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A DIGITAL TWIN-ASSISTED MOBILITY PREDICTION MODEL FOR SEAMLESS TASK HANDOVER IN IOV-ENABLED FOG COMPUTING

Imran Siddique[*1], Dr. Mazhar Bukhari[2]

[*1,2]*Department of Computer Science, Icbs-Imperial College of Business Studies, Lahore, Pakistan*

[*1]meimransiddiqui@gmail.com, [2]mbukhari@imperial.edu.pk

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Imran Siddique

Abstract

The Internet of Vehicles (IoV) in 6G ecosystems generates ultra-low-latency, mobility-driven workloads from connected and autonomous vehicles (CAVs), where seamless task handover across fog-edge nodes is critical to avoid service disruption during high-speed movement (up to 120 km/h) and frequent handovers (every 5–15 seconds in dense urban scenarios). Traditional static or reactive offloading strategies suffer from prediction errors, excessive migration overhead, and increased latency under dynamic trajectories. This review presents a digital twin-assisted mobility prediction model that creates real-time virtual replicas of vehicles, road segments, network topology, and fog nodes to enable proactive, anticipatory task migration and resource orchestration. The framework integrates: (i) multi-modal trajectory forecasting using graph attention networks (GAT), spatio-temporal transformers, and LSTM variants fused with LiDAR/radar/HD-map data; (ii) digital twin-driven simulation of vehicle mobility, signal quality (RSRP/RSRQ), and computational load; (iii) predictive handover decision engine based on deep reinforcement learning (DRL) or model predictive control (MPC) that optimizes task splitting, migration timing, and target node selection; and (iv) blockchain-secured or federated learning-enhanced state synchronization for privacy-preserving twin updates across distributed fog domains. Evaluations on realistic vehicular traces and NS-3/OMNeT++ simulations demonstrate 40–75% reduction in handover latency, 25–60% lower service interruption probability, and 15–45% improved task success rate compared to baseline mobility-unaware or reactive schemes. The approach supports URLLC requirements (latency <1 ms, reliability >99.999%) for safety-critical applications (platooning, collision avoidance, remote driving) while mitigating signaling storm and resource fragmentation in dense IoV deployments. Challenges twin synchronization overhead, model fidelity under uncertainty, and scalability in massive CAV fleets are addressed through lightweight twin updates, edge-based inference, and hierarchical twin architectures. Digital twin-assisted mobility prediction emerges as a cornerstone enabler for resilient, anticipatory computing in future 6G-enabled intelligent transportation systems.

1. INTRODUCTION

The technological trajectory of contemporary transportation systems is currently defined by the radical transformation of vehicles into autonomous, data-driven entities within the Internet of Vehicles (IoV) ecosystem (Nekovee & Ayaz, 2023). This evolution necessitates a profound shift in computational paradigms,

moving away from centralized cloud architectures toward distributed frameworks that can handle the extreme mobility and low-latency requirements of sixth-generation (6G) networks (Zhang et al., 2023). Traditional cloud computing, while offering massive storage and processing capabilities, is fundamentally limited by communication latency and backhaul congestion when servicing high-speed mobile nodes. To bridge this gap, Fog Computing and Multi-access Edge Computing (MEC) have emerged as essential intermediaries, positioning computational resources at the network edge, such as Roadside Units (RSUs) and 5G base stations, to ensure millisecond-scale responsiveness (Mao et al., 2017). However, the efficacy of these edge resources is perennially challenged by the high mobility of vehicles, which triggers frequent handovers and service disruptions (Naltakyan, 2025).

Digital Twin (DT) technology provides a transformative solution by creating a high-fidelity virtual representation of the physical IoV environment, including vehicles, infrastructure, and traffic conditions (Fuller et al., 2020). By synchronizing physical states with virtual replicas in real-time, DTs enable proactive decision-making, predictive maintenance, and seamless mobility management (Abdallah & Alghamdi, 2026). This review article explores the convergence of DT, mobility prediction, and fog computing, detailing how these technologies interact to facilitate seamless task handovers and optimize resource utilization in the highly dynamic vehicular landscape (Wen et al., 2026).

