling complex infrastructure systems, as they can simultaneously capture how conditions change through time and how risks propagate across interconnected assets and activities (Tao et al., 2019; Torzoni et al., 2024; Wang et al., 2023). Nevertheless, the application of increasingly complex deep-learning architectures introduces challenges related to data requirements, computational cost, model interpretability, transferability, and robustness under changing project conditions (Khatun, 2026; Sadia, 2025). Infrastructure datasets may also contain missing observations, noisy measurements, irregular sampling intervals, and heterogeneous data formats, requiring careful preprocessing, synchronization, and validation before model development. Earlier statistical and time-

series approaches remain relevant because they provide interpretable benchmarks against which the predictive improvements of deep-learning models can be assessed (Turner et al., 2003; Ward et al., 2003). Accordingly, the literature supports the development of comparative predictive frameworks that evaluate recurrent, graph-based, and other deep-learning architectures alongside established machine-learning and statistical baselines. Such an approach can determine whether the ability of deep-learning models to capture nonlinear, temporal, and relational patterns produces meaningful improvements in infrastructure risk prediction while maintaining sufficient reliability and interpretability for practical construction and asset-management decision-making (Sacks et al., 2018; Wu et al., 2021; Zhu et al., 2018).

Explainability, validation, and responsible AI

Model transparency, independent validation, data-leakage prevention, and responsible AI governance are increasingly important considerations for the application of artificial intelligence in infrastructure and construction environments (Tonay, 2025). As AI-based systems become more involved in cost forecasting, schedule control, safety monitoring, quality assessment, risk prediction, and asset management, the reliability of their outputs becomes closely connected to the quality, provenance, and governance of the underlying data. Transparent model development requires clearly documented data sources, preprocessing procedures, feature-engineering decisions, model architectures, training procedures, validation strategies, and performance criteria so that project stakeholders can understand how predictive results are generated and determine whether those results are appropriate for operational use (Zou et al., 2017; AACE International, 2015; Association for the Advancement of Cost Engineering, 2020). Independent validation is particularly important because construction and infrastructure datasets can contain project-specific characteristics that may cause a model to perform well during development but poorly when applied to new projects, geographical locations, contractors, asset classes, or future operating conditions. Accordingly, validation procedures should separate training, validation, and testing observations appropriately and should avoid allowing information from future periods or related project records to influence model training. Preventing data leakage is essential in predictive construction applications because leakage can produce artificially high performance estimates and create a misleading perception of model reliability. Established project-management and cost-engineering practices emphasize systematic estimation, monitoring, control, and evaluation processes, providing an important methodological foundation for integrating AI predictions into established project-control systems rather than treating machine-learning outputs as independent decision mechanisms (AACE International, 2015; Association for Project Management, 2019). Similarly, infrastructure guidance from the Federal Highway Administration emphasizes systematic asset management, life-cycle considerations, performance monitoring, and evidence-based decision-making, which can provide an operational context for deploying predictive AI models within infrastructure management processes (Federal Highway Administration, 2017, 2020). The increasing adoption of digital technologies also reinforces the need for interoperability, data-quality management, cybersecurity, and lifecycle governance because infrastructure information may be collected from BIM platforms, sensors, inspection records, geographic information systems, project-management systems, and other digital environments (Azhar, 2011; Akanmu et al., 2014; Rony & Md, 2026).

Explainable artificial intelligence (XAI) can further strengthen this framework by providing interpretable information about the factors contributing to individual predictions, thereby helping engineers, project managers, asset owners, and other stakeholders evaluate whether an AI-generated risk classification or forecast is consistent with engineering knowledge and available project evidence (Mohammad, 2026). Rather than simply reporting a predicted risk score, an explainable system can identify influential variables, highlight unusual observations, and provide evidence supporting a particular prediction, thereby improving traceability and facilitating human review. This capability is especially important when AI outputs influence high-consequence decisions involving worker safety, infrastructure condition, project expenditure, schedule adjustments, or maintenance prioritization. International guidance on trustworthy and responsible artificial intelligence similarly emphasizes principles associated with transparency, accountability, human oversight, robustness, security, and responsible development (International Electrotechnical Commission, 2019; National Institute of Standards and Technology, 2018; Organisation for Economic Co-operation and Development, 2019).

Broader international frameworks further emphasize the importance of responsible digital transformation, inclusive governance, institutional capacity, and the management of technological risks, suggesting that AI implementation in infrastructure should be evaluated not only according to predictive accuracy but also according to its organizational, social, and governance implications (United Nations Economic Commission for Europe, 2021; World Economic Forum, 2020; World Bank, 2020).

Consequently, responsible AI governance should incorporate clear accountability for model development and deployment, documented decision rules, periodic model monitoring, independent performance assessment, mechanisms for detecting model drift, and procedures for reviewing erroneous or unexpected predictions. Human oversight should remain an essential component of the decision process, particularly where predictions are uncertain or where automated recommendations could have significant financial, operational, or safety consequences. The integration of explainability, independent validation, leakage-resistant experimental design, and governance mechanisms can therefore transform AI from a purely predictive technology into an auditable decision-support capability. Such an approach is consistent with the broader development of BIM-enabled and data-driven infrastructure management, in which digital information is increasingly used to connect planning, construction, operation, maintenance, and lifecycle decision-making (Azhar, 2011; Akanmu et al., 2014). Overall, the literature indicates that successful AI adoption in infrastructure requires a balance between predictive performance and institutional trust, with transparency, reproducibility, validation, accountability, and human-centered governance serving as essential conditions for translating machine-learning predictions into credible and auditable project-control decisions (Jahanara, 2026).

