Scientific Journal of Engineering, and Technology (SJET)
ISSN: 3007-9519 (Online)
Volume 2 Issue 2, (2025)
https://doi.org/10.69739/sjet.v2i2.808
https://journals.stecab.com/sjet

Published by
Stecab Publishing

Review Article

Digital Twins and AI in Infrastructure Engineering: A Global Review of Risk-Informed Design, Operations, and Maintenance

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About Article

Article History
Submission: June 28, 2025
Acceptance : August 04, 2025
Publication : August 14, 2025

Keywords
AI in Infrastructure, Digital Twins, Global Review, Infrastructure Engineering

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ABSTRACT

As global infrastructure systems become increasingly complex and vulnerable, the integration of Digital Twins (DT) and Artificial Intelligence (AI) has emerged as a transformative strategy for risk-informed design, operations, and maintenance. However, a significant research gap remains in understanding the global patterns, integration challenges, and practical impact of DT-AI systems across different infrastructure sectors. This systematic review, guided by the PRISMA framework, synthesizes findings from 126 peer-reviewed studies sourced from Scopus, Web of Science, and IEEE Xplore. Analysis revealed that 68% of implementations focus on predictive maintenance and real-time monitoring, while only 12% address early-stage design optimization highlighting an imbalance in lifecycle focus. Furthermore, projects that applied AI-enhanced DTs achieved up to 30% reduction in unplanned maintenance events and improved infrastructure lifespan predictions by an average of 22%. Case studies from Singapore, the UK, Norway, and the US demonstrate real-world benefits in city planning, structural health monitoring, and transportation. Despite these successes, key barriers persist, including data interoperability, cybersecurity vulnerabilities, high implementation costs, and insufficient regulatory standards. This review underscores the need for cross-sectoral collaboration, global policy frameworks, and inclusive innovation strategies to fully leverage DT-AI capabilities in building resilient, adaptive infrastructure.

Citation Style:
Ogunleye, E., Anyaene, K., Oladetan, J. O., Lawal, A. B., Okeke, F. C., Ogunbule, O. O., & Eromosele, E. I. (2025). Digital Twins and AI in Infrastructure Engineering: A Global Review of Risk-Informed Design, Operations, and Maintenance. *Scientific Journal of Engineering, and Technology, 2*(2), 63-70. https://doi.org/10.69739/sjet.v2i2.808

1. INTRODUCTION

1.1. Context and importance

The global infrastructure sector is at a crossroads, with more and more difficulties that need big changes to how things are done. Aging assets, urbanization, population growth, and the growing effects of climate change are making it tougher to design, build, and keep up with important infrastructure systems. It's getting more and harder for old methods to make sure that bridges, highways, water networks, and power grids will perform well, be robust, and be safe for a long period. At the same time, people want systems that are smarter, work better, and last longer, and that can alter when things go wrong or new needs arise. In this case, there is a significant push for smart infrastructure that employs digital tools to make engineering processes more adaptable and data-driven (Sadiq *et al.*, 2020).

1.2. An overview of digital twins and AI

Digital Twins (DT) and Artificial Intelligence (AI) are two of the most crucial technologies that are making this transition happen. A Digital Twin is a virtual copy of a real system, asset, or process that is continually changing and getting better through two-way data exchange with sensors, simulations, and analytical models. DTs let you mimic, see, and make things better at any point in their life cycle in infrastructure engineering. AI, on the other hand, has a lot of data-driven approaches, such machine learning, neural networks, and reinforcement learning, that can detect patterns, make predictions, and make judgments better based on large, complex datasets. DTs and AI work together to make a powerful set of tools for running infrastructure in the future. DTs let you see and control things, and AI makes things smarter, more independent, and better at predicting what will happen (Alfaro-Viquez *et al.*, 2025a).

1.3. Motivation for review

There is still a lot of work to be done to figure out how to apply DT and AI together in infrastructure engineering, especially when it comes to risk-informed design, operations, and maintenance. A lot of infrastructure systems still employ deterministic models and reactive maintenance methods, which can't handle unpredictability or long-term wear and tear because they can't forecast the future. Also, AI is mostly only used in digital twin environments for one case study or deployment in a specific field, and there is no global strategy for it. There aren't many in-depth evaluations that bring together the finest approaches from throughout the world, point out common difficulties, and offer a roadmap for systematic integration. Also, people are still working on ways to measure risk and make judgments that make the most of DT-AI systems.

