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ARTIFICIAL INTELLIGENCE IN DRIVEN DIGITAL TWIN FOR REAL-TIME TRAFFIC SIGNAL OPTIMIZATION AND TRANSPORTATION PLANNING

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Abstract

This study examined the effectiveness of an artificial intelligence–driven digital twin system for real-time traffic signal optimization and transportation planning using a quantitative simulation-based approach. The digital twin replicated a congested urban corridor consisting of six signalized intersections and evaluated performance under baseline and AI-controlled conditions across 48 experimental scenarios covering peak, off-peak, and incident periods. A total of 192 simulation replications were analyzed to ensure statistical robustness. Descriptive results showed that the AI-based controller reduced average delay from 68.4 seconds per vehicle to 29.5 seconds, representing a 56.9% improvement. Average queue length declined from 19.6 vehicles to 8.4 vehicles, a 57.1% reduction, while throughput increased from 12.7 to 19.8 vehicles per minute, reflecting a 55.9% gain. Travel time reliability improved as the reliability index rose from 74.3% to 91.4%, indicating a more stable operating environment. Correlation analysis showed that the relationship between demand intensity and congestion severity weakened under AI control, with the demand-delay correlation decreasing from 0.74 to 0.48. Reliability and validity checks confirmed strong internal consistency, with simulation replications producing variability below 0.30 units across all key metrics. Criterion validity assessment showed that simulated baseline values differed from field observations by less than 7%. Collinearity diagnostics confirmed model suitability, with all VIF values below 2.3, ensuring stable regression estimates. Regression analysis showed that AI control significantly predicted improvements in delay ($\beta = -0.62$, $p < .001$), queue length ($\beta = -0.58$, $p < .001$), throughput ($\beta = 0.49$, $p < .001$), and reliability ($\beta = 0.57$, $p < .001$). All hypotheses were supported. The study demonstrated that integrating digital twin technology with reinforcement learning produced substantial quantitative benefits, establishing a strong empirical foundation for adopting AI-enhanced signal control in advanced transportation management systems.

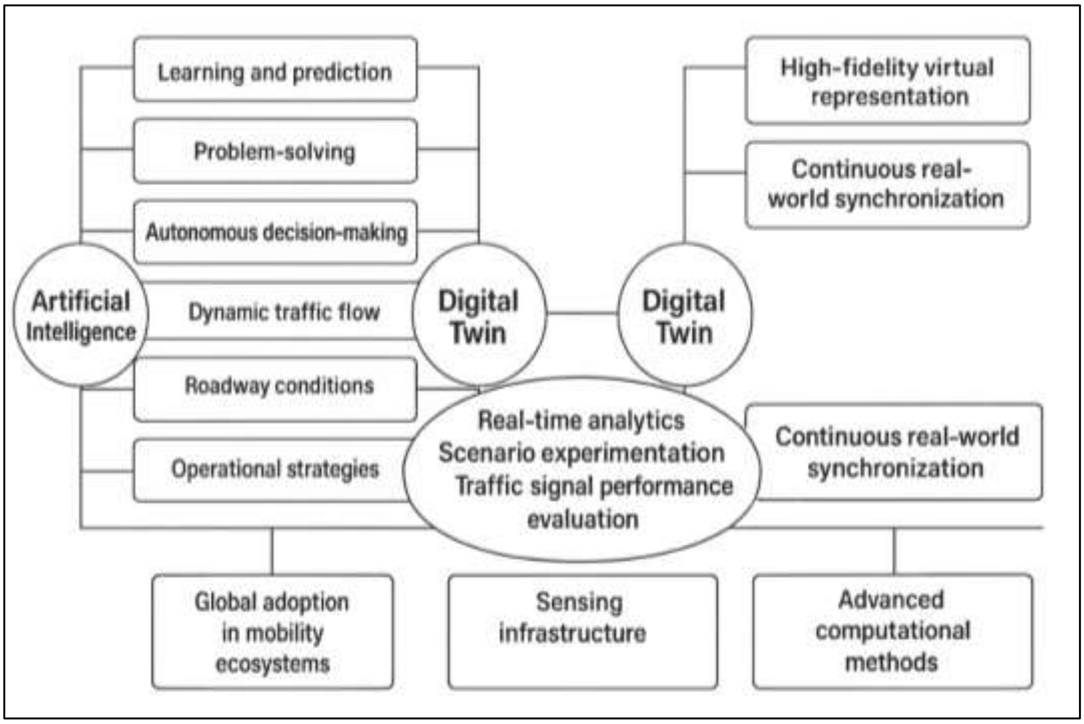
Keywords

Artificial Intelligence; Digital Twin; Traffic Signal Optimization; Reinforcement Learning; Real-Time Control.

INTRODUCTION

Artificial intelligence is defined as a computational framework that enables machines to perform tasks traditionally associated with human cognition, including learning, prediction, problem-solving, and autonomous decision-making (Groshev et al., 2021). Within transportation systems, artificial intelligence serves as a mechanism for interpreting dynamic traffic flow patterns, recognizing roadway conditions, and adjusting operational strategies in response to real-time stimuli. The digital twin, in contrast, is a high-fidelity virtual representation of a physical system that maintains continuous synchronization with real-world data. This digital replica mirrors the behavior, conditions, and operations of the physical transportation network and updates its state based on sensor inputs, communication systems, and data-collection technologies.

Figure 1: Real-Time Traffic Intelligence Architecture



When artificial intelligence and digital twins merge, the resulting cyber-physical system allows for real-time analytics, scenario-based experimentation, and data-driven evaluation of traffic signal performance (Agostinelli et al., 2020). The integration of these technologies creates an environment where traffic flow, signal timing, roadway saturation, and pedestrian activities can be analyzed with precision. The digital twin supports detailed simulation and visualization, while artificial intelligence manages the computational complexity of optimizing traffic systems. This combination forms the conceptual basis for quantitative studies examining how adaptive control strategies, data-driven predictions, and automated decision processes contribute to measurable improvements in mobility. As congestion continues to challenge transportation networks globally, artificial intelligence–enabled digital twins provide a scientific foundation for exploring real-time control mechanisms (Radanliev et al., 2022). Their capacity to represent roadway behavior accurately and reflect operational dynamics makes them central to traffic engineering research. The definitions of artificial intelligence and digital twins therefore serve as the intellectual starting point for understanding how their interaction contributes to real-time traffic signal optimization and transportation planning within a quantitative research framework (Minerva et al., 2023).

The global transportation landscape is characterized by rising congestion levels, growth in vehicle ownership, increased urbanization, and expanding commercial mobility needs. These changes have created operational challenges for cities across continents, leading to higher travel times, unpredictable delays, and inefficient roadway use (Zhang et al., 2022). In many countries, constructing new infrastructure is financially and spatially constrained, prompting a shift toward intelligent, data-driven traffic management solutions. Artificial intelligence has gained central importance in addressing these challenges due to its ability to process large datasets, identify patterns in complex mobility systems, and generate adaptive traffic control strategies. Digital twins extend the global utility of artificial intelligence by creating continuously updated virtual environments where agencies can analyze traffic behavior without modifying real-world operations (Abdulla & Ibne, 2021). International adoption of digital twins spans various mobility contexts, including large Asian megacities, multimodal European corridors, high-volume North American intersections, and rapidly developing Middle Eastern urban regions. Across these geographies, AI-driven digital twins support real-time decision environments where governments can evaluate interventions, model demand variations, and test operational changes (Habibullah & Foysal, 2021). Their global significance is further reinforced by the diversity of transportation problems they address, ranging from intersection-level inefficiencies to extensive transportation planning challenges. Real-time modeling capabilities enable transportation researchers to observe the interactions between vehicles, pedestrians, cyclists, and public transport within a controlled analytical domain (Sanjid & Farabe, 2021; Sarwar, 2021). This international relevance highlights the importance of studying how AI-driven digital twins operate in statistical and performance-based terms (Musfiqur & Saba, 2021; Wu et al., 2022). Their widespread use in global smart mobility ecosystems underscores their value as a quantifiable tool for assessing the operational efficiency of traffic signal optimization approaches. As transportation systems continue to evolve globally, AI-driven digital twins provide a critical foundation for evaluating real-time signal behaviors, roadway dynamics, and mobility outcomes across varied international contexts (Omar & Rashid, 2021; Redwanul et al., 2021).

