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AI-Driven Digital Twins for Smart Urban Infrastructure: A Comparative Survey of Monitoring and Predictive Maintenance Methodologies

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Abstract

The increasing complexity, ageing, and operational demands of urban infrastructure have created a need for intelligent approaches to continuous monitoring and predictive maintenance. Digital Twins (DTs) have emerged as a promising technology for creating dynamic virtual representations of physical infrastructure, while Artificial Intelligence (AI) enables automated analysis, anomaly detection, structural condition assessment, deterioration prediction, and maintenance planning. This paper presents a comparative survey of AI-driven Digital Twin methodologies for smart urban infrastructure, with particular emphasis on monitoring and predictive maintenance. Existing approaches are examined across key technological dimensions, including Digital Twin architecture, IoT-based sensing, machine learning and deep learning, Building Information Modelling (BIM), Geographic Information Systems (GIS), numerical simulation, Remaining Useful Life (RUL) prediction, and Explainable AI (XAI). The survey compares the capabilities, strengths, limitations, and application domains of existing methodologies to identify the extent to which these technologies are integrated for infrastructure management. The comparison indicates that existing studies have demonstrated significant advances in individual areas such as structural health monitoring, damage detection, predictive maintenance, and Digital Twin development; however, many approaches remain domain-specific or focus on limited combinations of technologies. In particular, integration of BIM, GIS, IoT, AI, simulation, explainability, and maintenance decision support within a scalable framework remains insufficiently addressed. The findings highlight the need for more integrated and generalizable Digital Twin methodologies capable of progressing from real-time infrastructure monitoring to predictive and decision-oriented maintenance. The survey provides a structured basis for identifying current research gaps and guiding the development of future AI-driven Digital Twin solutions for smart urban infrastructure.

Keywords: Digital Twin; Artificial Intelligence; Smart Urban Infrastructure; Structural Health Monitoring; Predictive Maintenance; Machine Learning; IoT; BIM; GIS; Explainable AI.

1. Introduction

Rapid urbanisation and the expansion of smart-city initiatives have resulted in increasingly complex infrastructure systems comprising bridges, roads, buildings, tunnels, transportation networks, and utility facilities. The reliable operation of these assets is essential for public safety, mobility, economic activity, and the overall resilience of urban environments. However, infrastructure assets are continuously exposed to ageing, increasing loads, environmental conditions, deterioration, and operational stresses. Consequently, continuous assessment of infrastructure condition and timely maintenance have become important requirements for modern infrastructure management. The research proposal underlying this survey identifies the limitations of conventional maintenance practices, particularly their dependence on manual inspection, periodic assessment, and reactive intervention, which can result in higher costs and unexpected failures.

Digital Twin (DT) technology has emerged as a promising approach for addressing these limitations. A Digital Twin provides a virtual representation of a physical asset that can be dynamically updated using information obtained from sensors and other data sources. Early research established the conceptual foundations of Digital Twins, while subsequent studies developed architectures for real-time synchronization between physical and virtual systems. The concept has subsequently expanded from industrial applications towards smart cities and infrastructure management.

The increasing availability of Artificial Intelligence (AI) has further enhanced the potential of Digital Twins. Machine learning and deep learning techniques can process large and heterogeneous infrastructure datasets to perform tasks such as anomaly detection, damage identification, structural condition assessment, deterioration prediction, and Remaining Useful Life (RUL) estimation. The literature reviewed in the proposal includes approaches based on Random Forest, Support Vector Machine, XGBoost, Artificial Neural Networks, Long Short-Term Memory networks, Graph Neural Networks, and other emerging architectures.

At the same time, Digital Twins increasingly depend on the integration of multiple sources of infrastructure information. Internet of Things (IoT) technologies enable continuous sensing and data acquisition; Building Information Modelling (BIM) provides information about the physical and lifecycle characteristics of assets; Geographic Information Systems (GIS) contribute spatial information; and numerical simulation can represent structural behaviour under different operating and environmental conditions. The integration of these technologies can potentially transform a Digital Twin from a virtual representation and monitoring tool into an intelligent platform for prediction and maintenance planning. The proposed research specifically identifies multi-source integration of IoT, BIM, GIS and infrastructure databases as an important requirement for synchronized infrastructure representation.

Despite these developments, existing research is characterized by considerable methodological diversity. Some studies concentrate primarily on Digital Twin architectures and real-time synchronization, whereas others focus on AI-based Structural Health Monitoring (SHM), IoT sensing, BIM-Digital Twin integration, predictive maintenance, or Explainable AI (XAI). For example, the reviewed literature reports AI-based SHM approaches that improve damage detection but remain insufficiently integrated with Digital Twins and BIM-GIS environments. Similarly, Digital Twin-based predictive maintenance studies demonstrate improvements in failure prediction and maintenance scheduling but face limitations concerning scalability across different infrastructure asset types.

These differences make a comparative examination of existing methodologies necessary. Merely identifying that AI, IoT, BIM, GIS, and Digital Twin technologies have been applied in infrastructure management does not reveal which methodological combinations provide advantages for monitoring, prediction, scalability, explainability, or maintenance decision-making. A comparative survey can instead examine how different approaches address these requirements, what types of data and AI techniques they employ, which infrastructure domains they target, and what limitations remain.

Recent studies demonstrate the movement towards more integrated approaches. Hybrid AI-IoT-Digital Twin frameworks have combined sensing, analytics, and simulation, while other studies have investigated cross-domain Digital Twin architectures, GNN-based infrastructure monitoring, and XAI-supported maintenance decisions. Nevertheless, the literature identified in the proposal indicates continuing limitations in large-scale validation, interoperability, generalisation across infrastructure types, explainability, and integrated decision support.

Therefore, this survey focuses specifically on the methodological comparison of AI-driven Digital Twin approaches for smart urban infrastructure monitoring and predictive maintenance. The study examines existing methodologies according to their technological components, AI techniques, monitoring capabilities, predictive capabilities, integration mechanisms, infrastructure domains, and limitations. Particular attention is given to the transition from conventional monitoring towards predictive and decision-oriented maintenance.

The remainder of the paper is organised around this comparative perspective. Existing Digital Twin, AI-based monitoring, and predictive maintenance methodologies are first examined, followed by a comparison of their technological and functional capabilities. The major research gaps are then identified, with particular emphasis on the need for integrated, scalable, and explainable approaches for smart urban infrastructure.

2. Related Work

Research on Digital Twins for infrastructure has evolved from conceptual representations of physical systems toward increasingly integrated platforms for monitoring, prediction and maintenance. Early work established the conceptual foundations of Digital Twins and their role in representing physical systems, while subsequent studies extended the concept to smart cities and infrastructure applications. Batty [1] examined the role of Digital Twins in urban planning, whereas Tao et al. [2] and Tao and Zhang [3] developed broader DT architectures emphasizing synchronization between physical and virtual systems. However, these early approaches were not specifically designed for AI-driven monitoring and predictive maintenance of heterogeneous urban infrastructure.

More recent research has focused on **Digital Twin-enabled smart infrastructure**. Lu et al. [5] reviewed DT applications in smart infrastructure and highlighted their potential for lifecycle management, while Qi and Tao [10] examined their application in smart cities. Zhou et al. [16] and Wang et al. [20] further explored smart-city DT architectures. These studies demonstrate the value of DTs for urban representation and management but also indicate limitations in achieving unified AI-enabled predictive maintenance across different infrastructure assets.

