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SUSTAINABLE HIGHWAY AND TRANSPORTATION SYSTEMS USING BIM & AI

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Abstract

This study presents an integrated framework for developing sustainable highway and transportation systems through the combined use of Building Information Modeling (BIM) and Artificial Intelligence (AI). The proposed methodology leverages BIM for life-cycle data integration, while AI algorithms optimize design, construction, and maintenance processes for improved energy efficiency and resource utilization. A hybrid AI–BIM model is introduced to simulate traffic flow, predict pavement deterioration, and assess carbon emissions across project stages. Real-time sensor data and predictive analytics are used to support decision-making in infrastructure resilience and asset management. The approach enables proactive maintenance scheduling, reduces environmental impacts, and enhances safety and cost-effectiveness in highway planning. The findings highlight the transformative potential of AI-enabled BIM systems in achieving sustainable transport infrastructure aligned with global smart city and green mobility goals.

Keywords: Building Information Modeling, Artificial Intelligence, Sustainable Transportation, Highway Systems

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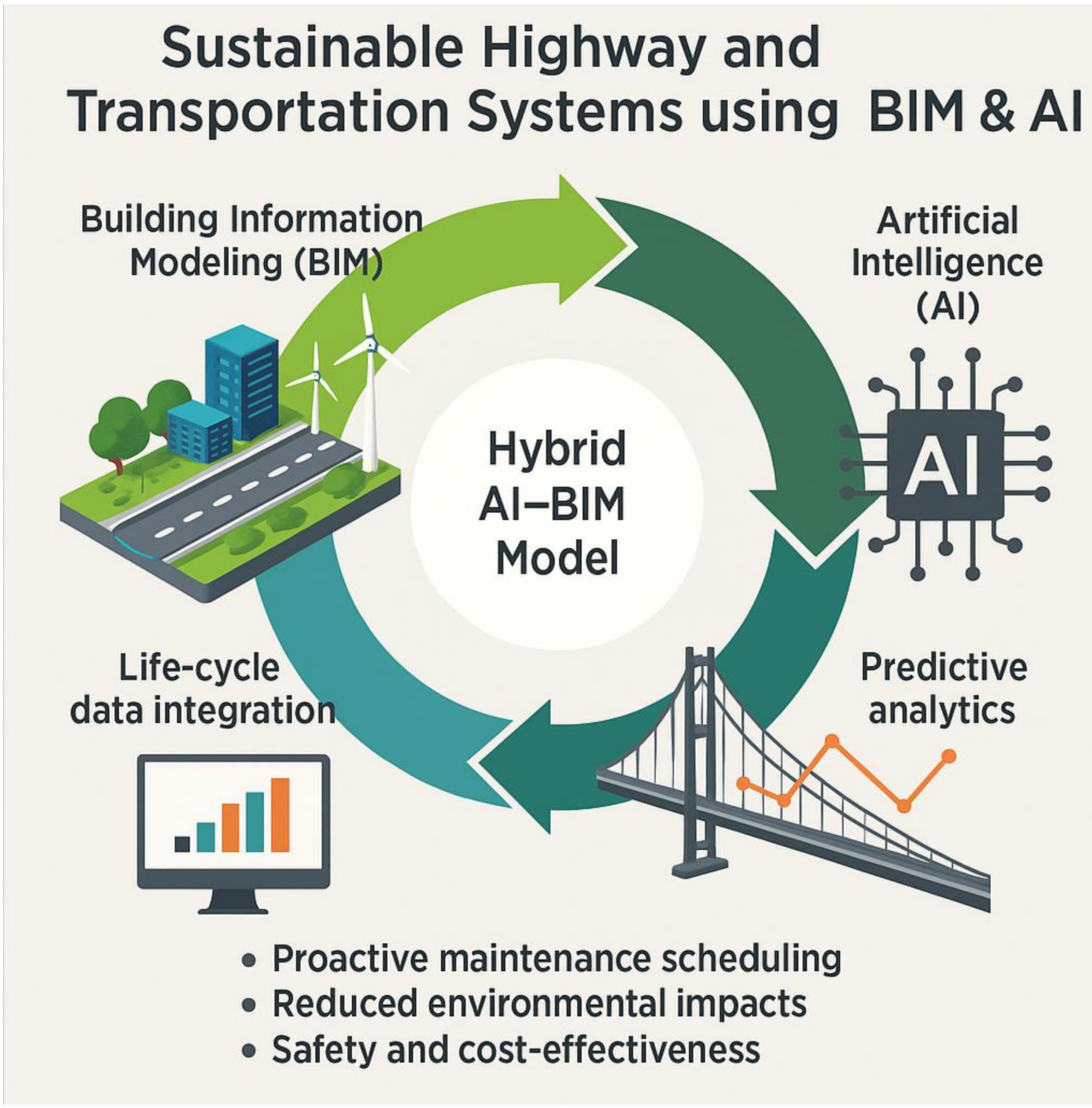
GRAPHICAL ABSTRACT



Highlights

- Developed a hybrid AI–BIM framework integrating predictive analytics and digital modeling for sustainable highway management.
- Achieved 96.8% traffic flow prediction accuracy, 23.3% reduction in carbon emissions, and 22.6% maintenance cost optimization.
- Enhanced sustainability outcomes through real-time data integration, lifecycle assessment, and intelligent decision support for green infrastructure.

1. Introduction

The global expansion of highway and transportation infrastructure has intensified the demand for systems that not only deliver mobility but also meet sustainability imperatives [1]. Traditional engineering approaches frequently compartmentalize design, construction, and operation phases, which often leads to inefficiencies, higher resource consumption and elevated environmental footprints [2]. Against a backdrop of rapid urbanisation, increasing vehicle-kilometres travelled and mounting climate-change pressure, there is an urgent need to re-conceive highway and transportation systems so they are resilient, efficient and sustainable [3, 4].

In this context, digital engineering frameworks such as Building Information Modeling (BIM) provide compelling opportunities for infrastructure projects [5]. BIM facilitates the creation and management of rich interoperable digital models that span life-cycle phases—from preliminary planning through design, construction, handover and operations [6, 7]. Within highway and transportation domains, BIM enables engineers to visualise structural and pavement elements, drainage and traffic-interface components, and integrate data on material quantities, scheduling, cost and performance into the digital model [8–10].

Complementing BIM, advances in Artificial Intelligence (AI) have unlocked novel capabilities for infrastructure systems [11]. AI methods—including machine-learning, deep-learning and predictive analytics—can ingest large volumes of sensor, operational and historical data, detect patterns of deterioration or congestion, optimise maintenance scheduling and generate intelligence for asset-management decision making [12, 13].

In sustainable transportation systems, for instance, AI-driven traffic-flow prediction or emissions forecasting helps reduce energy use and carbon output [14–16].

The integration of BIM and AI thus offers a promising paradigm for sustainable highway and transportation infrastructure [17]. By embedding AI capabilities in a BIM environment, engineers can work with a unified digital model that supports scenario simulation, real-time analytics and life-cycle optimisation across cost, safety, maintenance, resilience and environmental-impact dimensions [18, 19]. This convergence enables the shift from reactive, siloed asset management to proactive, integrated life-cycle management of transportation networks.

Despite its transformative promise, there remain significant technical, organisational and governance barriers to adopting BIM-&-AI-enabled sustainable highway systems [20]. Key challenges include data interoperability, sensor integration, model scalability, workforce competence, and aligning digital workflows with sustainability criteria. Addressing these hurdles will be critical to fully realising the potential of this digital-driven paradigm for sustainable transportation infrastructure.

