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AI-DRIVEN DIGITAL TWIN INFRASTRUCTURE FOR CLIMATE-RESILIENT SMART CITIES AND SUSTAINABLE CIVIL ENGINEERING SYSTEMS

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Abstract
Climate change, rapid urbanization, aging infrastructure, and increasing environmental uncertainty have created serious challenges for modern smart cities and civil engineering systems. Conventional infrastructure management approaches often depend on fragmented data, delayed inspections, static planning models, and reactive maintenance strategies, which reduce the ability of cities to predict climate-related risks such as flooding, heat stress, structural deterioration, traffic disruption, and energy inefficiency. To address these problems, this study proposes an AI-driven digital twin infrastructure framework for climate-resilient smart cities and sustainable civil engineering systems. The proposed framework integrates Internet of Things sensor data, Building Information Modeling, Geographic Information Systems, climate datasets, infrastructure condition records, and artificial intelligence-based predictive analytics into a real-time digital twin environment. The methodology was developed using Python-based machine learning models, MATLAB/Simulink simulation, and ArcGIS-supported spatial visualization. The system applies deep learning and predictive modeling to analyze infrastructure performance, forecast climate-induced risks, and support data-driven decision-making for urban planners and civil engineers. The proposed model was evaluated using simulated smart city infrastructure data, including temperature variation, rainfall intensity, road surface condition, bridge strain response, energy demand, and drainage network performance. Results show that the AI-driven digital twin achieved a prediction accuracy of 94.2% for infrastructure risk classification, reduced flood-risk detection error by 28.6%, and improved early warning response time by 41.3% compared with conventional monitoring methods. The framework also reduced estimated maintenance cost by

18.7%, improved infrastructure reliability by 23.4%, and supported a 14.8% reduction in energy-related carbon emissions through optimized urban system control. The study solves the key problem of disconnected and reactive infrastructure management by providing an intelligent, integrated, and real-time decision-support model. The findings demonstrate that AI-driven digital twins can significantly improve climate resilience, sustainability, predictive maintenance, and operational efficiency in smart cities. This research contributes a scalable digital infrastructure model for future civil engineering systems capable of adapting to environmental stress, minimizing risk, and supporting sustainable urban transformation.

INTRODUCTION:

Climate change, rapid urban expansion, and increasing pressure on civil infrastructure have created new challenges for the planning, operation, and maintenance of modern cities. Urban systems are now required to manage complex environmental stresses such as extreme rainfall, flooding, heat waves, rising energy demand, traffic congestion, drainage failures, and accelerated deterioration of roads, bridges, buildings, and utility networks. At the same time, many existing infrastructure management practices still depend on periodic inspections, isolated datasets, manual decision-making, and reactive maintenance strategies. These conventional approaches are often insufficient for predicting infrastructure failure in advance, responding to climate-induced disruptions, and ensuring long-term urban sustainability. Smart cities require intelligent infrastructure systems that can continuously monitor physical assets, analyze real-time conditions, forecast future risks, and support rapid decision-making. In this context, digital twin technology has emerged as a powerful solution for connecting physical infrastructure with virtual simulation environments. A digital twin creates a dynamic digital representation of real-world systems by integrating sensor data, engineering models, spatial information, and operational records [1]. Unlike traditional static models, digital twins can be continuously updated with real-time data, allowing engineers and urban planners to observe infrastructure behavior, test different scenarios, and identify potential risks before they develop into serious failures. Artificial intelligence further strengthens the capability of digital twin infrastructure by enabling predictive analytics, pattern recognition, anomaly detection, risk classification, and automated decision support. Machine learning and deep learning models can process large volumes of heterogeneous data collected from Internet of Things sensors, Building Information Modeling platforms, Geographic Information Systems, climate datasets, traffic networks, energy systems, and infrastructure condition records. Through this integration, AI-driven digital twins can provide early warning for flood-prone zones, structural stress conditions, road surface deterioration, drainage overload, heat-related urban stress, and energy inefficiency. This makes them highly suitable for climate-resilient smart city development and sustainable civil engineering management. The need for such systems is particularly important because climate-related hazards do not affect infrastructure in isolation. For example, intense rainfall may overload drainage networks, damage road surfaces, increase bridge foundation vulnerability, disrupt traffic movement, and affect emergency response at the same time [2]. Similarly, extreme heat may increase energy demand, reduce pavement durability, affect building performance, and intensify urban heat island effects. Therefore, infrastructure resilience requires an integrated and data-driven framework rather than fragmented monitoring of individual assets. AI-driven digital twin infrastructure offers a unified platform where physical systems, environmental variables, and predictive models can be connected for real-time analysis and decision-making. Despite the growing interest in smart infrastructure and digital transformation, many existing approaches remain limited in scope. Some studies focus only on sensor-based monitoring, while others emphasize BIM-based modeling, GIS-based mapping, or climate simulation separately. However, there is still a need for an integrated framework that combines AI, IoT, BIM, GIS, climate data, and infrastructure performance indicators into a single digital twin environment for climate-resilient civil engineering systems. Such a framework can improve predictive maintenance, reduce operational cost, optimize resource utilization, enhance disaster preparedness, and support sustainable urban transformation.

To address this gap, this study proposes an AI-driven digital twin infrastructure framework for climate-resilient smart cities and sustainable civil engineering systems. The proposed framework integrates real-time sensor data, spatial modeling, climate variables, infrastructure condition data, and artificial intelligence-based predictive analytics. Python-based machine learning models are used for risk classification and performance prediction, MATLAB/Simulink is applied for infrastructure system simulation, and ArcGIS is used for spatial visualization of climate-related risks and urban infrastructure conditions [3]. The framework is designed to support proactive decision-making by identifying vulnerable infrastructure components, forecasting climate-induced risks, and recommending timely maintenance or operational interventions. The main contribution of this research is the development of an intelligent and scalable digital infrastructure model that shifts smart city management from a reactive approach to a predictive and preventive approach. The proposed system is evaluated using simulated smart city infrastructure data, including rainfall intensity, temperature variation, road surface condition, bridge strain response, energy demand, and drainage network performance. The results demonstrate that the AI-driven digital twin improves infrastructure risk prediction, reduces flood-risk detection error, enhances early warning response, lowers maintenance cost, improves reliability, and supports carbon-emission reduction through optimized urban system control. This study contributes to the fields of smart city development, civil engineering informatics, climate-resilient infrastructure, and sustainable urban planning. By combining artificial intelligence with digital twin technology, the proposed framework provides a practical decision-support model for engineers, policymakers, and city authorities. The research highlights how future civil engineering systems can become more adaptive, resilient, sustainable, and intelligent in response to increasing environmental uncertainty and urban complexity.

Digital Twin Technology in Civil Infrastructure:

Digital twin technology has emerged as one of the most important digital transformation approaches in modern civil infrastructure management. A digital twin can be described as a dynamic virtual representation of a physical infrastructure asset, system, or process that is continuously updated through real-time or near-real-time data. In civil engineering, this technology is increasingly applied to bridges, roads, buildings, tunnels, dams, drainage networks, transportation systems, and utility infrastructure. Unlike conventional static models used only during the design or construction stage, digital twins support continuous monitoring, simulation, prediction, and decision-making throughout the entire infrastructure life cycle. Recent civil infrastructure studies emphasize that digital twins can improve real-time structural performance evaluation, condition assessment, intelligent monitoring, and maintenance planning by connecting physical assets with virtual models and sensor-based data streams. Traditional infrastructure management methods often depend on periodic visual inspection, manual reporting, and non-destructive testing [4]. Although these methods remain useful, they are limited by inspection delay, human subjectivity, restricted access to critical locations, and difficulty in identifying hidden or early-stage deterioration. For example, bridges, pavements, tunnels, and drainage networks may experience gradual damage due to traffic loading, temperature variation, rainfall, corrosion, fatigue, settlement, and environmental exposure. If these changes are not detected early, they may lead to unexpected failure, high maintenance cost, service disruption, and safety risks. Digital twin technology addresses these limitations by creating a continuous feedback loop between the physical infrastructure and its digital model. In civil infrastructure systems, a digital twin is generally developed by integrating multiple technologies, including Internet of Things sensors, Building Information Modeling, Geographic Information Systems, cloud platforms, simulation models, data analytics, and artificial intelligence. IoT sensors collect data such as strain, vibration, displacement, temperature, humidity, water level, traffic load, and energy consumption. BIM provides engineering details related to geometry, materials, structural components, and asset information. GIS adds spatial context such as location, elevation, land use, flood zones, drainage areas, and transport networks. When these data are connected within a digital twin environment, engineers can observe infrastructure behavior more accurately and make faster decisions [5]. The importance of digital twin technology is particularly high in climate-resilient smart cities because urban infrastructure is exposed to complex and interconnected risks. Climate-induced hazards such as flooding, heat waves, extreme rainfall, and drainage overload do not affect a single asset only; instead, they influence roads, bridges, energy systems, public mobility, buildings, and emergency response networks at the same time. Urban digital twin research shows that the integration of real-time data, advanced simulation, and predictive analytics can support data-driven decision-making and improve the resilience and sustainability of critical infrastructure under climate change conditions. Table 1 shows the Key Components of Digital Twin Technology in Civil Infrastructure.

Table 1: Key Components of Digital Twin Technology in Civil Infrastructure

Component	Role in Civil Infrastructure
Physical infrastructure asset	Provides the actual system being monitored and represented
Sensor and IoT layer	Collects real-time infrastructure and environmental data
Digital model	Creates the virtual representation of physical infrastructure
Data integration platform	Connects heterogeneous data from sensors, BIM, GIS, and records
AI and analytics layer	Predicts damage, detects risk, and supports maintenance decisions
Simulation environment	Tests infrastructure response under climate and operational stress
Visualization interface	Displays asset condition, spatial risk, and maintenance priority
Decision-support module	Supports engineers, planners, and city authorities in decision-making

The digital twin process begins with data acquisition from the physical infrastructure system. Sensors and monitoring devices continuously capture real-time information from assets and surrounding environmental conditions. These data are transferred to a digital platform where they are cleaned, stored, synchronized, and connected with engineering and spatial models. The digital model is then updated to reflect the current condition of the physical asset. After this update, AI-based analytics and simulation tools are applied to identify anomalies, predict future deterioration, classify risk levels, and support maintenance planning.