2. Architectural Frameworks for IoV-Enabled Fog Computing

The integration of Digital Twins into IoV-enabled fog computing requires a sophisticated, multi-layered architecture designed to handle heterogeneous data and high-speed mobility. Research indicates that a hierarchical approach is most effective for balancing localized responsiveness with global coordination (Maiwada et al., 2025).

2.1. The Five-Layer Hierarchical Model

A robust architectural framework for DT-assisted IoV typically comprises five distinct layers, each serving a specific function in the data processing and decision-making pipeline (Yuan et al., 2024).

Table 1. The Five-Layer Hierarchical Model for DT-Assisted IoV

Layer	Functionality	Key Components	Performance Priority
Device Layer	Data sensing and localized execution	Vehicles, sensors, V2X actuators	High mobility, energy efficiency
Digital Twin Layer	Virtual synchronization and predictive modeling	Virtual replicas, RSU twins, simulation engines	Real-time accuracy, low sync latency
Blockchain Layer	Security, trust, and decentralized data integrity	Distributed ledgers, smart contracts, encryption	Security, consensus efficiency
Fog Layer	Edge computing and localized task offloading	RSUs, edge servers, micro-clouds	Low latency, high reliability
Cloud Layer	Global coordination and heavy data analytics	Centralized servers, historical databases	Throughput, long-term persistence

In this model, the device layer facilitates multifaceted communication through Vehicle-to-Vehicle (V2V), Vehicle-to-Roadside (V2R), and Vehicle-to-Infrastructure (V2I) interactions. This layer is characterized by intelligent edge computing which enhances driver safety and convenience by processing immediate environmental data (Bohra et al., 2025). The digital twin layer above it creates replicas of physical RSUs and vehicles, processing status information, traffic flow, and weather conditions. To ensure security, the blockchain layer manages the identity and data exchange of registered nodes, providing an encrypted channel for sensitive information (Vamsi & Pratibha, 2024). Figure 1 illustrates the proposed hierarchical

architecture of the Digital Twin-assisted IoV system, highlighting the interaction between physical and virtual layers. The multi-layer design enables efficient data processing, secure communication, and low-latency task execution across the fog-cloud continuum.