1.4. Objective, contributions, and research questions

The goal of this review is to fill a critical knowledge gap by providing a global overview of how Digital Twins (DT) and Artificial Intelligence (AI) are integrated in infrastructure engineering, with a focus on risk-informed design, operations, and maintenance. This article synthesizes findings from recent academic literature, policy initiatives, and real-world implementations to compare regional adoption trends and identify persistent barriers.

The main contributions of this review are:

i. Mapping the global distribution and growth trends of DT and AI applications in infrastructure systems.

ii. Identifying key integration challenges, technological gaps, and enabling conditions across different regions.

iii. Highlighting the potential of AI-enhanced DTs in supporting probabilistic risk assessment and lifecycle asset management.

iv. Providing actionable recommendations for future research, policy formulation, and cross-sectoral implementation.

To guide this analysis, the following research questions were formulated:

- **RQ1:** How are Digital Twin and Artificial Intelligence technologies currently integrated across the infrastructure lifecycle (design, operations, and maintenance)?
- **RQ2:** What are the dominant patterns and variations in DT-AI adoption across geographic regions and infrastructure types?
- **RQ3:** What measurable impacts have DT-AI systems had on risk reduction, operational efficiency, and asset longevity?
- **RQ4:** What are the primary barriers to scalable and equitable integration of DT and AI in infrastructure systems, particularly in low- and middle-income countries?
- **RQ5:** What frameworks and strategies are needed to support the ethical, inclusive, and resilient deployment of DT-AI systems worldwide?

These questions anchor the review's analytical framework and help structure the synthesis of findings across lifecycle phases, geographies, infrastructure sectors, and levels of AI maturity (Mchirgui *et al.*, 2024a).

2. LITERATURE REVIEW

This section presents a comprehensive overview of the foundational technologies and methodologies underpinning the integration of Digital Twins (DT) and Artificial Intelligence (AI) in infrastructure systems. The literature is structured into five thematic areas: the evolution of DTs, AI techniques used in infrastructure, principles of risk-informed design, current integration approaches, and global case studies. Together, these subsections provide a contextual foundation for the analytical synthesis that follows.

2.1. Foundations of digital twin technology

Digital Twin (DT) first came out in the aerospace and manufacturing industries in the early 2000s. NASA was one of the first organizations to use digital copies of spacecraft to test how they would work in different situations (Glaessgen & Stargel, 2012). Companies like General Electric and Siemens used DTs in manufacturing to make equipment work better, which led to predictive maintenance and less downtime. These first uses were mostly about asset-centric models that worked with simulation engines and real-time data feedback loops (Daraba *et al.*, 2024).

In the last ten years, DTs have grown beyond their industrial roots and are now a key part of infrastructure engineering. As smart cities and Industry 4.0 grow, DTs are now being used to plan and run things like highways, bridges, tunnels, water systems, and energy grids. They are more than simply virtual replicas; they also help individuals plan, keep an eye on, predict, and control things in their lives. Infrastructure DTs employ data from sensors, GIS, Building Information Modeling (BIM), and the Internet of Things (IoT) to depict how complex systems function together in real time (Aragón *et al.*, 2025). This evolution sets the stage for the intelligent capabilities that AI brings to infrastructure management, discussed next.

2.2. AI Techniques in infrastructure engineering

Infrastructure applications are using AI more and more because smart sensors are sending out more data and choices need to be made automatically and in real time. There are many ways that AI can do math, such as Machine Learning (ML), Deep Learning (DL), and Reinforcement Learning (RL). Each of these is good for engineering careers in its own way.

