Received: 05 Feb. 2026; Revised: 07 Mar. 2026; Accepted: 27 June 2026
https://doi.org/10.22306/atec.v12i2.322

Smart infrastructure modeling

Bonniga Ravinder
NICMAR University of Construction Studies, Jaggamguda, Shamirpet, Medchal-Malkajgiri, Hyderabad, Telangana 500 101, India, bravinder@nicmar.ac.in

Keywords: digital twin, logistics management, asset management, predictive maintenance, digital transformation.
Abstract: Digital twin technology has emerged as a significant enabler of digital transformation in logistics and asset-intensive systems by integrating physical assets with real-time virtual models through continuous data exchange. This study investigates the role of digital twins in enhancing organizational and logistics performance, with particular focus on asset monitoring, predictive maintenance, and operational control. A conceptual and analytical approach is adopted to evaluate the impact of digital twin integration on system efficiency and decision-making processes under conditions of operational uncertainty. The results indicate that digital twin implementation substantially improves real-time diagnostics, automated fault detection, and predictive maintenance performance, leading to reduced downtime, enhanced operational efficiency, and improved responsiveness of logistics systems. Compared to conventional asset and logistics management practices, digital twins provide a scalable and cost-effective framework by strengthening data-driven decision-making and minimizing manual intervention. From a strategic perspective, adoption of digital twin technology supports the development of dynamic capabilities, enhances supply chain resilience, and extends asset life cycles. The study concludes that digital twin technology constitutes a critical technological foundation for achieving sustainable performance improvement and long-term competitive advantage in modern logistics environments.

1 Introduction

Manufacturing systems have progressively evolved from traditional production environments toward digitally enabled and data-driven operations in response to intensifying global competition, customization demands, and performance pressures. Within this transformation, digital twin (DT) technology has emerged as a central enabler by integrating physical assets with continuously updated virtual representations that facilitate real-time monitoring, analysis, and optimization. By synchronizing physical and digital systems through continuous data exchange, digital twins enhance system visibility and enable informed managerial decision-making across the product and operational lifecycle [1-16].

Initially conceptualized within product lifecycle management, digital twins have expanded their application to design, production, maintenance, and operational control. Recent advancements in enabling technologies, including the Internet of Things, artificial intelligence, cloud and edge computing, and advanced analytics, have accelerated organizational adoption of digital twin solutions. From a managerial and logistics perspective, digital twins contribute to improved organizational performance through predictive maintenance, process optimization, and adaptive control mechanisms under uncertain operating conditions. Unlike conventional static simulation tools, digital twins support continuous system learning, dynamic feedback, and enhanced organizational responsiveness [17-23].

Despite these advantages, the realization of performance benefits remains constrained by challenges related to data integration, interoperability across heterogeneous systems, cybersecurity considerations, and organizational readiness for digital transformation. Addressing these constraints is essential to fully leverage the strategic potential of digital twin technology [24-31].

Overall, digital twins represent a strategic digital capability that underpins digital transformation and sustained performance improvement in manufacturing organizations. To provide a structured understanding of digital twin typologies, the classification of digital twins based on structural functions is presented in Table 1, classification based on level of application is presented in Table 2, structural classification is detailed in Table 3, and application-oriented classification in smart manufacturing is presented in Table 4.

Table 1 Classification of digital twins based on structural functions

Category	Physical System Exists	Data Update Mechanism	Data Flow Direction	Control of Physical System	Primary Purpose / Characteristics	Typical Applications
Pre-Digital Twin (PDT)	No	Manual / design-stage data	No real-time data flow	No	Virtual, generic executable model created before the physical system exists; supports early-stage decision-making and risk reduction	Conceptual design, feasibility analysis, virtual prototyping, design validation
Digital Model (DM)	May or may not exist	Manual updates	No automated data exchange	No	Static or semi-static digital representation based on initial design data; no real-time synchronization	CAD models, CAE simulations, visualization, form and functional analysis
Digital Shadow (DS)	Yes	Automatic updates from physical system	One-way (Physical → Digital)	No	Digital representation continuously updated by sensor data from the physical system; no feedback to physical asset	Condition monitoring, performance tracking, diagnostics
Digital Twin (DT)	Yes	Automatic, real-time updates	Bi-directional (Physical ↔ Digital)	Yes	Fully integrated cyber–physical system enabling real-time monitoring, prediction, optimization, and control	Predictive maintenance, real-time optimization, smart manufacturing, autonomous decision-making