A parallel research direction has investigated **AI and machine learning for infrastructure health monitoring**. Deng et al. [6] reviewed AI techniques for structural health monitoring, while Nguyen et al. [8] examined machine-learning approaches for infrastructure monitoring. Saha et al. [18] demonstrated the application of deep learning to structural damage detection. These studies show the effectiveness of AI for condition assessment and damage identification, but their integration with Digital Twins and broader maintenance decision-making remains limited.

Another important direction is the integration of **IoT, BIM and GIS with Digital Twins**. IoT-based approaches enable continuous infrastructure monitoring [12], while BIM-DT integration improves asset representation and lifecycle management [13]. The combination of these technologies provides richer infrastructure information; however, existing approaches do not consistently integrate real-time sensing, spatial information, asset models and predictive intelligence within a single framework.

Recent studies have increasingly combined **AI, IoT and Digital Twins for predictive maintenance**. Zhang et al. [15] investigated machine-learning-based predictive maintenance using DTs, while Alourani et al. [21] proposed a hybrid AI-IoT-DT approach. Other recent studies have explored AI-driven maintenance decision-making, RUL prediction and domain-specific DT applications [22–27]. Although these approaches demonstrate the feasibility of predictive infrastructure management, limitations remain in scalability, interoperability, real-world validation and applicability across heterogeneous infrastructure.

Finally, **Explainable AI (XAI)** has emerged as an important research direction. Park et al. [14] investigated XAI for infrastructure health assessment, while more recent studies have explored the use of XAI within AI-driven DT environments. These studies address the interpretability problem of complex AI models, but integration of XAI with predictive maintenance and maintenance prioritization remains comparatively underdeveloped.

Overall, the related work demonstrates significant progress in individual technologies and in selected combinations of DT, AI, IoT, BIM and GIS. However, the literature remains **methodologically fragmented**, providing the motivation for a comparative examination of existing methodologies with respect to monitoring, prediction, explainability, maintenance decision support, scalability and validation. This comparative perspective is the focus of the following sections.

3. Digital Twin Methodologies for Smart Urban Infrastructure

Digital Twin methodologies have evolved considerably from conceptual virtual representations towards dynamic systems capable of integrating physical asset data, simulation models, and analytical processes. For smart urban infrastructure, the principal methodological distinction lies in the **purpose and level of interaction between the physical asset and its virtual counterpart**. Existing approaches range from conceptual and architectural models to real-time monitoring and increasingly predictive Digital Twin systems.

3.1 Foundational Digital Twin Approaches

The early Digital Twin literature primarily established the conceptual basis for representing complex physical systems through corresponding virtual models. Grieves and Vickers provided the theoretical foundation of Digital Twins for complex systems, while Tao and Zhang developed Digital Twin concepts for smart manufacturing and operational monitoring. These studies established important principles such as the relationship between physical and virtual entities and the exchange of information between them. However, their primary focus was industrial and manufacturing systems rather than urban civil infrastructure.

Batty extended the Digital Twin concept to urban systems and city planning, establishing its relevance to smart-city environments. Nevertheless, this work was largely conceptual and did not provide an AI-enabled implementation methodology for continuous infrastructure monitoring or predictive maintenance.

These foundational approaches therefore provide the **conceptual basis** for subsequent infrastructure Digital Twins but do not themselves address the complete monitoring-to-maintenance problem.

3.2 Digital Twin Architectures for Smart Cities

Subsequent research shifted towards developing architectures capable of representing complex urban systems. Such methodologies generally include physical assets, data acquisition, communication infrastructure, data management and virtual representations.

Research on Digital Twin-driven smart cities has examined architecture, enabling technologies, applications and implementation challenges. These approaches demonstrate the potential of Digital Twins for coordinating urban systems, but the literature indicates that comprehensive integration of AI-based predictive analytics with BIM, GIS and IoT remains limited.

More recent smart-city architectures have attempted to improve interoperability and scalability. However, a recurring limitation is that the Digital Twin often remains primarily a **representation and monitoring environment**, rather than becoming a complete predictive maintenance and decision-support platform.

3.3 IoT-Enabled Digital Twin Methodologies

IoT-enabled approaches introduce continuous sensor-based observation into the Digital Twin. Sensors can provide information concerning vibration, acceleration, strain, displacement, loading, environmental conditions and other operational parameters.

The major advantage of this methodology is its ability to establish a continuous connection between physical infrastructure and its virtual representation. IoT therefore addresses an important limitation of conventional inspection-based infrastructure management by enabling more frequent or real-time data acquisition.

However, IoT-based monitoring alone does not necessarily provide intelligence. The proposal's reviewed literature indicates that although IoT technologies have demonstrated real-time sensing and data acquisition capabilities, many approaches lack intelligent maintenance decision support.

Thus, the methodological progression can be expressed as:

Manual Inspection → IoT Monitoring → AI-Based Analysis → Predictive Digital Twin

3.4 BIM–Digital Twin Methodologies

BIM provides detailed digital information concerning infrastructure geometry, components and lifecycle characteristics. BIM-Digital Twin integration consequently enables a Digital Twin to incorporate more detailed information about the physical asset.

Existing BIM-Digital Twin methodologies have demonstrated improvements in infrastructure visualisation and lifecycle asset management. However, the reviewed research indicates that predictive intelligence and AI-driven decision-making are not sufficiently developed in many such approaches.

The strength of BIM-based methodologies is therefore **asset information and lifecycle representation**, whereas their principal limitation is the relatively weak connection between this information and predictive analytics.

3.5 GIS-Integrated Digital Twin Methodologies

GIS introduces geographical and spatial information into Digital Twin environments. This is particularly relevant to urban infrastructure because infrastructure assets rarely operate independently of their surrounding environment.

GIS can provide information concerning asset location, transportation networks, surrounding land use and spatial relationships. When combined with BIM, it allows infrastructure to be represented at both the asset level and city/spatial level.

The proposal consequently identifies BIM-GIS integration as an important component of the proposed infrastructure Digital Twin.

However, GIS and BIM integration primarily improves representation and contextualisation. It does not, by itself, provide deterioration prediction or maintenance optimisation. These functions require additional analytical methodologies.

3.6 AI-Integrated Digital Twin Methodologies

The integration of AI represents a major methodological development because it allows Digital Twins to move beyond observation towards prediction.

Existing studies have employed machine learning and deep learning techniques for:

- Anomaly Detection;
- Structural Damage Detection;
- Condition Classification;
- Deterioration Prediction;
- Failure Prediction; and
- RUL Estimation.

The proposal identifies Random Forest, SVM, XGBoost, ANN, LSTM and GNN among the principal AI methodologies considered in current infrastructure research.

More recent approaches also consider Vision Transformers and Transformer-based architectures. Their suitability, however, depends on factors such as available data, predictive performance, computational efficiency and scalability.

The major advantage of AI-integrated Digital Twins is therefore their ability to transform infrastructure data into predictive information. Their major challenge is ensuring that these predictions are reliable, interpretable, computationally efficient and transferable across different infrastructure assets.

3.7 Digital Twin Methodologies for Predictive Maintenance

Predictive maintenance represents a further evolution in which the Digital Twin is used not only to determine current infrastructure condition but also to anticipate future deterioration and maintenance requirements.