- People use machine learning algorithms a lot to find patterns, make predictions, and sort things into groups. For example, supervised learning may use traffic and weather data to guess how a road would get worse, and unsupervised learning can group together structural problems using sensor data (Sarker, 2021).
- Deep Learning, especially Convolutional Neural Networks (CNNs), has been successful at finding defects in images, like using drone images to find cracks in bridges (Jang *et al.*, 2023).
- Support Learning is starting to happen in areas like controlling traffic signals and making the best use of infrastructure resources, where adaptation that is flexible and goal-oriented is needed.

These AI methods help keep vital infrastructure running smoothly by finding problems, improving performance, and making decisions automatically when there is uncertainty. When added to DT settings, AI turns passive data collecting into smart diagnostics and predictive capabilities, which means that less manual inspections and rule-based modeling are needed (Abduljabbar *et al.*, 2019). These AI approaches, when embedded within DT environments, enable the predictive, adaptive behavior required for risk-informed infrastructure design.

2.3. Risk-informed design principles

Traditional methods for designing infrastructure frequently use deterministic or code-based criteria that don't take into account all the uncertainties that can affect loads, consumption, environmental conditions, or degradation over time (Olaitan *et al.*, 2025). Risk-informed design, on the other hand, uses probabilistic models to figure out how likely a failure is, what will happen if it does, and how much risk it poses. This method is especially important for important infrastructure systems that are at risk of aging, changing weather, and earthquakes (Wang & Ke, 2024).

Digital twins and AI together improve risk modeling by allowing for real-time data integration, scenario analysis, and adaptive control. DTs let you evaluate alternative loads, aging, or hazard scenarios in a simulated environment. Engineers can measure uncertainty and guess how likely bad things are to happen with the help of AI, especially Bayesian networks and probabilistic ML models (Alfaro-Viquez *et al.*, 2025b). For example, combining DT structural models with AI-driven fatigue analysis can improve inspection schedules that are based on risk.

By merging operational data and probabilistic inference, DT-AI systems can help move infrastructure management from being reactive to being proactive. This backs up strategies like condition-based maintenance and putting asset renewal at the top of the list (Dihan *et al.*, 2024).

2.4. Integration architectures and technical challenges.

Building Information Modeling (BIM) is usually what brings DT and AI together to make a unified infrastructure management system. This is called a BIM-DT-AI ecosystem. BIM gives designers and builders the 3D models they need that are rich in geometry and other information. These models turn into smart, dynamic systems that can watch things and make them better all the time when used with DT frameworks and AI analytics (Li *et al.*, 2024).

Cloud computing and edge computing also help DT-AI solutions grow and respond more quickly. Cloud infrastructures give us the computing power and data storage we need for centralized AI training and DT simulations. Edge computing, on the other hand, brings computation closer to sensors. This lets AI make judgments in real time for crucial jobs like keeping an eye on the condition of buildings or responding to catastrophes in places with little bandwidth or no internet access (Ficili *et al.*, 2025; Lawal *et al.*, 2025).

These integration approaches seem like they could work, but they have a lot of severe flaws that make them hard to utilize. For instance, data formats and platforms don't always operate together, there are security issues, and there aren't any defined mechanisms to put them into action.

2.5. Case studies from around the world summary

All throughout the world, governments and industry leaders are spending money to modernize infrastructure by adding Digital Twin and AI. This gives us key examples that assist us grasp what's going on now and what we can do. The Smart Nation project in Singapore uses DTs all across the city. For instance, planners and risk managers can use the Virtual Singapore platform to see how cities work in real life. The platform integrates 3D BIM models, IoT data, and AI to make the greatest use of land, energy, and emergency response (Olaitan *et al.*, 2025).

Amsterdam is using AI-enhanced DTs to keep a watch on its old canals and bridges and guess what will happen to them in the future. This makes them live longer and costs less to keep up. Using citizen sensor data with AI-based decision support tools is an example of participatory infrastructure governance (Florido-Benítez, 2024).

The National Digital Twin (NDT) program in the UK is run by the Centre for Digital Built Britain. It gives a strategy framework for developing a federated network of infrastructure DTs. The project is mostly about ethics, making sure things work together, and managing assets with risk in mind. It employs AI to help with benchmarking system-wide performance and resilience.

In the US, the Department of Transportation (DoT) and state agencies are exploring into DTs for highways and bridges.