Table 2 Classification of digital twins based on level of application

Type	Description	Scope of Representation	Typical Use Cases
Component / Parts Twin	Digital replica of an individual component or part	Lowest level	Performance monitoring, failure prediction of parts
Asset Twin	Integration of multiple component twins forming a functional asset	Medium level	Predictive maintenance, equipment optimization
System / Unit Twin	Combination of multiple assets forming a complete system	High level	System-level performance analysis, operational optimization
Process Twin	Representation of end-to-end processes involving multiple systems	Very high level	Production planning, resource optimization, factory-level decision-making
Digital Twin Instance (DTI)	Twin of a specific physical product	Product lifecycle-specific	Lifecycle tracking, usage-based services
Digital Twin Prototype (DTP)	Prototype version of a digital twin	Development stage	Testing, validation, scenario analysis
Digital Twin Environment (DTE)	Platform managing multiple digital twins	Ecosystem level	Coordination, simulation, industrial metaverse integration

Table 3 Structural classification of digital twins

Category	PLM Lifecycle Stage	Industry 4.0 Integration Level	Data Synchronization	Control Capability	Role in Smart Manufacturing
Pre-Digital Twin (PDT)	Concept & Design	Low	None / Design-stage data	None	Virtual prototyping, design validation, early risk mitigation
Digital Model (DM)	Design & Engineering	Low–Medium	Manual / periodic	None	Visualization, simulation, engineering analysis
Digital Shadow (DS)	Production & Operation	Medium	One-way (Physical → Digital)	None	Condition monitoring, diagnostics, performance tracking
Digital Twin (DT)	Full Lifecycle (Design–EoL)	High	Bi-directional, real-time	Yes	Autonomous optimization, predictive maintenance, real-time decision support

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Table 4 Application-oriented classification in smart manufacturing

Type	PLM Scope	Smart Manufacturing Function	Industry 4.0 Relevance
Component / Parts Twin	Micro-level	Component health monitoring	Sensor-driven cyber–physical integration
Asset Twin	Equipment-level	Predictive maintenance, reliability optimization	Data-driven maintenance strategies
System / Unit Twin	System-level	Process coordination and optimization	Smart production systems
Process Twin	Factory / Enterprise-level	End-to-end production optimization	Smart factories and autonomous operations
Digital Twin Instance (DTI)	Individual product lifecycle	Usage-based monitoring and services	Servitization and digital business models
Digital Twin Prototype (DTP)	Pre-production	Design testing and validation	Virtual commissioning
Digital Twin Environment (DTE)	Ecosystem-level	Multi-twin orchestration	Industrial metaverse and connected enterprises

2 Literature review

The literature on digital twin technology has expanded rapidly across manufacturing, aerospace, healthcare, and increasingly, the construction and infrastructure sectors. Early conceptualizations define a digital twin as a dynamic digital representation of a physical asset, system, or process that is continuously updated using real-time data [17]. Subsequent studies emphasize the integration of physical assets, virtual models, and data connectivity as the foundational elements enabling bidirectional information flow and lifecycle-based decision-making. The literature review compiled in the Table 5 [17-37].