Existing studies have demonstrated the potential of machine learning and Digital Twins to reduce unexpected failures and improve maintenance scheduling. However, the literature indicates that many methodologies remain limited to specific asset categories or lack scalability across heterogeneous infrastructure systems.

Recent cross-domain approaches have attempted to address this limitation by developing architectures capable of supporting maintenance decisions across different infrastructure domains. Nevertheless, the proposal identifies limited real-world deployment and validation as continuing challenges.

3.8 Comparative Methodological Perspective

The evolution of Digital Twin methodologies can therefore be viewed as a progression:

Methodology	Primary capability	Main strength	Major limitation
Conceptual Digital Twin	Virtual representation	Establishes DT foundation	No predictive capability
Smart-city DT	Urban system representation	Supports city-level modelling	Limited AI integration
IoT-enabled DT	Real-time monitoring	Continuous sensing	Limited intelligence
BIM-DT	Asset/lifecycle representation	Rich infrastructure information	Limited prediction
GIS-DT	Spatial representation	Urban context and relationships	Limited maintenance intelligence
AI-DT	Prediction and anomaly detection	Intelligent analysis	Data/computational requirements
DT + Predictive Maintenance	Deterioration and failure prediction	Proactive maintenance	Scalability and validation
DT + XAI	Explainable prediction	Improved transparency	Limited integration
Integrated AI-DT	Monitoring + prediction + decision support	Potential end-to-end management	**Integration remains incomplete**

This comparison demonstrates why simply stating that Digital Twins, AI, IoT, BIM and GIS have been used in infrastructure management is insufficient. The important issue is the degree to which these methodologies are integrated and what functional capability that integration provides.

4. AI Methodologies for Infrastructure Monitoring and Condition Assessment

The integration of Artificial Intelligence with Digital Twin technology has introduced data-driven approaches for infrastructure monitoring, structural health assessment, anomaly detection and damage prediction. However, AI-based Digital Twin systems do not rely on a single modelling technique. Different machine learning (ML) and deep learning (DL) methodologies have been adopted according to the type of infrastructure data, prediction task, temporal characteristics and computational requirements. The literature identified in the proposal includes Random Forest (RF), Support Vector Machine (SVM), XGBoost, Artificial

Neural Networks (ANN), Long Short-Term Memory (LSTM), Graph Neural Networks (GNN), Vision Transformers (ViT), and Transformer-based architectures.

For a comparative survey, these methodologies need to be examined not merely by their names but according to what type of infrastructure problem they solve, what type of data they require, their predictive capability, interpretability, computational requirements, and their suitability for integration with Digital Twins.

Machine-learning methodologies have also demonstrated their applicability to classification and intelligent decision-making problems in other domains. Previous work by Fatima and colleagues on adaptive machine-learning classification and machine-learning-based automated decision mechanisms illustrates the broader use of data-driven models for classification and dynamic decision tasks [42], [43]. Although these studies are outside infrastructure management, they provide methodological context for comparing machine-learning approaches considered for infrastructure applications.

4.1 Random Forest

Random Forest (RF) is identified in the proposed methodology as one of the baseline machine learning techniques for infrastructure condition assessment and predictive maintenance.

Within an infrastructure monitoring framework, RF can be used for classification and regression tasks, such as condition classification, damage identification and prediction of maintenance-related outcomes. Its principal methodological advantage is that it can provide a relatively robust baseline for structured infrastructure data.

However, RF does not inherently model the temporal evolution of structural behaviour. Consequently, when monitoring data represent progressive deterioration over time, additional temporal modelling may be required. This limits its suitability as a standalone methodology for long-term deterioration and RUL prediction.

4.2 Support Vector Machine

Support Vector Machine (SVM) is another machine learning approach identified in the proposal. It has been investigated for infrastructure monitoring and damage detection. The proposal specifically includes SVM among the candidate algorithms for condition assessment, anomaly detection and predictive maintenance.

SVM can be effective for classification problems where the distinction between healthy and damaged states is required. Its limitation in the context of large-scale Digital Twin environments is that infrastructure monitoring may involve heterogeneous, continuously arriving and high-dimensional data, potentially making direct deployment more challenging.

Thus, SVM is valuable as a **baseline classification methodology**, but it does not independently provide the complete data integration, temporal prediction or maintenance decision-support functions required by an integrated Digital Twin.

4.3 Extreme Gradient Boosting

Extreme Gradient Boosting (XGBoost) is also included among the candidate methodologies in the proposed research.

Its relevance to infrastructure monitoring lies in its ability to model complex relationships between multiple input variables. Infrastructure condition may depend simultaneously on structural response, loading, environmental conditions and historical observations. A tree-based boosting methodology can therefore provide a useful predictive model for structured datasets.

However, like RF, XGBoost does not inherently represent the physical relationships between interconnected infrastructure components or the sequential evolution of deterioration. These limitations become particularly important when the Digital Twin represents an infrastructure network rather than an isolated asset. The use of machine learning for automated decision processes in dynamic environments has also been explored in previous work by Fatima and Nayakwadi [43], providing methodological evidence of the suitability of data-driven models for decision-oriented applications.

4.4 Artificial Neural Networks

Artificial Neural Networks (ANNs) provide a more flexible nonlinear modelling approach. They can learn relationships between multiple infrastructure parameters and structural condition indicators.

In the proposed research, ANN is included as a candidate methodology for intelligent infrastructure monitoring and prediction.

The advantage of ANN is its capacity to approximate complex nonlinear relationships. However, conventional ANN architectures do not explicitly model spatial relationships between infrastructure components or temporal dependencies in sequential monitoring data. They may also require appropriate training data and careful model selection.

4.5 Long Short-Term Memory Networks

Infrastructure monitoring generates time-dependent observations. Structural deterioration is not normally an isolated event but a process that develops over time. Long Short-Term Memory (LSTM) networks are therefore particularly relevant when historical sensor observations are required to predict future structural conditions.

The proposal includes LSTM among the candidate AI methodologies for the proposed framework.

Compared with conventional ML approaches, LSTM provides a methodological advantage for **temporal modelling**. It can potentially learn patterns in sequential sensor observations and support deterioration or RUL prediction.

Its limitation is that temporal modelling alone does not capture the spatial relationships among multiple infrastructure components. For a city-scale Digital Twin involving interconnected roads, bridges, utilities or networks, a methodology capable of representing such relationships may be more appropriate.

4.6 Graph Neural Networks

Graph Neural Networks (GNNs) represent an important development for infrastructure monitoring because infrastructure systems naturally contain relationships between physical components.

For example, a road network can be represented as connected segments, while a bridge can be represented through interconnected structural components. GNNs can therefore incorporate spatial and relational information that conventional ML models may not explicitly represent.

The proposal identifies GNNs as a candidate methodology and cites recent work applying Digital Twin-driven GNNs to pavement health monitoring. That study reportedly captures spatial deterioration and supports proactive maintenance but remains focused specifically on pavements rather than multiple infrastructure asset types.

This illustrates an important methodological trade-off: GNNs offer stronger relational modelling, but existing applications may be domain-specific.

4.7 Vision-Based Deep Learning and Vision Transformers

Infrastructure monitoring increasingly involves visual information such as images of cracks, surface deterioration and other visible defects. Deep learning-based vision models can therefore complement sensor-based monitoring.