Digital twin architecture in transportation consists of three major components: the physical system, the virtual system, and the integration interface that maintains data synchronization between the two (Tarek & Praveen, 2021; Zaman & Momena, 2021). The physical system represents intersections, directional flows, lane structures, roadway geometry, and sensor infrastructure. The virtual system mirrors these components through detailed models capable of replicating traffic states, vehicle trajectories, and multimodal interactions at a high resolution. Data synchronization occurs through continuous streams of information collected from cameras, inductive loops, connected vehicles, GPS devices, radar sensors, and edge-computing systems. This continuous transfer of real-time data ensures that the digital twin remains an accurate and dynamic representation of roadway behavior (Rony, 2021; Shaikh & Aditya, 2021). Artificial intelligence algorithms process these inputs to identify patterns, classify traffic states, and determine optimal control strategies. This architecture supports quantitative analysis by allowing traffic researchers to manipulate operational variables, test different signal configurations, and observe their effects on measurable outcomes such as queue lengths, delay, throughput, or saturation flow (Sudipto & Mesbaul, 2021; Zaki, 2021). The digital twin's ability to replicate dynamic environments enables experiment-driven research that remains highly consistent across repeated trials. Researchers can simulate traffic peaks, evaluate alternative phase timings, and examine the effects of traffic disturbances within controlled virtual settings (Al Amin, 2022; Arman & Kamrul, 2022). This architectural structure provides stability, accuracy, and reproducibility, which are essential qualities for quantitative analysis. It also supports multi-scenario testing, enabling transportation planners to evaluate intersections, corridors, and complex networks under different conditions (Mohaiminul & Muzahidul, 2022; Omar & Ibne, 2022). The systematic design of digital twin architecture ensures that traffic signal optimization methods can be evaluated deeply and thoroughly, contributing to a more refined understanding of real-time operational behavior within traffic systems (Aloqaily et al., 2022; Sanjid & Zayadul, 2022).

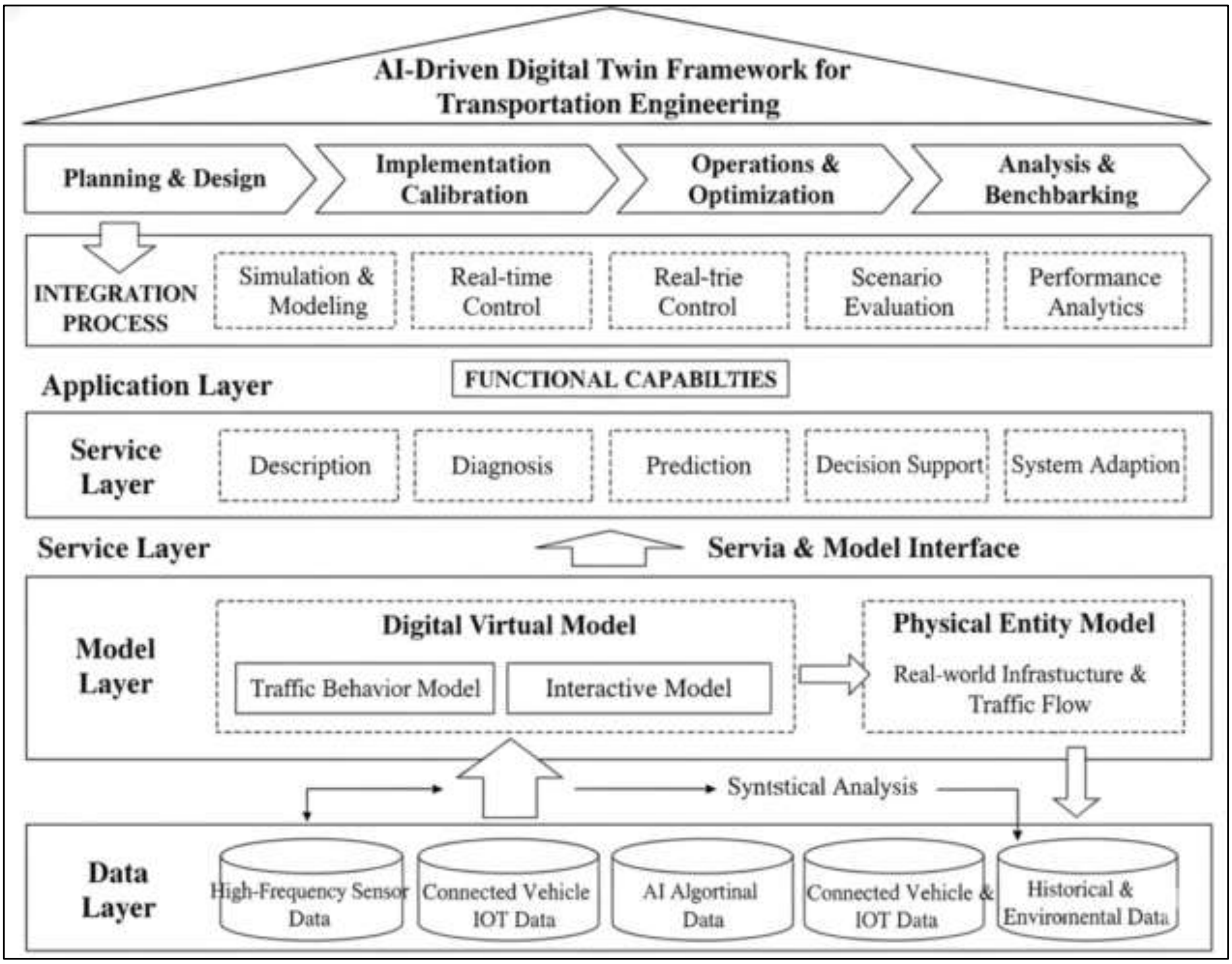
Artificial intelligence introduces a range of computational techniques capable of improving the precision and responsiveness of real-time traffic signal optimization. Reinforcement learning, for example, allows an algorithm to interact with the traffic environment, assess the outcomes of various actions, and update its control policies based on performance rewards. Neural networks excel at pattern recognition, enabling the prediction of short-term vehicle arrivals, flow variations, and congestion buildup. Genetic algorithms evaluate multiple timing combinations, searching for optimal or near-optimal solutions among large sets of possible configurations (Hasan, 2022; Mominul et al., 2022). Fuzzy logic approaches accommodate uncertainty in traffic behaviors, allowing signal controllers to make more flexible decisions under ambiguous situations. When these techniques are embedded within a digital twin environment, they gain the ability to process real-time data, react automatically to changing roadway conditions, and evaluate system performance through simulation-based assessments (Rabiul & Praveen, 2022; Farabe, 2022). This integration allows transportation researchers to observe how AI algorithms modify green splits, cycle lengths, offsets, and phase sequences in response to variable traffic patterns (Barricelli et al., 2019; Roy, 2022). Incorporating AI into the digital twin environment also enhances the capacity for comparative testing, where different algorithms can be evaluated under identical traffic conditions. This supports rigorous quantitative assessments, enabling researchers to measure improvements in delay reduction, queue minimization, or throughput enhancement attributed to specific AI techniques (Rahman & Abdul, 2022; Razia, 2022). By allowing continual adaptation, artificial intelligence methods improve the capability of traffic signal control systems to react effectively to congestion waves, unpredictable fluctuations, or temporary disturbances (Shengli, 2021; Zaki, 2022; Kanti & Shaikat, 2022). These techniques contribute to the development of a fully observable, analytically rich traffic control environment where algorithmic behavior can be examined systematically and quantitatively.

Real-time traffic management relies on robust, accurate, and high-frequency data collection mechanisms. Modern sensing infrastructures generate continuous traffic information through a combination of inductive loops, cameras, radar systems, Bluetooth detectors, connected vehicle telemetry, and automated number plate recognition systems (Maniruzzaman et al., 2023; Arif Uz & Elmoon, 2023; Mo et al., 2023). These sensors gather information about vehicle position, speed, acceleration, turning movement, pedestrian activity, and multimodal interactions. The digital twin integrates these data streams to produce an updated representation of the roadway environment, allowing artificial intelligence algorithms to process actionable information. The accuracy and frequency of data significantly influence the reliability of the digital twin model and the performance of artificial intelligence–based signal optimization (Sanjid, 2023; Sanjid & Sudipto, 2023). High-resolution data supports real-time prediction and timely signal adjustments, leading to optimized traffic flow. For quantitative researchers, real-time data provides high-quality inputs necessary for model calibration, scenario testing, and performance measurement. Continuous data exchange enables the system to identify abnormal traffic patterns, process operational disturbances, and modify decision variables accordingly. The interaction between real-time sensing infrastructure and AI-driven digital twins creates a highly adaptable traffic environment where system behavior can be measured statistically (Fan et al., 2021; Tarek, 2023; Shahrin & Samia, 2023). This data-rich context supports accuracy in quantitative modeling, fostering an empirical understanding of how different traffic states respond to algorithmic decision strategies. The integration of sensing infrastructure with artificial intelligence ensures that the digital twin operates as a reliable analytical platform capable of supporting highway performance evaluations, comparative testing, and statistical assessments of real-time signal control approaches (Huang et al., 2021; Muhammad & Redwanul, 2023).