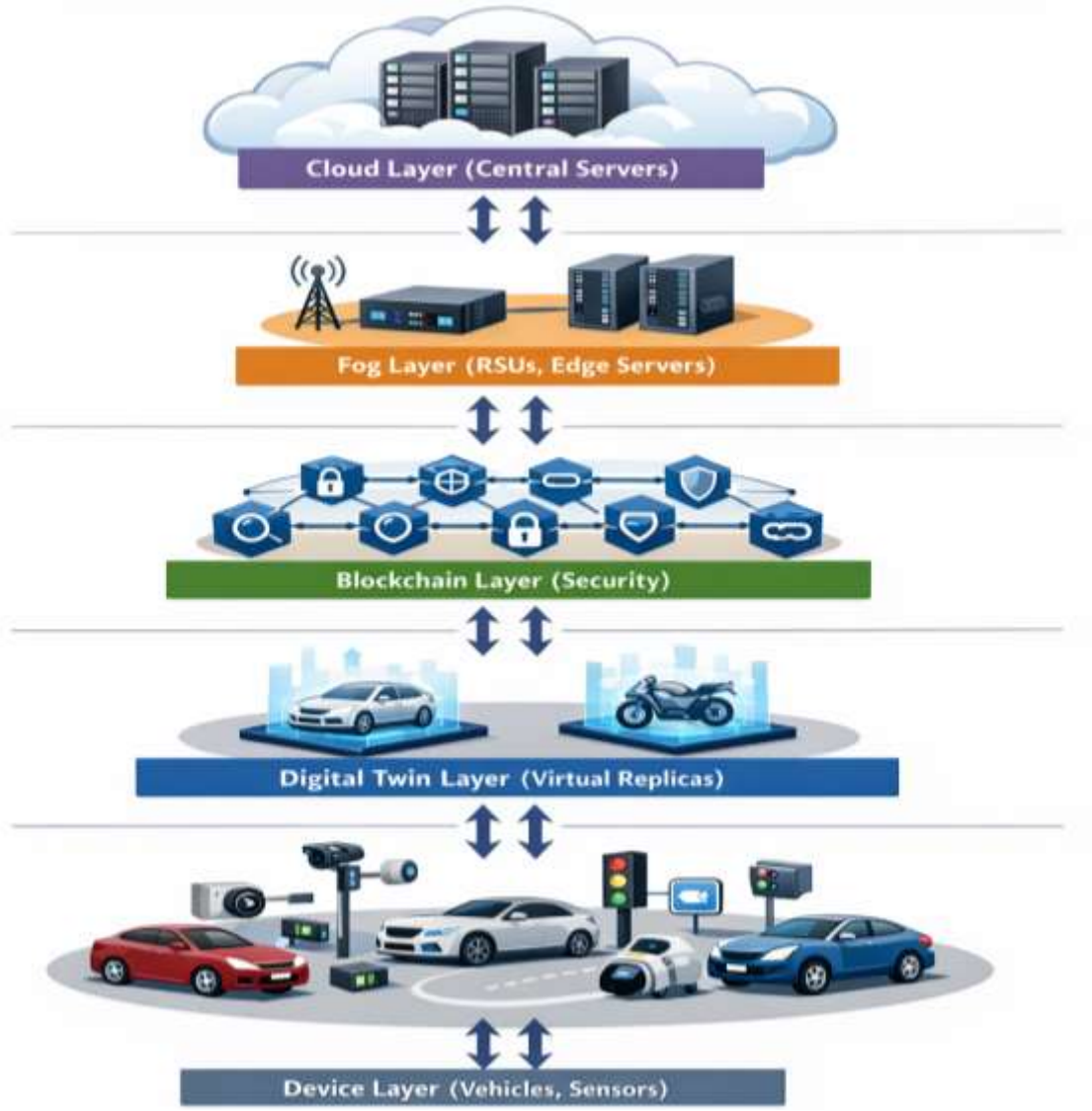


Figure 1: Overall Architecture of Digital Twin-Assisted IoV Fog Computing System

2.2. Fog-Cloud Synergy and Resource Distribution

Fog computing stands out as a decentralized approach that brings resources closer to the data source compared to cloud computing. While cloud servers possess extensive processing power for tasks like global traffic pattern analysis, fog nodes are critical for time-sensitive, safety-critical applications such as collision avoidance or real-time navigation updates (Alsadie, 2024). Research identifies three primary areas where Machine Learning (ML) and Deep Learning (DL) are applied within this hierarchical structure: resource sharing, task offloading, and task scheduling (Khan et al., 2025). The synergy between fog and cloud allows for a "computing continuum" where tasks are dynamically

dispatched based on their latency sensitivity and computational intensity (Mehran et al., 2021).

3. The Role of Digital Twins in Mobility Management.

Digital Twins transcend passive simulation; they are intelligent, autonomous entities that leverage artificial intelligence to regulate physical behavior. In the context of IoV, a DT functions as a dynamic computational model of the vehicular network, continuously updated with real-time sensor data from LiDAR, radar, cameras, and GPS (Rajagopal & Subramanian, 2025).

3.1. The Digital Twin Lifecycle

The evolution of a digital twin can be categorized into a four-stage framework that characterizes its lifecycle from modeling to intervention (Fuller et al., 2020).