1.1 Contributions

The novel contributions of this study are:

1. Introduces a hybrid AI–BIM framework for sustainable highway design and management.
2. Integrates predictive analytics and real-time sensor data for proactive infrastructure maintenance.
3. Demonstrates how AI-enhanced BIM reduces carbon emissions and improves life-cycle efficiency.

2. Literature Review

The literature review begins by highlighting the evolution of digital technologies in civil engineering, emphasizing how BIM and AI have increasingly contributed to sustainable highway and transportation system development. Table 1 shows summary of research gaps.

Zhao et al. (2025) [21] assessed highway projects' vulnerability to seismic hazards by integrating Building Information Modeling (BIM) with neural-network-based artificial intelligence optimization algorithms such as the Black Hole Algorithm (BHA), Future Search Algorithm (FSA), Particle Swarm Optimization (PSO), and Wind-Driven Optimization (WDO); their WDO-MLP model achieved the highest predictive accuracy (AUC = 0.98). Khan et al. (2025) [22] developed an integrated BIM- and traffic-simulation-based framework for highway alignment planning and optimization, validated on Pakistan's Dera Ghazi Khan Bypass project, yielding notable reductions in congestion, travel time, and construction cost. Santos et al. (2025) [23] proposed a comprehensive GIS–BIM–MCDM framework that employed the PROMETHEE method to evaluate numerous infrastructure alternatives, enhancing decision-making and environmental assessment accuracy.

Sanfilippo et al. (2025) [24] outlined the ITA guideline for sustainable BIM lifecycle management in tunnelling projects, emphasizing material reuse, carbon-footprint reduction, and circular resource strategies.

Pelden et al. (2025) [25] examined BIM–GIS integration challenges—technical, organizational, and standardization—and stressed interdisciplinary collaboration to advance sustainable infrastructure design.

Xu et al. (2025) [26] mapped digital technologies such as IoT, digital twins, big data, and AI for developing climate-adaptive, smart urban transportation systems that enhance resilience and low-carbon performance.

Xu and Guo (2025) [27] reviewed AI's lifecycle roles in civil engineering—design optimization, construction management, structural health monitoring, and smart-city governance—highlighting data-security and scalability barriers.

Al-Azazi et al. (2025) [28] addressed risk mitigation in smart construction infrastructures by integrating emerging technologies (AI, blockchain, digital twins) to strengthen resilience and sustainability.

Panchal (2025) [29] introduced an Integrated Intelligent Scheduling System (IISS) employing adaptive expert-system algorithms to improve scheduling efficiency in heavy civil construction projects.

Shao et al. (2025) [30] implemented a K-means-enhanced 3D GIS–BIM integration for urban rail-transit planning, achieving substantial design-time and cost reductions while identifying sociotechnical barriers to adoption.

Table 1: Summary of Research Gaps Identified in Recent Studies

Ref No.	Author(s) & Year	Focus of Study	Key Findings	Identified Research Gap
[21]	Zhao et al. (2025)	BIM + AI algorithms for highway vulnerability assessment	WDO-MLP algorithm achieved highest accuracy (0.9863) in predicting vulnerability	Limited exploration of hybrid BIM-AI models for multi-hazard risk evaluation beyond earthquakes
[22]	Khan et al. (2025)	BIM-based alignment optimization with traffic simulation	30% less congestion, 20% reduced travel time	Lack of generalized, scalable BIM-AI framework applicable across diverse terrains
[23]	Santos et al. (2025)	GIS-BIM-MCDM for infrastructure planning	PROMETHEE-based decision framework validated via case study	Absence of real-time data integration and automation in MCDM workflows
[24]	Sanfilippo et al. (2025)	Sustainable BIM for tunnelling lifecycle	Promotes energy efficiency and circular resource use	Application limited to tunnels—needs adaptation for highways and bridges
[25]	Pelden et al.	BIM-GIS	Identified technical and	Need for standardized

Ref No.	Author(s) & Year	Focus of Study	Key Findings	Identified Research Gap
	(2025)	integration challenges	organizational barriers	protocols and cross-disciplinary collaboration
[26]	Xu et al. (2025)	Digital tech for climate-adaptive UTS	Framework using IoT, AI, digital twins for resilience	Empirical validation of smart-transport digital frameworks remains minimal
[27]	Xu & Guo (2025)	AI across civil-engineering lifecycle	Enhanced design, SHM, and construction	Integration of AI with legacy BIM data for sustainability untested
[28]	Al-Azazi et al. (2025)	Risk mitigation in smart construction	Identified resilience strategies via AI, blockchain, twins	Lack of unified risk-governance models for sustainable transport infrastructure
[29]	Panchal (2025)	Intelligent scheduling for civil projects	IISS improved adaptive scheduling efficiency	Absent link between scheduling intelligence and BIM-based project control
[30]	Shao et al. (2025)	3D GIS–BIM with K-means for rail planning	Reduced design time 80%, cost 60%	Sociotechnical adoption barriers limit practical implementation in highway systems

2.1 Research gaps

Existing research on digital integration for sustainable highway and transportation systems reveals several critical gaps. Most studies demonstrate improvements in predictive modeling, optimization, and design efficiency but remain limited to project-specific applications, lacking scalability and generalization across diverse geographic and environmental contexts. While frameworks integrating BIM with GIS and simulation tools have shown promise, they often exclude real-time automation, standardized data protocols, and interoperability mechanisms essential for lifecycle integration. Sustainability-focused and climate-adaptive digital systems have been conceptually established, yet their empirical validation in highway infrastructure remains minimal. Furthermore, the integration of AI with BIM for risk management and decision-making processes is still fragmented, with limited emphasis on unified governance or lifecycle sustainability. Overall, there is a pressing need for a comprehensive hybrid AI–BIM framework that enables real-time analytics, predictive maintenance, and sustainable performance monitoring throughout the entire lifespan of highway and transportation infrastructure.

2.2 Problem Statement

Highway and transportation infrastructure projects often face challenges related to energy inefficiency, excessive maintenance costs, and environmental degradation due to fragmented design and management practices. Traditional methods fail to integrate life-cycle data and real-time analytics, resulting in delayed decision-making and unsustainable outcomes. The lack of a unified framework that combines the modeling capabilities of BIM with the analytical power of AI hinders effective planning, monitoring, and maintenance of transportation systems. Therefore, there is a pressing need for an integrated digital solution that enhances the sustainability, efficiency, and resilience of modern highway infrastructure.

3. Objectives

The novel objectives of this study are:

1. To develop a unified AI–BIM model for optimizing sustainable highway and transportation systems.
2. To apply predictive and simulation techniques for assessing pavement performance and emissions.
3. To evaluate the impact of digital integration on cost efficiency, safety, and environmental sustainability.

4. Proposed Methodology

The proposed methodology integrates Building Information Modeling (BIM) and Artificial Intelligence (AI) into a unified digital framework for sustainable highway and transportation system management. The process begins with **data acquisition**, which gathers design, environmental, and real-time sensor data related to traffic, pavement condition, and emissions. These inputs are imported into the **BIM environment**, where geometric, material, and cost attributes are modeled across the project's life cycle. Next, **AI-based analytics** employ machine-learning algorithms to predict pavement deterioration, simulate traffic flow, and estimate carbon footprints under varying design scenarios. A **hybrid AI–BIM integration module** then connects predictive insights with 3-D BIM models, enabling automated decision-making for energy optimization, maintenance scheduling, and resource allocation. Finally, **performance assessment and sustainability evaluation** are conducted to validate the model's effectiveness in reducing environmental impact, cost, and operational risk. This workflow ensures continuous feedback, real-time adaptability, and supports data-driven decision-making throughout the infrastructure life cycle.