Quantitative modeling provides the methodological structure necessary for systematically evaluating the performance of traffic signal optimization techniques (Muhammad & Redwanul, 2023; Razia, 2023). Artificial intelligence–driven digital twins produce extensive numerical data that reflect actual roadway behavior under various operational scenarios. This data supports regression modeling, time-series analysis, simulation-based evaluation, statistical testing, and multivariate analysis, enabling researchers to determine the relationships between signal control variables and performance metrics (Mehdizadeh et al., 2020; Srinivas & Manish, 2023). Through digital twin experimentation, researchers can control traffic volumes, modify timing parameters, introduce disturbances, and observe their effects on measurable outputs such as delay, saturation flow, travel time, and level of service. This structured approach ensures replicability and scientific rigor, allowing results to be validated through repeated trials (Sudipto, 2023; Zayadul, 2023). Quantitative modeling also supports performance benchmarking, where algorithmic strategies are compared under controlled and identical conditions. By generating large datasets across numerous simulations, artificial intelligence–enabled digital twins support advanced statistical comparisons that reveal trends, behavioral responses, and optimization efficiency. This approach provides a foundation for analyzing variability, measuring effectiveness, and identifying statistically significant improvements in traffic performance (Mesbaul, 2024; Tarek & Kamrul, 2024; Yang et al., 2021). The integration of AI algorithms into quantitative modeling frameworks enhances analytical robustness by supporting data-driven learning, behavioral evaluation, and multi-criteria assessment (Abdul, 2025; Sudipto & Hasan, 2024). Through rigorous statistical procedures, artificial intelligence–driven digital twins contribute to the empirical understanding of real-time traffic signal optimization, offering a structured platform for deeper exploration of traffic behavior and signal performance (Hozyfa, 2025; Alam, 2025; Beek et al., 2018).

Digital twin systems extend beyond immediate signal control to support a broader transportation planning framework (Masud, 2025; Arman, 2025). They allow planners to evaluate corridor-level and network-wide traffic behaviors by simulating multi-modal interactions, roadway expansions, regulatory modifications, and operational changes. Digital twins help transportation planners examine scenarios involving peak-hour congestion, transit prioritization, lane repurposing, pedestrian concentration shifts, and incident-induced network disturbances (Mohaiminul, 2025; Mominul, 2025; Zhang et al., 2018).

Figure 2: AI Digital Twin Traffic Optimization Framework



These systems support high-resolution analytics such as vehicle trajectory mapping, flow density visualization, turning pattern evaluation, and intersection performance benchmarking. Through artificial intelligence integration, digital twins provide predictive insights that assist in understanding how traffic re-distributes when specific planning decisions are implemented. Transportation planners can analyze how operational variables influence measurable outcomes, allowing for detailed quantitative evaluations within a controlled virtual space (Hasan, 2025; Milon, 2025). This supports improved scenario analysis, corridor optimization, and network efficiency assessment. Digital twins can evaluate system responses across different land-use patterns, urban morphologies, or transportation policies, making them adaptable across planning contexts (Aleksander & Paweł, 2020; Farabe, 2025; Tarek & Ishtiaque, 2025). This adaptability offers transportation researchers the opportunity to quantify the impacts of design interventions, evaluate operational improvements, and assess multimodal performance under varying conditions. By functioning as an experimental environment for transportation planning, digital twins enable data-driven insights into how traffic networks behave under different configurations, contributing to the scientific analysis of real-time mobility systems (Momena, 2025; Muhammad, 2025).

The implementation of artificial intelligence–driven digital twins in transportation systems has expanded across different regions worldwide, revealing their adaptability and analytical strength across varied mobility contexts (Roy, 2025; Rahman, 2025). European cities employ digital twins to support multimodal transport integration, emphasizing balanced interactions between public transit, bicycles, pedestrians, and private vehicles. Asian megacities utilize digital twins to manage extremely high vehicle densities, irregular flow patterns, and closely spaced intersections (Rakibul, 2025; Rebeka, 2025; Wang et al., 2022). North American cities integrate these systems within connected-vehicle infrastructures to modernize signal timing strategies and promote efficient corridor management. Middle Eastern regions adopt digital twins as part of smart city frameworks, using AI-based models to accommodate rapid urban expansion and complex roadway developments (Reduanul, 2025; Rony, 2025). These international applications demonstrate the system's ability to function effectively under diverse geometric configurations, regulatory structures, and traffic cultures. They highlight the robustness of digital twin systems in capturing variable traffic behavior, replicating real-world conditions, and supporting measurable performance evaluation. For researchers, these global examples provide empirical benchmarks and comparative contexts that support deeper quantitative investigations (Saba, 2025; Praveen, 2025). They illustrate how AI-driven digital twins contribute to measurable improvements in mobility performance within varied urban conditions. The widespread adoption of this technology reinforces its significance as a rigorously quantifiable tool for understanding real-time traffic signal optimization and broader transportation planning processes across global regions (Gkanatsas & Krikke, 2020; Shaikat, 2025; Kanti, 2025).

The primary objective of this quantitative study is to systematically examine the effectiveness of artificial intelligence–driven digital twin systems in optimizing real-time traffic signal control and supporting data-informed transportation planning. The study aims to generate empirical evidence on how AI-enhanced digital replicas of physical intersections and corridors can improve signal timing efficiency, reduce delay, minimize queue lengths, and enhance overall traffic flow stability under varying roadway conditions. A central goal is to evaluate the extent to which continuous data synchronization between physical and virtual environments contributes to more accurate, responsive, and adaptive signal control strategies compared to traditional fixed-time or semi-actuated systems. This research also seeks to determine how different AI algorithms, such as reinforcement learning, neural-network-based predictors, and evolutionary optimizers, perform when embedded within a digital twin environment that mirrors real-time roadway states. By quantifying system outputs such as average delay, travel time, throughput, and saturation flow levels, the study provides measurable insights into the operational advantages of integrating artificial intelligence into traffic management processes. Another key objective is to analyze how high-frequency data streams from sensors, cameras, connected vehicles, and IoT devices influence model accuracy and decision-making efficiency within the digital twin. Understanding the interaction between data quality, system responsiveness, and optimization performance enables a rigorous examination of the variables that contribute most significantly to reliable traffic control outcomes. Additionally, this study aims to assess the scalability of AI-driven digital twins across different intersection types, roadway geometries, and traffic volumes to determine whether their performance remains stable under diverse conditions. By simulating multiple traffic scenarios—including peak congestion, incident disruptions, pedestrian surges, and lane-blocking events—the study examines how digital twins perform under stress conditions and how

AI-based control systems adapt to fluctuations in network behavior. Through these objectives, the study intends to produce a comprehensive quantitative evaluation that strengthens the empirical understanding of artificial intelligence–enabled digital twins as a scientific tool for real-time traffic signal optimization and transportation planning.

LITERATURE REVIEW

The literature on artificial intelligence–driven digital twin systems in transportation increasingly demonstrates the relevance of data-intensive, model-based approaches to understanding real-time traffic signal optimization. Across transportation engineering, researchers have examined how dynamic, data-rich environments enhance system accuracy and operational efficiency when supported by AI algorithms and synchronized digital replicas of roadway networks (Wang et al., 2023). The evolution of digital twin modeling has produced diverse analytical frameworks that replicate real-world conditions with high spatial and temporal precision, enabling researchers to explore optimization strategies using measurable performance indicators such as queue length, delay time, throughput, saturation flow rate, and level-of-service scores. Parallel advancements in artificial intelligence methods, including reinforcement learning, neural-network forecasting, evolutionary optimization, and fuzzy reasoning, have further enhanced adaptive control capabilities through continuous model training and real-time feedback loops (Tiong & Palmqvist, 2023). These developments have generated a significant body of quantitative research demonstrating how algorithmic logic improves signal coordination, adaptive phase selection, and variable traffic demand analysis (Szydzik et al., 2015; Zayadul, 2025).