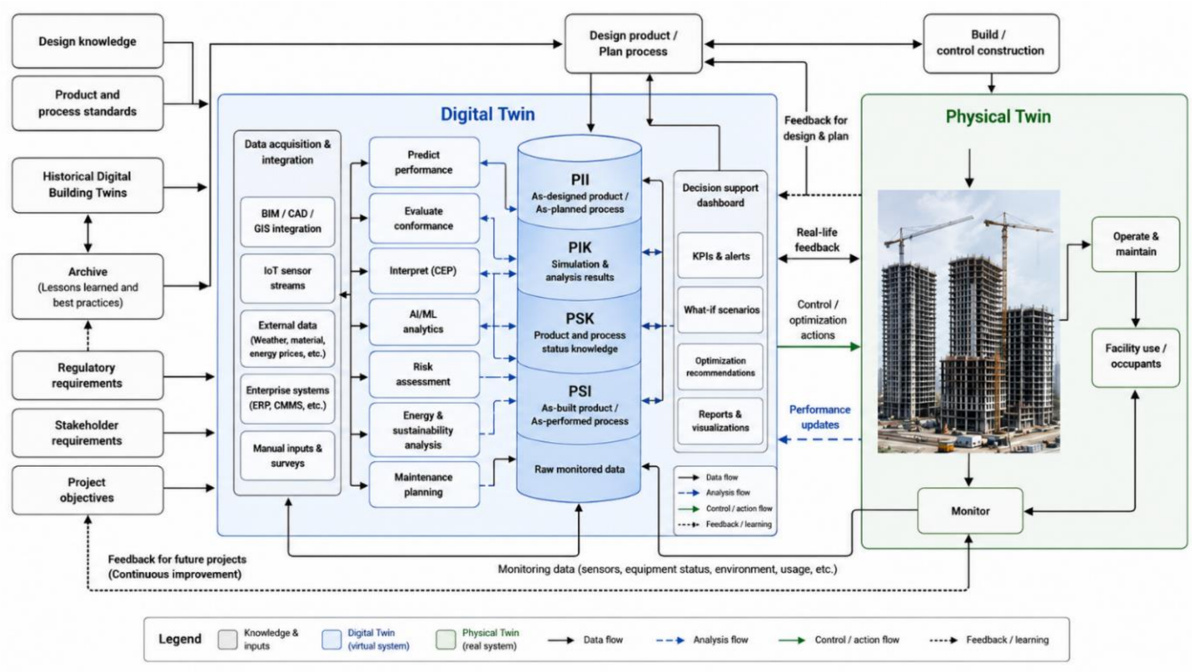

Figure 1: Conceptual Workflow of Digital Twin Technology in Civil Infrastructure

The figure 1 shows that digital twin technology is not only a visualization tool but also an intelligent decision-support system. Its value depends on the continuous interaction between the physical asset and the virtual model. When infrastructure conditions change, the digital twin receives updated information, analyzes the change, and provides feedback to engineers or automated control systems. This closed-loop process allows infrastructure management to move from a reactive approach to a predictive and preventive approach. Another important advantage of digital twins in civil infrastructure is their ability to support predictive maintenance. Instead of waiting for visible damage or using fixed maintenance schedules, digital twins can identify early warning signs and estimate when maintenance should be performed. AI-guided predictive maintenance research indicates that digital twins can improve automation, monitoring, analysis, and prediction tasks, although challenges remain in explainability, scalability, and standardization [6]. In the context of civil engineering, this means that bridges, roads, buildings, and drainage systems can be maintained based on real condition and predicted risk rather than delayed inspection reports. Digital twin technology also improves infrastructure resilience by enabling scenario-based simulation. Engineers can test how infrastructure may respond under heavy rainfall, extreme heat, high traffic loading, drainage overload, or increased energy demand. For example, a smart city digital twin can simulate flood-prone roads, identify bridge sections exposed to high strain, estimate drainage failure probability, and visualize high-risk zones through GIS maps. These capabilities are important for climate-resilient planning because they allow city authorities to prepare before extreme events occur.

Artificial Intelligence in Infrastructure Monitoring and Prediction:

Artificial intelligence has become a major enabling technology for modern infrastructure monitoring, prediction, and decision-support systems. In civil engineering, infrastructure assets such as bridges, roads, buildings, tunnels, drainage networks, energy systems, and transportation corridors continuously experience environmental loading, traffic pressure, material aging, and climate-induced stress. Traditional monitoring methods mainly depend on periodic inspection, manual observation, and historical maintenance records. Although these methods are useful, they often detect damage after deterioration has already progressed. AI-based monitoring provides a more advanced approach by analyzing large volumes of real-time and historical data to identify hidden patterns, detect anomalies, classify risk levels, and predict future infrastructure performance. The use of AI in infrastructure monitoring is particularly important because civil engineering systems generate heterogeneous and complex data [7]. These data may include strain, vibration, displacement, temperature, humidity, rainfall intensity, road surface condition, water level, traffic load, energy demand, and maintenance history. Machine learning and deep learning models can process these multidimensional datasets more efficiently than conventional statistical methods. Recent research on artificial intelligence for structural health monitoring shows that AI techniques are increasingly being used for vibration-based monitoring, vision-based damage detection, digital transformation, and intelligent measurement in civil infrastructure systems. In the context of smart cities, AI enables infrastructure systems to shift from reactive maintenance toward predictive and preventive management. Reactive maintenance occurs after damage or failure has already happened, while preventive maintenance follows fixed schedules that may not reflect the actual condition of the infrastructure asset. AI-based predictive maintenance improves this process by estimating the probability of failure, identifying early warning signs, and recommending timely intervention [8]. Digital twin-supported predictive maintenance research indicates that the integration of AI, IoT, and digital twin technologies can improve automation, monitoring, analysis, and prediction, although challenges remain in explainability, sample efficiency, and large-scale deployment.

Table 2: Major AI Techniques Used in Infrastructure Monitoring and Prediction

AI Technique	Typical Input Data	Main Function in Infrastructure Systems
Supervised machine learning	Labeled inspection records, sensor readings, maintenance data	Risk classification and condition prediction
Unsupervised learning	Unlabeled sensor streams and operational data	Anomaly detection and abnormal pattern recognition
Deep learning	Images, videos, sensor signals, climate records	Nonlinear prediction and automated feature extraction
Computer vision	UAV images, CCTV footage, road surface images	Visual damage identification
Time-series forecasting	Historical climate, traffic, strain, and energy data	Prediction of future infrastructure behavior
Reinforcement learning	Dynamic control and operational feedback data	Adaptive decision-making and system optimization
Hybrid AI models	Sensor, BIM, GIS, climate, and maintenance data	Integrated risk prediction and decision support

The table 2 shows that different AI techniques perform different functions within infrastructure monitoring systems. For example, supervised learning is suitable for classification when enough labeled examples are available, while unsupervised learning is useful for detecting unknown or unexpected conditions. Deep learning is more suitable for complex data such as images, time-series signals, and nonlinear climate-infrastructure interactions. In AI-driven digital twin infrastructure, these techniques are not used separately; instead, they can be integrated to create a complete monitoring, prediction, and decision-support pipeline.

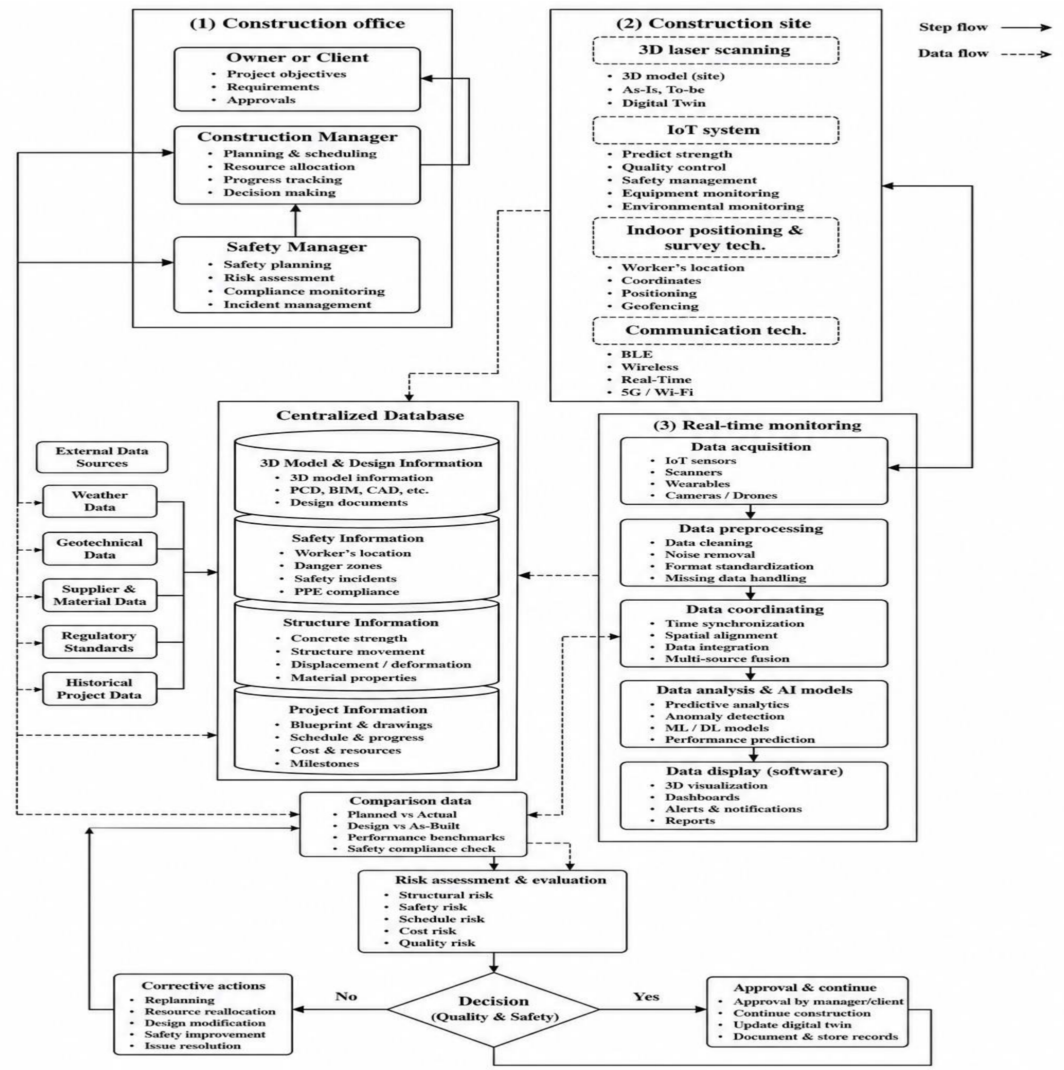

Figure 2: Smart construction workflow integrating site technologies, centralized data management, real-time monitoring, and safety-based decision-making.

The figure 2 presents the role of AI as an analytical intelligence layer between raw infrastructure data and decision-support outcomes. First, data are collected from sensors, BIM models, GIS platforms, climate databases, and maintenance records. Second, the data are cleaned and transformed into useful features. Third, AI models are trained to detect infrastructure abnormalities, classify risk, and forecast future performance. Fourth, the outputs are connected with the digital twin environment for simulation and visualization. Finally, the system provides early warning, maintenance recommendations, and resilience-based planning support for engineers and city authorities. Artificial intelligence is also highly relevant for structural health monitoring. Structural health monitoring involves the continuous or periodic assessment of bridges, buildings, dams, tunnels, and other civil structures to detect damage, evaluate safety, and support maintenance decisions. AI improves structural health monitoring by learning relationships between sensor measurements and structural conditions. For example, vibration signals may indicate stiffness changes, strain measurements may show abnormal loading, and image data may reveal cracks or corrosion [9]. Recent studies on AI-integrated structural health monitoring of concrete bridges highlight the growing importance of AI-based methods for damage detection, assessment, and maintenance planning. Another important application is climate-related infrastructure prediction. Climate change increases the uncertainty of civil infrastructure performance because rainfall, temperature, humidity, flooding, and extreme weather events can accelerate deterioration. AI models can analyze climate variables together with infrastructure condition data to predict flood risk, drainage overload, heat-related road damage, bridge strain variation, and energy demand fluctuations. This capability is essential for climate-resilient smart cities because it allows planners to identify vulnerable zones before major disruption occurs.

