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AI-Driven Digital Twin Framework for Intelligent Transportation Management and Infrastructure Planning in Smart Cities

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ABSTRACT—

Rapid urbanization and the growing number of vehicles have created significant challenges for transportation systems in smart cities, including traffic congestion, road accidents, fuel wastage, and environmental pollution. Existing navigation systems such as Google Maps provide real-time traffic updates and route guidance, but they do not support future infrastructure planning and cannot predict accidents before they occur. To address this gap, this paper proposes an AI-Driven Digital Twin framework for predictive transportation management and infrastructure planning in smart cities. The framework builds a real-time virtual model of the transportation network from data collected through IoT sensors, GPS-enabled vehicles, traffic cameras, and smart traffic signals, and combines Artificial Intelligence (AI), Machine Learning (ML), cloud computing, and Geographic Information Systems (GIS) to monitor and analyze traffic conditions continuously. Two key innovations are introduced: AI-based Future Infrastructure Planning, which recommends road widening, flyovers, underpasses, and traffic-signal improvements from long-term traffic patterns, and AI-based Accident Risk Prediction, which forecasts potential accidents from weather conditions, road status, vehicle speed, visibility, and historical accident data. LSTM and Transformer models forecast traffic conditions, Particle Swarm Optimization (PSO) performs multi-objective optimization of travel time, energy consumption, and operational cost, and a continuous feedback loop (Collect → Integrate → Predict → Simulate → Optimize → Decide → Update) keeps the twin synchronized with the physical network. The design is grounded in a systematic review of 30 research papers published between 2017 and 2026 and a comparative analysis of two case-study approaches. The framework enables proactive decision-making, improves road safety, supports sustainable urban planning, reduces congestion, and helps governments develop smarter and more efficient transportation systems.

Keywords—*Digital Twin, Smart Cities, Artificial Intelligence, Machine Learning, Intelligent Transportation Systems, Infrastructure Planning, Accident Risk Prediction, IoT, LSTM, Particle Swarm Optimization, GIS.*

1. Introduction

1.1 Background and Context

Urban populations and vehicle ownership are growing faster than the road networks that serve them. The result is a familiar set of problems for smart cities: recurring traffic congestion, road accidents, wasted fuel, and rising emissions. At the same time, cities are instrumenting their roads with IoT traffic sensors, GPS-enabled vehicles, traffic cameras, and smart traffic signals, which produce a continuous stream of data about how the network behaves.

Digital Twin (DT) technology turns this data into a decision tool. A Digital Twin is a real-time virtual representation of a physical system that is kept synchronized with it, so that the system can be monitored, simulated, predicted, and optimized without disturbing the real thing [1], [18], [22]. The idea matured in smart manufacturing, where a Digital Twin Shop-Floor was proposed to converge physical and virtual spaces [2], and it has since spread to industry [5], infrastructure [8], and intelligent vehicles and transportation systems [6], [12].

1.2 Limitations of Existing Traffic Systems

Widely used navigation systems such as Google Maps provide real-time traffic updates and route guidance. They describe the present state of the road, but they do not support long-term infrastructure planning and they do not warn of an accident before it occurs. Research on transportation Digital Twins has moved beyond this, yet individual studies tend to address one function at a time: adaptive signal control [3], [4], traffic-flow monitoring [7], emission management [15], or data processing and scheduling [26]. A planner who needs prediction, safety analysis, simulation, and infrastructure decisions together has to stitch several systems together.

1.3 Problem Statement

Transportation management in smart cities needs a single, continuously updated framework that is proactive rather than reactive. Five problems motivate this work. **(P1)** It is difficult to integrate and monitor real-time traffic data arriving from vehicles, sensors, cameras, GPS, and signals. **(P2)** Traffic changes with demand, peak hours, incidents, and road conditions, which makes future congestion hard to predict. **(P3)** Current management responds to conditions as they are, while accident risk needs to be predicted before incidents happen. **(P4)** Rapid growth in demand makes it hard to decide where road widening, flyovers, underpasses, or better signal infrastructure will be needed. **(P5)** Congestion and inefficient management consume large amounts of energy and produce avoidable carbon emissions.