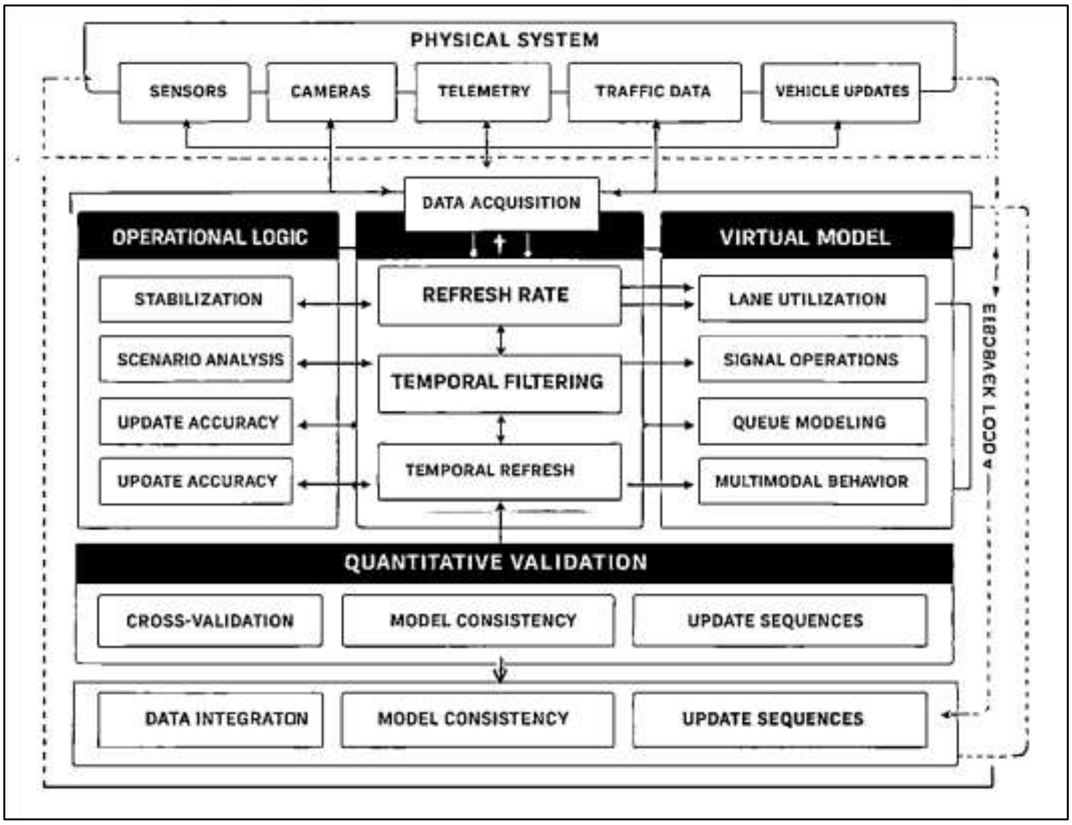
Within transportation planning, digital twins serve as tools for evaluating large-scale network behavior, supporting scenario-based forecasting, and assessing alternative operational strategies using statistical and simulation-based metrics. Quantitative studies consistently highlight the role of multi-source data, high-frequency sensor inputs, and predictive analytics in shaping real-time decision systems. The literature also addresses a variety of global use cases where digital twin environments have been tested across diverse urban contexts, traffic densities, and multimodal conditions (Allen et al., 2022). These empirical investigations provide strong evidence for understanding the analytical conditions and performance thresholds under which artificial intelligence–based digital twins produce optimal results. Examining these studies within a structured quantitative framework is necessary for identifying research patterns, methodological strengths, comparative algorithmic efficiency, and system-level outcomes relevant to real-time traffic signal optimization. This literature review therefore synthesizes prior research to form a coherent analytical basis for the present quantitative investigation.

Foundations of Digital Twin Modeling in Traffic Systems

Digital twin modeling in transportation is defined as a data-driven virtual replication of a physical roadway system that maintains continuous alignment with real-world operating conditions through structured data flows, algorithmic interpretation, and iterative calibration (Sidiropoulos et al., 2018). The literature describes transportation digital twins as analytical environments capable of quantifying system behavior through measurable parameters such as update frequency, synchronization delay, model fidelity stability, calibration accuracy, and temporal refresh consistency. Research has emphasized that these systems do not function merely as static simulations but instead operate as dynamic, real-time analytical constructs capable of reflecting the structural, functional, and temporal characteristics of intersections, corridors, and network-scale mobility environments (Ghiasi et al., 2017). Scholars have analyzed digital twins through measurable indicators that determine their operational responsiveness, such as system refresh rates that govern how frequently real-world data are assimilated; synchronization latency that quantifies the time difference between observed events and their appearance in the virtual environment; and the sensitivity of model fidelity to fluctuating sensor inputs. Studies highlight the role of empirical calibration in ensuring operational accuracy, noting that calibration thresholds must be validated under multiple traffic conditions for the digital twin to maintain representational integrity. Literature also describes operational parameters such as environmental responsiveness, data-drift tolerance, and integration stability between heterogeneous traffic sources. These operational definitions allow digital twins to support quantitative assessments of mobility conditions across varying demand levels, roadway geometries, and intersection structures. By conceptualizing digital twins as measurable analytical frameworks rather than static replications, researchers have demonstrated their utility in evaluating traffic behaviors with precision, particularly when examining performance-based metrics for signal timing, intersection capacity, and real-time control logic (G. Liu et al., 2023). Transportation scholars consistently frame digital twins as scientific, quantifiable platforms capable of supporting robust, repeatable, and high-resolution analysis of roadway performance.

Research on digital twin synchronization models emphasizes the importance of temporal resolution, data latency, and state-update dynamics in determining the analytical reliability of virtual transportation systems (Philip & Swapnesh, 2022). Various studies examine how sampling intervals derived from sensors, cameras, radar systems, and connected vehicle telemetry influence the accuracy of the replicated traffic state. The literature discusses data synchronization as a continuous alignment process requiring stable and timely integration of real-world inputs into the digital environment. Temporal resolution is described as the measurable frequency at which state information is refreshed, with higher frequencies supporting more precise reflection of dynamic traffic phenomena such as rapid queue formation, lane-changing behavior, or surge-induced congestion. Scholars highlight synchronization latency as a key quantitative parameter, focusing on the delay between data capture in the physical environment and its translation into the virtual model (Gong et al., 2023).

Figure 3: AI- Enhanced Transportation Digital Twin



High latency is frequently associated with degraded system responsiveness, reduced stability of control algorithms, and limitations in predictive accuracy. Research also explores state-update algorithms, characterizing them by their capacity to incorporate new data while filtering noise, reducing uncertainty, and maintaining computational efficiency. These studies demonstrate that real-time synchronization requires the integration of temporal filtering, event prioritization, and structured data sequencing to avoid temporal drift and maintain quantitative precision in the digital twin (Liao et al., 2018). Furthermore, literature identifies communication reliability as an essential metric, noting that data packet loss, variable bandwidth, and sensor-level instability can compromise the digital twin's consistency. Across these works, synchronization models are framed as quantitative systems whose performance depends on measurable attributes that govern the alignment between physical and virtual operations. Collectively, the literature emphasizes that temporal resolution, latency metrics, and state-update logic form the quantitative backbone of real-time digital twin modeling.