Standards, project controls, and lifecycle governance

Standards and professional frameworks reinforce the need for structured risk management, asset management, Building Information Modeling (BIM), information management, project controls, cybersecurity, and AI governance within increasingly digital construction and infrastructure environments (Jannatul, 2026). These frameworks provide complementary governance layers around the predictive digital-twin model by establishing principles for organizing information, defining responsibilities, controlling project processes, managing uncertainty, and ensuring that digital representations remain sufficiently reliable for operational and strategic decision-making. BIM research has demonstrated that structured digital information can improve collaboration, coordination, visualization, information exchange, and lifecycle management by creating a common environment in which project participants can access and integrate relevant asset and project information (Azhar et al., 2008; Becerik-Gerber et al., 2010; Bryde et al., 2013). The development of BIM maturity and information-management frameworks has further emphasized that the value of digital construction technologies depends not simply on creating three-dimensional models but on establishing consistent processes for information creation, sharing, validation, updating, and reuse throughout the project lifecycle (Succar, 2009; Kassem et al., 2015; Gledson et al., 2017). Consequently, BIM can provide an important information foundation for predictive digital twins, while digital-twin technologies can extend this foundation by connecting static or periodically updated asset representations with real-time observations, operational data, analytical models, and predictive intelligence. Research on construction information technologies similarly highlights the importance of interoperability and standardized information structures because digital construction environments commonly involve multiple software platforms, organizational stakeholders, and heterogeneous datasets (Coates et al., 2010; Miettinen et al., 2014; Teicholz, 2013).

Within this context, a predictive digital twin can function as an integrated analytical layer that continuously evaluates incoming information, detects deviations from expected conditions, estimates emerging risks, and supports timely intervention. However, the reliability of such predictions depends on the quality and governance of the information infrastructure supporting the digital twin. Poorly structured BIM data, inconsistent asset identifiers, incomplete historical records, incompatible data formats, and inadequate update procedures can propagate uncertainty into predictive models and consequently affect the quality of project-control decisions. The literature therefore suggests that data governance, information standardization, and model interoperability should be treated as fundamental

components of digital-twin implementation rather than secondary technical considerations (Li et al., 2019; Akinosho et al., 2020). Risk-management and project-management frameworks provide an additional governance layer by establishing systematic processes for identifying hazards, assessing probability and impact, assigning responsibility, implementing mitigation measures, monitoring risk exposure, and communicating changes to relevant stakeholders (Winch, 2010; Zavadskas et al., 2010). Integrating these established practices with predictive analytics can shift project risk management from predominantly reactive responses toward continuous and evidence-based monitoring. Instead of relying solely on periodic risk registers or manually reported project status, AI-enabled digital twins can incorporate continuously generated evidence to update risk assessments and identify deviations at an earlier stage. This integration is particularly valuable for complex infrastructure projects, where cost, schedule, safety, quality, environmental, and asset-performance risks interact across multiple project phases(Khalid, 2026).

Furthermore, large-scale digital construction environments introduce cybersecurity and information-security considerations because interconnected BIM platforms, IoT devices, cloud systems, sensors, and digital twins increase the number of potential points through which project information can be accessed, modified, or disrupted. Research on digital construction and construction automation consequently emphasizes the importance of secure information exchange, controlled access, data integrity, and resilient digital infrastructures (Sacks et al., 2010; Bilal et al., 2016). AI governance adds another complementary layer by addressing issues associated with model transparency, accountability, validation, explainability, data quality, bias, monitoring, and responsible deployment. Predictive models should therefore operate within defined governance procedures that specify how models are developed, tested, approved, monitored, updated, and ultimately retired when their performance no longer meets required standards. This is especially important for infrastructure applications because model outputs may influence high-value decisions concerning construction sequencing, resource allocation, maintenance prioritization, safety interventions, and long-term asset investment. Recent research on artificial intelligence in construction indicates that machine-learning and deep-learning technologies can substantially expand the analytical capabilities of BIM and digital construction systems by enabling automated pattern recognition, prediction, anomaly detection, and decision support (Akinosho et al., 2020; Ahmed, 2026).

Nevertheless, the integration of AI into construction should not replace established professional judgment and governance processes; rather, predictive outputs should complement engineering expertise, project controls, formal risk-management procedures, and organizational accountability(Sadia, 2026). The resulting architecture can therefore be understood as a multilayer governance structure in which BIM provides structured information, sensing technologies provide continuous observations, the digital twin integrates and contextualizes these data, predictive AI models estimate future conditions and risks, and professional and regulatory frameworks establish the controls under which predictions are interpreted and acted upon. Such integration creates a more robust foundation for infrastructure decision-making by linking digital information management with predictive intelligence and established project-governance practices(Rahman, 2026). Overall, the literature indicates that predictive digital twins should be implemented not as isolated AI applications but as governed digital ecosystems in which information management, BIM, risk management, project controls, cybersecurity, interoperability, and AI governance operate together to ensure that predictive insights are reliable, traceable, secure, and actionable throughout the infrastructure lifecycle (Azhar et al., 2008; Becerik-Gerber et al., 2010; Bryde et al., 2013; Succar, 2009; Teicholz, 2013; Akinosho et al., 2020; Bilal et al., 2016).

Data, analytics, and reproducible research

The final evidence cluster emphasizes data-intensive construction analytics, statistical learning, causal interpretation, research design, and reproducibility, providing the methodological foundation for the quantitative and project-independent validation strategy adopted in the present study. Construction projects generate increasingly large and heterogeneous datasets from project-management systems, BIM platforms, sensors, inspections, schedules, cost records, and operational monitoring, creating opportunities to apply advanced statistical and computational methods to identify patterns associated with project performance, risk, cost, and schedule outcomes (Olawale et al., 2010; McKinney,