1.4 Objectives & Research Contributions

This study reviews relevant transportation approaches, compares their strengths and limitations, and proposes an AI-Driven Digital Twin framework. The primary contributions are:

- **Integrated Digital Twin Framework:** A single framework that combines IoT, GIS, AI/ML, cloud computing, and traffic simulation instead of treating congestion, safety, and planning as separate problems.
- **Predictive Traffic Management:** LSTM and Transformer models that forecast future traffic conditions from historical and real-time data, supporting proactive congestion management.
- **AI-based Accident Risk Prediction:** An ML module that uses weather, road status, vehicle speed, visibility, and historical accident data to identify high-risk conditions and road segments before accidents occur.
- **AI-based Future Infrastructure Planning:** A module that applies GIS, long-term traffic patterns, and scenario simulation to recommend road widening, flyovers, underpasses, and signal improvements.
- **Multi-Objective Optimization:** PSO-based evaluation of transportation options against travel time, energy consumption, and operational cost.
- **Closed-Loop Feedback:** A continuous Collect → Integrate → Predict → Simulate → Optimize → Decide → Update cycle that keeps the Digital Twin synchronized with the physical network.
- **Comparative Literature Analysis:** A structured review of 30 papers, with limitations, advantages, performance metrics, and research gaps recorded for each.

1.5 Organization of the Paper

Section 2 reviews the related work and the research gaps. Section 3 presents the architecture of the proposed framework and its prediction, safety, planning, and optimization modules. Section 4 describes the implementation workflow, the two case studies, and the software and hardware requirements. Section 5 discusses the expected outcomes, the challenges identified from the literature, and the limitations of this work. Section 6 concludes the paper and outlines future work.

2. Literature Review & Related Work

A systematic investigation was conducted across 30 reference papers on Digital Twins, intelligent transportation, vehicular networks, and AI-enabled twinning. As Figure 2 shows, 28 of the 30 papers appear in IEEE venues, and 20 of them (about two thirds) were published in 2025–2026, which reflects how quickly the field is moving.

For every paper, the objective, limitations, advantages, performance metrics, and research gaps were recorded in a comparison table. The papers fall into six themes, summarized in Table I and discussed in Sections 2.2–2.7. The base paper [31] is discussed separately in Section 2.1.

TABLE I Thematic Grouping of the Reviewed Papers

Theme	Refs.	Main focus
Foundations and surveys	[1], [2], [5], [18], [22], [24], [28]	Concepts, enabling technologies, challenges
Signal control and flow monitoring	[3], [4], [7], [10], [26]	Adaptive signals, flow monitoring, traffic prediction
Infrastructure and vehicles	[6], [8], [9], [12]	Infrastructure health, CAVs, Transportation 5.0, deployments

Theme	Refs.	Main focus
Networks and federated twins	[13], [14], [17], [21], [23]	Network twins, model updates, federated learning
Sustainability and safety	[15], [19], [20]	Emissions, vulnerable road users, driver risk
GenAI, agentic and cross-domain	[11], [16], [25], [27], [29], [30]	Generative and LLM twins, other domains