Vision Transformers (ViTs) represent an emerging methodology for visual analysis and provide an alternative to conventional convolution-based architectures. A recent survey by Fatima et al. [44] examines ViT architectures, training paradigms and applications, providing a methodological basis for considering Transformer-based vision models in automated inspection tasks.

The principal advantage of vision-based approaches is their ability to analyse visual evidence of infrastructure deterioration. Their limitation is that visual information alone does not capture all structural conditions. Subsurface deterioration, vibration characteristics, strain and other physical responses may require sensor-based or simulation-based information. Consequently, visual AI is more appropriately considered as one information modality within a multimodal Digital Twin rather than a complete infrastructure monitoring solution.

This is a stronger use of your [44] citation because it is directly connected to what the paper is about.

4.8 Transformer-Based Architectures

Transformer-based architectures represent a further emerging direction identified in the proposed methodology.

Their potential relevance lies in modelling complex dependencies within large datasets and potentially combining multiple forms of infrastructure information. However, the proposal does not yet specify a particular Transformer architecture or establish its superiority over the other candidate methods. Therefore, in the context of this survey, Transformer-based approaches should be treated as an emerging methodological category requiring comparative experimental validation, rather than assuming that they are inherently better.

4.9 Comparative Analysis of AI Methodologies

The methodologies can now be compared according to their primary strengths and limitations:

AI Methodology	Main suitability	Key strength	Key limitation for DT infrastructure
RF	Classification/regression	Robust baseline for structured data	Limited temporal/spatial modelling
SVM	Damage/condition classification	Effective classification capability	Less suited to complex heterogeneous streams
XGBoost	Prediction/classification	Models nonlinear variable interactions	Does not inherently model spatial/temporal structure
ANN	Nonlinear prediction	Flexible nonlinear modelling	Limited explicit spatial/temporal representation
LSTM	Time-series prediction	Captures temporal dependencies	Limited spatial/relational modelling
GNN	Network/structural relationships	Captures spatial and relational dependencies	Existing applications often asset-specific
ViT	Image-based inspection	Strong visual feature modelling	Requires suitable visual data; limited physical-state coverage
Transformer	Complex/sequential or multimodal data	Potential long-range dependency modelling	Infrastructure applicability requires validation

This comparison reveals an important point for the survey: there is no single AI methodology that simultaneously addresses all requirements of an urban infrastructure Digital Twin. RF, SVM and XGBoost are useful for structured-data prediction; ANN provides nonlinear modelling; LSTM addresses temporal behaviour; GNN addresses spatial and relational dependencies; and vision-oriented architectures such as ViTs address image-based deterioration.

The selection of an appropriate methodology must therefore depend on the data characteristics and the intended Digital Twin function. Previous methodological studies using machine learning and vision-based learning further demonstrate that model selection should be determined by the characteristics of the underlying problem rather than by the algorithm alone [42]–[44].

5. AI-Based Predictive Maintenance Methodologies

Predictive maintenance is one of the most important applications of Artificial Intelligence within Digital Twin (DT)-enabled infrastructure management. Unlike conventional maintenance strategies that rely on fixed schedules or corrective intervention after failure, predictive approaches use condition information and historical or real-time data to estimate deterioration, detect abnormal behaviour, predict failures, and support maintenance decisions. Existing studies reviewed in the proposal demonstrate the increasing use of machine learning, deep learning, Digital Twins, and IoT for this purpose, although their methodological scope and level of integration differ considerably.

5.1 Condition-Based and Predictive Maintenance

Condition-based maintenance (CBM) determines maintenance requirements from the observed condition of an asset. Sensor measurements, inspection results, and infrastructure health indicators are used to identify deterioration or abnormal conditions. Predictive maintenance extends this approach by attempting to anticipate future deterioration or failure.

Within DT-based systems, continuous sensor information can be synchronized with the virtual representation of the physical asset, allowing the current condition to be reflected in the DT. Studies reviewed in the proposal indicate that this combination can improve fault detection, reduce unexpected failures, and support maintenance scheduling. However, many existing approaches remain focused on individual assets or specific application domains rather than providing a generalized urban infrastructure solution.

5.2 Machine-Learning-Based Failure Prediction

Traditional machine-learning algorithms such as Random Forest (RF), Support Vector Machine (SVM), and XGBoost have been applied to infrastructure condition assessment and failure prediction.

RF is useful when infrastructure condition is represented through structured features obtained from sensors or inspections. Its major advantage is robustness and its ability to model nonlinear relationships. SVM is particularly suitable for classification problems such as identifying different structural or infrastructure health states. XGBoost can model complex nonlinear relationships and is suitable for both classification and regression-based prediction.

However, these algorithms generally do not inherently represent temporal or spatial relationships. Consequently, their effectiveness in DT environments depends strongly on the quality of feature engineering and data representation. The proposal identifies RF, XGBoost, and SVM among the candidate algorithms for condition assessment, failure prediction, and maintenance-related tasks.

5.3 Deep-Learning-Based Predictive Maintenance

Deep learning provides greater capability for handling high-dimensional and sequential infrastructure data. Artificial Neural Networks (ANNs), Long Short-Term Memory (LSTM) networks, Graph Neural Networks (GNNs), Vision Transformers (ViTs), and Transformer architectures represent different methodological directions.

LSTM models are particularly relevant where infrastructure condition evolves over time because they can learn temporal patterns from sequential sensor observations. GNNs provide an alternative when the relationships between structural components, infrastructure assets, or urban networks are important. Vision-based deep learning and ViTs are more appropriate for image-based inspection, such as identifying visible damage from photographs or inspection imagery. Transformer-based approaches provide opportunities for modelling long-range relationships and potentially heterogeneous data streams.

The major limitation is that these models can require substantial datasets and computational resources, while their performance may not transfer directly across different infrastructure types. The proposal therefore emphasizes experimental comparison rather than assuming that one deep-learning model is universally optimal.

5.4 Remaining Useful Life Prediction

Remaining Useful Life (RUL) prediction attempts to estimate how long an infrastructure component can continue to operate before reaching a predefined failure or unacceptable-condition state. It is particularly valuable for predictive maintenance because it can shift maintenance from simply identifying current damage to anticipating future intervention requirements.

RUL prediction can use historical degradation measurements, sensor time series, health indices, or simulated deterioration data. Machine-learning and deep-learning models can learn relationships between observed condition and future deterioration. The proposal specifically identifies RUL estimation as one of the intended AI functions and includes it among the performance areas for evaluating the proposed methodologies.

Nevertheless, RUL prediction remains challenging for urban infrastructure because deterioration is influenced by environmental conditions, loading, age, usage, and maintenance history. A model trained for one asset or dataset may therefore have limited generalizability.

5.5 Digital Twin–AI Predictive Maintenance

The combination of DT and AI provides a stronger predictive-maintenance paradigm than either technology operating independently. The DT provides a continuously updated representation of the physical infrastructure, while AI models analyse current and historical information to estimate condition, deterioration, or failure.