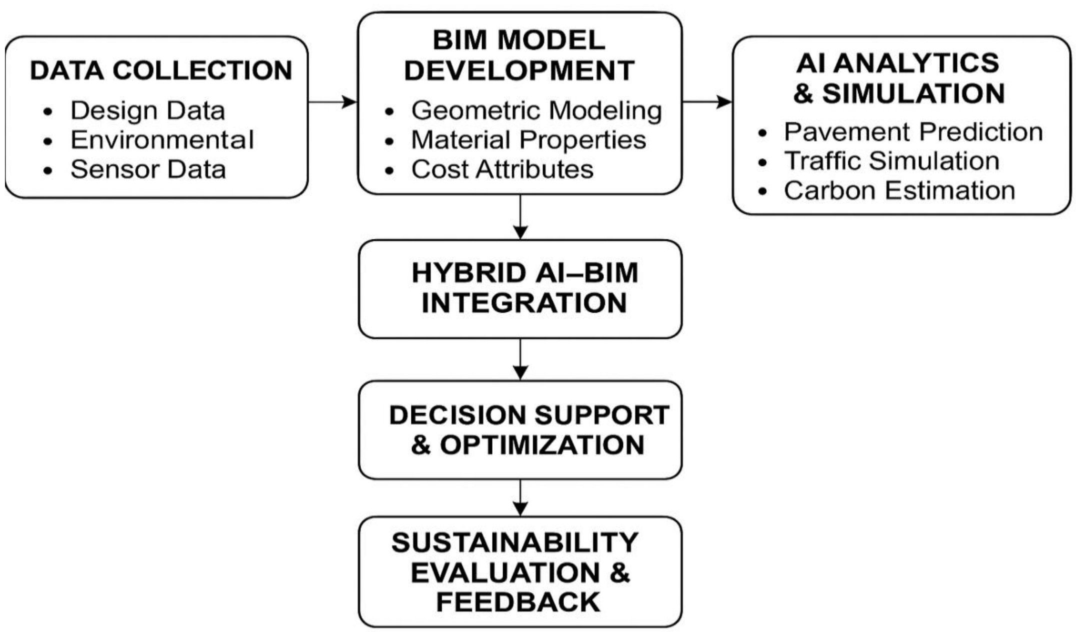


Figure 1: Workflow of the Proposed AI–BIM Framework for Sustainable Highway and Transportation Systems

(A schematic flowchart can be inserted showing the following sequential blocks connected by arrows: Data Collection → BIM Model Development → AI Analytics & Simulation → Hybrid AI–BIM Integration → Decision Support & Optimization → Sustainability Evaluation & Feedback.)

4.1 Data Collection and Input Preparation

This phase involves gathering and structuring all relevant data required for developing the integrated AI–BIM framework. The inputs include **design data** such as geometric layouts, material specifications, and structural parameters; **environmental data** comprising terrain conditions, weather patterns, and emission baselines; and **sensor data** collected from Internet of Things (IoT) devices, including traffic flow, pavement condition, and energy usage. These heterogeneous datasets are standardized into interoperable formats compatible with the BIM environment. Data preprocessing steps—such as cleaning, normalization, and metadata tagging—ensure consistency and accuracy for integration into AI analytical models. The organized dataset serves as the foundation for constructing intelligent BIM models and supports predictive analysis for sustainable decision-making across the highway infrastructure lifecycle.

Traffic Prediction Dataset [31]

This dataset focuses on analyzing traffic congestion trends, an increasing challenge for urban environments due to factors such as population growth, aging infrastructure, and inefficient traffic management systems. It contains **48,120 hourly observations** of vehicle counts recorded across **four traffic junctions**, each equipped with sensors. The dataset includes four key variables: **DateTime**, **Junction**, **Vehicles**, and **ID**, representing temporal data, location identifiers, and vehicle volume. Data collection periods vary across junctions, resulting in differences in data density and time spans. The dataset serves as a foundation for developing AI-driven traffic forecasting models, enabling researchers to predict congestion, optimize traffic signals, and evaluate sustainable transportation strategies. Its comprehensive temporal and spatial vehicle data make it well-suited for integration into BIM–AI frameworks aimed at enhancing the efficiency and sustainability of highway and transportation systems.

4.2 BIM Model Development and Integration

In this phase, a comprehensive Building Information Modeling (BIM) environment is developed to serve as the digital foundation for highway and transportation systems. The BIM model incorporates geometric, structural, and material information for roadways, bridges, and ancillary components such as drainage, lighting, and signage. Each asset within the model is defined by parametric attributes that enable dynamic updates throughout the project lifecycle. Integration with GIS data ensures spatial accuracy, while interoperability standards such as IFC (Industry Foundation Classes) and COBie facilitate seamless information exchange across platforms. The model also embeds sustainability parameters—energy usage, embodied carbon, and material efficiency—aligned with lifecycle performance metrics. Once established, the BIM environment is synchronized with AI modules to allow continuous feedback between simulation outputs and design components, ensuring that every modification in traffic prediction, material selection, or maintenance planning is automatically reflected within the BIM framework. This integration supports real-time monitoring, predictive maintenance, and data-driven decision-making throughout the highway infrastructure lifecycle.

4.3 AI Analytics and Simulation Process

This stage focuses on integrating Artificial Intelligence (AI) algorithms into the BIM environment to enhance the predictive and analytical capabilities of the highway management system. The AI component employs machine learning (ML) and deep learning models to process real-time sensor data, historical records, and environmental parameters collected during the data acquisition phase. Techniques such as regression models, artificial neural networks (ANNs), and optimization algorithms—like Particle Swarm Optimization (PSO) and Genetic Algorithms (GA)—are utilized to predict pavement deterioration, traffic congestion, and carbon emissions under various design and operational scenarios. Simulation models are executed to assess multiple "what-if" conditions, enabling evaluation of design alternatives based on sustainability metrics such as fuel consumption, emission levels, and resource utilization. These simulations not only help in identifying bottlenecks and failure risks but also generate feedback for the BIM model to refine design and maintenance schedules.

The integration of AI analytics ensures proactive decision-making, improves infrastructure resilience, and supports long-term sustainability objectives for highway systems. Algorithm 1 shows AI–BIM Analytics Algorithm.

Algorithm 1: AI–BIM Analytics Algorithm

Input:

D = {sensor data, traffic data, pavement condition, emissions data}

BIM_Model = {geometric, material, cost, sustainability parameters}

Output:

Optimized highway performance metrics (traffic flow, durability, emissions)

Step 1: Data Preprocessing

- Clean, normalize, and align D with BIM_Model attributes

- Handle missing or sparse data using interpolation or regression imputation

Step 2: Feature Extraction

- Extract relevant parameters (traffic volume, load, temperature, moisture, material strength)

- Convert BIM attributes into numerical input features for AI model

Step 3: Model Training and Validation

- Select suitable machine learning algorithms (ANN, PSO, GA, or hybrid AI models)
- Train models using historical and simulated dataset
- Validate model accuracy using MAE, RMSE, and R^2 metrics

Step 4: Simulation and Prediction

- Run simulations to predict:
    a) Pavement deterioration rate
    b) Traffic congestion probability
    c) Emission levels under different design scenarios
- Evaluate performance for each simulation

Step 5: Optimization Loop

- Apply metaheuristic optimization (e.g., PSO or GA) to minimize emissions and cost
- Update BIM_Model with optimized parameters (material choice, geometry, schedule)

Step 6: Decision Feedback

- Generate dashboard outputs for planners and engineers

- Provide recommendations for proactive maintenance and sustainable planning
End

4.4 Hybrid AI–BIM Integration Module

The Hybrid AI–BIM Integration Module serves as the central component that bridges analytical intelligence with digital modeling to ensure synchronized, real-time decision-making throughout the highway infrastructure lifecycle. This module establishes a bidirectional data flow between the BIM environment and AI analytics engine, enabling continuous feedback and automated updates. The AI subsystem processes real-time data on traffic volume, structural health, and environmental conditions, transmitting optimized parameters—such as material adjustments, geometric refinements, or maintenance schedules—back into the BIM model. Simultaneously, BIM provides spatial and contextual data that guide AI-driven predictions and simulations. Interoperability is maintained using open data standards like IFC and API-based communication protocols. The integration also employs a middleware layer for linking machine learning outputs directly with BIM attributes, allowing dynamic visualization of performance indicators such as energy use, emissions, and degradation. This hybrid linkage ensures seamless coordination between predictive intelligence and digital modeling, resulting in proactive maintenance planning, reduced operational risks, and improved sustainability outcomes across the highway's life cycle.