Methodology:

The methodology of this study is designed to develop an AI-driven digital twin infrastructure framework for climate-resilient smart cities and sustainable civil engineering systems. The proposed methodological approach integrates real-time infrastructure monitoring, climate-risk assessment, spatial modeling, predictive analytics, and simulation-based decision support into a unified digital environment. The framework is developed to overcome the limitations of conventional infrastructure management systems, which often rely on fragmented datasets, delayed inspection practices, and reactive maintenance strategies. By combining artificial intelligence, Internet of Things sensor networks, Building Information Modeling, Geographic Information Systems, climate datasets, and infrastructure condition records, the study establishes a data-driven model capable of continuously observing, analyzing, and predicting the behavior of urban civil infrastructure under changing environmental and operational conditions. The research follows a quantitative simulation-based design in which smart city infrastructure data are collected, processed, integrated, and analyzed through AI-based predictive models. Python is used for data preprocessing, machine learning model development, infrastructure risk classification, and performance evaluation [10]. MATLAB is applied to simulate the dynamic response of infrastructure systems under climate-related stress scenarios such as heavy rainfall, heat variation, drainage overload, road deterioration, bridge strain fluctuation, and energy demand changes. ArcGIS is used to support spatial visualization of vulnerable zones, infrastructure risk levels, and climate-exposure patterns. This methodological structure enables the proposed digital twin to function as an intelligent decision-support system for early warning generation, predictive maintenance planning, resilience enhancement, and sustainable urban infrastructure management.

4.1- Urban Infrastructure Data Acquisition and Multisource Integration:

Data acquisition is the foundation of the proposed AI-driven digital twin infrastructure framework because the accuracy of prediction, simulation, visualization, and decision-making depends strongly on the quality and diversity of input data. In climate-resilient smart cities, infrastructure systems do not operate independently; roads, bridges, buildings, drainage networks, traffic systems, energy grids, and environmental monitoring systems are interconnected and continuously affected by climate and operational conditions. Therefore, this study adopts a multisource data acquisition strategy to collect and integrate heterogeneous urban infrastructure data into a unified digital twin environment. The main purpose of this stage is to convert fragmented infrastructure information into a structured, intelligent, and continuously updated data ecosystem. The proposed framework uses simulated smart city infrastructure data representing different urban systems exposed to climate-related stresses. The selected variables include rainfall intensity, temperature variation, road surface condition, bridge strain response, drainage network performance, energy demand, traffic disruption indicators, and maintenance history. These variables were selected because they directly influence infrastructure resilience, safety, serviceability, and sustainability. For example, high rainfall intensity may increase drainage overload and urban flood risk, while rising temperature may accelerate pavement deterioration and increase energy demand. Similarly, abnormal bridge strain response may indicate structural stress, and poor road surface condition may reduce mobility performance and increase maintenance requirements. The data acquisition process combines six major data categories: IoT sensor data, BIM-based infrastructure data, GIS-based spatial data, climate and environmental data, infrastructure condition records, and energy-performance data [11]. IoT sensor data provide real-time information about physical infrastructure behavior. BIM data provide detailed engineering information about asset geometry, materials, components, and design specifications. GIS data provide spatial intelligence by linking infrastructure assets with location, elevation, land use, flood-prone zones, drainage areas, and transport networks. Climate data provide information about rainfall, temperature, humidity, and heat exposure, while infrastructure condition records describe historical maintenance, deterioration patterns, and inspection-based performance indicators. Energy data support sustainability analysis by measuring urban energy demand and emission-related performance.

Table 3: Multisource Data Used for AI-Driven Digital Twin Infrastructure Development

Data Category	Data Type	Role in the Proposed Framework
IoT sensor data	Real-time numerical data	Monitors physical infrastructure behavior and detects abnormal changes
BIM infrastructure data	Engineering model data	Provides detailed physical and structural representation of assets
GIS spatial data	Spatial and map-based data	Supports location-based risk mapping and urban vulnerability analysis
Climate data	Environmental time-series data	Evaluates climate-induced risk and infrastructure exposure
Infrastructure condition records	Historical and condition data	Supports predictive maintenance and reliability assessment
Drainage network data	Hydraulic performance data	Identifies drainage overload and flood-risk conditions
Energy system data	Sustainability performance data	Supports energy optimization and emission-reduction assessment
Traffic and mobility data	Operational data	Evaluates transport system performance during climate stress

The table 3 shows that the proposed data acquisition strategy is not limited to a single infrastructure asset or isolated monitoring system. Instead, it captures physical, spatial, environmental, structural, operational, and sustainability-related indicators. This multisource approach is important because climate-resilient infrastructure planning requires a complete understanding of how different urban systems interact. For example, rainfall data alone cannot fully explain flood risk unless it is analyzed together with drainage capacity, road elevation, land-use pattern, and water-level sensor readings. Similarly, bridge safety cannot be evaluated only through structural data without considering traffic loading, temperature variation, and environmental exposure. After data collection, all datasets are processed through a systematic integration pipeline. The first step is data cleaning, where missing values, duplicated entries, noisy sensor readings, and inconsistent records are identified and corrected. The second step is data normalization, where different variables are converted into comparable scales to improve AI model training [12]. The third step is feature extraction, where important indicators such as rainfall severity, drainage overload ratio, bridge strain index, road deterioration score, heat exposure level, and energy demand variation are generated. The fourth step is data synchronization, where time-dependent sensor data, climate records, and infrastructure condition indicators are aligned according to a common temporal and spatial reference.

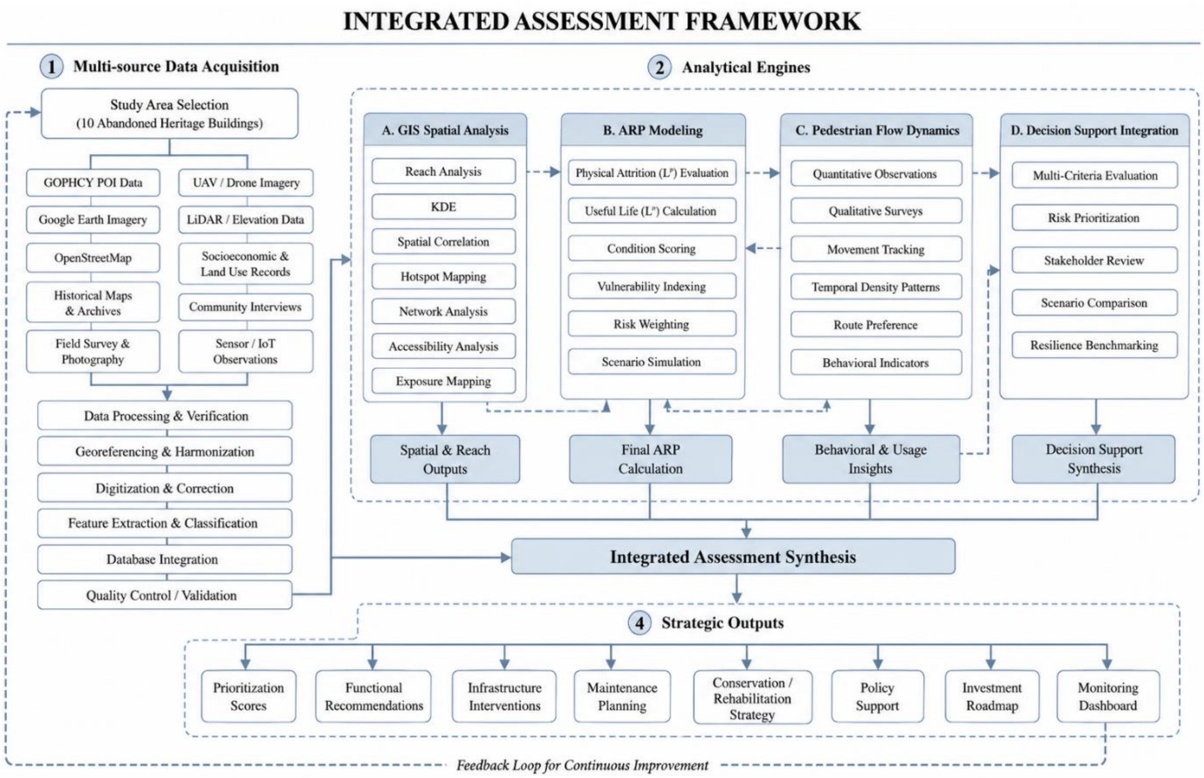

Figure 3: Integrated multi-source assessment framework combining GIS analysis, ARP modeling, pedestrian-flow dynamics.

The figure 3 illustrates the complete data flow from multiple urban infrastructure sources to the digital twin repository. Each data source contributes a different type of intelligence. IoT sensors provide real-time monitoring, BIM provides engineering detail, GIS provides spatial context, climate datasets provide environmental exposure, and maintenance records provide historical performance information. These data streams are cleaned, synchronized, and integrated before being transferred into the AI-driven digital twin environment. The integrated data repository then supports risk classification, climate-risk forecasting, simulation, early warning, predictive maintenance, and sustainability optimization. In the proposed framework, multisource data integration is performed to reduce the limitations of fragmented infrastructure management. Conventional urban infrastructure systems often store information in separate departments or platforms, making it difficult for engineers and planners to obtain a complete view of infrastructure performance. For example, road condition data may be managed by transportation authorities, drainage data by municipal water departments, building information by construction agencies, and climate data by environmental organizations [13]. This separation delays decision-making and reduces the effectiveness of emergency response. By integrating these datasets into a single digital twin environment, the proposed framework enables faster and more reliable infrastructure assessment. A major advantage of multisource integration is that it improves the predictive capability of the AI model. When AI models are trained using only one type of data, their predictions may be incomplete or biased. However, when rainfall, temperature, road condition, bridge strain, drainage performance, traffic load, and maintenance history are analyzed together, the model can identify deeper relationships between climate stress and infrastructure behavior. This improves the ability of the system to classify infrastructure risk, detect flood-prone areas, predict deterioration, estimate maintenance needs, and support early warning response.