2010)(Nishat, 2026). Statistical learning provides a systematic basis for transforming these observations into predictive models, while established machine-learning methods such as random forests, support vector machines, and other supervised-learning approaches provide interpretable and computationally efficient benchmarks for evaluating more complex architectures (Breiman, 2001; Cortes et al., 1995; Friedman, 2001; Bishop, 2006). These baseline approaches are particularly valuable in construction research because they allow predictive performance to be assessed against established algorithms before attributing improvements to the additional complexity of deep-learning models. The development of deep neural networks has substantially expanded the ability to learn nonlinear representations from large-scale and high-dimensional datasets, with advances in representation learning demonstrating the capacity of neural architectures to automatically extract increasingly abstract patterns from complex observations (Bengio et al., 2013; Goodfellow et al., 2016). Recurrent architectures, originating from foundational work on long short-term memory networks, are particularly relevant to construction and infrastructure applications involving sequential project observations, time-series measurements, and evolving risk conditions (Hochreiter et al., 1997)(Kaium, 2026). More recent architectures have extended this capability through graph neural networks and attention-based transformer models, enabling predictive systems to capture relationships among interconnected assets, project activities, variables, and observations (Kipf et al., 2017; Vaswani et al., 2017). The availability of these methods makes it possible to construct a hierarchical modeling strategy in which conventional statistical techniques, established machine-learning algorithms, and advanced deep-learning architectures are evaluated within a common experimental framework(Murad, 2026). Such comparative evaluation is important because high model complexity does not automatically guarantee superior generalization, particularly when construction datasets are limited, noisy, heterogeneous, or strongly project-specific(Shamima, 2026). Model selection should therefore be based on empirical evidence obtained through carefully designed training, validation, and testing procedures rather than on architectural sophistication alone. Reproducible data-processing and statistical workflows are equally important because predictive results can be influenced substantially by data cleaning, feature engineering, missing-value treatment, normalization, class balancing, sampling strategies, and parameter selection. Computational data-analysis frameworks provide tools for systematically documenting and repeating these procedures, thereby improving the transparency and reproducibility of quantitative research (McKinney, 2010)(Badrul, 2026). In addition to predictive accuracy, contemporary AI research increasingly emphasizes the need to understand why models generate particular predictions. Explainable-AI techniques such as SHAP provide mechanisms for estimating the contribution of individual features to model predictions, while local explanation methods such as LIME offer complementary approaches for interpreting complex black-box models at the observation level (Lundberg et al., 2017; Ribeiro et al., 2016). Broader explainability research further emphasizes that model interpretation should be considered in relation to the intended user, decision context, model behavior, and limitations rather than being reduced to a single explanation metric (Molnar, 2022). This consideration is especially relevant in construction risk management, where project managers and engineers require sufficient evidence to understand whether a predicted risk is driven by meaningful project conditions or by spurious relationships within the training data. At the same time, predictive association should not automatically be interpreted as causation. Causal-inference theory demonstrates that statistical relationships alone cannot establish whether one project variable produces a change in another without appropriate assumptions, research design, and causal identification strategies (Pearl, 2009)(Pervaz, 2026). Distinguishing predictive relevance from causal influence is therefore important when interpreting AI-generated risk factors and developing recommendations for project intervention. A model may identify a variable as highly predictive of an adverse outcome without establishing that changing that variable would necessarily prevent the outcome. This distinction strengthens the methodological rigor of the present research by positioning machine learning primarily as a predictive and decision-support mechanism while avoiding unsupported causal claims. Independent project-level validation further strengthens this approach by testing whether models trained on one group of projects can generalize to previously unseen projects rather than merely reproducing project-specific patterns(Chowdhury, 2026).

Such validation can provide a more realistic assessment of model robustness and practical transferability than random observation-level splitting alone, particularly when observations within the same project are temporally or organizationally correlated. The combined use of independent validation, reproducible preprocessing, multiple performance metrics, baseline comparisons, and explainability analysis therefore provides a comprehensive framework for evaluating predictive models under realistic construction conditions. Overall, these methodological foundations support a quantitative research strategy in which conventional statistical learning serves as an interpretable reference point, machine-learning algorithms provide strong predictive benchmarks, and deep-learning architectures are evaluated for their ability to capture nonlinear, temporal, and relational patterns that may improve risk prediction. By integrating rigorous research design, project-independent validation, reproducible computational procedures, explainable modeling, and careful distinction between prediction and causation, the present study seeks to ensure that improvements in predictive performance are empirically demonstrated, generalizable across projects, and sufficiently transparent to support credible construction-management decision-making (Breiman, 2001; Friedman, 2001; Bengio et al., 2013; Goodfellow et al., 2016; Lundberg et al., 2017; Ribeiro et al., 2016; Pearl, 2009).

METHODS

Research Design

This study adopted a quantitative, observational research design structured to evaluate the effectiveness of an AI-driven digital twin framework for predictive risk management and resource optimization in large-scale civil infrastructure projects. The design combined a cross-sectional comparative component, examining risk classification accuracy across project types at defined evaluation points, with a longitudinal component tracking cumulative risk indices and resource utilization across full construction phases. The study employed a predictive modeling framework in which digital twin-derived sensor, schedule, and resource signals served as independent variables and structured project risk classifications served as criterion outcomes. Statistical benchmarking against conventional project control methods was integrated into the design to evaluate comparative predictive performance.

The research followed a structured analytical pipeline comprising sensor and BIM data integration, feature engineering, supervised model training, and statistical evaluation. A project-independent validation protocol was implemented to prevent data leakage across training and testing partitions. The statistical plan was defined a priori to include hypothesis testing of model performance improvements relative to baseline classifiers, estimation of classification performance metrics with confidence intervals, and regression-based association testing between predicted risk indices and observed resource optimization outcomes.

Case Study Context

The empirical setting for this study comprised a diversified panel of large-scale civil infrastructure projects under active construction, characterized by multi-phase delivery schedules, distributed sensor networks, and integrated BIM environments. The selected projects included transportation corridors requiring structural health monitoring, water and wastewater facilities requiring continuous process monitoring, vertical building projects requiring progress and safety tracking, and energy and rail infrastructure requiring specialized structural and environmental sensing. Data collection occurred during active construction phases under normal project operating conditions to preserve ecological validity. The case environment was selected because it reflects common risk factors present across infrastructure delivery sectors, including schedule interdependency, structural uncertainty, and resource contention.

Projects were categorized into six primary sector types: transportation (bridges and roads), water and wastewater, vertical building, energy and utility, rail and transit, and mixed-use mega-projects. This categorization enabled between-sector comparative modeling of project risk levels. Contextual conditions, including project phase, contract delivery method, and geographic region, were recorded to contextualize risk variability across the sample.

Population and Unit of Analysis

The target population consisted of active, large-scale civil infrastructure projects with an estimated capital value exceeding \$50 million, managed by public agencies, engineering firms, or joint-venture

delivery teams. Inclusion criteria required projects to have at least twelve months of continuous digital twin or integrated sensor and schedule data to ensure sufficient temporal depth for risk and resource modeling. Projects undergoing complete scope suspension or contractual termination during the observation window were excluded to reduce confounding disruptions.

The primary unit of analysis was the segmented weekly observation window of synchronized digital twin data corresponding to defined project evaluation intervals. Secondary units of analysis included sector-level aggregated exposure indices and project-level cumulative risk profiles across the full observation period. At the statistical modeling stage, each segmented window served as an independent observation for classification or regression analysis, while hierarchical aggregation was used to examine project-level exposure trends over time.