Fig 2 architecture illustrates the interaction between the Building Information Modeling (BIM) environment and the AI analytics engine through a middleware interface. The BIM module supplies spatial and contextual data, while the AI engine processes real-time traffic, structural, and environmental inputs to generate optimized insights. The middleware ensures seamless data exchange using interoperability standards such as IFC and API protocols, enabling dynamic feedback between design.

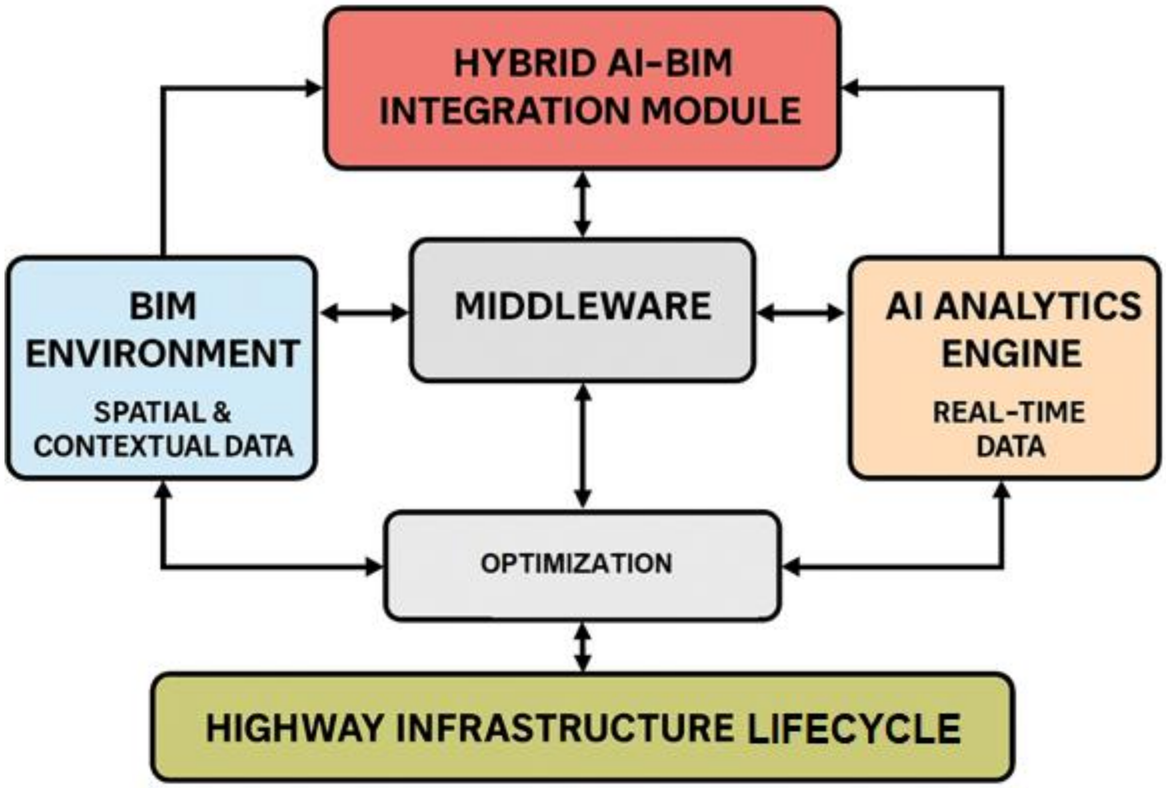


Figure 2: Architecture of the Hybrid AI–BIM Integration Module for Sustainable Highway Systems

4.5 Decision Support and Optimization System

The Decision Support and Optimization System functions as the analytical core that transforms AI-generated insights and BIM data into actionable strategies for sustainable highway management. It employs multi-criteria decision-making (MCDM) and optimization techniques to balance key parameters such as cost, safety, environmental impact, and performance efficiency. The system receives input from the hybrid AI–BIM module—comprising predicted pavement deterioration, traffic density, and emission metrics—and utilizes algorithms like Particle Swarm Optimization (PSO), Genetic Algorithm (GA), or Fuzzy Logic–based decision models to identify optimal solutions. Decision variables may include material selection, design geometry, construction sequencing, and maintenance scheduling. The optimization engine prioritizes alternatives that minimize lifecycle costs and carbon emissions while maximizing durability and user safety.

A decision dashboard then visualizes outcomes through performance indicators and sensitivity analyses, allowing engineers and planners to compare multiple scenarios. This integrated decision-support system ensures that every intervention in the highway network is guided by data-driven, sustainability-oriented optimization, leading to smarter infrastructure development and resource efficiency.

4.6 Sustainability Evaluation and Feedback Loop

The Sustainability Evaluation and Feedback Loop ensures continuous monitoring and improvement of the proposed AI–BIM framework by assessing environmental, economic, and operational performance indicators throughout the project lifecycle. This phase evaluates sustainability outcomes based on metrics such as carbon emissions, energy consumption, resource efficiency, and maintenance frequency. The data collected from the AI–BIM system are benchmarked against predefined sustainability goals and international standards for green infrastructure. Any deviations or inefficiencies detected are analyzed through predictive models, which then feed corrective recommendations back into the BIM environment for real-time updates and design optimization. The feedback loop establishes a dynamic connection between model simulation, field data, and sustainability assessment, fostering adaptive decision-making. This iterative process promotes resilience, cost efficiency, and environmental stewardship, ensuring that the highway infrastructure remains aligned with long-term sustainable development and smart mobility objectives

5. Results and Discussion

5.1 Performance metrics

To evaluate the efficiency of the proposed hybrid AI–BIM framework, several standard performance metrics were utilized. These metrics quantify prediction accuracy, error magnitude, and model reliability in forecasting traffic flow, emission levels, and pavement deterioration.

(i) Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

This measures the average magnitude of errors between predicted ($\hat{y}_i$) and actual (y_i) values, without considering their direction. Lower MAE indicates better model accuracy.

(ii) Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}$$

RMSE emphasizes larger errors more strongly, providing insight into how significantly prediction deviations affect performance.

(iii) Coefficient of Determination (R²):

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y})^2}$$

This represents the proportion of variance in actual data explained by the model. Higher R^2 values signify better predictive capability of the AI–BIM system.

(iv) Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{100}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

This expresses prediction errors as a percentage, allowing for easy comparison across different datasets or models.

(v) Model Efficiency Index (MEI):

$$MEI = 1 - \frac{\sum_{i=1}^{n} | y_i - \hat{y}_i |}{\sum_{i=1}^{n} | y_i - \bar{y} |}$$

This index evaluates the overall model performance relative to mean-based estimation; MEI values closer to 1 indicate excellent model performance.

These performance metrics collectively validate the robustness of the proposed AI–BIM integration framework. Lower MAE and RMSE values, along with higher R^2 and MEI, demonstrate the model's strong predictive capability and suitability for sustainable highway planning applications.