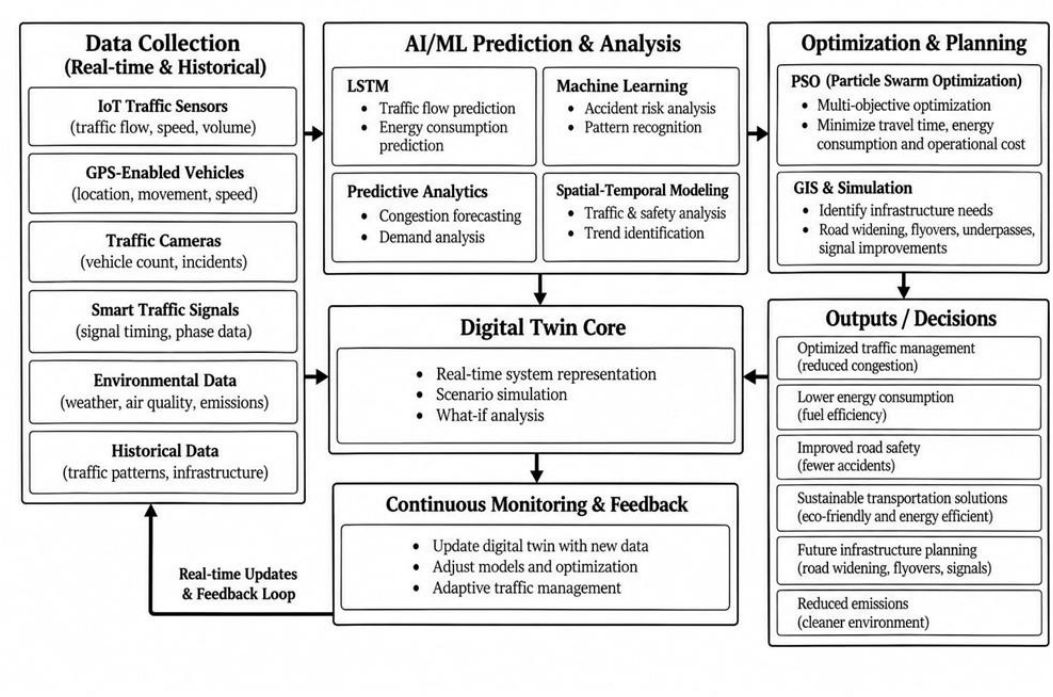


Figure 1: Architecture of the Proposed AI-Driven Digital Twin Framework for Intelligent Transportation Management and Infrastructure Planning

2.1 Base Paper

The base paper for this work is Zhou, Li, and He [31], who propose an integrated Digital Twin that manages urban energy and transportation together. An LSTM model forecasts traffic congestion, energy consumption, and grid load from IoT and smart-infrastructure data, and Particle Swarm Optimization performs multi-objective optimization of travel time, energy consumption, and operational cost under system constraints. A continuous feedback mechanism keeps sensor data, prediction models, and optimizers synchronized. The present framework keeps this predict-and-optimize core and extends it with accident risk prediction and long-term infrastructure planning.

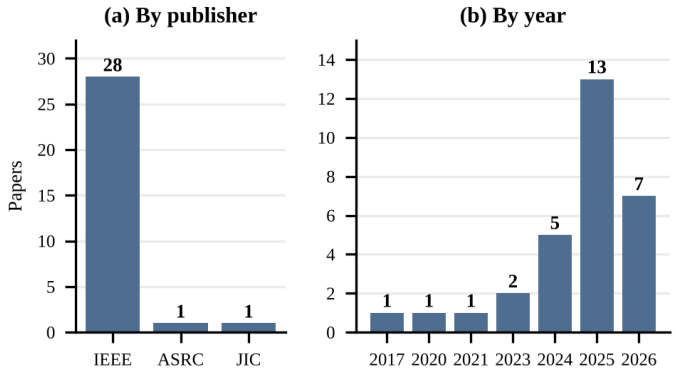


Figure 2: Distribution of the 30 reviewed papers: (a) by publisher (JIC = Journal of Intelligent Construction); (b) by year

2.2 Foundations and Surveys of Digital Twins

Fuller et al. [1] identify the enabling technologies of Digital Twins (IoT, sensors, analytics, AI, and simulation) and the open challenges of data management, interoperability, security, and scalability. Tao and Zhang [2] introduce the Digital Twin Shop-Floor, whose physical shop-floor, virtual shop-floor, service system, and twin data show how a twin can stay synchronized with its physical counterpart. Ai and Ziehl [5] review industrial applications and stress the role of AI, big data, IoT, and BIM, together with cybersecurity and standardization. Yu et al. [18] and Xu et al. [28] survey concepts, technologies, and tools, the latter for the Industrial IoT with blockchain-based approaches to trust. Wu et al. [22] survey Digital Twin Networks and their cloud and edge enablers, and Bhatia and Kumar [24] use scientometric analysis to map research on AI-integrated twins.

2.3 Digital Twins for Traffic Signal Control and Flow Monitoring

Shuvo [3] develops an AI-driven twin for real-time signal optimization and evaluates it in simulation under peak, off-peak, and incident conditions, measuring delay, queue length, and travel time. The adaptive signal control system of [4] uses real-time trajectory data, predicts demand, and runs parallel simulations to choose signal timings that reduce vehicle delay. Napolitano et al. [7] present FlowTwin, a modular twin for traffic-flow monitoring validated on the Bologna Mobility Digital Twin. Liu et al. [26] address task scheduling for real-time traffic information processing in the Internet of Vehicles, including a privacy-protecting transmission algorithm. Alvi et al. [10] build a predictive twin that combines historical, real-time, and forecast data, uses LSTM and Transformer models, and evaluates scenarios such as road closures and diversions.