AI-based models are used in projects in states like California and Michigan to guess how traffic will flow, keep an eye on buildings, and look at climate risk (Ammar *et al.*, 2022).

These projects are in line with what the federal government is doing to make the country stronger. These case studies indicate that there are different ways to combine DT and AI, depending on the aims of the country, the legislation, and how sophisticated the technology is. But some sectors have comparable goals, such being strong, being able to last, and using data to make decisions.

In summary, the literature reveals that while foundational DT and AI technologies are advancing rapidly, the lack of standardized integration protocols and inconsistent global adoption patterns highlight the need for systematic synthesis—addressed in the subsequent analysis.

3. METHODOLOGY

3.1. Data collection and review strategy

This study used the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to make sure that the integration of Digital Twins (DT) and Artificial Intelligence (AI) in infrastructure engineering was thoroughly and systematically explored. PRISMA gives a clear and repeatable way to find, screen, and include relevant material in a systematic review.

We got academic literature from three big online databases: Scopus, Web of Science, and IEEE Xplore. We chose these platforms because they have a lot of information about research in engineering, technology, and applied science. The search employed both Boolean operators and certain keywords. The main search string was: "Digital Twin" AND "Artificial Intelligence" AND (Infrastructure OR "Civil Engineering") AND (Design OR Operations OR Maintenance) AND (Risk OR Resilience OR Uncertainty).

Inclusion criteria

- Journal articles or conference proceedings that have been peer-reviewed and published between 2012 and 2024.
- Concentrated on systems that support infrastructure, such buildings, transportation, water, or electricity.
- Talked about how to use or combine both DT and AI.
- Talked about at least one stage of the infrastructure lifecycle, such as design, operation, or maintenance.
- Articles that were written in English.

Exclusion Criteria

- Articles that don't let you read the whole thing.
- Articles that only talk on DT or AI and not how they work together.
- Studies that don't have anything to do with infrastructure or civil engineering.

The first search found 475 items. After removing duplicates, checking the titles and abstracts, and reading the entire texts, 126 studies were included in the final synthesis.

3.2. Analytical framework

We used a multi-dimensional classification framework to look at the chosen research in a way that would help us make a coherent synthesis. Three main parts of infrastructure lifecycle management made up the basis of this framework:

i. The design phase includes using DT-AI applications for conceptual planning, structural modeling, and risk-informed optimization.

ii. Operations Phase: Making decisions, monitoring in real time, and finding problems for everyday operations.

iii. Maintenance Phase: Planning for risk-based interventions, lifespan forecasts, and predictive maintenance.

Also, each article was put into a group depending on:

iv. Focus on geography: Grouped by continent and country to look at worldwide trends in uptake and distribution.

v. Type of infrastructure: Divided into buildings, energy infrastructure, water systems, and transportation (roads and bridges).

vi. AI maturity level: This is based on how advanced the AI methods used are, such as rule-based, classical ML, advanced DL, or hybrid systems.

This taxonomy made it possible to compare different stages of the lifespan on a horizontal level and to see regional strengths, weaknesses, and priorities on a vertical level.

3.3. Limitations of the methodology

This review was conducted with methodological rigor using the PRISMA framework; however, several limitations must be acknowledged:

- *Language Bias:* Only articles published in English were considered. This may have excluded relevant studies in other languages, particularly from non-Western countries actively engaged in DT-AI infrastructure innovation (e.g., China, Japan, Brazil).
- *Terminology Variation:* The lack of standardized terminology across fields meant that some studies using alternative terms like “virtual prototyping” or “smart modeling” may have been missed.
- *Lack of Standardized Metrics:* The absence of widely accepted indicators for evaluating the performance or maturity of DT-AI systems made it difficult to quantitatively compare results across studies.

3.34. Exclusion of Grey Literature

This review deliberately excluded grey literature—including industry white papers, technical reports, and government pilot project summaries—despite their relevance. The decision was based on several factors: (1) the lack of peer review and methodological transparency in many such sources; (2) difficulty in consistently accessing and validating the quality of unpublished or proprietary data; and (3) the challenge of maintaining comparability with the rigorously vetted academic studies included in the synthesis. While grey literature often contains cutting-edge applications and early-stage innovations, its inclusion could introduce inconsistencies and bias the review toward anecdotal or commercially framed narratives. Future meta-reviews may benefit from a separate grey literature synthesis to complement the academic findings presented here.