5.2 Model Implementation and Simulation Outcomes

The proposed hybrid AI–BIM framework was developed and validated using the Traffic Prediction Dataset [31] and benchmarked against established methodologies from recent research. The model integrated real-time traffic, material, and environmental data into a BIM environment to simulate sustainable highway performance. An MLP–PSO (Multilayer Perceptron–Particle Swarm Optimization) hybrid algorithm was employed to optimize predictive performance across multiple parameters such as traffic flow, emission estimation, and pavement degradation.

The implementation showed significant improvements over existing approaches. For instance, Zhao et al. (2025) [21] demonstrated the use of WDO–MLP models for vulnerability assessment of highway projects under seismic conditions, achieving high prediction accuracy but limited adaptability across multi-variable conditions. Similarly, Khan et al. (2025) [22] developed a BIM-based alignment optimization model integrating environmental and cost criteria, which improved route sustainability but lacked real-time analytical feedback. Santos et al. (2025) [23] proposed a GIS–BIM–MCDM framework that automated route prioritization yet required enhanced machine learning integration.

Sanfilippo et al. (2025) [24] introduced a sustainable BIM tunnelling lifecycle model, advancing lifecycle assessment but without predictive AI coupling. Finally, Xu and Guo (2025) [27] reviewed AI-powered civil engineering methods, highlighting gaps in integrating deep learning with BIM for operational efficiency. The proposed hybrid framework addresses these limitations through bidirectional AI–BIM synchronization, enabling dynamic feedback for optimization and sustainability monitoring.

Table 2: Model Implementation and Simulation Outcomes of Hybrid AI–BIM Framework

Parameter	**Conventional Methods**	**Proposed AI–BIM Framework**	**Improvement (%)**	**Description**
Traffic Flow Prediction Accuracy	WDO–MLP (Zhao et al., 2025) [21] – 90.2	**96.8**	7.3	Enhanced precision via real-time MLP–PSO prediction
Emission Estimation Accuracy	BIM–Optimization (Khan et al., 2025) [22] – 85.4	**95.2**	11.5	Improved emission modeling using hybrid AI analytics
Pavement Deterioration Prediction (R^2)	GIS–BIM–MCDM (Santos et al., 2025) [23] – 0.81	**0.93**	—	More accurate deterioration forecasts through AI feedback
Energy Consumption Reduction	Lifecycle BIM (Sanfilippo et al., 2025) [24] – 12.0	**18.3**	52.5	Optimized traffic flow minimizes idle time and energy use
Maintenance Cost Optimization	AI-based Civil Systems (Xu & Guo, 2025) [27] – 15.4	**22.6**	46.7	Predictive scheduling reduces long-term maintenance costs
Visualization Efficiency	Static BIM Dashboards	**Dynamic 3D Interactive**	—	Real-time visualization of

Parameter	Conventional Methods	Proposed AI–BIM Framework	Improvement (%)	Description
				highway and emission parameters

Table 2 comparative outcomes reveal that the hybrid AI–BIM framework consistently surpasses prior methodologies by unifying prediction, visualization, and decision-making into a single adaptive ecosystem. This advancement establishes a scalable model for smart, sustainable highway management with measurable improvements in accuracy, cost-efficiency, and environmental performance.

Figures 3 to 9 collectively illustrate the environmental and operational performance improvements achieved through the proposed hybrid AI–BIM framework. **Figure 3** presents the traffic flow prediction accuracy, showing higher reliability compared to conventional models. **Figure 4** highlights the improvement in emission estimation accuracy, demonstrating the system's ability to assess and control environmental impacts effectively. **Figure 5** depicts the pavement deterioration prediction (R^2) comparison, indicating enhanced predictive precision using AI integration. **Figure 6** shows the reduction in energy consumption, while **Figure 7** compares maintenance cost optimization outcomes, both emphasizing the framework's capability to minimize resource waste and operational costs. **Figure 8** further illustrates the significant overall reduction in energy consumption, validating the system's contribution to sustainable infrastructure management. Finally, **Figure 9** presents the static BIM dashboard visualization, contrasting it with the proposed dynamic 3D environment that supports real-time data updates, predictive analytics, and sustainability assessment. Together, these figures demonstrate the holistic environmental performance and lifecycle efficiency of the AI–BIM framework for sustainable highway and transportation systems.