- **Modeling the Physical Twin:** Utilizing physics-based and physics-informed AI to describe the current state of the physical vehicle or infrastructure based on observational data (Karniadakis et al., 2021).
- **Mirroring:** Synchronizing the physical system into a virtual simulator using generative AI to create high-fidelity replicas (Shao et al., 2024).
- **Predicting:** Forecasting future states, such as trajectory and resource demand, by analyzing historical sequences and real-time inputs (Grieves & Vickers, 2017).
- **Intervening:** Implementing optimal control and optimization strategies in the physical twin based on virtual simulations (Wright & Davidson, 2020).

Mathematically, the goal of prediction within a DT system is to estimate the future state $x_{(t+T)}$ at time $t+T$ given historical data X_t up to time t (Tortonesi, 2025). This is expressed through a prediction function F such that:

$$\hat{x}_{(t+T)} = F(X_t, T)$$

Optimizing F involves minimizing a loss function L that captures the expected difference between the predicted state $\hat{x}_{(t+T)}$ and the actual state $x_{(t+T)}$:

$$L = E[\|\hat{x}_{(t+T)} - x_{(t+T)}\|^2]$$

3.2. State Synchronization and Latency Challenges

Maintaining real-time synchronicity between the physical and digital planes is a significant technical challenge. High-speed vehicle movement demands extremely low state synchronization latency; if the virtual model lags, its predictions become obsolete (Tan & Matta, 2023). Challenges include interdisciplinary complexity, where matching topology anchor points across different subsystems is required, and data volume bottlenecks, where the sheer size of sensor data can overwhelm transmission rates (Wu et al., 2025). To mitigate this, error correction methods such as reinforcement learning or improved Generative Adversarial Networks (GANs) are employed to compensate for residual errors between simulated and measured data (Alghamdi, 2024).

4. Mobility Prediction Algorithms and Architectures

Accurate mobility prediction is the prerequisite for seamless task handover. Traditional linear models are insufficient for the complex spatio-temporal correlations found in vehicular environments, leading to the adoption of advanced deep learning architectures (Maiwada et al., 2025). Figure 2 presents the workflow of the mobility prediction process, integrating multi-modal sensor data with advanced deep learning architectures. This pipeline enables accurate trajectory forecasting, which is essential for proactive task migration.