2.4 Transportation Infrastructure and Intelligent Vehicles

Chang et al. [8] review twins in roads, bridges, tunnels, and other infrastructure, covering inspection, structural health monitoring, maintenance, and lifecycle management, and list model complexity, real-time updating, and aging infrastructure as open issues. Gu et al. [6] survey twins for connected and autonomous vehicles, including safety, traffic management, and simulation-based testing. Han et al. [9] describe foundation intelligence for Transportation 5.0, linking twins, AI models, V2X connectivity, and distributed systems for cooperative driving and smart intersections. Ropac and DeFranco [12] examine deployments in Singapore, Dubai, and Los Angeles, and note high implementation cost, poor data quality, outdated infrastructure, and the need for specialized expertise as obstacles.

2.5 Vehicular Networks, Communication and Federated Twins

Poorzare et al. [13] study Network Digital Twins for what-if analysis, anomaly detection, and planning, and discuss the resource cost and limited scalability of current network models. Lu et al. [14] use cooperative perception and deep reinforcement learning to keep twins of non-intelligent connected vehicles up to date while minimizing the age of information. Yu et al. [21] propose the Internet of Federated Digital Twins to coordinate heterogeneous twins, with smart-mobility demonstrations in path planning and collision prediction. Tan et al. [23] combine federated learning with twin-driven 6G vehicular networks to cut training delay and energy use, and Guo et al. [17] survey large language model–driven twins for traffic prediction, resource allocation, and fault diagnosis.

2.6 Sustainability and Safety-Aware Twins

Duran et al. [15] propose the Digital Twin-Empowered Eco-Regulation framework, which predicts CO_2 emission levels with MLP, BANE embeddings, and bidirectional LSTM and clusters high-emission risk zones. On the safety side, Fu et al. [19] build a cyber-physical twin that includes vulnerable road users, and Li et al. [20] use pan-tilt cameras and cooperative sensing to predict network-wide traffic conditions and driver risk before incidents happen. These two studies are the closest in spirit to the accident risk module proposed here.

2.7 Generative, Agentic and Cross-Domain Twins

Chiaro et al. [25] survey Generative AI-empowered twins and give a taxonomy of applications. Goyal et al. [11] examine agentic AI in twins for autonomous, adaptable systems, and note data quality, computational demand, explainability, and cybersecurity as limitations. Duran et al. [30] present GenTwin, which uses generative AI to adapt twins of IoT networks and reports 19% more relation extraction and up to 53% lower response time under high network dynamicity. Outside traffic, Malaekeh et al. [16] predict productivity problems at the construction workface, Ferdousi et al. [27] combine LLMs with a twin for railway defect inspection, and Maqbool et al. [29] use twin scenarios for structured training and validation of AI-based systems.

2.8 Identified Research Gaps

Across the comparison table of the 30 papers, the same limitations and gaps recur: dependence on real-time data, difficulty of real-time synchronization, scalability, interoperability, data quality, security and privacy, and limited real-world validation. Most traffic-oriented studies concentrate on monitoring, signal control, or short-term prediction. Within the reviewed set, none combines real-time monitoring, congestion prediction, accident risk prediction, scenario simulation, optimization, and long-term infrastructure planning in one framework. The proposed framework is designed to fill this gap.

3. Proposed System Architecture & Design

3.1 Framework Overview

The framework, shown in Figure 1, is organized into six cooperating blocks: Data Collection (real-time and historical), AI/ML Prediction & Analysis, the Digital Twin Core, Optimization & Planning, Outputs/Decisions, and Continuous Monitoring & Feedback. Data flows from the collection block into the prediction block and the twin core. Prediction results feed the optimization and planning block, whose decisions are applied and fed back so the twin is updated with new data. This is summarized by the cycle **Collect → Integrate → Predict → Simulate → Optimize → Decide → Update**.

3.2 Data Collection Layer

The data layer gathers six kinds of input. IoT traffic sensors report traffic flow, speed, and volume. GPS-enabled vehicles report location, movement, and speed. Traffic cameras supply vehicle counts and incident information. Smart traffic signals provide signal timing and phase data. Environmental sources provide weather, air quality, and emission data. Historical records provide traffic patterns and infrastructure information. Real-time and historical streams are integrated so that every downstream model sees a consistent picture of the network.