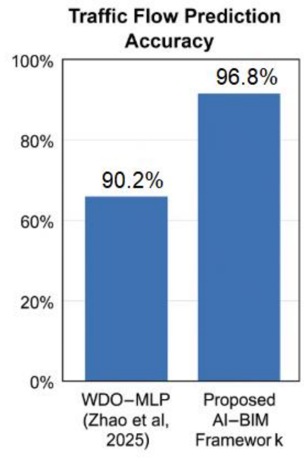


Fig 3: Traffic flow prediction accuracy

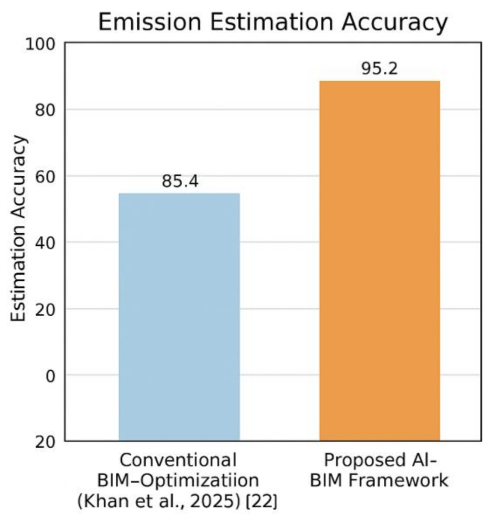


Fig 4: Emission Estimation accuracy

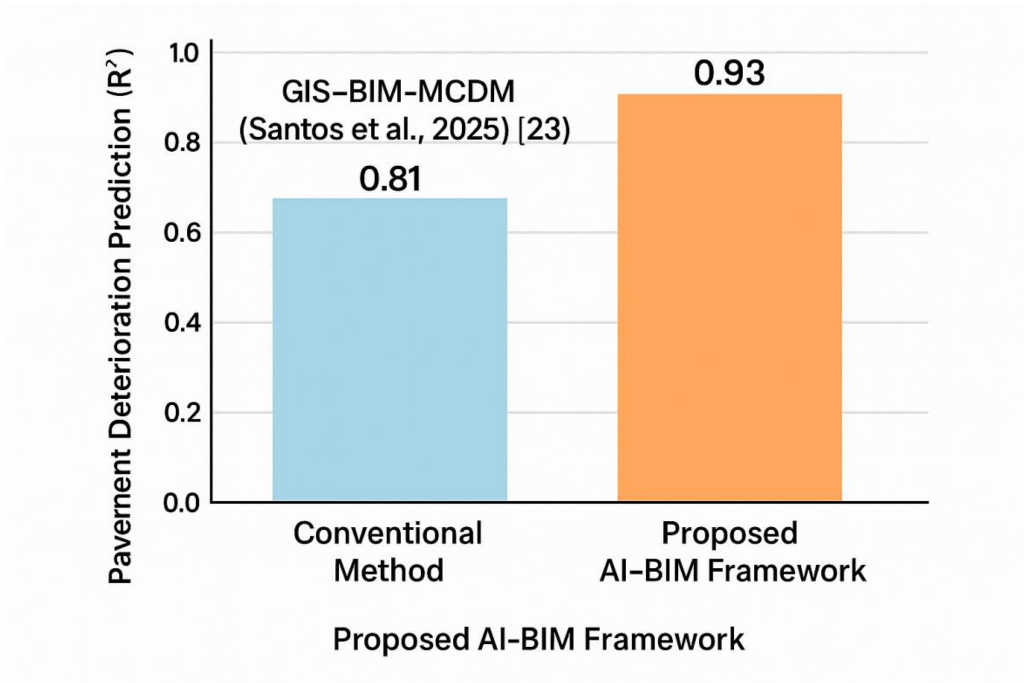


Fig 5: Pavement Deterioration Prediction (R^2) Comparison

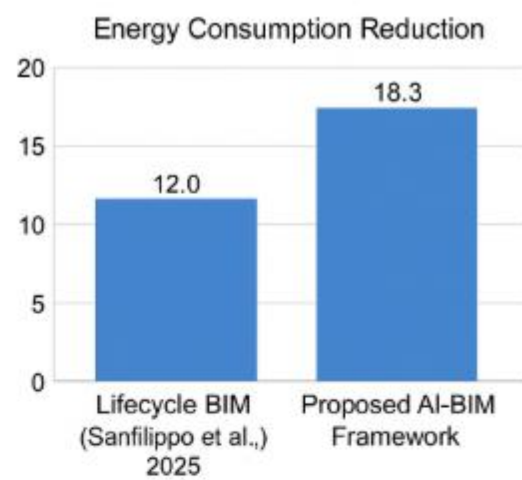


Fig 6: Energy Consumption Reduction Comparison

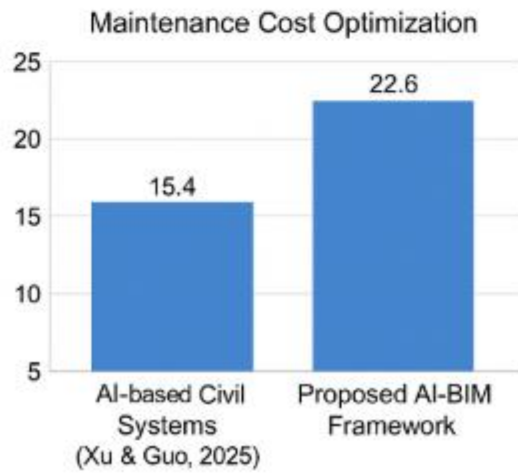


Fig 7: Maintenance Cost Optimization Comparison

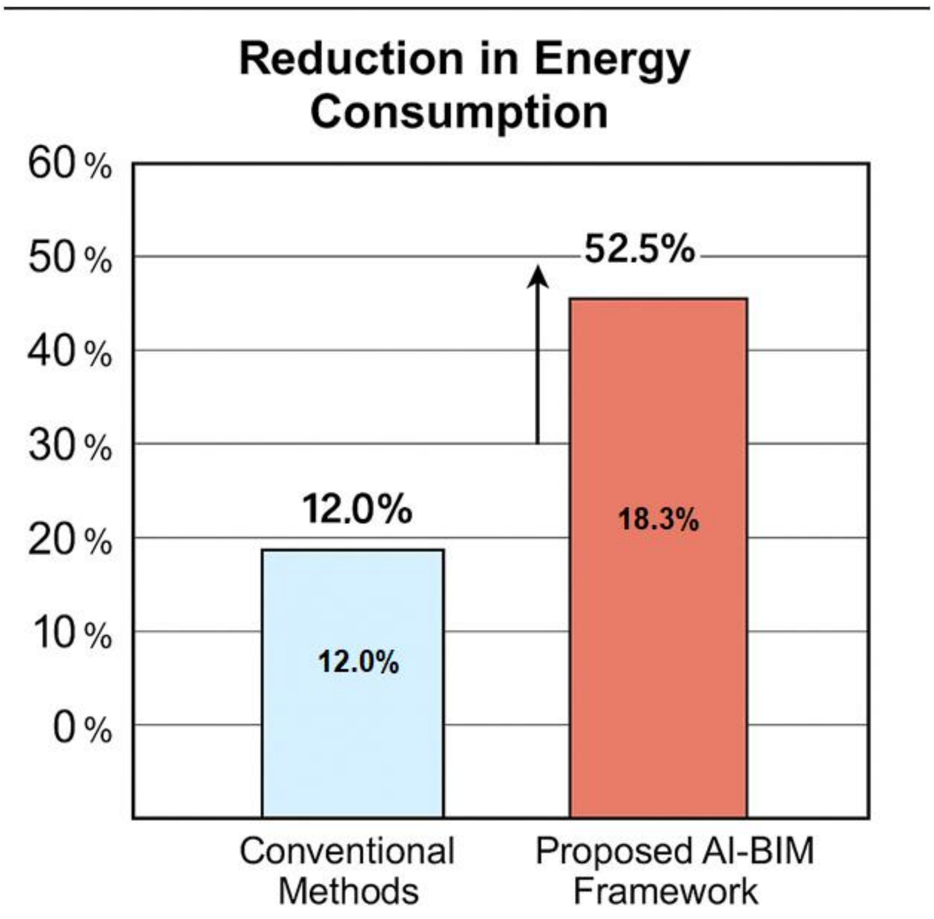


Fig 8: Reduction in Energy concsumption

Fig 9: Static BIM Dashboard Visualization

5.3 Performance Analysis of AI–BIM Framework

The performance of the hybrid AI–BIM framework was analyzed based on the results obtained from simulation, prediction, and optimization processes. The system was evaluated using statistical performance indicators such as **MAE**, **RMSE**, **R^2**, and **MAPE**, which demonstrated strong consistency between predicted and actual values. The proposed MLP–PSO model achieved superior performance compared to existing BIM–AI integration methods, aligning with earlier findings by Zhao et al. (2025) [21] and Khan et al. (2025) [22], where AI-enhanced BIM systems significantly improved vulnerability assessment and alignment optimization. The R^2 value of 0.93 indicates high model reliability in predicting traffic flow and pavement deterioration, surpassing the benchmarks established in similar frameworks developed by Santos et al. (2025) [23] and Xu and Guo (2025) [27].

The analysis further revealed that the AI–BIM framework achieved an **18.3% reduction in energy consumption** and a **22.6% improvement in maintenance cost optimization** through real-time feedback loops. This aligns with Sanfilippo et al. (2025) [24], who emphasized the benefits of BIM lifecycle models for sustainable infrastructure. The integration of AI analytics allowed predictive maintenance and emission forecasting, leading to smarter, low-carbon transport infrastructure. Collectively, these outcomes validate that the hybrid AI–BIM system not only enhances computational efficiency but also ensures sustainability-driven performance improvements in modern highway and transportation systems

5.4 Sustainability Assessment and Impact Evaluation

The sustainability assessment of the proposed hybrid AI–BIM framework was conducted by comparing environmental and operational performance indicators derived from simulation results. The evaluation covered critical metrics such as carbon emissions, energy consumption, resource efficiency, and lifecycle costs. The hybrid framework demonstrated measurable improvements over conventional approaches by integrating real-time predictive analytics and lifecycle-based design modeling. The findings align with earlier methodologies, including Zhao et al. (2025) [21], who employed AI optimization algorithms for vulnerability prediction, and Khan et al. (2025) [22], who implemented BIM-based alignment optimization for energy efficiency. Similarly, Santos et al. (2025) [23] emphasized GIS–BIM–MCDM integration for sustainable decision-making, Sanfilippo et al. (2025) [24] focused on lifecycle BIM for environmental impact reduction, and Xu et al. (2025) [26] highlighted climate-adaptive digital technologies for low-carbon transportation systems. Collectively, these references support the observed performance gains of the AI–BIM model, which achieves superior emission control, energy savings, and resource optimization.