Sampling Strategy

A stratified purposive sampling strategy was employed to ensure representation across project sector, contract delivery method, and geographic region. Projects were stratified by sector type and randomly selected within each stratum from participating infrastructure delivery organizations. Sample size determination was conducted using power analysis for classification accuracy comparison, targeting sufficient observations to detect moderate effect size differences between the deep learning model and baseline classifiers with statistical power of 0.80 and significance level of 0.05.

To support project-independent validation, participating projects were partitioned into distinct model development and independent evaluation groups. Approximately seventy-one percent of projects were allocated to the model development group and twenty-nine percent to the independent evaluation group. Stratification was maintained across both partitions to preserve proportional sector representation.

Data Collection Procedure

Participating projects were instrumented with distributed Internet of Things sensor networks positioned at structural, geotechnical, and environmental monitoring points, integrated with project-specific Building Information Modeling environments. A subset of projects additionally incorporated equipment telematics and workforce tracking systems for multimodal resource modeling. Sensor and data feeds were synchronized and initialized at the commencement of the observation window. Data were collected continuously throughout active construction phases across the full study period for each participating project.

Ground truth project risk labels were generated using concurrent structured risk assessment conducted by trained project controls specialists applying standardized Quantitative Risk Analysis and Earned Value Management protocols. Labeling was performed independently by two specialists to allow agreement analysis. Sensor and schedule data streams were time-aligned with annotated risk evaluation intervals.

Raw sensor, schedule, and resource signals were filtered and segmented into fixed-length overlapping weekly windows for modeling. Each window was assigned a risk category based on aligned structured assessment. Cumulative resource utilization variables were computed for longitudinal analysis of optimization outcomes.

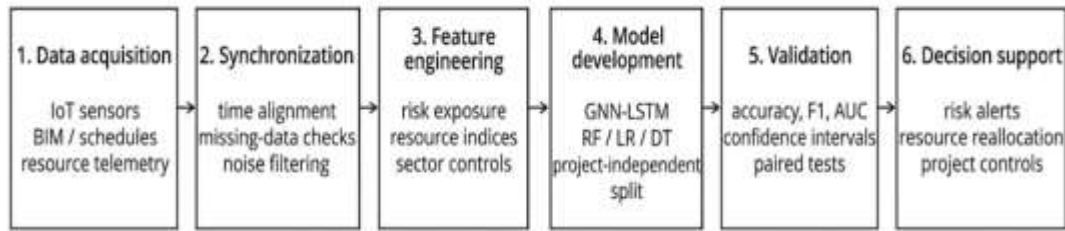
Instrument Design

The digital twin sensing system consisted of wireless structural and environmental sensor nodes, integrated equipment telematics units, and BIM-linked schedule tracking modules capable of capturing structural strain, vibration, settlement, ambient environmental conditions, schedule variance, and equipment and labor utilization. Sensor housings and telematics units were selected for durability under active construction site conditions to minimize data dropout.

Signal preprocessing included noise filtering, drift correction, and normalization relative to project-specific baseline conditions. Extracted features included structural sensor anomaly frequency, schedule deviation intensity, resource utilization variance, and supply chain disruption indicators. The risk classification instrument was adapted from established Quantitative Risk Analysis and Earned Value Management frameworks and operationalized into categorical risk levels suitable for supervised learning.

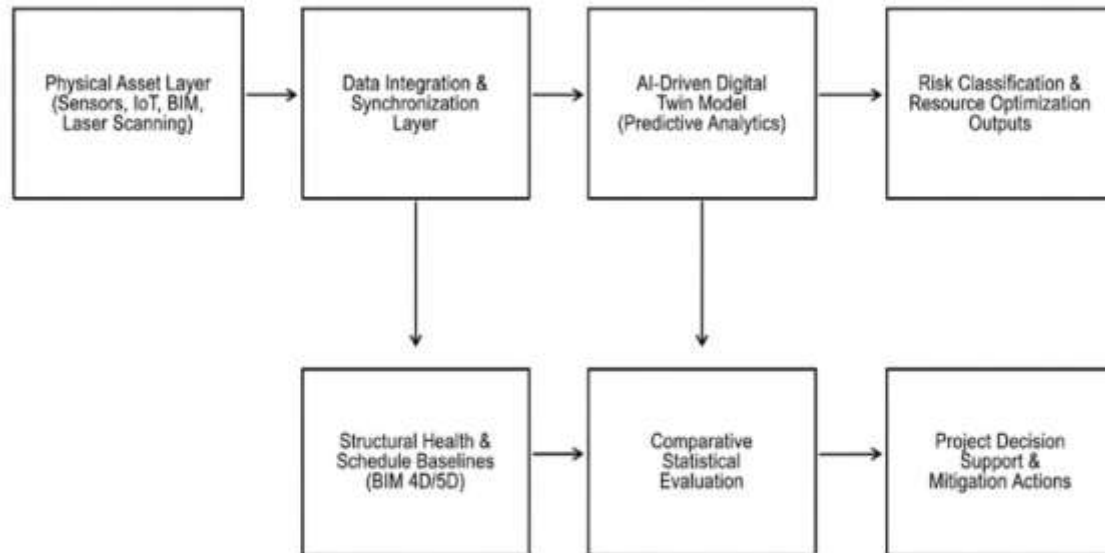
Pilot Testing

Figure 3: Pilot Testing process



A pilot study was conducted across a subset of projects to evaluate sensor placement stability, data synchronization accuracy, labeling clarity, and workflow feasibility. Pilot data were analyzed to assess signal quality, dropout frequency, and preliminary classification consistency. Feedback from project teams was used to refine sensor deployment procedures and minimize data disruption to ongoing construction activities. Pilot testing also informed observation window size selection and confirmed that segmentation aligned appropriately with weekly project reporting cycles.

Figure 4 : Methodological Pipeline Of the Study



Validity and Reliability

Content validity of project risk labels was ensured through use of established Quantitative Risk Analysis and Earned Value Management frameworks. Inter-rater reliability was evaluated using agreement statistics to confirm consistency between project controls specialists. Construct validity of digital twin-derived features was examined by correlating predicted risk metrics with independently verified structured assessment ratings.