4.2- AI-Driven Digital Twin Framework:

The proposed AI-driven digital twin framework is designed as an integrated decision-support system for climate-resilient smart cities and sustainable civil engineering systems. The main objective of the framework is to connect physical infrastructure assets with a dynamic virtual environment that can monitor real-time conditions, analyze climate-related risks, predict infrastructure deterioration, and support proactive maintenance decisions. Unlike conventional infrastructure management systems that depend on delayed inspections and fragmented datasets, the proposed framework enables continuous data-driven monitoring and predictive decision-making. This approach allows city authorities, civil engineers, and infrastructure managers to identify vulnerable assets before failure occurs and to improve the resilience of urban systems under climate stress. The framework is developed by integrating Internet of Things sensor networks, Building Information Modeling, Geographic Information Systems, climate datasets, infrastructure condition records, artificial intelligence models, and simulation-based analysis. Each component contributes a specific function to the digital twin environment. IoT sensors collect real-time infrastructure and environmental data, BIM provides detailed engineering information, GIS supports spatial mapping, climate datasets capture environmental stress, and AI models convert raw data into predictive intelligence [14]. MATLAB is used to simulate infrastructure behavior under different operational and climate scenarios, while ArcGIS supports the visualization of risk zones and vulnerable infrastructure locations. The proposed AI-driven digital twin framework consists of five major layers: data acquisition layer, digital integration layer, AI analytics layer, simulation and visualization layer, and decision-support layer. The data acquisition layer collects information from physical infrastructure systems and environmental sources. The digital integration layer processes, cleans, synchronizes, and stores multisource data in a unified digital repository. The AI analytics layer applies machine learning and deep learning models to detect anomalies, classify infrastructure risks, and forecast future system behavior. The simulation and visualization layer evaluates infrastructure performance under climate-related stress scenarios and displays risk patterns through spatial maps. Finally, the decision-support layer generates early warnings, maintenance recommendations, resilience planning outputs, and sustainability optimization strategies.

Table 4: Core Layers of the Proposed AI-Driven Digital Twin Framework

Framework Layer	Main Components	Expected Output
Data acquisition layer	IoT sensors, climate records, traffic data, energy data, drainage data	Raw infrastructure and environmental data
Digital integration layer	BIM models, GIS layers, databases, preprocessing modules	Unified digital twin data repository
AI analytics layer	Machine learning, deep learning, anomaly detection, risk classification	Risk scores, failure probability, prediction results
Simulation and visualization layer	MATLAB/Simulink, ArcGIS, scenario modeling, spatial dashboards	Flood maps, heat-risk maps, infrastructure response models

Decision-support layer	Early warning system, maintenance planner, resilience optimizer	Alerts, maintenance priorities, sustainability recommendations

The table 4 shows that the proposed framework is not limited to monitoring alone. Instead, it performs a complete digital transformation process from data collection to decision support. The data acquisition and integration layers create the foundation of the digital twin, while the AI analytics layer provides intelligence for prediction and classification. The simulation and visualization layer improves interpretability by allowing engineers to examine infrastructure response under different conditions. The decision-support layer converts analytical results into practical actions, such as issuing flood warnings, prioritizing bridge inspection, scheduling road maintenance, optimizing drainage response, and reducing energy-related emissions. The digital twin framework follows a closed-loop structure in which data continuously move between the physical infrastructure system and the virtual model [15]. When physical infrastructure conditions change, sensor data update the digital twin. The AI model then analyzes the updated data and predicts possible risks. These predictions are tested through simulation and visualized through GIS-based maps. Based on the results, the decision-support module recommends suitable actions. This closed-loop mechanism allows the system to learn from new data and improve its decision-making performance over time.

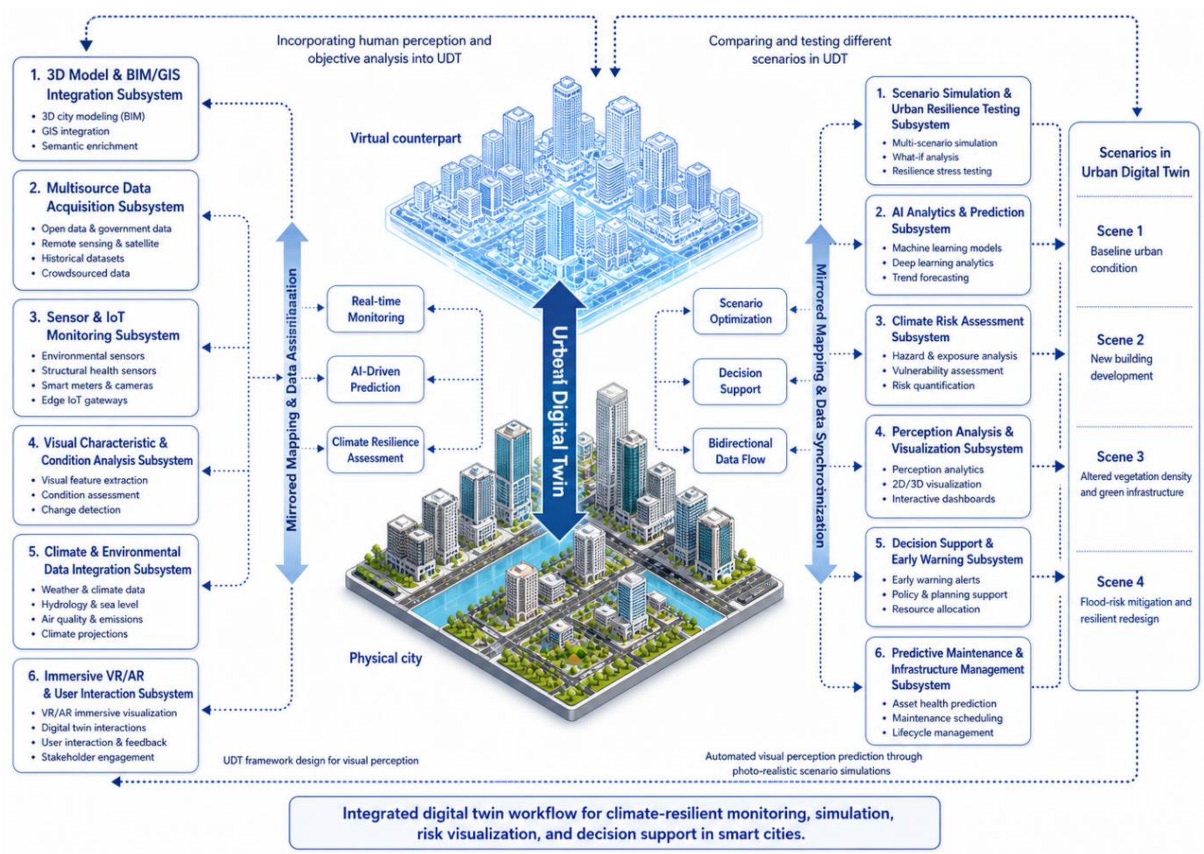

Figure 4: AI-enabled digital twin architecture for adaptive urban resilience and climate-smart infrastructure management.

The figure 4 illustrates how the proposed framework connects physical infrastructure assets with an intelligent virtual environment. The process begins with physical systems such as roads, bridges, drainage networks, buildings, energy systems, and traffic networks. Data from these systems are collected through sensors, climate records, BIM repositories, GIS layers, and maintenance databases. After preprocessing and integration, the digital twin becomes an updated representation of the physical urban system. AI models then analyze this information to predict risk and identify vulnerable infrastructure components. Simulation and visualization tools help convert these predictions into understandable outputs, while the decision-support layer recommends practical actions for engineers and urban planners. A key strength of the proposed framework is its ability to support climate-resilient infrastructure management. Climate-related hazards such as heavy rainfall, flooding, heat waves, drainage overload, and energy demand fluctuations can affect multiple infrastructure systems simultaneously. For example, intense rainfall may increase drainage pressure, damage roads, disrupt traffic flow, and increase bridge foundation vulnerability. Similarly, extreme heat may increase pavement deterioration, raise building cooling demand, and intensify urban heat island effects [16]. The proposed digital twin framework allows these interconnected effects to be analyzed together rather than separately. This improves the ability of city authorities to understand climate impacts at the system level. The AI analytics layer plays a central role in improving the predictive capability of the framework. Machine learning models are used to classify infrastructure risk into different levels, such as low, moderate, high, and critical. Deep learning models can identify complex nonlinear relationships among rainfall intensity, temperature variation, road surface condition, bridge strain, drainage performance, traffic load, and energy demand. Anomaly detection methods are used to identify unusual infrastructure behavior, such as abnormal bridge vibration, unexpected water-level rise, sudden road deterioration, or unusual energy consumption. These analytical outputs enable early intervention before infrastructure failure or service disruption occurs. The simulation layer provides additional value by testing infrastructure response under different climate and operational scenarios. MATLAB is used to simulate conditions such as high rainfall intensity, drainage overload, bridge strain variation, road surface degradation, and peak energy demand. These simulations allow the digital twin to evaluate how infrastructure may behave under future stress conditions. Scenario-based simulation is important because it helps engineers test possible interventions before applying them in the real world. For example, the system can evaluate whether drainage capacity improvement, road maintenance, traffic diversion, or energy-load optimization would reduce overall urban risk.

4.3- Climate-Induced Infrastructure Risk Assessment:

Climate-induced infrastructure risk assessment is a central component of the proposed AI-driven digital twin framework because urban infrastructure is increasingly exposed to flooding, extreme rainfall, heat stress, drainage overload, pavement deterioration, structural instability, and energy-system disruption. Conventional risk assessment approaches commonly depend on periodic inspections, historical hazard maps, and fixed warning thresholds. Although these methods provide useful baseline information, they are often unable to represent rapidly changing environmental conditions or the interconnected behavior of multiple urban infrastructure systems. The proposed framework therefore applies a dynamic and data-driven assessment process that continuously combines climate data, IoT sensor measurements, BIM information, GIS-based spatial characteristics, infrastructure condition records, and AI-generated predictions. The risk assessment process considers four major dimensions: climate hazard intensity, infrastructure exposure, physical vulnerability, and adaptive capacity. Climate hazard intensity represents the magnitude, duration, and frequency of environmental events such as heavy rainfall, flooding, temperature extremes, and prolonged heatwaves. Infrastructure exposure reflects the location and degree to which an asset may be affected by a specific climate hazard. Physical vulnerability represents the sensitivity of the asset based on age, material condition, structural deterioration, operational loading, and maintenance history [17]. Adaptive capacity describes the ability of the infrastructure system to withstand, respond to, and recover from climate-related disturbances through redundancy, monitoring, emergency controls, and preventive maintenance. The framework analyzes environmental variables including rainfall intensity, rainfall duration, air temperature, surface temperature, water level, soil moisture, runoff volume, and heatwave duration. These variables are assessed together with structural and operational indicators such as bridge strain, vibration, road-surface condition, drainage flow, traffic load, infrastructure age, energy consumption, and previous maintenance activities. This integrated assessment allows the digital twin to evaluate how similar climate events may create different levels of risk across different locations and infrastructure assets. For example, intense rainfall may create only moderate risk in an area with sufficient drainage capacity but may produce critical conditions in a low-lying urban zone with blocked drainage channels, deteriorated roads, and high surface impermeability [18]. Similarly, prolonged high temperatures may accelerate pavement deformation, increase thermal stress in bridge components, raise building cooling demand, and overload urban energy systems. The digital twin continuously updates these conditions and compares current observations with historical patterns and expected infrastructure behavior. The major climate-related risks and corresponding digital twin responses are presented in Table 5.