Several studies in the reviewed literature demonstrate this direction. Zhang, Wang and Li (2024), for example, combine machine learning with DT-based predictive maintenance to reduce unexpected failures and improve maintenance scheduling. Other reviewed studies integrate AI, IoT and DT to enable condition-based maintenance and automated maintenance decisions. However, the literature also indicates limitations concerning scalability, real-world validation, interoperability, and integration across different infrastructure asset types.

5.6 AI-Based Maintenance Prioritization

Prediction alone does not determine which infrastructure asset should be maintained first. For urban infrastructure management, maintenance prioritization must consider condition, risk, failure consequences, available resources, cost, and potentially service importance.

AI-based decision-support methodologies therefore extend predictive maintenance by converting predictions into maintenance priorities. The proposal identifies decision support as an important component, with maintenance ranking based on factors such as condition, risk, resources, and cost.

This represents an important distinction between predictive analytics and maintenance decision support. Many existing studies concentrate on detecting deterioration or predicting failure, whereas comparatively fewer approaches integrate those predictions into a comprehensive maintenance-prioritization process.

5.7 Comparative Analysis of Predictive Maintenance Methodologies

Methodology	Primary objective	Main strength	Major limitation
Condition-Based Maintenance	Identify current condition	Directly uses observed asset condition	Mainly reactive to observed deterioration
ML Failure Prediction	Predict abnormality/failure	Effective with structured data	Limited temporal/spatial representation
LSTM-Based Prediction	Model deterioration over time	Captures temporal dependencies	Requires sequential data and training
GNN-Based Prediction	Model asset/component relationships	Captures spatial/relational dependencies	Often developed for specific infrastructure networks
Vision/DL	Detect visible damage	Automated image-based inspection	Dependent on image quality and coverage
RUL Prediction	Estimate remaining service life	Supports proactive intervention	Sensitive to data quality and degradation assumptions
DT + AI	Continuous monitoring and prediction	Combines physical and virtual information	Integration and scalability remain challenging
AI + DSS	Prioritize maintenance actions	Connects prediction with decisions	Requires reliable risk, cost and resource information

5.8 Comparative Perspective

The comparison indicates a progression from **condition detection → failure prediction → RUL estimation → maintenance prioritization**. Traditional condition-based methods primarily describe the present state, while machine-learning and deep-learning approaches increasingly attempt to predict future infrastructure behaviour. DT-based methodologies add continuous synchronization between the physical and virtual infrastructure, potentially enabling predictive maintenance to operate within a continuously updated environment.

However, the literature reviewed in the proposal reveals that these capabilities are frequently implemented separately. AI models may provide accurate predictions without being connected to BIM/GIS or a continuously synchronized DT, while DT studies may provide visualization and monitoring without advanced predictive intelligence. The resulting gap is therefore not simply the absence of another prediction algorithm, but the **limited integration of monitoring, prediction, explainability, and maintenance decision-making within a common infrastructure-oriented DT environment**.

This comparative finding is particularly important for the subsequent analysis of **BIM, GIS, IoT, numerical simulation, and explainable AI integration**, which determine how predictive models can be incorporated into a broader urban infrastructure Digital Twin.

6. Integration of IoT, BIM, GIS and Numerical Simulation in Digital Twin Methodologies

The effectiveness of a Digital Twin for smart urban infrastructure depends not only on the AI model used for prediction but also on the quality and diversity of information supplied to the virtual environment. The literature reviewed in the proposal indicates that IoT, BIM, GIS, numerical simulation and AI are often investigated as separate or partially integrated technologies. Their integration is therefore an important methodological dimension when comparing existing DT approaches.

6.1 IoT-Enabled Digital Twins

IoT provides the connection between the physical infrastructure and its Digital Twin. Sensors can continuously generate information related to structural response, environmental conditions, traffic, vibration, temperature, or other operational parameters. This allows the DT to be updated using near-real-time observations rather than relying solely on periodic inspections.

The reviewed studies identify IoT-enabled DTs as effective for continuous monitoring and real-time infrastructure information. However, IoT by itself does not provide predictive intelligence. Sensor data must be processed through suitable analytical or AI models before it can support deterioration prediction or maintenance decisions. Furthermore, large-scale urban deployment introduces challenges involving sensor density, data volume, communication, interoperability, and computational requirements.

6.2 BIM–Digital Twin Integration

Building Information Modelling (BIM) provides detailed information about the physical and functional characteristics of an infrastructure asset. When combined with a DT, BIM can provide the underlying asset representation and lifecycle information required for visualization, modelling and management.

The literature reviewed in the proposal indicates that BIM-DT integration improves asset representation and lifecycle management. Pan and Zhang (2023), for example, emphasize the role of BIM in DT integration, while the proposal identifies BIM as one of the important data sources for the proposed infrastructure framework.

However, BIM primarily describes the asset and its information rather than predicting its future condition. Consequently, BIM-DT approaches require additional sensor and AI capabilities to support continuous monitoring and predictive maintenance.

6.3 GIS-Integrated Digital Twins

GIS contributes the **spatial dimension** to Digital Twins. While BIM can represent an individual asset in considerable detail, GIS can place infrastructure within its wider urban and geographical context. This is particularly relevant when multiple infrastructure assets need to be monitored and prioritized at city scale.

The proposal identifies GIS as an important component for integrating infrastructure information and specifically includes GIS platforms and spatial datasets among the intended technological resources.

The principal advantage of GIS-DT methodology is therefore its ability to support spatial analysis and asset-level visualization within the broader urban environment. Its limitation is that spatial representation alone does not provide deterioration prediction or maintenance intelligence.

6.4 Numerical Simulation and Digital Twins

Numerical simulation provides another important source of information for infrastructure DTs, particularly where real-world failure data are limited. Finite Element Method (FEM) simulations can model structural response under different loading and damage conditions and can therefore complement measured sensor observations.

The proposal explicitly identifies numerical modelling and FEM simulation as part of the methodology and proposes tools such as ANSYS, ABAQUS and OpenSees for generating or analysing infrastructure behaviour.

The advantage of simulation-based DT methodologies is that they can provide information about infrastructure states that may be difficult or expensive to obtain experimentally. However, simulation accuracy depends on the assumptions, model parameters and representation of real-world conditions. Therefore, simulation should complement rather than simply replace observational data.

6.5 Multisource Data Integration

The comparison of existing methodologies suggests that each technology contributes a different type of information:

- **IoT** → real-time physical and environmental observations
- **BIM** → asset geometry, components and lifecycle information
- **GIS** → geographical and urban context
- **Numerical simulation** → estimated structural/physical behaviour
- **AI** → pattern recognition and prediction
- **Digital Twin** → integration and synchronization of these information sources

The proposal accordingly identifies the integration of BIM, GIS, IoT, AI and numerical modelling as a central requirement for an infrastructure-oriented DT.