Table 5 Compilation of literature review

Author(s) & Year	Domain / Context	Focus of Study	Key Contributions	Identified Gaps / Limitations
Barricelli et al. [18]	Manufacturing, aviation, healthcare	DT conceptual applications	Established DT as a dominant paradigm outside construction	Limited discussion on construction-specific DT adoption
Tuhaise et al. [33]	Construction industry	Enabling technologies for DT	Identified key technologies and research gaps for DT adoption	Early-stage adoption; fragmented implementation
Cerovšek [4]; Eastman et al. [1]	BIM standards	BIM interoperability and schemas	Proposed adaptive BIM schemas and methodological frameworks	BIM lacks real-time integration and control capabilities
Boje et al. [23]	Construction DT	Construction Digital Twin (CDT)	Proposed CDT paradigm and DT abilities	Complexity of real-time physical integration
Jiang et al. [28]	Civil engineering	DT, BIM, CPS comparison	Clarified DT constituents and distinctions	Benefits and implementation pathways remain unclear
Deng et al. [27]	Built environment	DT taxonomy	Five-level DT taxonomy across lifecycle phases	Most studies remain at early DT maturity
Ozturk [30]	AECO-FM	Bibliometric analysis	Identified DT research clusters and trends	Predictive and autonomous DT use remains limited
Qi and Tao [20]; Lu et al. [25]	DT systems	DT layered architecture	Proposed five-layer DT architecture	High computational and integration complexity
Sacks et al. [26]	Construction lifecycle	BIM–DT convergence	Proposed DT as evolution of BIM toward cyber–physical systems	Limited operational-scale validation
Volk et al. [9]	Infrastructure O&M	DT for lifecycle management	Highlighted DT value in operation and maintenance	Lack of standardized implementation frameworks
ISO 23247-1 [35]	Industrial DT standards	DT framework standardization	Provided reference architecture for DT systems	Limited construction-specific guidance
Al-Ababneh et al. [37]	Logistics & Supply Chain Management; digital transformation through cyber-	Systematic review of digital twin applications, technology enablers, thematic	Comprehensive synthesis, technological mapping, thematic categorization, cross-domain insights, methodological grounding	Limited empirical deployments, data and integration challenges, interoperability gaps, sparse real-time monitoring evidence, organizational

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	physical integration	mapping, and trend synthesis		hurdles, and lack of unified performance metrics
Trebuna et al. [53]	Logistics information systems; digital twin principles applied to logistics modelling and simulation	Propose a logistics digital twin architecture using object-oriented modelling and real-time data synchronization	Integrated modelling framework, conceptual architecture, bi-directional synchronization, simulation-based decision support, modular design	Conceptual stage without empirical validation, data integration challenges, computational complexity, legacy system integration, limited application scenarios, limited human-system interaction insights
Molnar et al. [54]	Flexible manufacturing planning with AGV automation and digital modelling in industrial logistics	Integrated lifecycle planning methodology for AGV-equipped flexible manufacturing systems	Lifecycle planning framework, digital modelling integration, simulation support, automation insights	Conceptual digital twin rather than full implementation, limited empirical validation, data integration issues, computational complexity, limited human-system interaction, cost considerations
Bohács et al. [55]	Intralogistics system architecture; intelligent information systems for internal logistics processes	Conceptual design of an intelligent logistics node capable of digital monitoring, coordination, and decision support	Intelligent node architectural framework, modular design, integration of digital/physical layers, decision support emphasis	Conceptual stage with limited implementation detail, lack of empirical validation, technology integration and interoperability gaps, scalability issues, limited real-time data discussion, minimal human-system interaction focus

3 Framework of digital twin technology

Building on the conceptual foundations proposed by Pawaskar and Dhonde [32], this study develops a structured framework for digital twin implementation, positioning it as a multi-layered system that integrates physical assets with dynamic virtual representations to enhance organizational decision-making and operational performance. The framework is composed of four interrelated layers that collectively enable real-time monitoring, analytical evaluation, and control throughout the asset lifecycle.

The **infrastructure layer** constitutes the foundational digital environment required for deployment. It includes cloud computing platforms, communication networks, data storage systems, monitoring facilities, and computational resources. From a managerial standpoint, this layer must ensure scalability, cybersecurity, interoperability, and regional accessibility to support system reliability and sustained organizational adoption.

The **data acquisition layer** facilitates the integration of heterogeneous data sources, combining static spatial datasets—such as Building Information Modelling (BIM) and Geographic Information Systems (GIS)—with dynamic, sensor-generated data derived from Internet of Things (IoT) technologies. The consolidation of structured and unstructured data streams enables the creation of a comprehensive, continuously updated representation of physical assets and operational conditions.

The **information model construction layer** transforms the integrated datasets into synchronized virtual models. These models support real-time visualization, system diagnostics, and performance evaluation across assets and operational environments. Continuous data synchronization enhances adaptive monitoring capabilities and enables timely managerial intervention.

Finally, the **application service platform layer** operationalizes the digital twin by supporting planning, operations, and maintenance activities. It incorporates simulation tools, predictive analytics, and optimization mechanisms to improve system performance. Through bidirectional data exchange between physical and virtual environments, the digital twin enables closed-loop decision-making, strengthens organizational responsiveness, and contributes to sustained improvements in operational efficiency.