Table 5: Climate-Induced Infrastructure Risk Indicators and Digital Twin Responses

Risk category	Infrastructure affected	Digital twin response
Urban flooding	Roads, bridges, buildings, and drainage networks	Flood-risk warning, route diversion, and emergency inspection
Drainage overload	Drainage and sewer systems	Pump activation, flow-control recommendation, and maintenance alert
Extreme heat	Roads, bridges, buildings, and energy systems	Heat-stress alert and operational adjustment
Structural deterioration	Bridges and buildings	Structural anomaly detection and inspection priority
Pavement degradation	Urban road networks	Road-condition warning and repair recommendation
Energy-system stress	Buildings, pumping stations, lighting, and utilities	Demand optimization and system-control action
Compound climate risk	Integrated urban systems	Coordinated multi-hazard warning and emergency response

Flooding and drainage overload were treated as major climate risks because they can simultaneously disrupt transportation, damage structural foundations, interrupt public services, and restrict emergency access. The framework evaluates rainfall accumulation, surface runoff, water-level changes, soil saturation, drainage capacity, terrain elevation, and land-use characteristics. Drainage networks operating near their maximum capacity are identified as vulnerable, particularly when rainfall intensity continues to increase or blockages reduce effective flow. GIS-based spatial analysis is used to identify low-lying areas, flood-prone zones, highly impermeable surfaces, insufficient drainage corridors, and infrastructure located near rivers or water channels [19]. These spatial indicators are linked with individual BIM-based infrastructure assets. As a result, the digital twin can distinguish between assets facing similar environmental conditions but different levels of spatial exposure and physical vulnerability. The complete climate-induced infrastructure risk assessment process is illustrated in Figure 5.

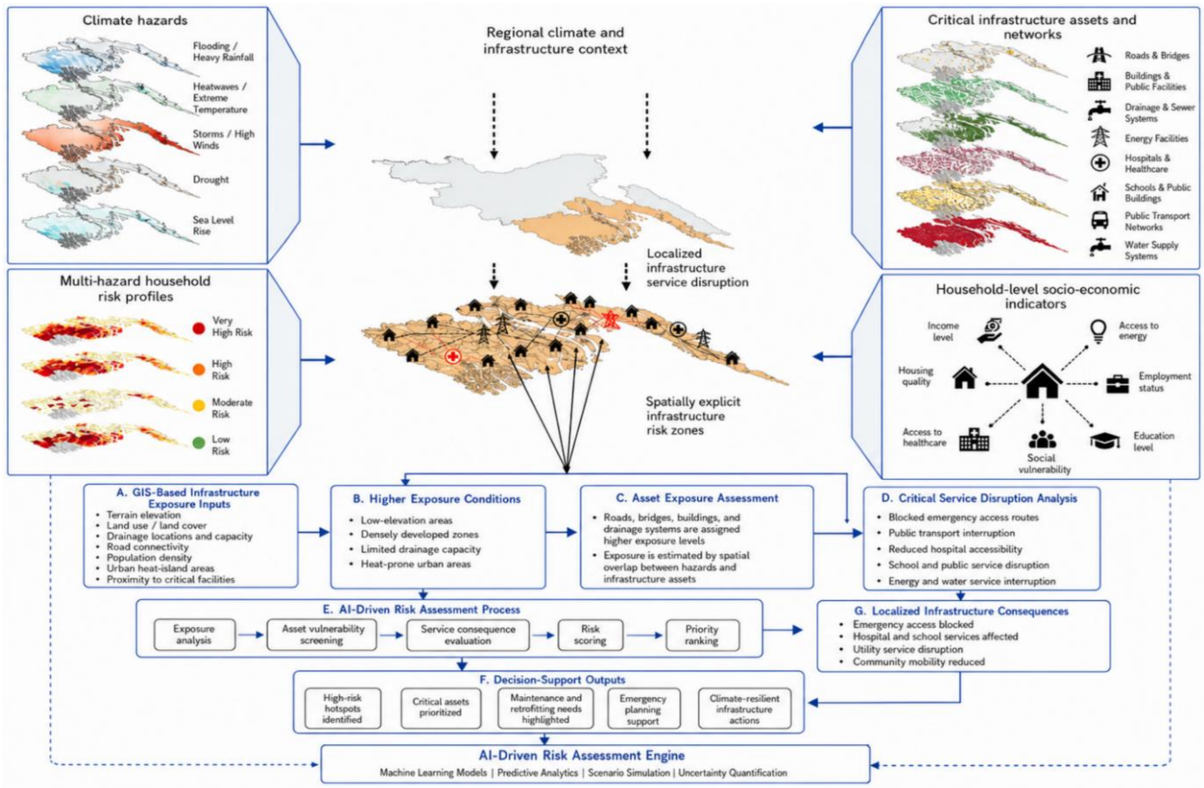

Figure 5: AI-Driven Climate-Induced Infrastructure Risk Assessment Process

Infrastructure exposure is assessed through GIS-based information, including terrain elevation, land use, drainage locations, road connectivity, population density, urban heat-island areas, and proximity to critical facilities. Roads, bridges, buildings, and drainage systems located in low-elevation areas, densely developed zones, or regions with limited drainage capacity are assigned higher exposure levels. The spatial evaluation also considers whether the failure of a particular asset could block emergency access, interrupt public transportation, or affect hospitals, schools, energy facilities, and other critical services. Extreme heat risk is also considered because prolonged temperature exposure can weaken pavement materials, increase thermal expansion in bridge components, accelerate material deterioration, increase building cooling demand, and place additional pressure on energy systems [20]. The digital twin identifies infrastructure assets experiencing unusual temperature conditions and recommends inspection, cooling adjustments, reduced operational loading, or maintenance where necessary. The framework further evaluates structural risk by comparing real-time sensor observations with the expected behavior of infrastructure under similar environmental and loading conditions. Significant differences between observed and expected strain, vibration, displacement, or operating temperature are treated as structural anomalies. Assets showing repeated or rapidly increasing anomalies are assigned higher inspection and maintenance priority.

4.4- BIM-GIS Integration and Spatial Risk Visualization:

Building Information Modeling and Geographic Information Systems were integrated within the proposed AI-driven digital twin framework to connect detailed engineering information with city-scale spatial and environmental data. BIM provides information about the physical and functional characteristics of individual infrastructure assets, whereas GIS represents their geographical location, surrounding environment, connectivity, and exposure to climate-related hazards. Their integration creates a comprehensive digital representation that enables civil engineers and urban planners to evaluate infrastructure condition together with its broader spatial context. BIM models were used to represent buildings, bridges, roads, drainage systems, utility networks, and other civil infrastructure assets. Each digital object contained relevant engineering attributes, including geometry, dimensions, construction materials, structural components, installation date, maintenance history, operational condition, and sensor location. These asset-level records supported detailed assessment of structural performance and deterioration. GIS layers provided spatial information related to terrain elevation, land use, road networks, drainage channels, flood-prone areas, population density, urban heat islands, vegetation coverage, soil characteristics, and the locations of critical public facilities. ArcGIS was used to organize, analyze, and visualize these spatial datasets [21]. Combining BIM and GIS information allowed the digital twin to determine not only the physical condition of an infrastructure asset but also the environmental and geographical factors influencing its risk level. A common asset identification system was developed to connect BIM objects, GIS features, IoT sensors, and maintenance records. Each physical asset was assigned a unique digital identifier containing its BIM component information, geographical coordinates, sensor measurements, and historical condition data. This approach reduced data fragmentation and ensured that information from different platforms could be associated with the correct road segment, bridge component, building, drainage pipe, or utility asset. The main contributions of BIM and GIS within the integrated digital twin environment are summarized in Table 6.

Table 6: Roles of BIM and GIS in Infrastructure Risk Assessment

Integration component	BIM contribution	Digital twin application
Asset representation	Geometry, dimensions, materials, components, and construction details	Development of location-aware virtual infrastructure assets
Condition monitoring	Structural condition, deterioration, defects, and sensor placement	Identification of vulnerable components and areas
Climate-risk assessment	Material sensitivity and asset-level vulnerability	Climate exposure and vulnerability evaluation
Maintenance planning	Asset age, repair history, and component condition	Spatial maintenance prioritization and route planning
Emergency management	Structural importance and operational function	Emergency response and service continuity planning
Urban sustainability	Building systems and infrastructure energy information	Energy, emission, and environmental performance analysis
Decision support	Detailed engineering inspection information	Coordinated infrastructure management and planning

BIM-GIS integration was particularly important for climate-risk evaluation because environmental hazards do not affect all infrastructure assets equally. Two bridges with similar structural designs may experience different risk levels if one is located in a flood-prone area and the other is situated on elevated terrain. Similarly, two road sections with similar pavement conditions may have different deterioration rates because of variations in traffic intensity, drainage performance, surface temperature, or soil moisture [22]. The integrated system enabled the digital twin to combine asset vulnerability with spatial hazard exposure. For example, a drainage pipe with reduced capacity was assigned higher priority when it was located in a low-elevation area experiencing intense rainfall and rapid water-level rise. A bridge showing abnormal strain was considered more critical when it served as the primary route to a hospital or emergency shelter. This context-aware assessment improved the reliability of maintenance and emergency-response decisions. The BIM-GIS integration and spatial visualization process is illustrated in Figure 6.