3.3 Digital Twin Core

The Digital Twin Core maintains a real-time representation of the transportation network built from the integrated data. It provides three capabilities: real-time system representation, scenario simulation, and what-if analysis. GIS adds the spatial dimension by placing traffic, safety, and infrastructure information on the road network. Before any change is applied to the physical system, the twin can simulate how different traffic conditions or infrastructure changes would play out.

3.4 AI/ML Prediction & Analysis

This block holds the learning models. **LSTM** networks forecast traffic flow and energy consumption from time-series data. A **Transformer** model provides a second forecasting option for future traffic conditions, as used in [10]. **Reinforcement Learning (RL)** supports adaptive traffic-signal control that responds to changing conditions. **Predictive analytics** covers congestion forecasting and demand analysis, and **spatial-temporal modeling** supports traffic and safety analysis and trend identification across the network.

3.5 Accident Risk Prediction Module

Existing traffic management mainly responds to current conditions. The accident risk module instead combines historical accident data with real-time transportation information. Weather, road condition, vehicle speed, and visibility are treated as risk factors. ML models identify patterns associated with high-risk situations, and the Digital Twin represents high-risk road segments and simulates possible traffic situations on them. The output is a forecast of where and under what conditions accidents are likely, so interventions can be taken before an incident occurs.

3.6 Future Infrastructure Planning Module

Long-term traffic data is analyzed to identify rising demand and recurring congestion. The Digital Twin simulates future transportation scenarios under different demand levels, GIS represents the results spatially, and AI-based predictive analysis estimates what infrastructure will be needed. The module recommends where road widening, flyovers, underpasses, or traffic-signal improvements are required, which is the planning support that navigation systems lack.

3.7 Multi-Objective Optimization using PSO

Transportation decisions are evaluated with Particle Swarm Optimization, which balances travel time, energy consumption, and operational cost under system constraints. A common way to express this is a weighted objective:

$$F(x) = w_1 T(x) + w_2 E(x) + w_3 C(x), \quad w_1 + w_2 + w_3 = 1 \qquad (1)$$

where T, E, and C denote travel time, energy consumption, and operational cost for a candidate decision x. Each particle i has a position x and velocity v, updated at every iteration as:

$$v_i(t+1) = \omega\, v_i(t) + c_1 r_1 [p_i - x_i(t)] + c_2 r_2 [g - x_i(t)] \qquad (2)$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \qquad (3)$$

where ω is the inertia weight, c_1 and c_2 are acceleration coefficients, r_1 and r_2 are random numbers in [0, 1], p is the particle's best position, and g is the swarm's best position. The weights and constraints are set by the transport authority, so the same optimizer can favor shorter travel time, lower energy use, or lower cost.

3.8 Continuous Monitoring & Feedback

The framework is a loop, not a pipeline. After decisions are applied, new sensor data updates the Digital Twin, the models and optimization are adjusted, and traffic management adapts. This real-time update and feedback loop keeps the twin synchronized with the physical network and lets decisions improve over time.

4. Implementation Details

4.1 Implementation Workflow

The framework is implemented as the following sequence of steps:

1. Collect data from IoT sensors and GPS.
2. Integrate historical and real-time data.
3. Create and continuously update the Digital Twin.
4. Predict traffic using AI/ML.
5. Analyze accident-risk conditions.
6. Simulate future transportation scenarios.
7. Use GIS for infrastructure analysis.
8. Apply optimization for better decisions.
9. Continuously update the Digital Twin with new data.

4.2 Case-Study Analysis

Two case-study approaches were analyzed to show how the framework's capabilities combine. **Case Study 1, Digital Twin-Based Traffic Monitoring,** performs real-time monitoring and prediction: IoT sensors, GPS, and cameras feed the Digital Twin, LSTM or Transformer models predict future traffic, and simulation evaluates possible conditions to support proactive congestion management. **Case Study 2, AI-Based Predictive Transportation Planning,** adds accident and road-condition data, uses AI/ML to predict congestion and accident risk, uses GIS to locate places that need improvement, simulates future scenarios in the twin, and uses PSO for multi-objective optimization to plan road widening, flyovers, and underpasses. Table II compares them. Both rely on AI/ML, real-time data, a Digital Twin, and simulation.