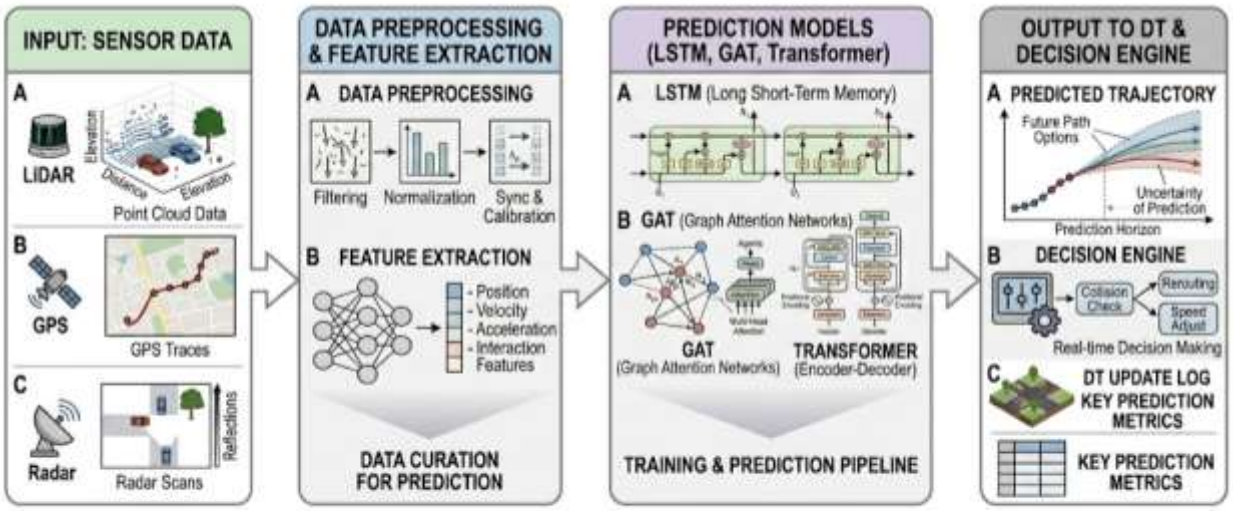


Figure 2: Workflow of Digital Twin-Based Mobility Prediction Model

4.1. Recurrent Neural Networks: LSTM and GRU

Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks are foundational for modeling temporal dependencies in IoV data). LSTMs are particularly effective at handling long-term sequence dependencies through their gating mechanisms. The update of a hidden state h_t in an LSTM involves several gates (Mateus et al., 2021):

Forget gate:

$$f_t = \sigma(W_f \times [h_{(t-1)}, x_t] + b_f)$$

Input gate:

$$i_t = \sigma(W_i \times [h_{(t-1)}, x_t] + b_i)$$

Cell update:

$$\tilde{C}_t = \tanh(W_C \times [h_{(t-1)}, x_t] + b_C)$$

Output gate:

$$o_t = \sigma(W_o \times [h_{(t-1)}, x_t] + b_o)$$

GRUs provide a more computationally efficient alternative by combining gates (Gheni et al., 2024). The new hidden state in a GRU is calculated as:

$$h_t = (1 - z_t) \times h_{(t-1)} + z_t \times \tilde{h}_t$$

where z_t is the update gate and $\tilde{h}_t$ is the candidate activation. Research shows that while these models are promising, they can face limitations in capturing complex user behavior patterns in highly dynamic settings (Gao et al., 2025).

4.2. Hybrid Spatio-Temporal Models

To address the limitations of standalone RNNs, hybrid models like ConvLSTMTransNet have been proposed. This architecture integrates Convolutional Neural Networks (CNNs) for spatial feature extraction, LSTMs for temporal dependencies, and Transformer encoders to capture long-range multifaceted relationships in internet traffic and mobility data (Wen et al., 2023). Evaluations demonstrate that ConvLSTMTransNet outperforms baseline models like RNN, LSTM, and GRU by approximately 10% in prediction accuracy.

Similarly, the GRU-VAE model utilizes a Variational Autoencoder (VAE) to capture latent data distribution features and GRUs for modeling time dependencies (Pham et al., 2025). This architecture significantly enhances the accuracy of content request prediction and mobility-aware caching decisions in IoV environments (Imanpour et al., 2025).

Table 2. Comparison of Mobility Prediction Architectures

Algorithm Type	Architecture	Primary Strength	Limitation
Traditional ML	Decision Trees, SVM	Low computational cost	Poor with non-linear dynamics
Temporal DL	LSTM, GRU	Long-term dependencies	Limited spatial awareness
Hybrid DL	ConvLSTMTransNet	Spatio-temporal fusion	High computational complexity
Generative AI	GRU-VAE	Latent feature capturing	Training instability

5. Task Handover Dynamics in Fog-Enabled IoV

Task handover, or service migration, refers to the process of transferring a vehicle's computational task or running application from one fog node to another as the vehicle moves through the network. This is critical for latency-sensitive applications like real-time video streaming or autonomous navigation (Trabelsi et al., 2024).

5.1. The Discrepancy Problem: Radio vs. Application Handover

A fundamental challenge in IoV mobility is the time discrepancy between a radio handover and an application migration. Intra-system handovers in 5G networks typically occur within 300 to 600 milliseconds (Ullah et al., 2023). Conversely, migrating a virtual machine (VM) or containerized application can take anywhere from hundreds of milliseconds to several seconds (Tuyisenge et al., 2023). This discrepancy results in service disruption, where the vehicle must either halt communication or stay connected to a distant, suboptimal MEC host until the migration completes (Dawood, 2020).