6.6 Comparative Analysis of Integration Methodologies

Integration approach	Main information provided	Major advantage	Key limitation
IoT–DT	Real-time sensor data	Continuous monitoring	Data and connectivity challenges
BIM–DT	Asset and lifecycle information	Detailed asset representation	Limited predictive capability
GIS–DT	Spatial/urban information	City-scale spatial context	Limited condition intelligence
Simulation–DT	Modelled infrastructure behaviour	Supports scenario and damage analysis	Depends on model assumptions
AI–DT	Prediction and anomaly detection	Intelligent analysis	Requires suitable training data
IoT + AI + DT	Sensor-driven prediction	Near-real-time predictive monitoring	Computational and integration challenges
BIM + GIS + DT	Asset + spatial representation	Strong urban asset context	Limited predictive maintenance

IoT + BIM + GIS + AI + DT	Integrated monitoring and prediction	Potential end-to-end infrastructure management	High integration, interoperability and scalability requirements

6.7 Methodological Gap

The comparative analysis demonstrates that integration is a more significant research issue than the isolated development of another individual technology. Existing methodologies provide strong capabilities in particular areas—IoT for sensing, BIM for asset representation, GIS for spatial context, simulation for physical modelling, and AI for prediction—but the proposal's literature review identifies limited availability of a single framework that combines these capabilities with explainability and maintenance decision support.

Thus, the major methodological gap emerging from the survey is the need for interoperable, scalable and predictive Digital Twin architectures capable of transforming heterogeneous infrastructure data into actionable maintenance decisions. This leads naturally to the next comparison: Explainable AI and Decision-Support Methodologies, since prediction alone is insufficient when infrastructure managers must understand and act upon AI-generated recommendations.

7. Explainable AI and Decision-Support Methodologies for Infrastructure Maintenance

AI-based Digital Twins can provide accurate predictions of infrastructure condition and deterioration; however, **prediction alone does not necessarily provide an actionable maintenance decision**. For infrastructure managers, it is also important to understand why an AI model produces a particular prediction and how that prediction should influence maintenance priorities. Consequently, Explainable Artificial Intelligence (XAI) and Decision-Support Systems (DSS) have become important methodological components of intelligent infrastructure management.

7.1 Explainable AI for Infrastructure Assessment

Many advanced AI models, particularly deep-learning models, can provide high predictive performance but are difficult to interpret. In infrastructure management, this creates a practical concern because maintenance decisions may involve safety, cost, risk and service continuity.

XAI methodologies attempt to identify the factors responsible for an AI prediction. The proposal specifically identifies **SHAP and LIME** as candidate explainability techniques. These approaches can be used to determine the contribution of individual input variables to a model's prediction and thereby improve transparency.

The literature reviewed in the proposal includes work on XAI-based infrastructure health assessment. Such approaches improve transparency and interpretability, but the review also identifies a limitation: XAI is often developed independently rather than being fully integrated with a Digital Twin and maintenance decision-support environment.

7.2 Model-Specific and Model-Agnostic Explainability

XAI approaches can broadly be considered according to how they interact with the predictive model.

Model-agnostic approaches can be applied to different machine-learning models without requiring access to their internal structure. LIME and SHAP can therefore be used to interpret predictions from different AI models.

This flexibility is particularly useful in a comparative DT framework because different AI algorithms may be selected for different infrastructure tasks. However, explanations must remain meaningful in the engineering context. Simply identifying statistically important variables does not necessarily establish a physical cause of deterioration.

7.3 AI-Based Decision-Support Systems

A Decision-Support System extends AI prediction by converting analytical results into information useful for infrastructure management. Rather than reporting only that an asset has a high probability of failure, a DSS can assist in determining **which asset requires attention first and why**.

The proposal identifies maintenance prioritization based on factors including:

- Infrastructure Condition,
- Risk,
- Maintenance Resources,
- Cost, And
- Predicted Deterioration Or Failure.

The resulting system can rank infrastructure assets according to their maintenance priority.

This is particularly important at urban scale, where authorities may have many infrastructure assets but limited maintenance budgets and resources.

7.4 Risk-Based Maintenance Prioritization

Risk provides an important link between AI prediction and maintenance action. Two assets with similar predicted deterioration may not have the same maintenance priority if their consequences of failure differ.

A risk-based DSS can therefore combine predicted condition with factors such as asset importance, likelihood of failure, potential consequences, cost and resource availability. This creates a more practical maintenance strategy than relying solely on an AI-generated condition score.

The proposal explicitly identifies **maintenance prioritization and decision support** as AI functions to be evaluated, rather than treating prediction accuracy as the only measure of system effectiveness.

7.5 Comparative Analysis of XAI and Decision-Support Methodologies

Methodology	Primary purpose	Main strength	Major limitation
Black-box AI prediction	Condition/failure prediction	Potentially high predictive performance	Limited interpretability
SHAP	Explain feature contributions	Detailed feature-level explanation	Can increase computational cost

LIME	Local prediction explanation	Model-agnostic and flexible	Explanations are primarily local
XAI + DT	Explain DT-based predictions	Improves transparency of DT analytics	Still relatively limited in integrated infrastructure applications
AI-based DSS	Convert predictions into actions	Supports maintenance decisions	Requires reliable decision criteria
Risk-based DSS	Prioritize assets by risk	Links condition with consequences	Requires risk and consequence information
AI + XAI + DSS	Prediction, explanation and action	End-to-end decision support	Greater integration and validation complexity

7.6 Comparative Perspective

The literature suggests a methodological progression from prediction to explanation and finally to decision support. Conventional AI approaches primarily answer *"What is the condition or predicted failure state?"* XAI additionally addresses *"Why did the model produce this prediction?"* DSS then addresses *"What maintenance action should be prioritized?"*

This distinction is important for Digital Twin-based infrastructure management. A technically accurate AI model may still have limited practical value if its prediction cannot be interpreted or translated into an appropriate maintenance action. The proposal therefore positions XAI and DSS as complementary components of the broader AI-driven DT architecture.

Overall, the comparative review indicates that the strongest methodological direction is not simply the use of more complex AI models, but the integration of prediction, explainability, risk assessment and maintenance prioritization. Nevertheless, the proposal's literature review identifies insufficient integration of these capabilities within a unified, scalable infrastructure DT framework.

8. Comparative Analysis of Existing Methodologies

Study / Approach	DT	IoT	BIM/GIS	AI	Prediction	XAI	DSS	Main limitation
Batty (2018)	✓	–	–	–	–	–	–	Primarily conceptual urban DT
Tao et al. (2019)	✓	✓	–	Limited	–	–	–	Industrial/manufacturing focus
Deng et al. (2023)	–	✓	–	✓	✓	–	–	Limited DT and BIM/GIS integration
Nguyen et al. (2023)	–	✓	–	ML	✓	Limited	–	Limited real-time implementation
Pan & Zhang (2023)	✓	–	✓	Limited	Limited	–	–	Limited predictive intelligence
Park et al. (2024)	–	–	–	✓	✓	✓	–	No DT integration
Zhang et al. (2024)	✓	✓	–	ML	✓	–	✓	Limited scalability across asset types

Ghosh & Gupta (2024)	–	–	–	✓	✓	–	✓	No continuous DT synchronization
Saha et al. (2024)	–	✓	–	DL	✓	–	–	Focused mainly on damage detection
Li et al. (2024)	✓	✓	BIM/GIS proposed	✓	✓	Limited	Limited	Need for stronger integrated implementation
Wang et al. (2025)	✓	✓	BIM/GIS	✓	✓	Limited	Limited	Lack of unified scalable framework
Alourani et al. (2025)	✓	✓	Limited	✓	✓	–	–	Limited large-scale urban validation
Arun Prasath & Vishnupriya (2025)	✓	✓	Limited	ML	✓	–	✓	No BIM-GIS/FEM validation
Rezown et al. (2025)	✓	✓	–	✓	✓	–	✓	Limited real-world deployment
Topu et al. (2025)	✓	✓	–	GNN	✓	–	✓	Pavement-specific
Oluwaseyi et al. (2026)	✓	✓	–	GNN/XAI	✓	✓	✓	Requires broader infrastructure validation
Koyande & Shirke (2026)	✓	✓	–	ML/DL	✓	✓	✓	Computational/deployment challenges
Integrated AI-DT direction	✓	✓	✓	✓	✓	✓	✓	Integration and scalability remain challenging

The preceding sections examined Digital Twin architectures, AI-based monitoring and predictive maintenance, multisource data integration, and explainable decision-support approaches separately. This section brings these methodological dimensions together to provide a **comparative assessment of the existing studies**. The objective is not merely to identify what technologies have been used, but to determine how comprehensively they address the requirements of smart urban infrastructure monitoring and predictive maintenance.