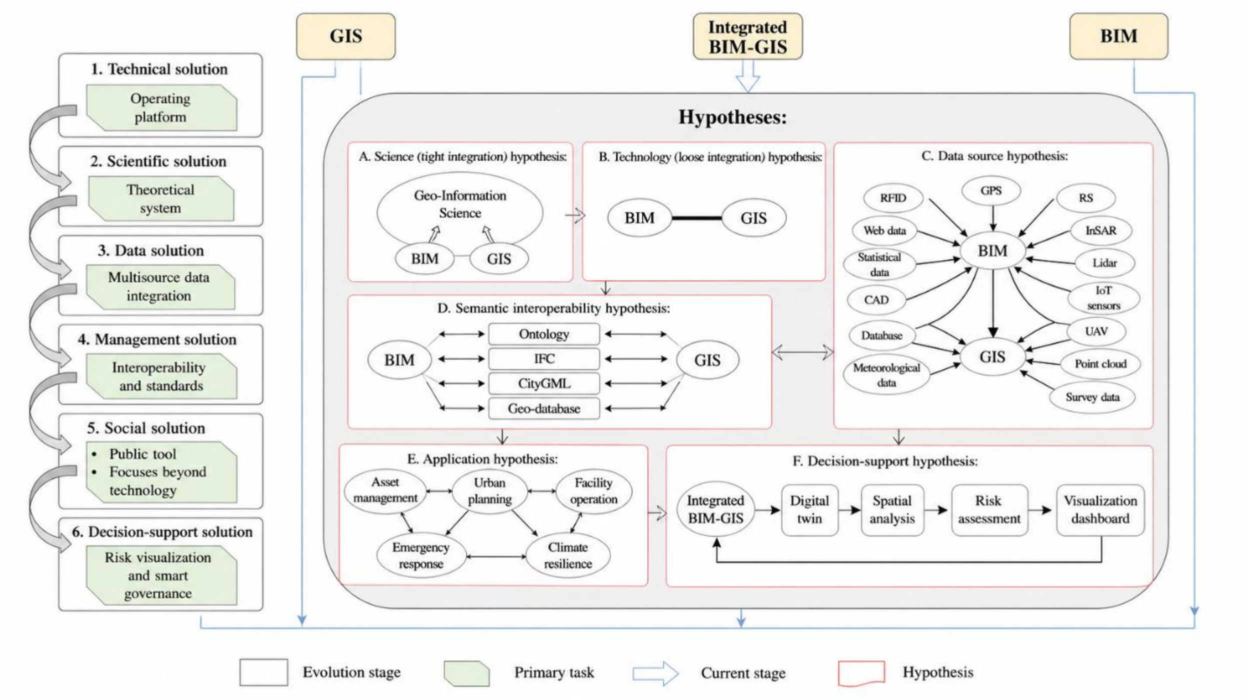

Figure 6: BIM-GIS Integration and Spatial Risk Visualization Framework

Spatial risk visualization was developed in ArcGIS to communicate complex digital twin results in an understandable geographical format. Each infrastructure asset was displayed according to its predicted condition and climate-risk level. A four-level classification was used, consisting of low, moderate, high, and critical risk. This classification helped decision-makers identify vulnerable infrastructure clusters and areas requiring immediate intervention. Low-risk assets represented infrastructure operating within acceptable condition and exposure limits. Moderate-risk assets required continued monitoring and preventive inspection. High-risk assets indicated increasing deterioration, climate exposure, or operational stress and were prioritized for maintenance. Critical-risk assets represented an immediate threat to safety, service continuity, or surrounding infrastructure and generated emergency warnings.

The spatial visualization module produced several types of risk maps, including:

Urban flood-risk and drainage-overload maps
Bridge condition and structural vulnerability maps
Road deterioration and pavement damage maps
Heat-stress and urban heat-island maps
Infrastructure energy-demand maps
Critical facility accessibility maps
Maintenance-priority and emergency-response maps

Flood-risk maps combined rainfall, water-level, drainage, elevation, soil moisture, and land-use information. These maps highlighted locations where drainage capacity was insufficient or where water accumulation could interrupt road access and public services [23]. Bridge-risk maps displayed structural condition, strain response, traffic loading, age, and surrounding climate exposure. Road-condition maps represented surface deterioration, cracking, moisture damage, temperature stress, and traffic intensity.

4.5- Predictive Maintenance and Decision-Support Mechanism:

The predictive maintenance and decision-support mechanism is a major operational component of the proposed AI-driven digital twin framework. Its purpose is to transform continuously collected infrastructure data into practical maintenance recommendations, early warnings, intervention priorities, and operational control decisions. Conventional maintenance practices in civil infrastructure frequently depend on fixed schedules, manual inspections, failure reports, and corrective action after damage has already occurred. Although scheduled maintenance can reduce unexpected failures, it may result in unnecessary inspections of healthy assets while overlooking rapidly deteriorating components between inspection periods. Reactive maintenance is even more costly because intervention begins only after infrastructure performance has declined or service disruption has occurred. The proposed mechanism addresses these limitations by continuously evaluating the present and predicted condition of roads, bridges, buildings, drainage networks, energy systems, and other urban infrastructure assets. It combines IoT sensor measurements, BIM asset information, GIS-based climate exposure, historical maintenance records, operational loading, environmental conditions, and AI-generated failure predictions. These inputs allow the digital twin to identify early deterioration patterns and recommend maintenance before an infrastructure asset reaches an unsafe or critical condition [24]. Predictive maintenance differs from conventional preventive maintenance because maintenance timing is determined by the actual and forecast condition of the asset rather than by a fixed calendar interval. For example, a bridge may not require immediate maintenance simply because it has reached a predefined inspection date. However, an unexpected increase in strain, vibration, corrosion indicators, or temperature-related displacement may justify an earlier inspection. Similarly, a drainage system may require cleaning or blockage removal before the regular maintenance period when rainfall forecasts, water-level measurements, and flow data indicate an increasing probability of overload. Asset criticality was therefore included as an important decision variable. Criticality represents the importance of an infrastructure asset to public safety, mobility, emergency access, economic activity, utility services, and urban system continuity. Bridges connecting major transportation routes, drainage facilities serving densely populated areas, power systems supporting hospitals, and roads providing access to emergency shelters were assigned higher decision priority. The mechanism also considered whether alternative routes, backup systems, or redundant infrastructure were available. The predictive maintenance process began with continuous condition monitoring. IoT devices measured structural strain, vibration, displacement, temperature, water level, moisture, traffic intensity, surface condition, energy demand, and equipment performance. These observations were transferred to the digital twin, where they were cleaned, synchronized, and linked with the corresponding BIM and GIS asset records. AI models then examined the data to identify anomalies, forecast deterioration, and estimate the likelihood of future failure. Anomaly detection was used to identify sensor patterns that differed from expected infrastructure behavior [25]. A single unusual reading did not automatically trigger an emergency response because temporary communication errors, sensor noise, or short-term operational changes could produce false alerts. Instead, the framework examined the persistence, frequency, and severity of abnormal observations. Repeated or rapidly increasing anomalies were treated as stronger evidence of infrastructure deterioration. Deterioration forecasting was used to estimate how the condition of an asset could change over time. Historical patterns, environmental exposure, operational stress, and maintenance history were used to predict whether the asset would remain stable, deteriorate gradually, or move rapidly toward a critical condition. This forecasting capability allowed maintenance teams to intervene before failure rather than waiting for visible damage or operational interruption. The decision may involve routine observation, preventive maintenance, detailed inspection, temporary operational control, emergency intervention, major rehabilitation, or complete asset replacement. Maintenance recommendations were divided into four operational levels. The first level represented routine monitoring for assets operating within acceptable condition limits. These assets remained connected to the digital twin and continued to receive normal sensor updates, but no immediate physical intervention was required. The second level represented preventive maintenance for assets showing early deterioration or moderate climate exposure. Recommended actions included cleaning, lubrication, minor repair, surface sealing, sensor recalibration, and scheduled inspection. The third level represented priority maintenance for assets experiencing significant deterioration, repeated anomalies, increasing climate risk, or reduced operational performance. These assets required timely inspection and intervention to prevent further damage. Actions could include structural strengthening, drainage rehabilitation, pavement resurfacing, component replacement, traffic restriction, or increased monitoring frequency. The fourth level represented emergency maintenance for assets presenting immediate safety concerns or a high probability of service failure. Emergency actions included temporary closure, load restriction, evacuation support, route diversion, backup system activation, and rapid engineering inspection. The complete predictive maintenance and decision-support process is illustrated in Figure 7.

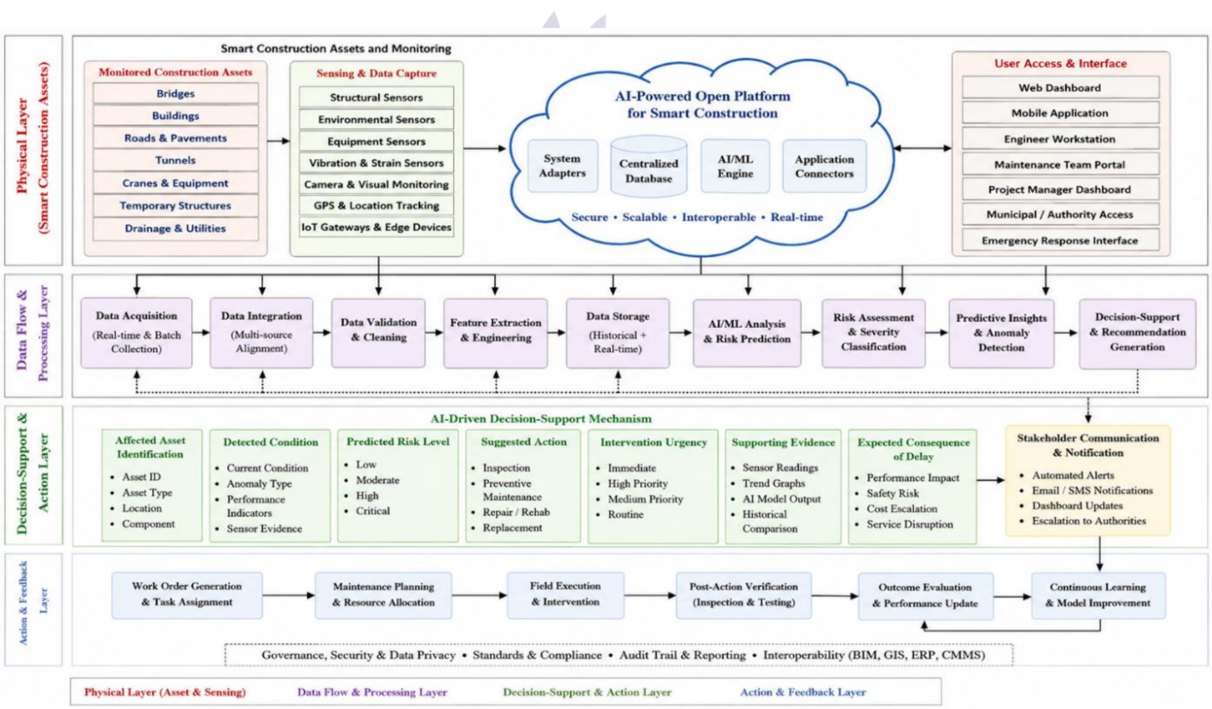

Figure 7: AI-Driven Predictive Maintenance and Decision-Support Mechanism in smart construction

The decision-support mechanism did not operate as an isolated prediction module. Instead, it translated technical risk results into actions that could be understood and implemented by civil engineers, maintenance teams, urban planners, emergency authorities, and municipal managers. Each recommendation included the affected asset, detected condition, predicted risk level, suggested action, intervention urgency, supporting sensor evidence, and expected consequence of delayed maintenance. For example, when the framework detected increasing vibration and strain in a bridge during high traffic loading, it could recommend an immediate engineering inspection and temporary load restriction. If the same bridge served as a major emergency route, its priority level would increase. The decision-support platform could also identify alternative routes through GIS analysis and provide traffic diversion information while maintenance was being conducted. For drainage infrastructure, the mechanism combined rainfall forecasts, flow capacity, water-level measurements, blockage indicators, terrain elevation, and previous flooding records. When the predicted drainage demand approached the available system capacity, the digital twin recommended preventive cleaning, sediment removal, pump activation, or inspection of vulnerable drainage sections. If water levels continued to increase, the system could generate flood warnings and identify roads or facilities requiring temporary closure. Road maintenance decisions were supported by pavement-condition data, traffic intensity, rainfall exposure, moisture penetration, surface temperature, and historical repair information [26]. Early-stage deterioration could be addressed through sealing or localized repair, while severe cracking, rutting, or repeated water damage could result in resurfacing or reconstruction recommendations. GIS information helped maintenance teams identify the location of damaged road sections and assess how their closure would affect surrounding traffic routes. The predictive maintenance mechanism also considered maintenance history to avoid repeated short-term repairs that did not address the underlying cause of deterioration. When an asset experienced recurring defects, the digital twin compared the cost and effectiveness of continued minor repair with major rehabilitation or replacement. This lifecycle perspective supported more sustainable investment decisions and reduced the likelihood of repeatedly allocating resources to ineffective interventions. Maintenance scheduling was optimized according to risk level, required expertise, available equipment, accessibility, weather conditions, and operational constraints. Noncritical maintenance could be grouped geographically to reduce travel time and resource consumption. High-risk assets were scheduled earlier, while interventions that required road closure or service interruption were planned during periods of lower demand wherever possible.