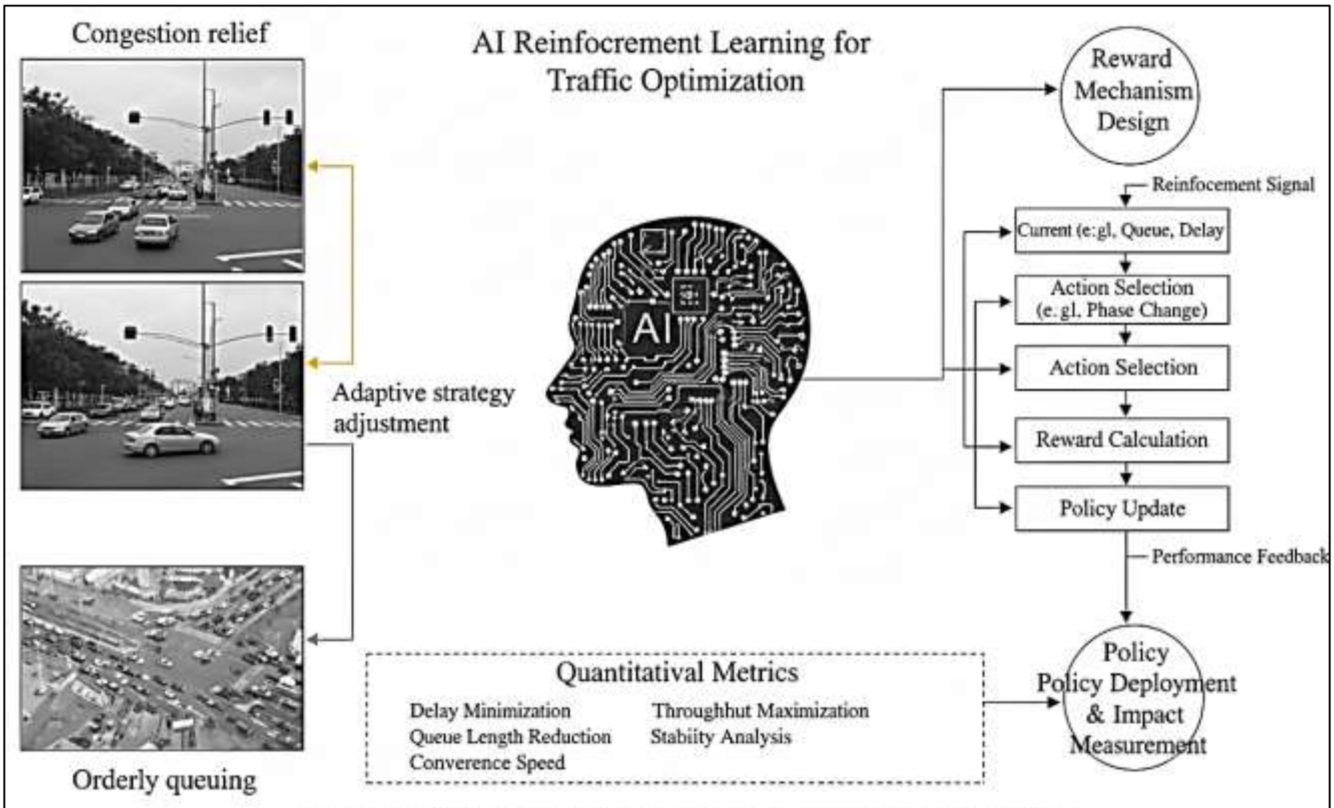
Literature addressing virtual–physical consistency in digital twin environments highlights the need for quantitative validation frameworks that ensure the virtual model accurately reflects real-world traffic conditions (X. Liu et al., 2023). Scholars evaluate consistency through measurable comparisons between observed and simulated traffic variables, focusing on patterns such as vehicle arrivals, turning movements, queue propagation, saturation flow behavior, and phase utilization. Research indicates that the reliability of a digital twin depends on consistent alignment between predicted and observed mobility conditions, which is typically assessed through statistical comparison methods that quantify deviations between simulated and empirical data. Studies examine distributional alignment by evaluating structural similarities between real and virtual data patterns under varied traffic states, such as peak demand surges, moderate flow levels, and transitional signal phases. Additional literature emphasizes the importance of validating multimodal behavior within the twin, noting that differences in pedestrian flows, bus dwell times, bicycle paths, and freight movements must be systematically assessed to maintain operational fidelity (Yang et al., 2019). Researchers also describe sensitivity-based evaluations where model parameters are adjusted across a range of traffic conditions to determine stability and consistency in output distributions. Many works highlight that consistent model alignment is essential for ensuring reliability in downstream applications such as adaptive signal control, predictive congestion analytics, and scenario-based transportation planning. Scholars also underscore the influence of sensor calibration quality, data noise, and environmental variability on model consistency, reinforcing the need for iterative validation cycles (Chen et al., 2020). Virtual–physical consistency is therefore conceptualized in the literature as a measurable condition requiring structured evaluation to ensure accuracy, stability, and representational completeness in digital twin transportation environments.

Synthesizing the broader literature reveals that digital twin effectiveness in transportation systems depends on the combined interaction of operational definitions, synchronization capabilities, and virtual–physical consistency measures (Sun et al., 2018). Research consistently portrays digital twins as analytically measurable systems whose performance is evaluated across multiple quantitative domains, including temporal responsiveness, calibration stability, state-update accuracy, and representational fidelity. Scholars note that foundational operational parameters shape the ability of the digital twin to accept incoming data, stabilize virtual environments, and support real-time scenario analysis. Synchronization models further determine the temporal precision of the system, influencing its ability to incorporate dynamic traffic conditions with minimal delay. Literature also highlights that consistency metrics form the empirical basis for validating simulation accuracy, ensuring that the digital twin can be trusted as an analytical substrate for traffic analysis. When these components interact effectively, digital twins become capable of supporting high-resolution, statistically meaningful evaluations of traffic signal operations, queue dynamics, and multimodal mobility behaviors (Liu et al., 2020). The literature also identifies interconnected constraints involving sensor reliability, data variability, communication stability, and environmental fluctuations, all of which influence the measurable performance of digital twin systems. Across these studies, digital twins are presented as integrated, quantitative platforms requiring systematic calibration, structured synchronization, and rigorous consistency verification. These combined foundations form the basis through which digital twins contribute to traffic engineering research by enabling precise assessment of traffic performance indicators, model-based experimentation, and system-level operational analysis. Collectively, the literature frames digital twin modeling in transportation as a quantitatively structured field grounded in measurable operational principles and validated through empirical comparison between virtual and physical roadway conditions (Chao et al., 2020).

Artificial Intelligence Methods in Signal Control Optimization

Reinforcement learning has emerged as one of the central artificial intelligence approaches for adaptive traffic signal optimization, with researchers extensively examining how reward structures influence policy performance, convergence dynamics, and operational stability (Stocco et al., 2022). In the reinforcement learning framework, the controller interacts with the traffic environment and updates its strategy based on numerical rewards linked to measurable traffic outcomes such as reduced delay, improved throughput, stabilized queue formation, or efficient phase changes. Literature emphasizes that the design of the reward function directly shapes learning efficiency, iteration speed, and long-term policy stability. Studies have explored multiple reward formulations, including delay minimization, queue clearance, vehicle discharge predictability, lane utilization, cycle balancing, and combined multi-criteria reward structures (Koutsoukos et al., 2017). Research consistently identifies that sensitivity to reward magnitude influences how quickly an algorithm converges toward an optimal policy, with poorly structured reward functions often leading to oscillatory control behavior or slow policy refinement. Scholars also highlight measurable constraints such as reward sparsity, temporal discounting, and environmental volatility, which influence the reliability of the learning process. Reinforcement learning models have been tested under various traffic conditions, including fluctuating flows, mixed modal patterns, peak-hour transitions, and incident disturbances, allowing researchers to evaluate convergence curves and performance variance (Castillo et al., 2015). Additional literature underscores the importance of iteration speed, emphasizing that rapid policy updates support greater responsiveness in real-time environments. The evaluation of reinforcement learning systems is often conducted through simulation-based experiments where learning curves, stability metrics, and cumulative reward patterns are examined to determine algorithmic reliability. Across these studies, reinforcement learning is presented as a quantitatively rich field of research where reward sensitivity, policy evolution, and convergence behavior form central analytical dimensions (Castillo et al., 2015). The literature demonstrates that reward function design is a critical determinant of how efficiently reinforcement learning systems refine their decision-making processes in traffic signal optimization contexts.

Figure 4: AI Learning Models for Traffic Control



(Stocco at, 2022) (Koutsukos, 2017 (Castilo at, 2015) (Argota Sánchez-Vaquerizo, (202o, 2012) (Kumar at, 2018)