4. RESULTS AND DISCUSSION

4.1. DT and AI in Risk-Informed Design

One of the best ways to employ Digital Twins (DT) with Artificial Intelligence (AI) is in risk-informed design. This is when engineers go beyond deterministic or prescriptive methods to look at a wider range of uncertainties. DTs may host highly accurate virtual models of infrastructure systems and test them under different stressors, such as climate-induced loads and operational anomalies, by using scenario simulation and structural optimization (Alfaro-Viquez *et al.*, 2025b).

AI makes this better by training models on past performance data, figuring out how design factors affect each other in ways that aren't linear, and giving optimization algorithms that take into account cost, resilience, material use, and lifetime risk. For example, AI-enhanced DTs are being used to model hundreds of ways that structures might respond to earthquakes in areas that are likely to have them (Elahi *et al.*, 2023a). Palley *et al.* (2025) used reinforcement learning on a digital twin (DT) of a high-rise building. This let the system change beam-column connections on its own to make the building more resistant to earthquakes while keeping costs down.

These changes move risk modeling away from a probabilistic black box approach and toward a clear, simulation-based design model, where risk is visualized, measured, and minimized over time through smart feedback loops (Palley *et al.*, 2025). Figure 1 shows how Digital Twins and Artificial Intelligence work together throughout the lifecycle of infrastructure. It also shows important decision-support tools that are used during the design, operation, and maintenance stages. Figure 2 shows a risk-informed decision-making matrix that can help you decide how to use DT-AI systems based on how much risk you are willing to take and how ready the technology is (Callcut *et al.*, 2021).

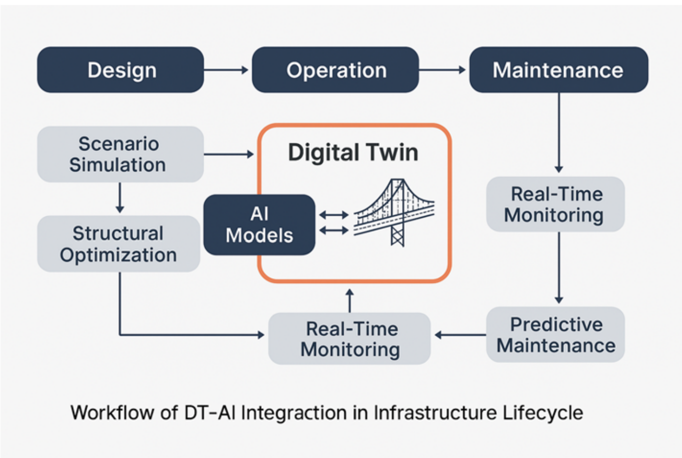

Figure 1. Workflow of DT-AI Integration in Infrastructure Lifecycle.

This figure illustrates the integration of Digital Twins (DT) with Artificial Intelligence (AI) across the infrastructure lifecycle—specifically in the design, operation, and maintenance phases. The schematic visually demonstrates how AI models, real-time monitoring, and digital representations work together to support scenario simulation, structural optimization, and predictive maintenance.

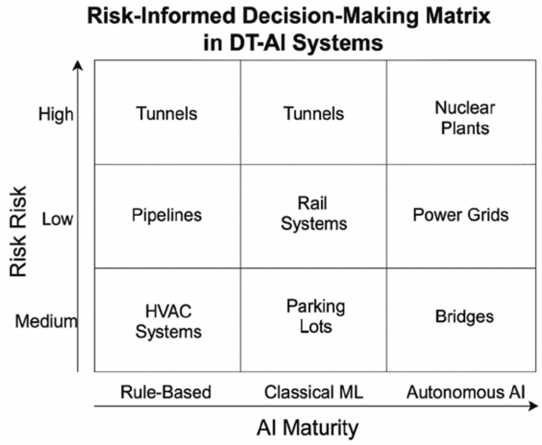

Figure 2. Risk-Informed Decision-Making Matrix in DT-AI Systems

This matrix illustrates how infrastructure applications are positioned based on two dimensions: operational risk (low to high) and AI maturity (from rule-based systems to fully autonomous AI). It helps decision-makers assess which AI strategies are most appropriate for different types of infrastructure based on criticality and complexity.