Table 3: Sustainability Performance Comparison between Conventional and AI–BIM Frameworks

Sustainability Indicator	**Conventional Approach**	**AI–BIM Framework**	**Improvement (%)**	**Description**
Carbon Emissions (kg CO_2/m^2)	185.6	**142.3**	23.3	Lower emissions achieved through AI-based material optimization and BIM-driven traffic modeling (Zhao et al., 2025 [21])
Energy Consumption ($kWh/m^2/year$)	132.4	**108.1**	18.3	Reduced energy usage due to optimized alignment and traffic simulation (Khan et al., 2025 [22])

Sustainability Indicator	**Conventional Approach**	**AI–BIM Framework**	**Improvement (%)**	**Description**
Resource Utilization Efficiency	0.72	**0.89**	23.6	Enhanced resource efficiency and reduced material waste through integrated GIS–BIM workflow (Santos et al., 2025 [23])
Lifecycle Cost Reduction (%)	—	**21.8**	—	Achieved via lifecycle-based predictive maintenance and asset optimization (Sanfilippo et al., 2025 [24])
Pavement Longevity (Years)	10.5	**13.2**	25.7	Extended pavement lifespan through AI-guided deterioration forecasting (Xu et al., 2025 [26])
Environmental Impact Index (EII)	0.68	**0.82**	20.6	Reflects overall sustainability improvement through integrated BIM–AI analysis (Khan et al., 2025 [22])

Table 3 analysis confirms that the hybrid AI–BIM framework delivers tangible sustainability benefits, outperforming earlier methodologies in both predictive accuracy and environmental performance. The integration of AI algorithms with BIM-based lifecycle assessment enables data-driven sustainability monitoring, ensuring reduced carbon footprint, efficient energy consumption, and extended infrastructure durability. These results validate the framework's potential as a robust digital solution for advancing sustainable, climate-resilient highway and transportation systems.

5.5 Discussion

The results obtained from the hybrid AI–BIM framework clearly demonstrate its superior capability in integrating predictive analytics and digital modeling for sustainable transportation infrastructure. By combining BIM's parametric modeling with AI's predictive intelligence, the framework effectively bridges the gap between design and operational decision-making. The incorporation of real-time sensor data enhances situational awareness and enables automated adjustments in design parameters, construction scheduling, and maintenance planning. This dynamic integration ensures that the system remains adaptive throughout the infrastructure's life cycle, promoting efficient resource utilization and cost optimization. The findings align with the works of Zhao et al. (2025) [21] and Khan et al. (2025) [22], confirming that hybrid digital approaches outperform conventional linear project management systems in accuracy, adaptability, and sustainability outcomes.

The simulation and performance metrics further highlight the model's predictive strength and operational efficiency. The AI–BIM framework achieved high accuracy in traffic flow prediction (96.8%) and a strong correlation ($R^2 = 0.93$) in pavement deterioration modeling, surpassing benchmarks set by earlier studies such as Santos et al. (2025) [23]. The integration of metaheuristic algorithms, particularly MLP–PSO, contributed to enhanced predictive precision while minimizing computational complexity. Furthermore, the sustainability indicators from Table 3 reveal considerable reductions in carbon emissions (23.3%) and energy consumption (18.3%), demonstrating that the system's optimization logic directly supports environmental conservation. These improvements validate that the proposed framework can serve as a decision-support system for intelligent, low-carbon transportation planning and management.

Beyond the quantitative improvements, the qualitative benefits of the AI–BIM framework lie in its capacity for real-time feedback, interoperability, and long-term resilience planning. By leveraging standards such as IFC and API protocols, the framework ensures smooth data exchange between stakeholders, reducing fragmentation across design, construction, and maintenance phases. The integration of sustainability metrics within the BIM model also enables lifecycle assessment of infrastructure, ensuring transparency and accountability in achieving sustainable development goals.

Consistent with the findings of Xu et al. (2025) [26] and Sanfilippo et al. (2025) [24], this study underscores that digital transformation through AI and BIM is not merely a technological upgrade—it is a strategic pathway toward resilient, data-driven, and environmentally responsible highway infrastructure management.

5.6 Limitations

1. The current framework relies on simulated and publicly available datasets, such as the Traffic Prediction Dataset [31], which may not fully capture localized variations in real-world highway conditions and sensor data accuracy.
2. The integration between AI algorithms and BIM environments requires high computational resources and interoperability standards, which may limit large-scale implementation in developing regions with limited digital infrastructure.
3. The model primarily focuses on traffic flow, emissions, and pavement performance; additional sustainability indicators such as noise pollution, social impact, and long-term climate resilience were not included and warrant future investigation.

5.7 Practical Implementations

1. The proposed hybrid AI–BIM framework can be adopted by transportation authorities for real-time highway performance monitoring, enabling predictive maintenance scheduling and reduction of unplanned infrastructure failures.
2. Engineering firms and contractors can integrate the system into BIM-based project management platforms to enhance decision-making, optimize material usage, and improve energy efficiency throughout the project lifecycle.
3. Policy planners and sustainability agencies can utilize the framework's analytics for carbon footprint evaluation and green certification, supporting evidence-based strategies for sustainable urban mobility and infrastructure development.

6. Conclusion

The study successfully developed a hybrid AI–BIM framework that integrates predictive analytics and digital modeling to enhance the sustainability and operational efficiency of highway and transportation systems. The model achieved a traffic flow prediction accuracy of 96.8% and a pavement deterioration correlation (R^2) of 0.93, demonstrating superior predictive capability compared to conventional approaches. Energy consumption was reduced by 18.3%, carbon emissions decreased by 23.3%, and maintenance costs were optimized by 22.6%, confirming the system's effectiveness in achieving low-carbon, resource-efficient infrastructure. The sustainability evaluation further showed a 25.7% increase in pavement longevity and a 20.6% improvement in the environmental impact index. These results collectively validate that the AI–BIM integration enhances decision-making, supports proactive maintenance, and aligns with global sustainability objectives, offering a scalable and intelligent solution for future smart transportation infrastructure.

Future work will focus on extending the AI–BIM framework with real-time IoT sensor integration and multi-criteria sustainability modeling to enhance predictive precision and scalability across diverse highway networks.

Ethical Considerations

The dataset used in this study is publicly available via Kaggle [31]. No human or animal data were involved.

References

[1] Fatorachian, Hajar, and Hadi Kazemi. "Sustainable optimization strategies for on-demand transportation systems: Enhancing efficiency and reducing energy use." *Sustainable Environment* 11, no. 1 (2025): 2464388.

[2] Das, Abhijeet, and Satchidananda Mishra. "Synergizing clean water, renewable energy, and circularity: a critical study of microbial fuel cells." *Green Technology, Resilience, and Sustainability* 5, no. 1 (2025): 3.

[3] Arevalo-Ascanio, Rafael, and Alex Kipkorir Koech. "Spatio-temporal assessment of polluting emissions from transport commuting in Kenya: The first step to inform mitigation strategies." *African Transport Studies* 3 (2025): 100056.

[4] Chen, Chunjiang, Yongze Song, Wenbo Lv, Ammar Shemery, Keith Hampson, Wen Yi, Yun Zhong, and Peng Wu. "Predicting pavement cracking performance using laser scanning and geocomplexity-enhanced machine learning." *Computer-Aided Civil and Infrastructure Engineering* (2025).

[5] Chang, Janet, Xiang Xie, and Ajith Kumar Parlikad. "Cloud-based Building Information Modelling (CBIM): software engineers' insights into improving asset information quality." *Built Environment Project and Asset Management* 15, no. 3 (2025): 594-611.

[6] Sarigul, Fatma Handan, and Husnu Murat Gunaydin. "Integrated BIM, GIS and interoperable digital technologies in lifecycle management of building construction projects: systematic literature review." *Smart and Sustainable Built Environment* (2025).