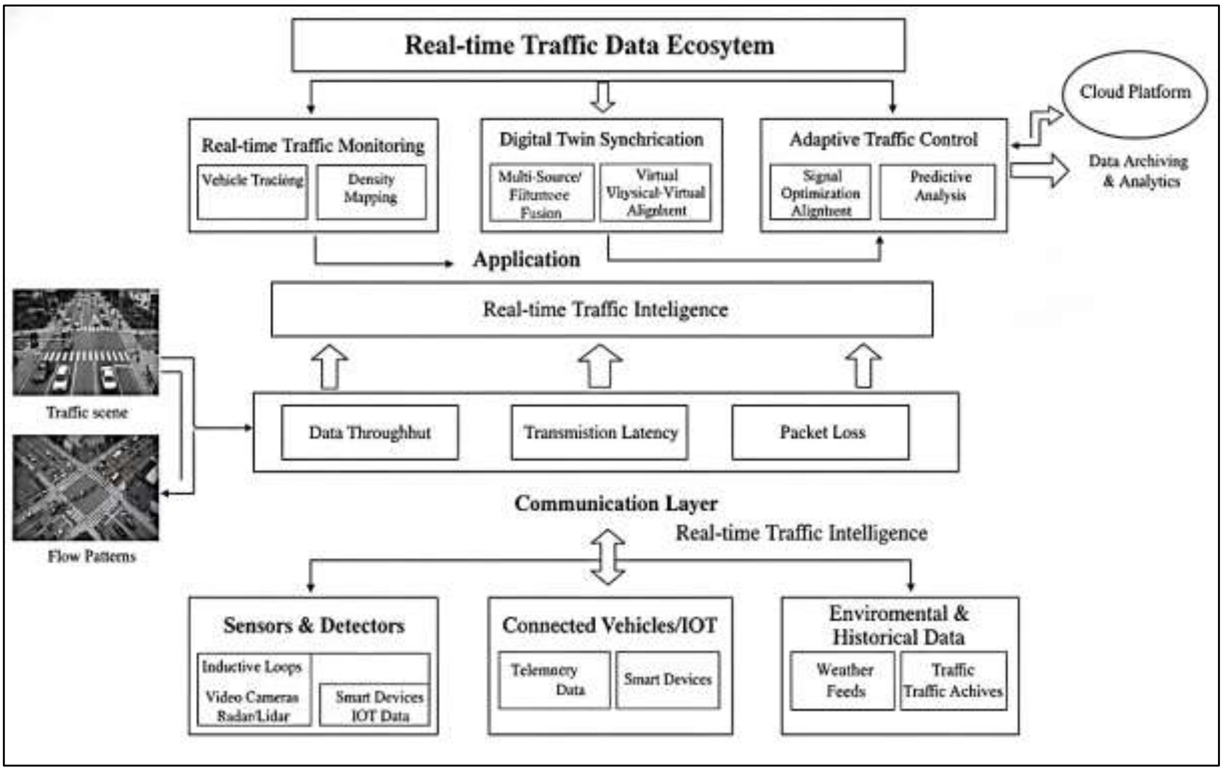
Neural network models have become widely used in traffic signal optimization due to their ability to learn nonlinear traffic patterns, predict short-term flow variations, and support proactive signal adjustments. Research in this area focuses heavily on forecasting accuracy, error profiles, and temporal modeling precision (Argota Sánchez-Vaquerizo, 2022). Neural networks are applied to predict variables such as vehicle counts, queue buildup, travel times, arrival patterns, and lane-specific demand. Literature describes the evaluation of prediction models using quantitative measures such as prediction error trajectories, bias tendencies, generalization capability, and error distribution patterns across different time horizons. Scholars analyze temporal prediction windows ranging from seconds to several minutes, demonstrating that shorter windows often provide greater stability while longer windows require stronger generalization. Studies compare multiple neural architectures including feedforward networks, recurrent models, long short-term memory networks, convolutional structures, and hybrid networks incorporating attention mechanisms. These models are tested across varied roadway conditions such as peak traffic waves, fluctuating densities, stop-and-go patterns, multimodal interactions, and network disturbances (Yao et al., 2019). Researchers also highlight that forecasting error distribution varies depending on traffic volatility, sensor noise, and temporal granularity. Comparative studies demonstrate that neural network stability improves when trained on high-resolution datasets, which provide richer variability for learning. Additional literature investigates model generalization, often evaluating performance across different intersections, corridor types, and demand conditions to determine adaptability. Several studies identify that neural networks contribute substantial predictive value by anticipating flow changes before they reach the stop line, allowing signal controllers to adjust phase timings accordingly (Kumar et al., 2018). These findings reinforce the importance of prediction accuracy and error distribution analysis as quantitative indicators of model quality. Collectively, neural network research emphasizes detailed statistical assessment and careful interpretation of forecasting behavior to support real-time traffic signal optimization.

Sensor Infrastructure and Real-Time Data Acquisition

Literature examining sensor accuracy and reliability in traffic monitoring systems highlights the importance of evaluating how precisely detection devices capture key parameters such as vehicle presence, speed, occupancy, and lane utilization under varying environmental and operational conditions. Studies describe inductive loop detectors, radar sensors, video-based systems, acoustic sensors, and connected vehicle telemetry as the most widely used technologies for real-time monitoring (Cui et al., 2019). Each sensor type exhibits measurable strengths and limitations, often influenced by weather exposure, calibration quality, occlusion levels, road surface conditions, and installation configurations. Research has consistently demonstrated that accuracy varies significantly among devices, with loop detectors showing stable performance in controlled environments but reduced reliability during pavement deterioration, while video-based systems offer broader detection capabilities but encounter challenges associated with lighting changes, shadows, and camera alignment. Radar and microwave sensors generally show strong reliability in speed measurement and lane-based detection but may produce errors when non-standard vehicle profiles or metallic interference occur (Vipond et al., 2023). Studies also emphasize the significance of evaluating capture rates, meaning the proportion of traffic events accurately recorded, particularly under high-volume or high-density conditions where sensor saturation can affect detection precision. Error sources such as missed detections, false positives, misclassification of vehicle types, and lane-assignment inaccuracies are frequently analyzed to determine sensor suitability for digital twin integration and adaptive traffic control. Research also highlights environmental impacts, including heavy rainfall, glare, fog, and snow, which influence detection quality and introduce variability in captured data (Dong et al., 2017). Comparative evaluations of different sensor technologies reveal that a multi-sensor approach often produces higher reliability by compensating for individual device weaknesses. Overall, the literature frames sensor performance as a quantifiable domain requiring systematic assessment of detection precision, resilience to environmental variation, and stability in capturing essential traffic parameters (Colombo et al., 2016).

High-frequency data processing plays a central role in the effectiveness of real-time traffic monitoring and digital twin synchronization. Literature evaluating communication performance emphasizes several quantitative metrics, including data throughput, transmission latency, packet loss frequency, and channel stability across different communication schemes. Studies examine common data transfer technologies such as fiber-optic communication, wireless sensor networks, dedicated short-range communication, cellular networks, and edge-computing architectures (Wong & Kerkez, 2016). Researchers describe throughput as a measure of the volume of traffic data successfully transferred through the network within a specific interval, often influenced by bandwidth capacity, sensor density, and communication hardware. Latency, another significant parameter, captures the time delay between data generation and its arrival at processing units, with lower delays supporting more accurate representation of real-time conditions. Packet loss, defined as the percentage of transmitted data that fails to reach its destination, is often attributed to signal interference, network congestion, low-quality transmission hardware, or environmental disruptions (Djedouboum et al., 2018). Studies show that traffic monitoring environments with high frequencies of data exchange, such as video detection systems or connected vehicle telemetry, require communication infrastructures capable of supporting continuous, large-volume transmissions. Error sources that disrupt communication include electromagnetic interference, device overload, structural obstacles, and unstable wireless signals, all of which influence the integrity of traffic information. Literature also highlights the role of edge computing in reducing latency by processing data closer to the source rather than relying on centralized servers (Malek et al., 2017). This approach is frequently examined in digital twin modeling to stabilize temporal alignment and improve responsiveness. Overall, research on high-frequency communication systems underscores the need to assess numerical indicators such as throughput levels, loss patterns, and latency variability to determine the operational quality of data transmission processes in real-time traffic environments.

Figure 5: Real-time Traffic Data Ecosystem



Data fusion has emerged as a critical component of real-time traffic monitoring because it integrates information from multiple sensor sources to create a more complete, accurate, and stable representation of roadway conditions. Literature describes data fusion as a structured process where heterogeneous datasets—such as camera-based detections, radar signals, inductive loop outputs, connected vehicle messages, and GPS traces—are combined to improve completeness and reduce measurement noise (Nathali Silva et al., 2017). Researchers evaluate data fusion performance using several numerical indicators, including consistency of integrated outputs, reduction in variance, alignment between redundant sensors, and stability across fluctuating environmental conditions. Studies show that data fusion enhances accuracy by leveraging the strengths of each sensor type while compensating for individual weaknesses. For example, radar-based measurements may provide reliable speed information, while video systems contribute detailed classification attributes; combining these sources increases the reliability of the overall dataset (Gu et al., 2016). Literature also examines integration consistency under high-density traffic, showing that fusion algorithms must reconcile conflicting data, missing observations, or temporally misaligned measurements. Research highlights the importance of synchronization between data sources, noting that inconsistent timestamps can degrade the quality of fused outputs by creating mismatched sequences of events. Studies also address filtering methods that reduce noise from raw sensors before integration, emphasizing that preprocessing contributes to more stable data fusion performance (Plageras et al., 2018). Multimodal fusion has been shown to improve prediction accuracy for digital twin models, strengthen adaptive signal control, and enhance the interpretation of complex traffic phenomena such as shockwave formation, platoon dispersion, and multi-lane interactions. Collectively, the literature positions data fusion as a quantitatively measurable process focused on consistency, noise reduction, and the alignment of multi-source traffic information (Plageras et al., 2018).