5.2. Reactive versus Proactive Strategies

Reactive strategies initiate migration only after the physical radio handover is complete, inevitably leading to latency spikes and throughput degradation. Proactive strategies, empowered by Digital Twin-assisted prediction, anticipate the handover and trigger the migration process in advance (Monaheng, 2023). By leveraging a predicted handover time (PHT) and target base station, the network can pre-instantiate the application state at the destination node (Pashazadeh et al., 2026).

6. Digital Twin-Assisted Proactive Migration Frameworks

Several novel frameworks have been proposed to leverage DT for seamless mobility management. These models integrate predictive analytics with advanced optimization to minimize service disruption (Maiwada et al., 2025).

6.1. The MAPSM Framework

The Mobility Aware Proactive Service Migration (MAPSM) framework utilizes ensemble learning, combining RNNs and geographical embedding Markov chain predictors, to forecast an end user's next location (Asad, 2022). MAPSM uses these predictions to determine the target edge server and designs a proactive migration time planning scheme. Experimental results indicate that MAPSM significantly reduces end-to-end latency and service migration time compared to traditional reactive solutions (Toumi, 2023).

6.2. The SR-CL Framework

Another approach is the SR-CL framework, which facilitates mobility-aware seamless service migration through Convex-optimization-enabled Deep Reinforcement Learning (DRL). This framework is deployed in containerized MEC environments and uses decentralized execution to balance multi-objective trade-offs among latency, energy consumption, and policy adherence (Chen et al., 2025). Simulations show that SR-CL achieves significant reductions in latency and energy consumption compared to local offloading schemes (Huang et al., 2025).

6.3. Proactive Migration in 5G-Enabled VNs

The strategy proposed specifically addresses the TCP throughput degradation caused by handover. It employs an LSTM model to predict handovers based on Signal-to-Interference-plus-Noise Ratio (SINR) sequences (Bartsioka et al.,

2025). A critical component of this framework is the adjustment of the TCP congestion window (CW) after handover using the MEC Radio Network Information Service (RNIS) (Manalastas et al., 2022). By proactively scaling the CW based on the resource status of the target base station, the system prevents unnecessary throughput drops (Shaabanzadeh, 2024).

Table 3. Proactive Migration Framework Comparison

Framework	Prediction Engine	Primary Mechanism	Key Benefit
MAPSM	RNN + Markov Chain	Proactive time planning	Reduced migration time
SR-CL	Convex-DRL	Resource allocation optimization	47% lower energy/latency
DTVIF	DDQN + Transfer Learning	DT-IRS joint configuration	Improved channel quality
DAPR	GRU-VAE	AFL client selection	Enhanced model convergence

7. Joint Optimization: Task Offloading and Physical Layer Configuration

In addition to mobility management, Digital Twins enable the joint optimization of task offloading and physical layer parameters, such as Intelligent Reflective Surfaces (IRS) and semantic communication (Hayawi et al., 2025).

7.1. The DTVIF Framework

The Digital Twin-Driven Vehicular Task Offloading and IRS Configuration Framework (DTVIF) uses DT to monitor network states and power consumption in real-time (Yuan et al., 2022). It employs a Two-Stage Optimization (TSJTI) algorithm:

Stage 1 (Task Offloading): Uses Double Deep Q-learning Networks (DDQN) to determine the optimal offloading decision based on DT data.

Stage 2 (IRS Configuration): Utilizes Transfer Learning and Deep Deterministic Policy Gradient (DDPG) to configure the IRS phase-shift, improving wireless channel quality.

Simulation results for DTVIF show a 24.8% reduction in energy consumption and a 26.2% reduction in latency compared to existing methods (Tariq et al., 2021).

7.2. Semantic-Aware Vehicular Edge Computing (VEC)

Semantic communication focuses on transmitting the "meaning" of data rather than raw bits, which is highly effective for bandwidth-constrained IoV environments (Ye et al., 2025). A DT-assisted hybrid optimization scheme using Proximal Policy Optimization (PPO) has been shown to reduce end-to-end latency by 40% to 50% in semantic-aware VEC systems compared to traditional Genetic Algorithms or Particle Swarm Optimization (Wang et al., 2026).