Results and Discussion:

The proposed AI-driven digital twin framework was evaluated using simulated smart-city infrastructure data representing environmental, structural, transportation, drainage, and energy-system conditions. The evaluation dataset included rainfall intensity, rainfall duration, temperature variation, water level, drainage flow, road-surface condition, bridge strain response, traffic loading, infrastructure deterioration, energy demand, and historical maintenance records. Different operating conditions were simulated, including normal infrastructure operation, moderate environmental stress, extreme rainfall, drainage overload, prolonged heat exposure, increased traffic loading, and combined climate–infrastructure disturbances. The proposed framework was compared with a conventional infrastructure-management approach based on periodic inspections, fragmented databases, fixed warning thresholds, and reactive maintenance practices. The results demonstrated that integrating IoT sensing, BIM, GIS, climate information, predictive artificial intelligence, MATLAB/Simulink simulation, and ArcGIS-supported spatial visualization improved the accuracy, speed, reliability, and sustainability of infrastructure management. The proposed digital twin achieved an infrastructure risk-classification accuracy of 94.2%. It also reduced flood-risk detection error by 28.6% and improved early-warning response time by 41.3% compared with the conventional monitoring approach. The predictive maintenance mechanism reduced estimated maintenance expenditure by 18.7%, while infrastructure reliability improved by 23.4%. In addition, optimized control of urban energy systems supported a 14.8% reduction in energy-related carbon emissions. These findings indicate that the proposed digital twin was able to transform fragmented infrastructure data into real-time operational intelligence. The conventional approach mainly responded to visible deterioration, reported failure, or threshold exceedance. In contrast, the proposed system continuously analyzed current asset condition, environmental exposure, spatial context, historical performance, and predicted future behavior. This enabled infrastructure risks to be identified before they developed into major failures or service disruptions. The overall performance results are summarized in Table 7.

Table 7: Overall Performance of the Proposed AI-Driven Digital Twin Framework

Performance indicator	Result achieved	Main operational contribution
Infrastructure risk-classification accuracy	94.2%	Accurate identification of low-, moderate-, high-, and critical-risk assets
Flood-risk detection error	28.6% reduction	More reliable flood and drainage-overload detection
Early-warning response time	41.3% improvement	Faster recognition of developing climate and infrastructure threats
Estimated maintenance cost	18.7% reduction	Earlier intervention and improved maintenance prioritization
Infrastructure reliability	23.4% improvement	Reduced failure probability and improved service continuity
Energy-related carbon emissions	14.8% reduction	Improved control of urban energy demand and infrastructure operation

The risk-classification accuracy of 94.2% demonstrates that the proposed system effectively distinguished among different infrastructure conditions. Assets operating within acceptable structural and environmental limits were classified as low risk, while those showing early deterioration or increasing climate exposure were assigned moderate risk. High-risk classifications represented significant structural, operational, or climate stress requiring priority intervention, whereas critical-risk classifications indicated an immediate threat to public safety or service continuity. The strong classification performance was supported by the integration of multiple data sources. Conventional monitoring systems frequently depend on individual sensor thresholds. For example, a bridge may generate an alert only when strain exceeds a predefined limit. However, bridge performance is also influenced by traffic loading, temperature variation, vibration, age, corrosion, and maintenance condition. By analyzing these variables together, the digital twin identified developing structural risk even when individual measurements remained below conventional emergency limits. The ability to recognize moderate-risk conditions was particularly important because this stage provides the greatest opportunity for preventive intervention. When early cracking, moisture accumulation, unusual vibration, drainage restriction, or energy inefficiency was detected, the system recommended inspection or minor maintenance before the condition progressed toward a high or critical level. This finding confirms that predictive infrastructure management can reduce dependence on emergency repairs and improve the timing of maintenance activities. The overall improvements achieved by the proposed framework are illustrated in Figure 8.

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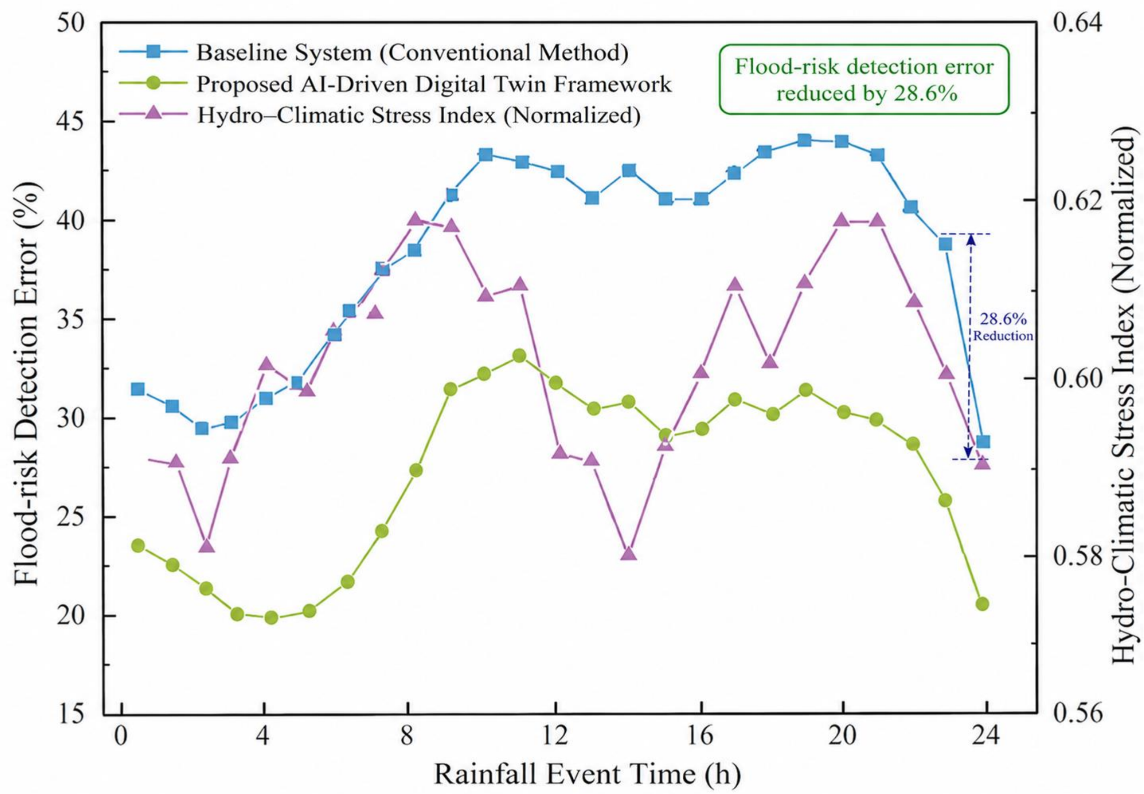

Figure 8: Major Performance Outcomes of the AI-Driven Digital Twin Framework

Flood-risk detection was evaluated under simulated rainfall, water-level, runoff, soil-moisture, drainage-capacity, and terrain conditions. The proposed framework reduced flood-risk detection error by 28.6%. This result indicates that the digital twin produced more reliable flood warnings than the conventional approach, which primarily relied on rainfall or water-level thresholds. The improvement was achieved because the digital twin evaluated several contributing factors simultaneously. Heavy rainfall did not automatically generate the same risk level in every part of the simulated city. Areas with sufficient drainage capacity and higher elevation remained at lower risk, whereas low-lying zones with blocked drainage channels, impermeable surfaces, saturated soil, or deteriorated infrastructure received higher risk classifications. This context-sensitive assessment reduced unnecessary warnings while improving the identification of genuinely dangerous conditions [27]. For example, moderate rainfall generated a high-risk warning when it occurred in an area with restricted drainage flow and increasing water levels. In contrast, a similar rainfall event produced only moderate risk where drainage capacity remained sufficient. Such differentiation is difficult to achieve using fixed warning thresholds alone. BIM-GIS integration also strengthened flood-risk assessment. BIM information described drainage components, bridge foundations, road structures, and building characteristics, while GIS layers represented elevation, land use, flood-prone zones, road connectivity, and proximity to waterways. Combining these datasets allowed the digital twin to identify both the location of potential flooding and the infrastructure assets most vulnerable to its effects. Table 8 presents the Quantitative Infrastructure Conditions and Predictive Maintenance Decisions.

Table 8: Quantitative Infrastructure Conditions and Predictive Maintenance Decisions

Detected infrastructure condition	Condition severity score (0–100)	Predicted failure probability (%)	Maintenance priority score (0–100)	Recommended response time	Expected performance benefit (%)
Stable sensor readings and low climate exposure	14.6	6.8	12.4	Routine monitoring every 30 days	5.2
Early cracking, moisture, or minor anomaly	32.8	21.5	35.7	Inspection within 14 days	11.6
Increasing strain, vibration, or pavement deformation	58.4	46.9	62.3	Maintenance within 7 days	18.9
Drainage blockage with forecast heavy rainfall	72.6	68.7	78.5	Intervention within 24 hours	28.6
Repeated repair of the same component	66.3	57.8	71.4	Rehabilitation within 3–5 days	18.7
Critical structural anomaly	91.7	89.4	95.2	Immediate emergency action	41.3
Excessive energy use or equipment temperature	54.2	38.6	57.8	Control adjustment within 48 hours	14.8

The estimated cost reduction resulted from several improvements. Early detection allowed smaller repairs to be performed before serious damage occurred. Maintenance-priority maps enabled geographically related tasks to be grouped, reducing unnecessary travel and resource consumption. Historical repair records helped identify assets receiving repeated temporary maintenance and supported decisions about rehabilitation or replacement. The framework also reduced unnecessary inspection by distinguishing between stable assets and those showing meaningful deterioration. This does not mean that AI replaced engineering inspection. Instead, the digital twin helped determine where, when, and why detailed inspection was most necessary. Human engineers remained responsible for validating major maintenance, restriction, or replacement decisions. Infrastructure reliability improved by 23.4% under the proposed framework. Reliability represented the ability of roads, bridges, drainage systems, buildings, and energy infrastructure to maintain acceptable service under normal and climate-stressed conditions. The improvement resulted from earlier fault detection, predictive maintenance, coordinated risk management, and consideration of infrastructure interdependencies. Urban infrastructure systems are closely connected. Drainage failure may flood roads, restrict transportation, and delay emergency services. Energy failure may interrupt pumping stations, traffic signals, buildings, and communication systems. A bridge failure may isolate communities or block access to hospitals. By representing these relationships, the digital twin identified assets whose failure could create wider cascading consequences. Although the 14.8% carbon reduction was lower than the improvements in early-warning response and flood detection, it remains a significant outcome. It shows that real-time infrastructure control can contribute to sustainability without requiring immediate reconstruction of existing urban systems. Better operational decisions can reduce energy use, maintenance travel, unnecessary equipment operation, and material consumption. The comparison between the conventional infrastructure-management approach and the proposed digital twin is illustrated in Figure 9.