8.1 Comparative Dimensions

The existing methodologies can be compared across the following dimensions:

1. **Digital Twin capability** – whether the study develops or uses a DT and whether it supports continuous synchronization.
2. **IoT integration** – whether real-time or continuous sensor data are incorporated.
3. **BIM integration** – whether detailed asset and lifecycle information are included.
4. **GIS integration** – whether spatial and city-level information is incorporated.
5. **AI methodology** – the machine-learning or deep-learning technique used.
6. **Predictive capability** – whether the methodology performs anomaly detection, deterioration prediction, failure prediction or RUL estimation.
7. **Explainability** – whether the reasoning behind AI predictions can be interpreted.

8. **Decision support** – whether predictions are converted into maintenance priorities or actions.
9. **Scalability** – whether the methodology can extend beyond a single asset or narrowly defined application.
10. **Validation** – whether the approach has been validated using real datasets, benchmark data, simulation or practical case studies.

8.2 Comparative Evaluation of Representative Studies

Study / Approach	DT	IoT	BIM/GIS	AI	Prediction	XAI	DSS	Main limitation
Batty (2018)	✓	–	–	–	–	–	–	Primarily conceptual urban DT
Tao et al. (2019)	✓	✓	–	Limited	–	–	–	Industrial/manufacturing focus
Deng et al. (2023)	–	✓	–	✓	✓	–	–	Limited DT and BIM/GIS integration
Nguyen et al. (2023)	–	✓	–	ML	✓	Limited	–	Limited real-time implementation
Pan & Zhang (2023)	✓	–	✓	Limited	Limited	–	–	Limited predictive intelligence
Park et al. (2024)	–	–	–	✓	✓	✓	–	No DT integration
Zhang et al. (2024)	✓	✓	–	ML	✓	–	✓	Limited scalability across asset types
Ghosh & Gupta (2024)	–	–	–	✓	✓	–	✓	No continuous DT synchronization
Saha et al. (2024)	–	✓	–	DL	✓	–	–	Focused mainly on damage detection
Li et al. (2024)	✓	✓	BIM/GIS proposed	✓	✓	Limited	Limited	Need for stronger integrated implementation
Wang et al. (2025)	✓	✓	BIM/GIS	✓	✓	Limited	Limited	Lack of unified scalable framework
Alourani et al. (2025)	✓	✓	Limited	✓	✓	–	–	Limited large-scale urban validation
Arun Prasath & Vishnupriya (2025)	✓	✓	Limited	ML	✓	–	✓	No BIM-GIS/FEM validation
Rezown et al. (2025)	✓	✓	–	✓	✓	–	✓	Limited real-world deployment
Topu et al. (2025)	✓	✓	–	GNN	✓	–	✓	Pavement-specific
Oluwaseyi et al. (2026)	✓	✓	–	GNN/XAI	✓	✓	✓	Requires broader infrastructure validation
Koyande & Shirke (2026)	✓	✓	–	ML/DL	✓	✓	✓	Computational/deployment challenges
Integrated AI-DT direction	✓	✓	✓	✓	✓	✓	✓	Integration and scalability remain challenging

8.3 Evolution of Existing Methodologies

The reviewed literature indicates a gradual methodological evolution:

Conceptual DT → IoT-enabled DT → AI-enabled DT → Predictive DT → Explainable DT → Decision-support-oriented DT

Early Digital Twin studies primarily established the concept of connecting physical and virtual representations. Subsequent approaches introduced IoT for continuous data acquisition and synchronization. AI methodologies then extended DTs from representation and monitoring towards anomaly detection, condition assessment and prediction.

More recent studies increasingly incorporate predictive maintenance, XAI and decision-support capabilities. However, these developments have generally occurred **incrementally rather than as a completely integrated methodology**. This observation is consistent with the explicit research gaps identified in the proposal.

8.4 Comparison of AI Methodologies Across Infrastructure Tasks

An important finding of the survey is that AI algorithms should not be compared solely according to predictive accuracy. Their suitability depends on the type of infrastructure data and the task being performed.

Infrastructure task	More suitable methodologies	Primary reason
Condition classification	RF, SVM, XGBoost, ANN	Structured condition features
Anomaly detection	RF, Isolation Forest, DL	Identification of abnormal patterns
Time-series deterioration	LSTM, Transformer	Temporal dependency modelling
Network/structural relationships	GNN	Spatial and relational representation
Image-based damage detection	CNN/DL, ViT	Visual feature extraction
Failure prediction	XGBoost, LSTM, ANN, Transformer	Nonlinear and/or temporal prediction
RUL estimation	LSTM, Transformer, ANN	Degradation sequence modelling
Maintenance prioritization	ML + DSS	Combines prediction with decision criteria
Explainable prediction	SHAP, LIME + AI model	Interpretation of model outputs

8.5 Major Findings from the Comparative Review

Four major findings emerge from the comparison.

First, no single methodology provides all required capabilities. IoT is strong in sensing, BIM in asset representation, GIS in spatial context, numerical simulation in physical modelling, and AI in prediction. Their individual strengths therefore need to be combined.

Second, prediction is more developed than maintenance decision support. A substantial portion of the literature focuses on damage detection, condition assessment or failure prediction, while comparatively fewer studies connect these predictions directly to maintenance prioritization.

Third, explainability remains insufficiently integrated. Although XAI techniques such as SHAP and LIME can improve transparency, their integration with DT-based predictive maintenance and decision support remains limited.

Fourth, scalability and generalization remain major challenges. Several reviewed approaches are developed for a particular infrastructure type—such as pavements, railways, buildings or specific structural systems—and therefore cannot automatically be generalized to heterogeneous urban infrastructure. The proposal explicitly identifies the need for a flexible, scalable framework capable of supporting multiple infrastructure asset types.

8.6 Overall Comparative Assessment

Existing studies demonstrate strong individual capabilities in Digital Twins, IoT monitoring, AI prediction, BIM/GIS integration, numerical simulation, XAI and decision support. The principal weakness is the limited integration of these capabilities into a unified infrastructure-oriented methodology.

Therefore, the key research opportunity identified by this survey is not simply to introduce another AI algorithm, but to investigate how heterogeneous infrastructure information, AI-based prediction, Digital Twin synchronization, explainability and maintenance decision support can operate together within a scalable framework. This conclusion directly reflects the research gaps and proposed contributions identified in the underlying research proposal.