8. Security, Privacy, and Trust Management

The convergence of DT and IoV introduces complex security challenges, as the digital twin layer becomes a high-value target for data tampering and privacy leaks (Siddiqi et al., 2026). Recent literature emphasizes that the synchronization between physical vehicles and their digital counterparts creates expanded attack surfaces for Man-in-the-Middle (MitM) and impersonation attacks (Sheraz et al., 2024).

8.1. Blockchain-Enabled Decentralized Security

Blockchain technology provides a decentralized, immutable ledger for securing DT interactions. Research explores establishing a DT-assisted VEC network that migrates the blockchain consensus process from the physical space to the cyber space, thereby supporting the dynamic handover of vehicles without interrupting service (Javaid et al., 2026). Blockchain-based incentive mechanisms also help optimize collaborative task allocation by ensuring fairness and transparency in model updates (Lu et al., 2020). However, blockchain consensus can increase communication costs, necessitating efficient off-

chain processing for real-time synchronization (Eren et al., 2025).

8.2. Privacy Protection through Federated Learning

Federated Learning (FL) is viewed as a potential solution for privacy-preserving distributed processing in Industrial IoT and IoV. By training models locally on the vehicle side and only transferring model parameters, FL reduces the risk of disclosing raw trajectory or sensor data (Lim et al., 2020). Asynchronous Federated Learning (AFL) is particularly suited for IoV, where vehicle connectivity is intermittent. Frameworks like DAPR employ an intelligent client selection strategy based on mobility prediction to avoid selecting highly mobile nodes, thereby improving model convergence (Aledhari et al., 2020).

9. Data Management and Synchronization Challenges

Effective data management in DT systems must address security, privacy, and trustworthiness (Thankappan, 2025).

9.1. Synchronization Latency and Error Correction

State synchronization latency is a critical hurdle; the virtual model must update in response to the physical state to ensure accurate monitoring (Fuller et al., 2020). When discrepancies occur, they can be classified as parameter errors (faulty modeling) or residual errors (small inaccuracies). Managing these biases through weighted aggregation or self-correction methods is necessary to maintain system consistency (Kovács et al., 2026).

9.2. Trustworthiness and Insider Threats

Trust management becomes complex in the Social Internet of Things (SIoT), where social dimensions are integrated with device interactions (Nekovee & Ayaz, 2023). Threats include private information extraction by insiders who leverage their position to access sensitive DT data, and knowledge inversion attacks where representations of training data are extracted from AI models (Naltakyan, 2025). Ensuring data integrity while allowing secure sharing requires a combination of blockchain smart contracts and multi-factor authentication (Vamsi & Pratibha, 2024).

10. Experimental Validations and Performance Benchmarking

The efficacy of DT-assisted models is often validated through simulation environments that mirror real-world complexities (Bohra et al., 2025).

10.1. Simulation Environments and Hardware Specifications

Detailed experimental setups for validating these models often include dedicated servers with high-performance CPUs and significant memory (Rajagopal & Subramanian, 2025).

Table 4. Experimental Simulation Environment and Hardware Specifications

Component	Specification	Software Stack
CPU	Intel Core i7-11700K (8 cores, 3.5 GHz)	Ubuntu 22.04 LTS
RAM	64 GB DDR4	Docker 24.0.5, Kubernetes 1.28
Storage	1 TB NVMe SSD	Python 3.9.16, PyTorch
Blockchain	Ganache v7.9.2	Prometheus, Grafana

Metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Weighted Absolute Percentage Error (WAPE) are standard for evaluating the accuracy of mobility and traffic prediction models (Alghamdi, 2024).