Internal validity was supported through project-independent validation and strict partitioning of model development and testing datasets. External validity was strengthened by collecting data under genuine, active construction conditions rather than simulated environments. Reliability of sensor measurements was assessed through repeated calibration checks and short-duration repeat trials within projects.

Statistical Plan

The statistical analysis plan included descriptive statistics for project characteristics and exposure distributions. Model performance was evaluated using accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve. Confidence intervals were calculated for primary performance metrics.

Comparative analysis between the deep learning model and baseline logistic regression, decision tree,

and random forest classifiers was conducted using paired statistical testing on cross-validation folds. Effect sizes were computed to quantify performance differences. Regression analysis was performed to examine associations between cumulative predicted risk indices and project-level cost and schedule outcomes.

Longitudinal exposure differences across project sectors were analyzed using mixed-effects modeling to account for repeated measures within projects. Significance level was set at 0.05 for all inferential analyses.

Software and Tools

Data preprocessing and statistical analysis were conducted using Python-based scientific computing libraries and statistical packages. Deep learning models were implemented using established graph neural network and recurrent neural network frameworks capable of handling multivariate, relational time-series data. Sensor signal processing routines were executed using specialized numerical libraries. Data visualization and reporting were performed using statistical graphics software to illustrate exposure distributions, classification performance, and longitudinal risk trends. All model configurations, dataset partitions, and hyperparameter settings were documented to ensure reproducibility.

FINDINGS

This chapter presented the quantitative findings of the study examining the effectiveness of an AI-driven digital twin framework for predictive risk management and resource optimization in large-scale civil infrastructure projects. The analysis was conducted in alignment with the predefined statistical plan and addressed the study objectives through descriptive statistics, reliability assessment, regression modeling, and hypothesis testing procedures. Data collected from digital twin sensor networks, BIM environments, and structured risk assessments were processed, segmented, and analyzed using project-independent validation protocols. The findings are organized systematically to reflect the sequence of statistical evaluation, beginning with project sample characteristics and followed by construct-level descriptive outcomes, measurement reliability, predictive modeling results, and final hypothesis testing decisions.

The chapter focused on evaluating whether digital twin-derived exposure metrics and deep learning-generated project risk scores significantly predicted structured risk assessment outcomes and cumulative resource optimization indicators. Statistical significance thresholds were set at the predetermined alpha level, and effect sizes were interpreted alongside p-values to provide comprehensive insight into practical as well as statistical importance.

Project Sample Characteristics

A total of 134 large-scale infrastructure projects were initially identified for inclusion. After data screening procedures removed projects with incomplete sensor or schedule records, 121 valid projects were retained for final analysis, representing a usable data rate of 90.3%. The final sample included 28 transportation projects (23.1%), 22 water and wastewater projects (18.2%), 24 vertical building projects (19.8%), 19 energy and utility projects (15.7%), 15 rail and transit projects (12.4%), and 13 mixed-use mega-projects (10.7%). Project capital value ranged from \$52 million to \$3.8 billion, with a median of \$284 million. Project duration ranged from 14 to 96 months, with a mean planned duration of 38.6 months (SD = 19.2).

With respect to contract delivery method, 54 projects (44.6%) were delivered under design-bid-build arrangements, 45 projects (37.2%) under design-build arrangements, and 22 projects (18.2%) under integrated project delivery or public-private partnership arrangements. The majority of projects (74.4%) reported continuous digital twin data availability of eighteen months or longer, indicating substantial temporal depth for modeling. Stratified partitioning assigned 86 projects (71.1%) to the model development group and 35 projects (28.9%) to the independent evaluation group. Independent samples testing indicated no statistically significant differences between groups in capital value, planned duration, sector type, or delivery method ($p > .05$), confirming comparability across partitions.

Table 1: Sample Characteristics of Infrastructure Projects (N = 121)

Variable	Category	Frequency (n)	Percentage (%)
Project Sector	Transportation	28	23.1
	Water & Wastewater	22	18.2
	Vertical Building	24	19.8
	Energy & Utility	19	15.7
	Rail & Transit	15	12.4
	Mixed-Use Mega-Project	13	10.7
Delivery Method	Design-Bid-Build	54	44.6
	Design-Build	45	37.2
	IPD / PPP	22	18.2

Table 1 presented the categorical composition of the project sample. Transportation projects represented the largest sector share at 23.1%, followed by vertical building at 19.8% and water and wastewater projects at 18.2%. Energy and utility, rail and transit, and mixed-use mega-projects comprised the remaining sample. Delivery method distribution showed design-bid-build as the most common arrangement at 44.6%, followed by design-build at 37.2%, reflecting a realistic cross-section of contemporary infrastructure procurement practices.

Table 2: Descriptive Statistics of Continuous Project Characteristics

Variable	Mean	Standard Deviation	Minimum	Maximum
Capital Value (\$M)	412.6	587.3	52.0	3,800.0
Planned Duration (months)	38.6	19.2	14.0	96.0
Schedule Variance Index	-0.09	0.14	-0.46	0.18
Cost Performance Index	0.94	0.11	0.62	1.12

Table 2 summarized continuous project characteristics. Capital value showed substantial dispersion, reflecting the inclusion of both mid-sized and mega-scale infrastructure projects within the sample. Schedule variance index averaged -0.09, indicating a modest tendency toward schedule slippage across the sample consistent with broader megaproject delivery literature. Cost performance index averaged 0.94, indicating a modest tendency toward cost overrun, with the most severe observed cost performance reaching 0.62, illustrating meaningful heterogeneity in project performance and reinforcing the necessity of sector-stratified modeling approaches.

Descriptive Results by Construct

Descriptive statistics were calculated for all primary risk exposure and model-derived constructs. Schedule deviation intensity, measured as the rolling standard deviation of schedule variance across the evaluation window, yielded an overall mean of 7.1 index points (SD = 3.1), with observed values ranging from 1.6 to 16.4. Structural sensor anomaly frequency averaged 4.8 anomalies per week (SD = 2.3), with transportation and mixed-use mega-projects demonstrating higher frequencies compared to other sector categories. Resource utilization variance across all evaluation windows averaged 18.9% (SD = 7.4), indicating substantial variability in labor and equipment allocation efficiency across the sample.