9. Challenges and Research Gaps

The comparative analysis demonstrates that substantial progress has been made in Digital Twin, Artificial Intelligence, IoT, BIM, GIS and predictive maintenance methodologies. However, the existing literature remains fragmented, particularly when these technologies are considered together for smart urban infrastructure. The major challenges and research gaps identified from the reviewed studies are discussed below.

9.1 Lack of Unified Integration

A major limitation is the absence of a **single integrated framework** combining Digital Twins, IoT, BIM, GIS, AI and numerical modelling. Existing studies frequently concentrate on one or two technological components, resulting in fragmented solutions.

The literature review in the proposal explicitly identifies the lack of integration of BIM, GIS, IoT and AI within a single DT environment as a significant research gap.

9.2 Monitoring-Oriented Rather Than Prediction-Oriented DTs

Many Digital Twin implementations primarily provide visualization, asset representation and monitoring. Although these capabilities are useful, they do not necessarily provide information about **future infrastructure condition or failure**.

The proposal identifies this limitation by noting that existing DT implementations are often focused on visualization rather than predictive capabilities. Consequently, there is a need to move from *"what is happening now?"* towards *"what is likely to happen next?"* and *"what maintenance action should be taken?"*

9.3 Limited Generalization Across Infrastructure Types

A considerable number of existing AI-DT studies are developed for specific infrastructure domains, including buildings, pavements, railways, microgrids or individual structural systems.

Although domain-specific models can achieve strong performance, their direct application to heterogeneous urban infrastructure is difficult. Bridges, roads, tunnels, buildings and utility networks exhibit different structural characteristics, deterioration mechanisms, sensing requirements and data formats.

Thus, a major research challenge is developing **flexible and scalable methodologies** that can accommodate different infrastructure asset types without requiring an entirely separate framework for each application.

9.4 Data Heterogeneity and Interoperability

An urban Digital Twin may receive data from multiple sources, including IoT sensors, BIM models, GIS databases, infrastructure records, inspection reports and numerical simulations. These sources differ in structure, scale, frequency and format.

Consequently, effective data interoperability becomes essential. Without appropriate mechanisms for data integration and synchronization, the DT may contain incomplete or inconsistent representations of the physical infrastructure.

The proposal therefore emphasizes integration of BIM, GIS, IoT, infrastructure databases and numerical modelling within the DT architecture.

9.5 Explainability of AI Predictions

Advanced AI models can provide powerful predictions but may operate as black-box systems. In infrastructure management, this is problematic because maintenance decisions can have significant safety and financial implications.

Although XAI approaches such as SHAP and LIME provide mechanisms for interpreting AI predictions, the reviewed literature indicates insufficient integration of explainability with DT-based infrastructure management and maintenance decision-making.

The challenge is therefore not merely to improve prediction accuracy but to provide **understandable evidence supporting the prediction**.

9.6 From Prediction to Maintenance Decision

Another important gap concerns the transition from AI prediction to actual maintenance planning. Predicting that an asset is deteriorating does not automatically determine:

- which asset should be treated first,
- when intervention should occur,
- what resources are required,
- what the expected cost will be, or

- how the consequences of delaying maintenance should be considered.

The proposal consequently identifies maintenance prioritization and decision support as important components of the intended framework.

9.7 Scalability and Computational Complexity

A city-scale DT can involve large numbers of assets, continuous sensor streams, complex AI models and potentially computationally intensive numerical simulations. Consequently, computational efficiency becomes an important consideration.

The proposal identifies training and inference time, computational complexity, memory requirements, scalability and throughput among the performance measures for evaluating the proposed methodologies.

Therefore, an algorithm with slightly lower predictive accuracy may sometimes be preferable if it provides substantially better computational efficiency and scalability.

9.8 Limited Real-World Validation

Several studies reviewed in the proposal demonstrate promising methodologies but have limitations related to large-scale or real-world validation. Some approaches rely primarily on simulation, benchmark datasets or specific case studies.

For a smart urban infrastructure DT, validation needs to establish not only AI prediction accuracy but also **physical–virtual consistency, synchronization, robustness, scalability and usefulness for maintenance decisions**. These aspects are explicitly included among the proposed validation and evaluation criteria.

9.9 Summary of Research Gaps

The major gaps identified through the comparative survey can therefore be summarized as follows:

Research gap	Limitation in existing studies	Required methodological direction
Technology integration	BIM, GIS, IoT and AI often operate separately	Unified DT architecture
Predictive capability	Many DTs emphasize visualization/monitoring	AI-driven deterioration and failure prediction
Infrastructure coverage	Many approaches are asset-specific	Multi-asset and scalable framework
Explainability	AI predictions may be difficult to interpret	Integrated XAI
Maintenance decisions	Prediction does not always lead to action	AI-enabled DSS and prioritization
Data interoperability	Heterogeneous sources are difficult to integrate	Standardized and interoperable data architecture
Computational scalability	Complex DT/AI systems can be resource-intensive	Efficient and scalable computation
Validation	Limited large-scale real-world validation	Benchmark, simulation and case-study validation

9.10 Research Gap Emerging from the Survey

The central finding of the comparative survey is that the research gap lies primarily in integration rather than the absence of individual technologies. Digital Twins, IoT, AI, BIM, GIS, numerical simulation, XAI and predictive maintenance have each demonstrated significant potential. What remains insufficiently addressed is their coordinated implementation within a scalable framework for heterogeneous urban infrastructure.

Accordingly, the literature supports the need for a methodology that can progress through the complete chain:

Data acquisition → Digital Twin synchronization → condition assessment → anomaly/deterioration prediction → RUL/failure prediction → XAI → risk assessment → maintenance prioritization → decision support.

This integrated perspective provides the principal justification for the research direction proposed in the underlying study.

10. Future Research Directions

The comparative review indicates several directions for future research in AI-driven Digital Twins for smart urban infrastructure.

First, future studies should focus on **integrated DT architectures** that combine IoT, BIM, GIS, AI and numerical simulation rather than developing these technologies independently.

Second, greater attention is required to **explainable and trustworthy AI**, particularly where AI predictions are used to support infrastructure maintenance decisions.

Third, research should move towards **scalable multi-asset Digital Twins** capable of supporting heterogeneous urban infrastructure rather than being restricted to individual asset types.

Finally, future work should emphasize **real-world validation, interoperability and computational efficiency**, together with decision-support mechanisms that translate predictions into practical maintenance priorities.

Overall, the future direction is toward **integrated, predictive, explainable and scalable Digital Twin environments** capable of supporting infrastructure managers throughout the monitoring-to-maintenance lifecycle.

11. Conclusion

The comparative survey shows that Digital Twin technology has evolved from primarily representing and monitoring physical assets toward increasingly intelligent systems incorporating IoT, AI and predictive maintenance. Machine-learning and deep-learning methods provide capabilities for condition assessment, anomaly detection, deterioration prediction and RUL estimation, while BIM and GIS enhance asset and spatial representation.

However, existing methodologies remain fragmented, with limited integration of IoT, BIM, GIS, AI, numerical simulation, XAI and maintenance decision support within a unified and scalable infrastructure framework. The principal research opportunity is therefore to develop Digital Twins that do not merely visualize infrastructure condition but predict future behaviour, explain predictions and support maintenance decisions.

This comparative assessment establishes the methodological foundation for developing more comprehensive AI-driven Digital Twin solutions for smart urban infrastructure.

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