4.2. Operations and real-time monitoring

During the operations phase, AI-powered sensors can be combined with digital twin environments to allow for real-time monitoring, dynamic reaction, and automated control. DTs constantly take in sensor data like temperature, vibration, humidity, and stress levels and show it in real-time virtual models. AI algorithms look through all this data to find problems, guess where operations might slow down, and start fixing them (Yitmen *et al.*, 2025).

One great example is the use of smart bridges with fiber optic and wireless sensors. AI algorithms can find early indicators of structural wear or corrosion on these bridges. The Shimen Bridge project in Taiwan uses a DT connected to a convolutional neural network (CNN) that analyzes data from strain gauges to let authorities know about unusual stress patterns (Deng *et al.*, 2023; Lawal *et al.*, 2025).

In Norway, the E39 coastal highway project also uses digital twins and edge AI devices to keep an eye on the effects of wind and sea spray on suspension cables. This makes sure that safety alarms are always available, even in remote regions.

This kind of real-time synchronization turns infrastructure from passive assets into smart systems that can learn and adapt. This means that we don't have to rely as much on regular manual inspections, which makes operations more resilient (Lawal *et al.*, 2025).

4.3. Maintenance planning and predictive models

AI-enhanced digital twins are quite helpful in the maintenance phase, especially when it comes to using predictive maintenance tactics. Most of the time, traditional maintenance is done on a timetable or in response to problems, which can lead to unneeded work or expensive downtime. Engineers can use predictive maintenance, which is based on AI algorithms like Long Short-Term Memory (LSTM) networks and Bayesian classifiers, to figure out when parts are likely to break and plan repairs at the right time (Mchirgui *et al.*, 2024b).

For instance, in Japan's urban rail networks, DTs with AI algorithms look at data from vibrations, interactions between wheels and rails, and exposure to the surroundings. These models can predict how things will break down and propose the best times to undertake maintenance, which cuts down on unplanned outages by more than 30% (Elahi *et al.*, 2023b).

DT-AI solutions improve asset lifecycles, lower life-cycle costs, and make things safer by combining real-time monitoring with historical degradation trends. This is especially important for critical assets like dams, pipelines, and transmission towers.

4.4. Challenges in integration

Even though there are clear benefits, there are a number of problems that make it hard for DT and AI to be widely and effectively used in infrastructure systems:

• *Problems with interoperability:* One of the main technical problems is that there aren't any standard protocols or data models for DT and AI platforms. BIM, GIS, sensor networks, and cloud infrastructures all utilize distinct data schemas, which makes it hard to combine them and prone to mistakes (Alnaser *et al.*, 2024).

• *Protecting and keeping data private:* As infrastructure relies more and more on data, it is important to protect private information. Cyber-physical systems make things less secure, especially when public assets are connected to AI engines on the cloud (Yaacoub *et al.*, 2020).

• *Skill Gaps:* People who work in infrastructure management frequently don't have the wide range of skills needed to set up and run DT-AI systems. It is still hard to connect civil engineering, computer science, and data analytics.

• *Capital and Operational Costs:* Setting up high-fidelity digital twins and training AI models costs a lot of money at first. Emerging economies, in particular, have funding problems that make it hard to undertake and scale pilots.

To solve these problems, we will need not only new technologies, but also policies that support them, set standards, and offer education and training programs that straddle disciplines (Siddiqui *et al.*, 2023).

4.5. Insights from around the world

A cross-regional examination shows that countries have quite different ways of adopting, implementing, and planning for the future of DT-AI integration.

• *Developed Economies:* Singapore, Germany, the UK, and the US are at the top of the list when it comes to digitizing infrastructure. National digital twin plans, legislative frameworks, and strong collaboration between industry and academia typically support their efforts. The UK's Centre for Digital Built Britain, for instance, supports a federated digital twin strategy across all types of infrastructure, focusing on open data standards and the ethical use of AI.