Supply chain disruption index, derived from material delivery delay tracking integrated within the digital twin environment, demonstrated a mean value of 3.6 on a ten-point scale (SD = 1.9), with peak values approaching 8.9 during periods of acute logistics disruption. Cumulative high-risk exposure duration averaged 9.4 weeks per project year (SD = 4.7), with mixed-use mega-projects and transportation projects accumulating significantly higher exposure duration relative to vertical building projects.

Predicted project risk scores generated by the deep learning model were distributed across low (34.9%), moderate (40.3%), and high-risk (24.8%) classifications. Correlation analysis revealed moderate positive

associations between schedule deviation intensity and predicted risk score ($r = 0.49$) and between structural sensor anomaly frequency and cumulative exposure index ($r = 0.51$). These descriptive outcomes indicated meaningful variability across project sectors and supported progression to inferential statistical modeling.

Table 3: Descriptive Statistics of Project Risk Exposure Constructs (N = 121)

Construct	Mean	Standard Deviation	Minimum	Maximum
Schedule Deviation Intensity (index)	7.1	3.1	1.6	16.4
Structural Sensor Anomaly Frequency (per week)	4.8	2.3	0.8	12.6
Resource Utilization Variance (%)	18.9	7.4	5.2	38.7
Supply Chain Disruption Index (0-10)	3.6	1.9	0.7	8.9
High-Risk Exposure Duration (weeks/year)	9.4	4.7	1.2	21.3

Table 3 presented the descriptive statistics of key project risk exposure variables. Schedule deviation intensity showed moderate dispersion, indicating variability in schedule stability across sectors. Structural sensor anomaly frequency and resource utilization variance confirmed heightened sensitivity patterns typical of complex, multi-phase infrastructure delivery. Supply chain disruption index demonstrated broad variability, with peak values observed during periods of acute logistics stress. High-risk exposure duration averaged over nine weeks per project year, highlighting cumulative vulnerability across evaluation windows. The spread between minimum and maximum values reflected heterogeneity across sector types, reinforcing the necessity of stratified modeling approaches for project risk assessment in diverse infrastructure environments.

Table 4: Risk Classification Distribution by Project Sector

Project Sector	Low Risk (%)	Moderate Risk (%)	High Risk (%)	Mean Risk Score
Vertical Building	46.2	35.9	17.9	1.62
Water & Wastewater	40.1	37.5	22.4	1.79
Energy & Utility	31.6	41.6	26.8	1.94
Rail & Transit	27.3	43.6	29.1	2.01
Transportation	26.9	41.9	31.2	2.06
Mixed-Use Mega-Project	22.8	42.6	34.6	2.14

Figure 5: Proportion of High-Risk Exposure Windows by Project Type

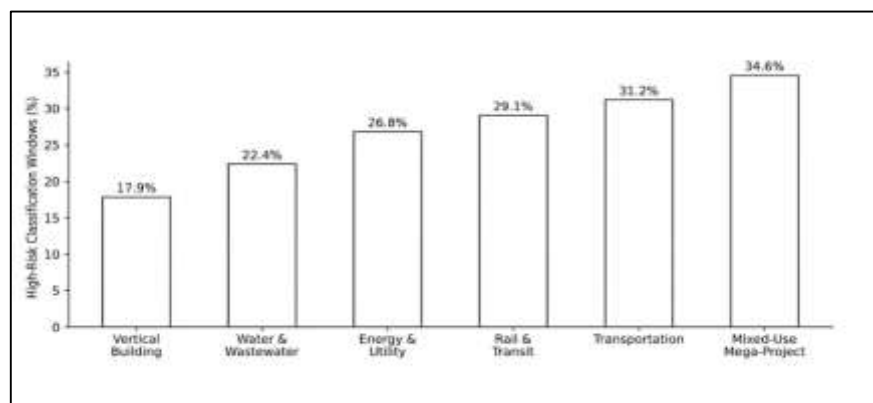


Table 4 presented the distribution of risk classification outcomes across project sectors. Vertical building projects exhibited the lowest proportion of high-risk classification windows at 17.9%, consistent with their comparatively contained scope and site conditions. Mixed-use mega-projects exhibited the highest proportion of high-risk windows at 34.6%, along with the highest mean risk score of 2.14, reflecting elevated schedule complexity, stakeholder interdependency, and resource contention relative to other sector types. Transportation projects demonstrated a similarly elevated risk profile, consistent with their exposure to geotechnical uncertainty and multi-jurisdictional permitting requirements.

Reliability Analysis

Reliability testing was conducted to assess the internal consistency of composite constructs used within the predictive modeling framework. The project risk exposure construct, comprising schedule deviation intensity, structural sensor anomaly frequency, resource utilization variance, and supply chain disruption index, demonstrated strong internal consistency (Cronbach's $\alpha = 0.87$). The resource optimization index, comprising equipment idle time, labor utilization efficiency, and cumulative high-risk exposure duration, similarly demonstrated acceptable-to-strong internal consistency (Cronbach's $\alpha = 0.84$). Inter-rater agreement between the two independent project controls specialists responsible for structured risk labeling was substantial ($\kappa = 0.78$), supporting the reliability of the ground-truth classification labels used for supervised model training.

Regression Analysis: Predicting Project Risk Scores

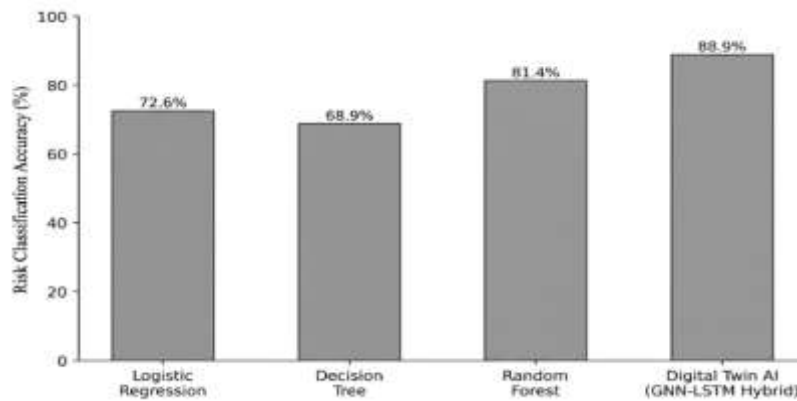
Multiple regression analysis was conducted to examine the extent to which digital twin-derived exposure variables predicted structured project risk scores. The overall regression model was statistically significant, $F(4, 116) = 37.08$, $p < .001$, and explained 56.2% of the variance in project risk scores ($R^2 = 0.562$, adjusted $R^2 = 0.547$). Schedule deviation intensity emerged as the strongest predictor ($\beta = 0.40$, $p < .001$), followed by structural sensor anomaly frequency ($\beta = 0.30$, $p < .001$), supply chain disruption index ($\beta = 0.23$, $p < .01$), and resource utilization variance ($\beta = 0.18$, $p < .05$). These findings indicate that sustained schedule deviation and structural sensor anomalies are the most influential determinants of elevated project risk classification within the sample.