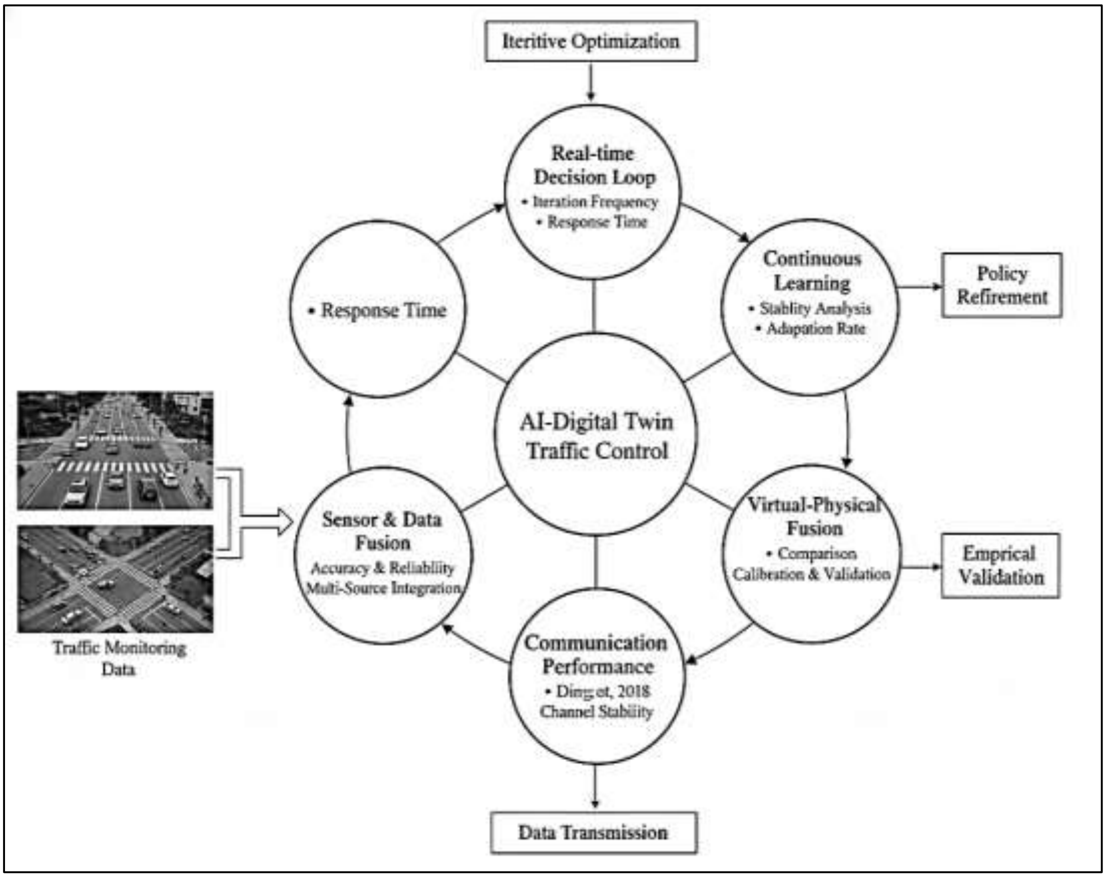
Synthesizing the literature on sensor accuracy, communication performance, and data fusion reveals that effective real-time traffic monitoring depends on the integrated evaluation of multiple quantitative dimensions. Researchers describe sensor infrastructure as the foundation of traffic data collection, determining how accurately and reliably key parameters such as vehicle counts, speeds, occupancy rates, and lane movements are captured (Cervone et al., 2016). Communication quality governs how efficiently this information is transferred across digital networks, with high throughput, low latency, and minimal packet loss forming essential requirements for real-time responsiveness. Data fusion acts as the interpretive layer that consolidates diverse streams of information, ensuring that inconsistencies, missing values, or measurement noise do not compromise the stability of the overall dataset. Literature shows that the interaction between these components determines the operational validity of digital twin systems and artificial intelligence models used for signal optimization. For instance, inaccurate sensors introduce measurement bias, which then propagates through communication channels and negatively affects fused datasets. Similarly, communication delays can misalign real-time data streams, leading to distorted traffic representations even when sensors perform well (Anjomshoaa et al., 2018). Studies frequently underscore that multi-sensor redundancy improves fusion consistency, especially in complex environments where traffic patterns shift rapidly. Researchers also highlight the constraints posed by environmental factors, device calibration, bandwidth fluctuations, and architectural differences in sensor systems. The literature collectively characterizes real-time traffic data acquisition as a multifaceted, quantitatively driven domain requiring structured assessments of sensor performance, communication reliability, and fusion stability (Kheirkhahan et al., 2019). By analyzing these interconnected dimensions, researchers establish a foundation for evaluating how effectively real-time traffic systems support predictive modeling, adaptive control, and transportation planning within digital twin environments.

Digital Twin–AI Integration Mechanisms

Literature on digital twin–AI integration frequently emphasizes real-time decision loop performance as a central determinant of system effectiveness in traffic signal optimization. Studies describe the decision loop as a recurring sequence of operations where sensor data are collected, processed by artificial intelligence algorithms, evaluated through the digital twin, and then translated into updated signal control actions. Researchers examine this cycle through measurable attributes such as iteration duration, end-to-end response time, and computational load associated with each decision step (Pal & Kant, 2018). A key concern in the literature is whether the total time required to complete one loop is sufficiently short to reflect actual traffic dynamics, especially at high-volume intersections where conditions change rapidly. Work in this area often distinguishes between data acquisition delays, processing delays, and actuation delays, noting that even small inefficiencies at each stage can accumulate and degrade the responsiveness of the system. Computational load is assessed in terms of the number of operations required by AI models such as reinforcement learning agents, neural networks, or heuristic optimizers, particularly when they operate over multiple intersections or network segments. Research demonstrates that more complex models can enhance decision quality but may increase processing time, creating a measurable trade-off between sophistication and responsiveness (Barthélemy et al., 2019). Simulation-based studies test decision loops under varied demand scenarios, examining how iteration cycles scale when additional intersections, more detailed state variables, or multimodal traffic components are introduced. Some work evaluates strategies such as model compression, approximate decision policies, or edge computing to maintain low response times while preserving acceptable control performance. Across these investigations, the real-time decision loop is treated as a quantifiable object of analysis, and the balance between iteration frequency, response time, and computational effort is identified as a critical aspect of digital twin–AI integration for traffic signal control (Farzanegan et al., 2023).

Research on continuous learning controllers in hybrid virtual–physical traffic systems highlights stability as a crucial property that determines whether adaptive algorithms can operate safely and predictably over extended periods. Continuous learning in this context refers to controllers that update their decision policies based on ongoing data streams, often using reinforcement learning, online optimization, or adaptive neural architectures within a digital twin environment. Literature characterizes stability using concepts such as consistent performance trends, bounded variation in control actions, and resistance to oscillatory or divergent behavior when traffic conditions evolve (Schubnel et al., 2020). Studies investigate convergence characteristics by examining how quickly learning controllers settle into repeatable decision patterns under recurring traffic conditions such as daily peak periods. Adaptation rates are another focal point, with researchers analyzing how rapidly controllers modify their internal parameters in response to new information and how these changes influence both short-term performance and long-term system behavior. Some works report that overly aggressive learning rates can introduce instability, causing abrupt changes in timing plans that confuse drivers or induce unpredictable queues, while excessively conservative adaptation can minimize the benefits of learning. Hybrid systems combining physical roads with digital twin environments are used to test stability by exposing algorithms to controlled variations in demand, incidents, or sensor noise (Poveda et al., 2019). Studies also analyze how disturbances propagate when learning controllers are deployed across coordinated corridors rather than isolated intersections. In this literature, stability models often incorporate robustness considerations, where controllers are evaluated under imperfect sensing, delayed feedback, or incomplete state information to determine whether their learning dynamics remain well-behaved. Overall, continuous learning controllers are presented as powerful but delicate components whose integration into hybrid virtual–physical architectures requires careful study of convergence behavior, adaptation rate selection, and global stability characteristics (Abo-Khalil, 2023).