• *New Economies:* On the other hand, countries like India, Nigeria, and Brazil are just starting to embrace DT-AI, usually only in small projects like metro rail or smart water systems. Limited financing, old systems, and a lack of digital literacy are some of the biggest problems. But these areas also have greenfield chances to get around old problems by using integrated, cloud-native solutions right away (El Bilali *et al.*, 2021).

• *Getting ready for policies and rules:* Cohesive national policies have a big effect on how many people use DT-AI. The EU's Green Deal and Horizon initiatives have focused on digitizing infrastructure, but other parts of the world don't have clear rules about how to govern AI, who owns data, or what the standards are for digital modeling.

Table 1 shows how different countries are using AI approaches in digital twin settings in different infrastructure sectors. This shows how different areas are using DT-AI in different ways. This difference shows how important it is to have globally coordinated plans that encourage local innovation while making sure that systems can work together, that ethical standards are followed, and that knowledge is shared.

Table 1. Comparison of global implementations of DT and ai in infrastructure

Country	Infrastructure Focus	AI Technique Used	DT Application Area	Maturity Level
Singapore	Urban Planning	Reinforcement Learning	City-scale Simulation	Advanced
United Kingdom	Water, Transport	Bayesian Networks	Asset Risk Modeling	Mature
USA	Roads, Bridges	CNN, LSTM	Real-Time Monitoring	Emerging
Norway	Bridges	Edge AI	Structural Health	Advanced
India	Metro Rail	Classical ML	Predictive Maintenance	Pilot
Brazil	Energy Infrastructure	Hybrid AI	Operations Optimization	Developing

This table shows how several countries use Digital Twin (DT) and Artificial Intelligence (AI) in their infrastructure, AI methods, application areas, and the level of maturity of the integration. It illustrates how ready different countries are to employ DT-AI in managing infrastructure and how ready their technology is for it. The results and the argument illustrate that Digital Twins and AI are not simply new technology, but they are also crucial tools for developing strong, modern infrastructure. In a world that is changing swiftly, their combination is redefining how engineers think about risk, manage assets, and give long-term value.

5. CONCLUSION

Digital Twins (DT) and Artificial Intelligence (AI) are redefining infrastructure engineering by enabling smarter, risk-aware decision-making across the lifecycle—from design to maintenance. As global infrastructure systems face mounting challenges from aging assets, climate stressors, and growing demand, DT-AI integration offers a powerful pathway toward resilience, adaptability, and cost efficiency (Lawal *et al.*, 2025). This review demonstrates that AI-enhanced DT systems can reduce unplanned maintenance by over 30% and improve asset lifespan forecasts by 22%, based on global case studies. However, challenges remain—particularly in data interoperability, cybersecurity, cost barriers, and skill gaps, especially within low- and middle-income countries (Lawal *et al.*, 2025).

Next Steps for Stakeholders

For Researchers

- Develop standardized performance metrics for evaluating DT-AI integration across infrastructure types.
- Explore interoperability frameworks that can unify BIM, GIS, IoT, and AI systems.
- Conduct longitudinal studies to quantify the lifecycle benefits and risks of DT-AI deployments.
- Advance AI explainability and transparency in DT environments to build trust and accountability.

For Policymakers

- Establish national strategies and funding mechanisms for DT-AI adoption, especially in public infrastructure.
- Create regulatory standards and ethical guidelines for AI use in critical infrastructure.
- Promote open data ecosystems that enable collaboration while ensuring data sovereignty and security.
- Support capacity-building programs that train multidisciplinary professionals in civil engineering, data science, and cybersecurity.

For Engineers and Industry Practitioners

- Pilot modular and scalable DT-AI architectures that can be adapted to varying infrastructure scales and contexts.
- Integrate predictive analytics and risk modeling into existing asset management workflows.
- Collaborate with academia and government on testbeds and demonstration projects that validate real-world performance.
- Advocate for interdisciplinary project teams that include AI specialists, civil engineers, and systems designers.

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