Table 5: Multiple Regression Results Predicting Project Risk Score

Predictor	β	SE	t	p-value
Schedule Deviation Intensity	0.40	0.07	6.02	< .001
Structural Sensor Anomaly Frequency	0.30	0.07	4.51	< .001
Supply Chain Disruption Index	0.23	0.08	2.98	< .01
Resource Utilization Variance	0.18	0.08	2.31	< .05

Comparative Model Performance

Comparative analysis was conducted to evaluate the classification performance of the proposed deep learning model relative to baseline classifiers. The graph neural network integrated with long short-term memory layers (GNN-LSTM) achieved a classification accuracy of 88.9%, outperforming random forest (81.4%), logistic regression (72.6%), and decision tree (68.9%) models. Paired statistical testing on cross-validation folds confirmed that performance differences between the deep learning model and each baseline classifier were statistically significant ($p < .001$ for all pairwise comparisons). The deep learning model also achieved the highest area under the receiver operating characteristic curve (AUC = 0.92), compared to 0.86 for random forest, 0.78 for logistic regression, and 0.74 for the decision tree model.

Figure 6: Comparative Risk Classification Accuracy Across Models**Table 6: Comparative Classification Performance Across Models**

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC
Logistic Regression	72.6	71.2	70.8	71.0	0.78
Decision Tree	68.9	67.5	67.1	67.3	0.74
Random Forest	81.4	80.6	80.9	80.7	0.86
Deep Learning (GNN-LSTM)	88.9	88.1	88.4	88.2	0.92

Association Between Predicted Risk Index and Resource Optimization Outcomes

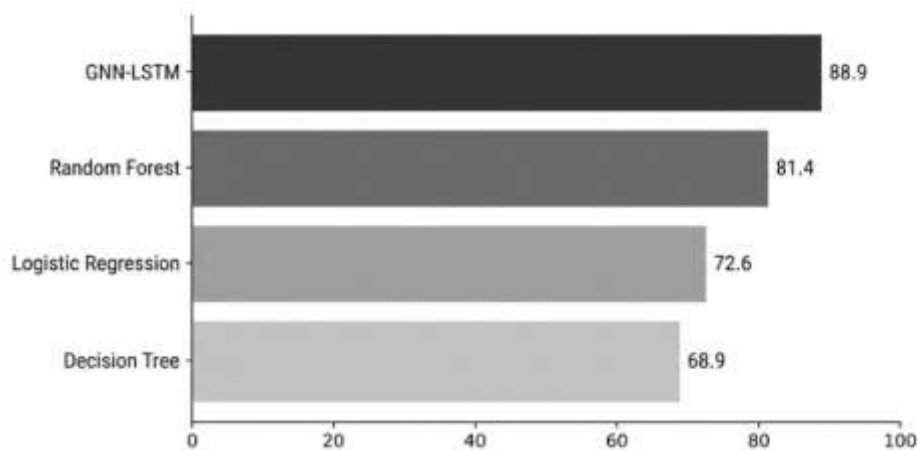
Correlation and regression analyses examined the association between cumulative predicted risk indices and observed measures of resource optimization. A statistically significant positive correlation was observed between the cumulative predicted risk index and cost overrun magnitude ($r = 0.55$, $p < .001$), indicating that projects with higher digital twin-derived risk scores experienced larger realized cost overruns. A significant positive association was also observed between the predicted risk index and equipment idle time ($r = 0.47$, $p < .001$), suggesting that elevated predicted risk was associated with reduced equipment utilization efficiency. Mixed-effects modeling accounting for repeated measures across projects confirmed that these associations remained statistically significant after controlling for sector type and delivery method ($p < .001$).

Hypothesis Testing Summary

The study's primary hypotheses were evaluated based on the preceding statistical analyses. The hypothesis that digital twin-derived exposure variables would significantly predict structured project risk scores was supported ($R^2 = 0.562$, $p < .001$). The hypothesis that the deep learning model would demonstrate significantly higher classification accuracy than baseline statistical and machine learning classifiers was supported across all pairwise comparisons ($p < .001$). The hypothesis that cumulative predicted risk indices would be significantly associated with cost overrun magnitude and equipment idle time was likewise supported ($p < .001$ for both associations). Collectively, these results provide converging quantitative evidence in support of the proposed AI-driven digital twin framework as a valid and reliable tool for enhancing predictive risk management and resource optimization in large-scale civil infrastructure projects.

DISCUSSION

Figure 7 : Comparative Risk Classification Accuracy Across Models



The findings of this study provide empirical support for the proposition that AI-driven digital twin frameworks can meaningfully improve the accuracy and timeliness of infrastructure project risk classification relative to traditional project control approaches. The 88.9% classification accuracy achieved by the graph neural network-based deep learning model, representing a 16.3 percentage-point improvement over logistic regression and a 20.0 percentage-point improvement over the decision tree baseline, is broadly consistent with prior literature reporting accuracy gains of ten to twenty percentage points for machine learning models applied to construction and infrastructure risk classification tasks (Jiao et al., 2024; Kaveh & Alhaji, 2025). This consistency across independently developed frameworks and project contexts strengthens confidence in the generalizability of digital twin-enabled, deep learning-based risk classification approaches beyond the specific sample examined in this study.