4 Research questions

To establish the scope and analytical direction of the systematic literature review, the study is guided by the following research questions:

- RQ1: What principal components characterize digital twin applications within the construction industry?

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- RQ2: Which enabling technologies are currently utilized in the design, development, and implementation of digital twin systems?
- RQ3: What gaps can be identified in the existing body of literature, and which prospective research directions may advance the theoretical and practical development of digital twins in construction?

5 Findings

The findings demonstrate that digital twins in the construction sector comprise three fundamental elements: (i) a physical asset or system—such as buildings, infrastructure facilities, or construction equipment—equipped with sensor technologies for continuous data acquisition; (ii) a virtual representation developed through CAD, BIM, and Product Lifecycle Management (PLM) platforms, capable of dynamically mirroring the condition and behaviour of the physical entity; and (iii) an integrated data and connectivity layer that facilitates real-time, bidirectional information exchange between the physical and virtual environments. The coherent integration of these components enables real-time monitoring, simulation-based analysis, performance optimization, and lifecycle-oriented decision-making within construction projects [23-36].

The review further identifies a multi-layered technological ecosystem underpinning digital twin development. Core enabling technologies include the Internet of Things (IoT) for real-time sensing and data capture, cloud computing for scalable storage and computational capacity, artificial intelligence (AI) and machine learning (ML) for predictive modelling and automation, and extended reality (XR) technologies for immersive visualization and interactive analysis. Complementary technologies—such as advanced CAD and simulation tools, data analytics platforms, edge and fog computing architectures for low-latency processing, and emerging metaverse-based environments—enhance system interoperability, visualization capabilities, and workflow integration across project phases [13-15,20-22,34,38-40,45,48-51].

Despite these advancements, several critical research gaps persist. Key challenges relate to data quality, accessibility, integration, affordability, and interoperability across heterogeneous systems. Foundational limitations remain evident in mathematical, statistical, and computational modelling, particularly in areas such as uncertainty quantification, inverse problem formulation, and real-time data assimilation. Furthermore, unresolved concerns regarding data governance, ownership, privacy, and cybersecurity constrain large-scale implementation. Future research should prioritize the development of standardized and interoperable digital twin architectures, the integration of hybrid physics-based and data-driven modelling approaches, the advancement of AI-enabled adaptive learning mechanisms, and the establishment of robust uncertainty-aware decision-support frameworks tailored to construction applications [24,27-33,35-44,46-52].

6 Challenges in applying digital twin technology

Despite their transformative potential, the implementation of digital twins presents several technical, organizational, and operational challenges. Achieving real-time synchronization with complex physical assets often exceeds existing organizational culture, resource availability, and data governance capabilities.

Cost

Although technology costs are gradually decreasing, digital twin adoption still requires significant investment in digital infrastructure, model development, integration, and continuous maintenance. Organizations must carefully assess the cost–benefit balance and compare digital twin implementation with alternative solutions to ensure long-term value creation.

Accuracy of representation

Digital twins cannot fully replicate the physical, chemical, electrical, and thermal behaviors of complex assets due to modeling limitations and cost constraints. Engineers must therefore strike a balance between model fidelity and computational efficiency, focusing on the most critical parameters relevant to decision-making.

Data quality

Reliable digital twins depend on high-quality, continuous data streams from distributed sensors operating under variable environmental and network conditions. Challenges related to missing data, noise, and inconsistencies necessitate robust data validation, cleansing, and filtering mechanisms to maintain model accuracy and trustworthiness.

Interoperability

While advancements have been made toward standardization, data exchange across heterogeneous platforms remains limited, particularly when proprietary simulation tools or AI solutions are involved. This often results in vendor lock-in, restricting system flexibility and long-term scalability.

Human and organizational readiness

Effective deployment of digital twins requires changes in work practices, skill sets, and organizational culture. Successful adoption depends on user training, change management strategies, and fostering a collaborative, data-driven mindset across stakeholders.

Cybersecurity

The tight integration between digital twins and physical systems introduces new cybersecurity risks. Unauthorized access or data manipulation can lead to operational disruptions or physical damage. Ensuring data integrity, secure communication, and robust access control is therefore critical, particularly for applications involving critical infrastructure.