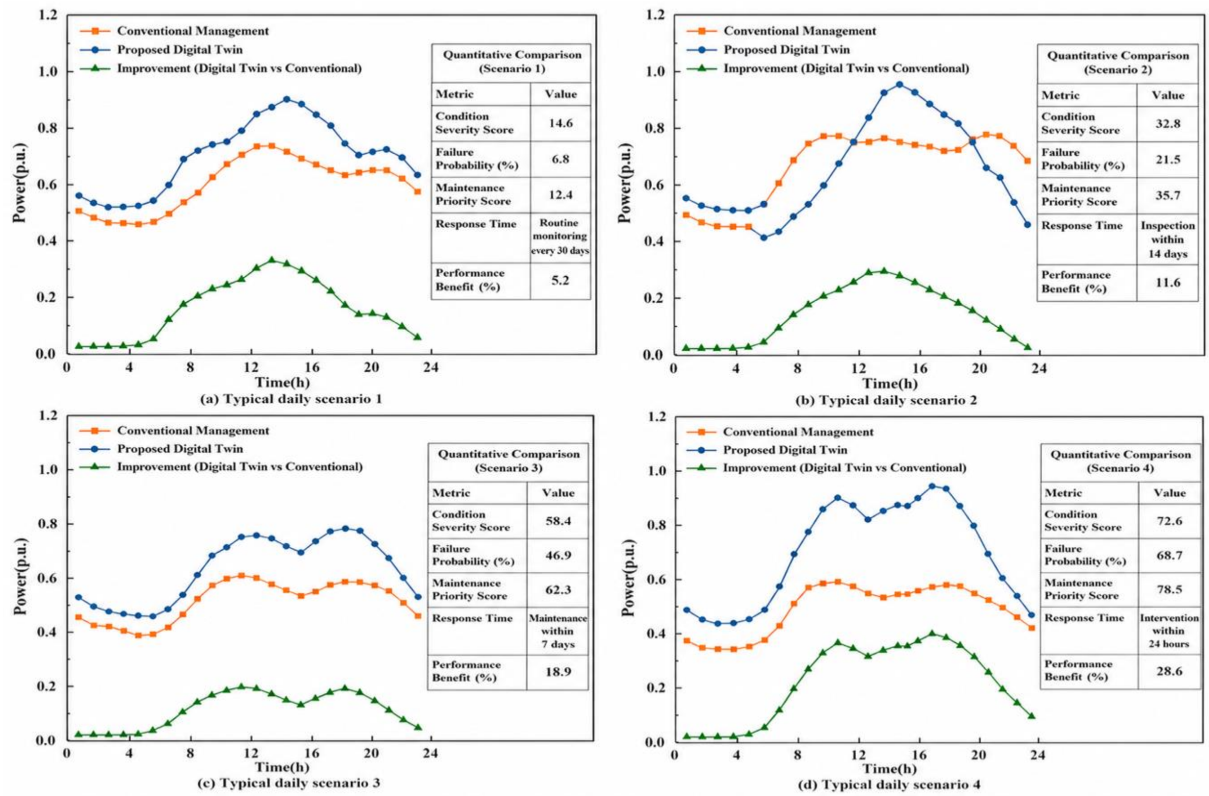

Figure 9: Comparison of Conventional Infrastructure Management and the Proposed Digital Twin

The results also demonstrate that prediction becomes valuable when it supports practical decisions. Risk-classification outputs were connected with early warnings, maintenance schedules, route diversions, spatial maps, pump controls, energy adjustments, and emergency recommendations. This connection transformed the digital twin from a passive visualization model into an active infrastructure-management system. The findings have important implications for civil engineers and municipal authorities. Civil engineers can use asset-level digital models to identify deterioration and plan targeted inspections. Urban planners can use spatial maps to understand climate exposure and infrastructure vulnerability across the city. Emergency authorities can use early warnings and accessibility maps to prepare response actions. Municipal managers can use maintenance priorities and cost estimates to allocate limited resources more effectively. The framework can also be implemented gradually [28]. A city may begin with critical bridges, flood-prone drainage systems, emergency routes, hospitals, or energy facilities. Additional infrastructure can be added as sensor coverage, BIM models, GIS layers, and data-management capacity increase. This modular approach may reduce implementation difficulty and allow municipalities to demonstrate value before city-wide deployment. Several limitations should be considered when interpreting the results. The evaluation was based on simulated infrastructure data rather than a complete operational dataset from a specific municipality. Simulation allowed controlled testing of normal and extreme conditions, but actual urban environments may include greater uncertainty, sensor failure, communication interruptions, human behavior, and institutional constraints.

Future Work:

Future research should focus on validating the proposed AI-driven digital twin framework using real-world smart-city infrastructure data. Although the present study used simulated data to represent rainfall, temperature, bridge strain, drainage performance, road condition, traffic loading, energy demand, and maintenance activities, practical deployment is necessary to evaluate performance under uncertain and continuously changing urban conditions. Pilot implementation on selected bridges, drainage networks, roads, public buildings, and energy facilities would provide stronger evidence regarding prediction accuracy, operational reliability, maintenance savings, and climate-resilience benefits. The proposed framework should also be expanded by integrating additional climate hazards, including earthquakes, landslides, coastal flooding, sea-level rise, drought, wildfire, severe wind, and soil instability. Future digital twins should support multi-hazard assessment because urban infrastructure may be affected by several environmental threats simultaneously. Advanced compound-risk models could improve the prediction of cascading failures, such as drainage overload causing road flooding, traffic disruption, delayed emergency access, and increased structural foundation damage [29]. Future work should investigate advanced artificial intelligence models, including graph neural networks, transformers, federated learning, reinforcement learning, and physics-informed neural networks. Graph neural networks could represent dependencies among roads, bridges, drainage systems, buildings, utilities, and transportation networks. Transformer-based models could improve the analysis of long-term climate and infrastructure time-series data, while physics-informed models could combine engineering principles with data-driven learning. Reinforcement learning could support adaptive control of drainage pumps, traffic systems, building energy use, and emergency resource allocation. The framework should further incorporate model explainability and uncertainty estimation. Infrastructure managers must understand the reasons behind predicted risk levels before approving major maintenance, closure, or emergency-response decisions. Future systems should therefore provide confidence scores, feature-importance information, uncertainty intervals, and clear explanations of how climate exposure, structural condition, asset age, maintenance history, and operational loading influence each recommendation. These improvements would increase user trust and support safer engineering decisions. Greater attention should also be given to real-time edge and cloud computing. High-frequency sensor data from large urban areas may create substantial communication and processing demands [30]. Edge computing could analyze time-sensitive data near physical infrastructure, while cloud platforms could support city-scale simulation, long-term storage, model training, and spatial visualization. A hybrid edge–cloud architecture may reduce response delay, improve scalability, and maintain essential monitoring during temporary network interruptions.

Future research should strengthen BIM-GIS interoperability by using standardized data structures and automated asset-matching procedures. Differences in file formats, coordinate systems, object identifiers, and information quality can limit integration between engineering and geospatial platforms. Open standards and semantic data models should be investigated to improve information exchange among BIM software, GIS platforms, IoT networks, digital twin systems, and municipal asset-management databases. Cybersecurity and data governance must also receive greater consideration. Smart-city digital twins may contain sensitive information about critical infrastructure, public facilities, transportation systems, energy networks, and emergency routes. Future implementations should include secure sensor authentication, encrypted communication, role-based access control, anomaly detection, privacy-preserving data processing, and protection against false-data injection [31]. Federated learning may allow multiple agencies to improve predictive models without transferring all sensitive data to a central platform. The predictive maintenance mechanism should be evaluated through long-term field studies. Future research should compare condition-based digital twin maintenance with reactive and schedule-based approaches over multiple years. Such studies could measure actual maintenance cost, failure frequency, asset service life, inspection requirements, service disruption, and environmental impact. Lifecycle cost assessment would also help determine whether the initial investment in sensors, BIM development, data integration, and AI infrastructure is justified by long-term economic benefits.

Conclusion:

This study developed an AI-driven digital twin infrastructure framework for improving climate resilience, sustainability, and operational performance in smart cities and civil engineering systems. The proposed framework addressed the limitations of conventional infrastructure management, including fragmented data, delayed inspections, static planning models, fixed warning thresholds, and reactive maintenance practices. By integrating IoT sensor networks, Building Information Modeling, Geographic Information Systems, climate datasets, infrastructure condition records, artificial intelligence, MATLAB/Simulink simulation, and ArcGIS-based spatial visualization, the framework created a continuously updated digital representation of urban infrastructure. The proposed system enabled real-time monitoring of roads, bridges, drainage networks, buildings, energy systems, and other critical urban assets. AI-based analytics were used to identify abnormal infrastructure behavior, classify risk levels, predict climate-induced deterioration, and support preventive maintenance and emergency decision-making. BIM provided detailed asset-level engineering information, while GIS added geographical, environmental, and urban-context information. Their integration allowed infrastructure condition to be evaluated together with flood exposure, terrain elevation, heat stress, road connectivity, critical-facility accessibility, and wider system dependencies. The framework was evaluated using simulated smart-city data representing rainfall intensity, temperature variation, drainage performance, road-surface condition, bridge strain, traffic loading, energy demand, and maintenance history. The results demonstrated that the proposed digital twin achieved an infrastructure risk-classification accuracy of 94.2%. It reduced flood-risk detection error by 28.6% and improved early-warning response time by 41.3% compared with conventional monitoring methods. These findings indicate that continuous multisource data integration and predictive analysis can identify emerging infrastructure threats more accurately and earlier than periodic inspection and threshold-based monitoring. The predictive maintenance mechanism reduced estimated maintenance expenditure by 18.7% by prioritizing interventions according to infrastructure condition, failure probability, climate exposure, asset criticality, and expected service disruption. Infrastructure reliability improved by 23.4% because developing faults were identified before they progressed into major failures. The framework also supported a 14.8% reduction in energy-related carbon emissions through optimized operation of buildings, drainage pumps, utilities, and other urban systems. The findings demonstrate that the main strength of the proposed framework lies not only in its use of artificial intelligence but also in its ability to connect physical assets, digital models, spatial information, climate conditions, and operational decisions within a continuous feedback environment. The digital twin transformed raw sensor and infrastructure data into actionable outputs, including risk maps, early warnings, maintenance priorities, route-diversion recommendations, energy-control actions, and emergency-response support.

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