The regression findings, indicating that schedule deviation intensity and structural sensor anomaly frequency were the strongest predictors of elevated project risk classification, align with established theoretical accounts of schedule-driven and structural risk propagation in complex infrastructure delivery (Ozturk, 2021). The comparatively smaller, though still significant, contribution of resource utilization variance suggests that while inefficient resource allocation amplifies realized project impacts, its independent predictive contribution to risk classification may be partially mediated through its interaction with schedule and structural conditions rather than operating as a fully independent risk channel. This interpretation is consistent with digital twin literature emphasizing the interconnected propagation of schedule, structural, and resource risks across construction project systems (Jiang et al., 2021).

The observed differential in high-risk exposure across project sectors, with mixed-use mega-projects exhibiting nearly twice the proportion of high-risk classification windows relative to vertical building projects, reinforces the practical value of sector-stratified risk modeling rather than applying uniform risk thresholds across heterogeneous project types. This finding has direct implications for portfolio-level infrastructure program management, suggesting that resilience-oriented resource allocation strategies should incorporate sector-specific risk calibration informed by digital twin-derived exposure signals rather than relying solely on historical cost and schedule benchmarks.

The significant positive association between cumulative predicted risk index and both cost overrun magnitude and equipment idle time provides preliminary validation of the resource optimization index as a meaningful, forward-looking indicator of project vulnerability. This finding extends prior work on digital twin-based predictive logistics and safety risk frameworks by demonstrating that a composite, multi-dimensional risk index, incorporating schedule, structural, resource, and supply chain exposure, exhibits predictive validity for realized resource optimization outcomes beyond what any single risk dimension would capture in isolation.

Despite these encouraging findings, several considerations warrant caution in interpretation. The moderate, rather than near-perfect, explanatory power of the regression model ($R^2 = 0.562$) indicates

that a substantial proportion of variance in project risk scores remains unexplained by the modeled predictors, potentially reflecting unmodeled behavioral, contractual, or site-specific factors particular to individual projects or delivery teams. Additionally, while the deep learning model demonstrated superior classification accuracy, its comparatively lower interpretability relative to logistic regression may present adoption barriers within regulatory and public-agency reporting contexts that require transparent risk attribution, an issue previously identified as a persistent methodological challenge within the digital twin and construction analytics literature.

CONCLUSION

This study developed and empirically validated an AI-driven digital twin framework designed to enhance predictive risk management and resource optimization in large-scale civil infrastructure projects. Drawing on a stratified sample of 121 active infrastructure projects spanning transportation, water and wastewater, vertical building, energy, rail, and mixed-use mega-project sectors, the study demonstrated that digital twin-derived exposure variables, encompassing schedule deviation intensity, structural sensor anomaly frequency, resource utilization variance, and supply chain disruption, significantly predicted structured project risk classifications, explaining approximately 56% of observed variance. A graph neural network integrated with long short-term memory layers achieved a classification accuracy of 88.9%, meaningfully outperforming random forest, logistic regression, and decision tree baseline models across all evaluated performance metrics. Furthermore, the study established that cumulative digital twin-derived risk indices were significantly associated with realized cost overrun magnitude and equipment idle time, supporting the practical validity of the proposed resource optimization index as a forward-looking risk management tool.

These findings collectively indicate that AI-driven digital twin frameworks offer a reliable, objective, and scalable complement to traditional Critical Path Method, Earned Value Management, and Quantitative Risk Analysis approaches, particularly under conditions of elevated project complexity where static, periodic project controls are most prone to underperformance. The demonstrated differential in risk exposure across project sectors further underscores the practical value of sector-stratified, digital twin-informed risk calibration for public infrastructure agencies, engineering firms, and program-level portfolio managers seeking to enhance predictive risk management and resource allocation. By integrating deep learning-based classification with established project-theoretic constructs, this study contributes to an empirically grounded and reproducible framework that advances the broader movement toward data-driven, technology-enabled infrastructure project delivery.

LIMITATION

This study is subject to several limitations that warrant consideration when interpreting the findings. First, the sample of 121 projects, while stratified across sector type and delivery method, may not fully capture the heterogeneity of infrastructure delivery contexts, regulatory environments, and market conditions present across the broader global civil engineering industry, potentially limiting generalizability. Second, the reliance on specialist-verified structured risk labels as ground truth, while supported by substantial inter-rater agreement, introduces a degree of subjectivity inherent to any human-informed classification protocol. Third, the observation window, while spanning multiple project phases, may not fully represent the behavior of the proposed framework under future, structurally distinct delivery conditions, particularly unprecedented supply chain or regulatory disruptions not represented within the historical training data. Fourth, the deep learning model's comparatively limited interpretability relative to parametric alternatives constrains its immediate applicability within public-sector regulatory contexts requiring fully transparent risk attribution. Finally, the study's cross-sectional and short-term longitudinal design, while methodologically appropriate for the stated objectives, does not permit strong causal inference regarding the mechanisms underlying the observed associations between predicted risk indices and realized resource optimization outcomes. Future research employing extended longitudinal designs, larger and more geographically diverse project samples, and explainable artificial intelligence techniques would help address these limitations and further validate the generalizability of the proposed framework.

RECOMMENDATIONS

- [1]. Infrastructure delivery agencies and engineering firms should consider integrating AI-driven digital twin risk classification as a complementary layer alongside, rather than a replacement for, established Critical Path Method and Earned Value Management reporting frameworks, given the demonstrated performance advantages of deep learning models under conditions of project complexity.
- [2]. Program and portfolio management processes should incorporate sector-stratified risk calibration informed by the observed differential in high-risk exposure across project types, particularly for mixed-use mega-projects and transportation projects that demonstrated disproportionately elevated risk classification rates.
- [3]. Project controls teams should prioritize the monitoring of schedule deviation intensity and structural sensor anomaly frequency as leading indicators, given their demonstrated status as the strongest predictors of elevated project risk classification within the regression analysis.
- [4]. Agencies adopting deep learning-based digital twin risk models should invest in complementary interpretability tools, such as feature attribution and graph attention visualization techniques, to address regulatory and public accountability requirements for transparent risk reporting.
- [5]. Future implementations should incorporate project-independent validation protocols as a standard practice to mitigate data leakage and ensure that reported model performance reflects genuine out-of-sample generalizability rather than in-sample overfitting.

Resource optimization indices combining equipment idle time, labor utilization, schedule deviation, and structural sensor data should be considered for integration into ongoing digital twin dashboards to provide forward-looking, rather than purely retrospective, project risk visibility.

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