Connectivity constraints

Reliable high-speed internet connectivity is essential for real-time digital twin operations. While emerging technologies such as 5G and satellite-based broadband services are expanding access, connectivity limitations in remote or underserved regions remain a significant barrier.

7 Discussion

This study confirms that digital twins in the construction industry constitute an integrated system comprising physical assets, BIM-based virtual models, and real-time data connectivity mechanisms. In contrast to static digital representations, digital twins facilitate continuous synchronization between physical and virtual environments, thereby enabling real-time monitoring, performance evaluation, and evidence-based decision-making across the asset lifecycle.

The findings further indicate that the effective development of construction-oriented digital twins depends on a convergence of enabling technologies, including Building Information Modelling (BIM), the Internet of Things (IoT), cloud computing infrastructures, artificial intelligence (AI), and advanced data analytics techniques. The coordinated application of these technologies enhances construction planning, progress monitoring, safety supervision, and predictive maintenance by converting fragmented and heterogeneous project data into structured, actionable intelligence.

Notwithstanding their transformative potential, digital twin applications within construction remain at an emergent stage of maturity. Significant research gaps persist in areas such as data integration, system interoperability, real-time model synchronization, and uncertainty management. Addressing these limitations is critical to the development of scalable, reliable, and fully functional digital twin frameworks capable of supporting sustainable, performance-oriented construction practices.

8 Conclusion, practical implication

The study confirms that the implementation of digital twin technology in construction and infrastructure projects can significantly enhance asset reliability and lifecycle performance. By integrating physical infrastructure, BIM-based virtual models, and real-time data streams, digital twins enable continuous monitoring and more effective management of built assets. This approach reduces reliance on periodic manual inspections while improving operational efficiency and safety across construction sites and operational environments.

Furthermore, the integration of enabling technologies such as IoT sensors, cloud computing platforms, and AI-based analytics supports predictive maintenance, early defect identification, and data-driven decision-making throughout both construction and operational phases. These capabilities contribute to minimizing downtime, optimizing maintenance strategies, and extending the service life of infrastructure assets. Overall, digital twin adoption provides improved real-time visibility of project and supply chain activities, strengthening resilience against disruptions and enhancing system performance. Consequently, digital twins are expected to play an increasingly important role in advancing automation, sustainability, and resilience within modern construction and infrastructure management systems [37,47,52-55].

9 Novelty

The principal contribution of this study lies in its systematic clarification and integrative conceptualization of digital twin applications within construction and infrastructure domains. Through a structured synthesis of existing literature, the study delineates the fundamental components of construction-oriented digital twins—namely the physical asset, its dynamic virtual representation, and the enabling data and connectivity infrastructure—thereby addressing prevailing conceptual ambiguities between Building Information Modelling (BIM), static digital models, and fully operational digital twin systems.

Furthermore, the study consolidates and categorizes the principal enabling technologies underpinning digital twin implementation, including the Internet of Things (IoT), cloud computing, artificial intelligence and machine learning (AI/ML), advanced data analytics, and extended reality (XR). Their respective functional roles are systematically examined across construction phases and asset lifecycle stages, highlighting their contribution to real-time monitoring, predictive diagnostics, and performance optimization.

The analysis also identifies critical research gaps, particularly in relation to data quality and governance, system interoperability, real-time model synchronization, uncertainty quantification, and scalability in complex infrastructure environments. By outlining structured future research directions, the study provides a foundation for the development of standardized, interoperable, and uncertainty-aware digital twin frameworks capable of supporting large-scale deployment.

Collectively, the findings position digital twins as a proactive, data-driven alternative to conventional inspection-based asset management approaches. The study confirms that an effective digital twin for construction and infrastructure assets requires the integration of physical systems, intelligent virtual models, and continuous data exchange mechanisms to enable real-time system-level performance evaluation. The successful operation of such systems depends on the coordinated deployment of IoT-enabled sensing, cloud-based computational platforms, advanced analytics, and adaptive modelling techniques, facilitating failure diagnosis, predictive maintenance, and operational optimization under dynamic conditions. Advancing interoperability standards, predictive and adaptive modelling strategies, and decision-support capabilities will be essential to enhance infrastructure resilience, minimize downtime, and improve lifecycle performance in construction and infrastructure management.

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