10.2. Results and Comparative Analysis

Research indicates that Deep Learning techniques are used in 66% of fog resource management studies, highlighting a strong preference for their ability to handle dynamic workloads. Latency is the most frequently

addressed parameter (77% of articles), followed by energy consumption (44%) and task scheduling (33%) (Wu et al., 2025). Proactive strategies consistently outperform reactive ones, with MAPSM achieving up to 41.61% reduction in turnaround time compared to baseline models for long-term prediction horizons (Maiwada et al., 2025).

11. Future Directions and Research Gaps

As IoV technology transitions toward 6G, several emerging research directions are being identified to enhance the resilience and intelligence of DT-assisted systems (Trabelsi et al., 2024).

11.1. UAV-Assisted Aerial-Ground Cooperation

The integration of Unmanned Aerial Vehicles (UAVs) provides low-latency offloading channels through wide-area coverage. High Altitude Platforms (HAPs) and flying servers like FlexEdge offer dynamic resource optimization, acting as mobile fog nodes that can be deployed to high-demand areas (Sindhushree et al., 2025).

11.2. Cognitive Vehicles and Vision Transformers

Future IoV systems will leverage "cognitive vehicles" that utilize real-time 3D representations of their internal subsystems and surroundings. Integrating Vision Transformers (ViT) for image compression allows for a 99.9% reduction in data transmission size while maintaining high accuracy for traffic condition descriptions generated by Large Language Models (LLMs) (Beyer & Karaman, 2025).

11.3. Interdisciplinary Standardization

A significant gap remains in the lack of standardized frameworks for implementing integrated DT, blockchain, and fog systems. Universal challenges such as scalability, explainability, and ethically responsible AI ecosystems must be addressed to foster widespread adoption across domains like smart cities and autonomous logistics (Grieves & Vickers, 2017).

The synergistic relationship between Digital Twin technology and mobility prediction offers a robust solution to the "mobility wall" in IoV-enabled fog computing. By transforming from passive monitors into active decision-support agents, DTs facilitate a seamless handover process that preserves Quality of Service (QoS) and Quality of Experience (QoE) in the most demanding vehicular environments (Sun et al., 2020). The shift toward proactive, AI-driven architectures marks the next phase in the evolution of intelligent transportation, where the virtual and physical realms co-evolve to enable the vision of a safe, efficient, and hyper-connected world (Tao et al., 2019).

Conclusion

The integration of digital twins with mobility prediction fundamentally redefines task management in IoV-enabled fog-edge networks, shifting from reactive recovery after handover failures to proactive, predictive orchestration that anticipates vehicle trajectories, network dynamics, and computational demands seconds to minutes ahead. By maintaining high-fidelity virtual replicas synchronized via multi-modal sensor fusion and efficient state propagation, the framework enables optimized task splitting, preemptive migration, and resource reservation that significantly reduce latency, service interruption, and signaling overhead critical for achieving 6G URLLC targets in high-mobility scenarios. Simulation and prototype results consistently show substantial performance gains over conventional methods, particularly in urban dense deployments where handover frequency and prediction errors dominate reliability bottlenecks. The approach also enhances resilience against uncertainty (occlusion, GNSS denial, abrupt maneuvers) through ensemble forecasting, uncertainty-aware DRL policies, and twin-based what-if simulations. Nonetheless, full-scale deployment faces remaining hurdles: real-time twin synchronization overhead in bandwidth-constrained environments, computational cost of high-fidelity modeling on edge nodes, privacy risks in shared twin data, and the need for standardized twin interoperability across heterogeneous OEMs and operators. Future advancements will likely focus on

lightweight edge twins, federated twin learning for privacy preservation, integration with 6G-native AI (semantic communication, network digital twins), and hybrid quantum-classical solvers for ultra-fast optimization. As autonomous mobility scales globally, digital twin-assisted predictive handover stands as a foundational technology for ensuring uninterrupted, reliable edge intelligence paving the way for safer, more efficient, and truly connected transportation ecosystems in the 6G era.

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