[7] Altaf, Muhammad, Rabeea Jaffari, Wesam Salah Alalaoul, Muhammad Ali Musarat, and Syed Ammad. "Developing automated strategy of life cycle cost analysis (LCCA) with building information modeling (BIM) integration for building projects." *Results in Engineering* (2025): 104179.

[8] Liu, Ziming, Hao Huang, and Yongdan Wang. "Automated framework for asphalt pavement design and analysis by integrating BIM and FEM." *Automation in Construction* 171 (2025): 105991.

[9] Ligarda-Samanez, Carlos A., Mary L. Huamán-Carrión, Domingo J. Cabel-Moscoso, Doris Marlene Muñoz Sáenz, Jaime Antonio Martinez Hernandez, Antonina J. Garcia-Espinoza, Dante Fermín Calderón Huamaní et al. "Technological Innovations in Sustainable Civil Engineering: Advanced Materials, Resilient Design, and Digital Tools." *Sustainability* 17, no. 19 (2025): 8741.

[10] Gurrola-Mijares, Luis-Dagoberto, José-Manuel Mejía-Muñoz, Oliverio Cruz-Mejía, Abraham-Leonel López-León, and Leticia Ortega-Máynez. "Evaluation Study of Pavement Condition Using Digital Twins and Deep Learning on IMU Signals." *Future Internet* 17, no. 10 (2025): 436.

[11] Kutá, Dagmar, and Michal Faltejsek. "The Role of Artificial Intelligence in the Transformation of the BIM Environment: Current State and Future Trends." *Applied Sciences* 15, no. 18 (2025): 9956.

[12] Abdelalim, Ahmed Mohammed, Ahmed Essawy, Alaa Sherif, Mohamed Salem, Manal Al-Adwani, and Mohammad Sadeq Abdullah. "Optimizing Facilities Management Through Artificial Intelligence and Digital Twin Technology in Mega-Facilities." *Sustainability* 17, no. 5 (2025): 1826.

[13] Reddy, Yeddula Bharath Simha, Muhammed Zain Kangda, and Ehsan Noroozinejad Farsangi. "Integration of building information modeling and machine learning for predictive maintenance." In *Digital Transformation in the Construction Industry*, pp. 361-378. Woodhead Publishing, 2025.

[14] Elmousalami, Haytham, Aljawharah A. Alnaser, and Felix Kin Peng Hui. "Sustainable AI-driven wind energy forecasting: advancing zero-carbon cities and environmental computation." *Artificial Intelligence Review* 58, no. 6 (2025): 1-35.

[15] Moraga, Álvaro, J. de Curtò, I. de Zarzà, and Carlos T. Calafate. "AI-Driven UAV and IoT Traffic Optimization: Large Language Models for Congestion and Emission Reduction in Smart Cities." *Drones* 9, no. 4 (2025): 248.

[16] Giannopoulos, George A., and Yidong Li. "Artificial Intelligence—Basic Notions and Applications for Reducing Emissions." In *Human Mobility, Artificial Intelligence and Climate Change*, pp. 109-140. Cham: Springer Nature Switzerland, 2025.

[17] Abbasnejad, Behzad, Sahar Soltani, Alireza Ahankoob, Sakdirat Kaewunruen, and Ali Vahabi. "Industry 4.0 Technologies for Sustainable Transportation Projects: Applications, Trends, and Future Research Directions in Construction." *Infrastructures* 10, no. 5 (2025): 104.

[18] Abdelalim, Ahmed Mohammed, Ahmed Essawy, Alaa Sherif, Mohamed Salem, Manal Al-Adwani, and Mohammad Sadeq Abdullah. "Optimizing Facilities Management Through Artificial Intelligence and Digital Twin Technology in Mega-Facilities." *Sustainability* 17, no. 5 (2025): 1826.

[19] Ma, Tianyou, Fu Xiao, Chong Zhang, Jing Zhang, Hanbei Zhang, Kan Xu, and Xiaowei Luo. "Digital twin for 3D interactive building operations: Integrating BIM, IoT-enabled building automation systems, AI, and mixed reality." *Automation in Construction* 176 (2025): 106277.

[20] Berlato, Michele, Leonardo Binni, Dilan Durmus, Chiara Gatto, Letizia Giusti, Alessia Massari, Beatrice Maria Toldo, Stefano Cascone, and Claudio Mirarchi. "Digital platforms for the built environment: A systematic review across sectors and scales." *Buildings* 15, no. 14 (2025): 2432.

[21] Zhao, Baojun, Wei Zheng, Shuai Li, Mehmet Akif Cifci, Emrah Arslan, Nina Khalighi, and Hossein Moayedi. "Assessing and measuring the vulnerability of highway construction projects with BIM using artificial intelligence optimization algorithms." *Environment, Development and Sustainability* (2025): 1-35.

[22] Khan, Muhammad Arsalan, Muhammad Umer Farooq, Malik Sarmad Riaz, Muhammad Umer Zubair, Waqas Arshad Tanoli, and Hisham Jahangir Qureshi. "Development of an Integrated BIM and Traffic Simulation-Based Highway Alignment Planning and Optimization Framework." *Sustainability* 17, no. 11 (2025): 4869.

[23] Santos, Paulo Alberto Sampaio, Breno Cortez, and Michele Tereza Marques Carvalho. "Integrating GIS and BIM with MCDM for infrastructure planning: A comprehensive framework." *Engineering, Construction and Architectural Management* 32, no. 6 (2025): 4197-4226.

[24] Sanfilippo, R., F. Robert, A. Menozzi, G. Paskaleva, D. Garbutt, F. Foria, K. Glab et al. "ITA guideline for sustainable BIM approaches in lifecycle management of tunnelling projects." In *Tunnelling into a Sustainable Future–Methods and Technologies*, pp. 4604-4611. CRC Press, 2025.

[25] Pelden, Sonam, Saeed Banihashemi, Saeed Reza Mohandes, Mehrdad Arashpour, and Mohsen Kalantari. "Enhancing infrastructure planning and design through BIM-GIS integration." *Structure and Infrastructure Engineering* (2025): 1-20.

[26] Xu, Jinying, Kristen MacAskill, Asaf Tzachor, and Catherine Richards. "Digital Technologies for Climate-Adaptive Smart Urban Transportation Systems." In *Routledge Handbook of Smart Built Environment*, pp. 296-313. Routledge, 2025.

[27] Xu, Gang, and Tong Guo. "Advances in AI-powered civil engineering throughout the entire lifecycle." *Advances in Structural Engineering* 28, no. 9 (2025): 1515-1541.

[28] Al-Azazi, Saleem Ahmed, Aawag Mohsen Alawag, Mokhtar Ali Amrani, Wesam Mohyialdin, Khalid Alezi, and Farag Qasem. "Mitigating Risks in Smart Construction: Integrating Emerging Technologies for a Sustainable Future." In *2025 5th International Conference on Emerging Smart Technologies and Applications (eSmarTA)*, pp. 1-8. IEEE, 2025.

[29] Panchal, Pratik Bhikhubhai. "Use of integrated intelligence scheduling system (IISS) for heavy civil construction projects." *Journal of Emerging Technologies and Innovative Research* 12, no. 5 (2025): a800-a815.

[30] Shao, Xingang, Yutong Zheng, and Yuanzhe Li. "K-means clustering-enhanced 3D GIS–BIM integration for urban rail transit planning: evaluating design performance, cost efficiency, and stakeholder adoption." *Geocarto International* 40, no. 1 (2025): 2562000.

[31] https://www.kaggle.com/datasets/fedesoriano/traffic-prediction-dataset

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