TABLE II Comparison of the Two Case Studies

Case Study 1	**Case Study 2**
Real-time monitoring	Predictive management
Current traffic conditions	Future traffic conditions
Traffic prediction	Traffic + accident prediction
Congestion management	Infrastructure planning
Digital Twin monitoring	Digital Twin simulation
LSTM / Transformer	LSTM / PSO / AI-ML
Short-term decisions	Long-term decisions
Traffic efficiency	Safety + sustainability

4.3 Software and Hardware Requirements

The software stack is built on open-source Python tools, and the hardware requirement for the analytics workstation is modest, with sensing infrastructure supplied by the city. Table III lists both.

TABLE III Software and Hardware Requirements

Category	Requirement
Operating system	Windows / Linux
Programming	Python
Machine learning	Scikit-learn
Deep learning	TensorFlow / Keras
Data processing	Pandas / NumPy
GIS	QGIS
Visualization	Matplotlib / Plotly
Database	MySQL / PostgreSQL
Development	VS Code / Jupyter
Compute	Intel Core i3 or above, 8 GB RAM recommended, 10 GB or more free storage, GPU optional for deep learning
Connectivity	Stable Internet connection
Field infrastructure	IoT traffic sensors, GPS-enabled vehicles, traffic monitoring cameras, smart traffic signals

5. Results & Discussion

5.1 Expected Outcomes of the Framework

The framework is a design contribution supported by a literature analysis and case-study comparison. Its expected outcomes, which follow from the capabilities described in Section 3, are that it will:

- predict future traffic congestion and support proactive traffic management;
- identify accident-risk conditions before incidents occur and improve transportation safety;
- identify future infrastructure requirements and recommend road widening, flyovers, underpasses, and signal improvements;
- reduce congestion and travel delays; and
- support energy-efficient and sustainable planning by considering congestion, energy consumption, and emissions.

5.2 Comparative Discussion

Compared with navigation systems that report current conditions, the proposed framework adds three things: forecasting of future traffic, prediction of accident risk, and recommendations for long-term infrastructure. Compared with the monitoring-oriented twins in the literature [4], [7], it adds the safety and planning modules. Compared with the base paper [31], it keeps the LSTM and PSO core for prediction and optimization but extends the scope from energy and traffic management to safety and infrastructure decisions.

Case Study 1 serves short-term decisions such as congestion management, while Case Study 2 serves long-term decisions such as infrastructure planning and safety. The two share the same data and twin, so a city can start with monitoring and add the planning capability without rebuilding the system.

5.3 Challenges Identified from the Literature

The reviewed studies repeatedly report the same challenges, and each affects this framework: data integration and data quality [1], [12]; prediction accuracy and real-time adaptation [10], [14]; scalability and continuous updating of the twin [6], [8]; interoperability and standardization [5], [9]; and

security and privacy [11], [26]. The framework addresses integration through its unified data layer and GIS, and addresses adaptation through its feedback loop. Security, scalability, and cost remain open and are discussed next.

5.4 Operational Limitations & Implementation Scope

In keeping with academic integrity, the contribution of this paper must be separated from future work. The framework is a proposed design: this term paper does not report measured accuracy, delay, or emission figures from a deployed system, and no numerical performance claims are made. Its practical operation depends on sensor coverage and data quality, on the computational cost of LSTM, Transformer, and PSO models, on the availability of historical accident data, and on the implementation cost that [12] identifies as a barrier for many cities. These constraints are targeted in the future work below.

6. Conclusion & Future Work

This research proposed an AI-Driven Digital Twin framework for intelligent transportation management and infrastructure planning in smart cities. By integrating AI/ML, a Digital Twin, IoT, and GIS, the framework enables real-time traffic monitoring, predicts future traffic conditions, forecasts accident risk, supports what-if simulation, optimizes transportation decisions, and recommends future infrastructure such as road widening, flyovers, underpasses, and signal improvements. A review of 30 papers showed that existing work handles these problems separately and leaves gaps in real-time integration, scalability, and real-world validation, which the integrated Collect → Integrate → Predict → Simulate → Optimize → Decide → Update cycle is designed to close.

Future work will focus on four advancements: (1) implementing the framework on real or simulated traffic datasets and reporting prediction error, delay, and queue-length metrics against a baseline; (2) using federated twins [21] and federated learning [23] to scale across districts while protecting data privacy; (3) exploring generative, agentic, and LLM-driven twins [11], [17], [25], [30] for explainable decision support; and (4) adding vulnerable road users to the twin [19] for safer, more user-aware mobility.

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