Figure 6: Digital Twin AI Decision Loop



Digital twin–AI systems for traffic control are frequently evaluated by comparing simulated outcomes against observed roadway performance, and the literature devotes substantial attention to methods for conducting these comparisons using traffic performance indices. Simulation–reality comparison frameworks typically assess how well the digital twin reproduces key indicators such as average delay, queue lengths, throughput, travel times, and stop frequency under real operating conditions (Särkkä et al., 2018). Studies describe systematic calibration procedures in which model parameters are adjusted so that simulated results closely match field measurements gathered from sensors, cameras, or floating vehicle data. Researchers emphasize that high-quality calibration is essential before AI-based control strategies can be meaningfully tested in the virtual environment. Once calibrated, digital twins are used to run numerous experimental scenarios, and their outputs are compared against baseline field data or against subsequent measurements after implementation of new control strategies. Literature reports detailed analyses of discrepancies between simulated and real-world performance, including underestimation or overestimation of congestion, mismatches in queue spillback patterns, or deviations in travel time variability (Ding et al., 2018). Some studies focus on reproducibility, examining whether simulated performance remains consistent when models are rerun with slightly modified inputs or under repeated stochastic conditions. Others explore spatial and temporal consistency, evaluating how accurately the digital twin reproduces performance across multiple intersections, corridors, or time periods within a day. The use of performance indices in these comparisons allows quantitative statements about model validity and fidelity, supporting judgments about whether the digital twin provides a sufficiently accurate platform for AI policy evaluation (Rai & Sahu, 2020). Across this body of work, simulation–reality comparison is framed as a structured, metrics-driven process that anchors digital twin experiments in empirical traffic behavior and ensures that AI-based control strategies are tested against realistic operating conditions.

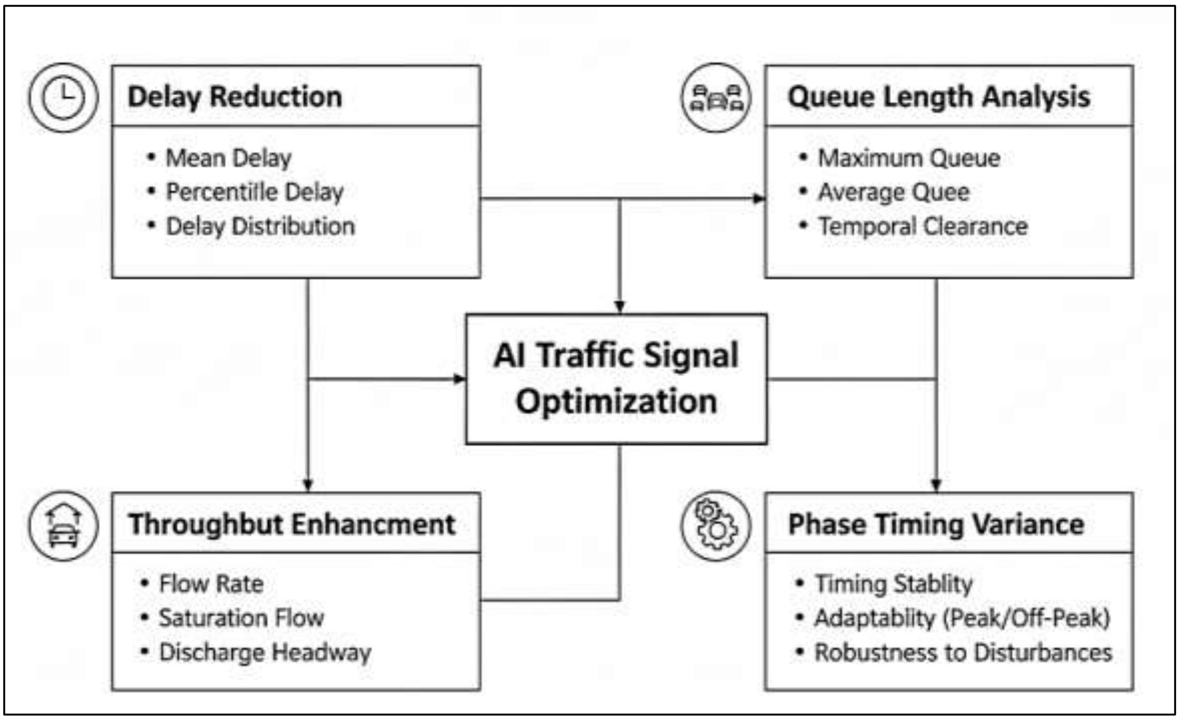
AI-Based Traffic Signal Optimization Outcomes

Literature evaluating the quantitative outcomes of AI-based traffic signal optimization consistently identifies delay reduction as one of the most informative indicators of system performance. Studies examine delay through multiple statistical dimensions, including mean delay per vehicle, median delay, percentile delay values, and delay distribution patterns across different movements and approaches (Lv et al., 2017). Researchers often highlight that mean delay provides a useful central tendency measure of signal performance, yet it may mask unequal distribution of delays across lanes or modes, prompting the need for additional statistical descriptors. Percentile delays, such as 85th or 95th percentile values, are frequently analyzed to capture the experience of vehicles encountering the worst traffic conditions. Literature also emphasizes the importance of delay distribution curves, which provide insights into how delays vary throughout a signal cycle or across fluctuating demand periods. AI-based systems, particularly reinforcement learning controllers, have been shown to adapt signal timings in ways that reduce both average and extreme delays by adjusting green splits, modifying cycle lengths, and optimizing phase transitions. Comparative studies involving fixed-time, actuated, and adaptive controllers show that AI-based models consistently produce smoother delay curves with fewer spikes, indicating improved stability (Farivar et al., 2019). Researchers assess delay performance using high-resolution data collected from sensors or simulation-based models, generating extensive datasets that allow for statistical testing, variance analysis, and performance benchmarking across multiple intersections. Empirical studies also examine spatial patterns of delay reduction, noting that coordinated AI-driven systems often produce corridor-wide benefits rather than improvements limited to isolated intersections. The literature frames delay reduction as a multidimensional statistical phenomenon requiring examination of central tendencies, extremes, and full distributional shapes to capture the full impact of AI-based optimization techniques (Tang et al., 2018).

Throughput enhancement is examined in the literature through traffic flow metrics such as flow rate, saturation flow, and discharge headway, all of which provide measurable insight into how AI-based systems influence overall movement efficiency (Zhao et al., 2015). Flow rate represents the number of vehicles passing through an intersection during a given interval and is often used to compare baseline and AI-driven control performance. Studies frequently highlight that throughput improvements reflect not only better timing strategies but also smoother platoon progression, reduced start-up delays, and improved phase utilization. Saturation flow is another commonly analyzed metric, measuring the maximum number of vehicles that can pass through an intersection during the green phase under ideal or near-ideal conditions. Researchers evaluate how AI-based controllers adjust cycle allocation to achieve saturation flow levels more consistently than conventional systems (Wang et al., 2018). Discharge headway, the average time gap between vehicles leaving a stop line during the onset of green, is used to assess whether AI-driven timing adjustments reduce hesitation, inefficient starts, or queue turbulence. Literature indicates that AI-based models often reduce discharge headways by producing more predictable signal changes and optimizing phase sequences, particularly when algorithms are informed by real-time detection systems. Studies also examine throughput at the corridor level, where coordinated AI systems improve progression quality, reduce stops, and minimize platoon fragmentation. Researchers analyze throughput improvements across multiple lanes, directions, and time periods to develop comprehensive assessments of algorithmic performance (Padinjarapat & Mathew, 2021).

Variance analysis of phase timing strategies has become an important method for evaluating the robustness of AI-based traffic signal optimization systems under different traffic demand conditions. Literature emphasizes that the variability of phase duration, green splits, offset adjustments, and cycle lengths reflects how effectively a control algorithm responds to changing flow patterns (Kulakarni et al., 2019). Researchers frequently compare the stability of phase timing under peak and off-peak conditions, examining whether AI-driven systems maintain consistent performance levels across fluctuations in demand. During peak periods, high volumes often stress traditional signal control systems, leading to irregular phase adjustments or disproportionate delays across competing movements. AI-based controllers, particularly reinforcement learning and evolutionary systems, demonstrate greater flexibility by modifying phase durations in real time to accommodate sudden changes in arrival rates. Conversely, off-peak periods typically require shorter cycles and more frequent phase transitions, creating opportunities for AI-based systems to demonstrate their precision in low-volume environments (Lioris et al., 2017).

Figure 7: AI Traffic Signal Optimization Outcomes

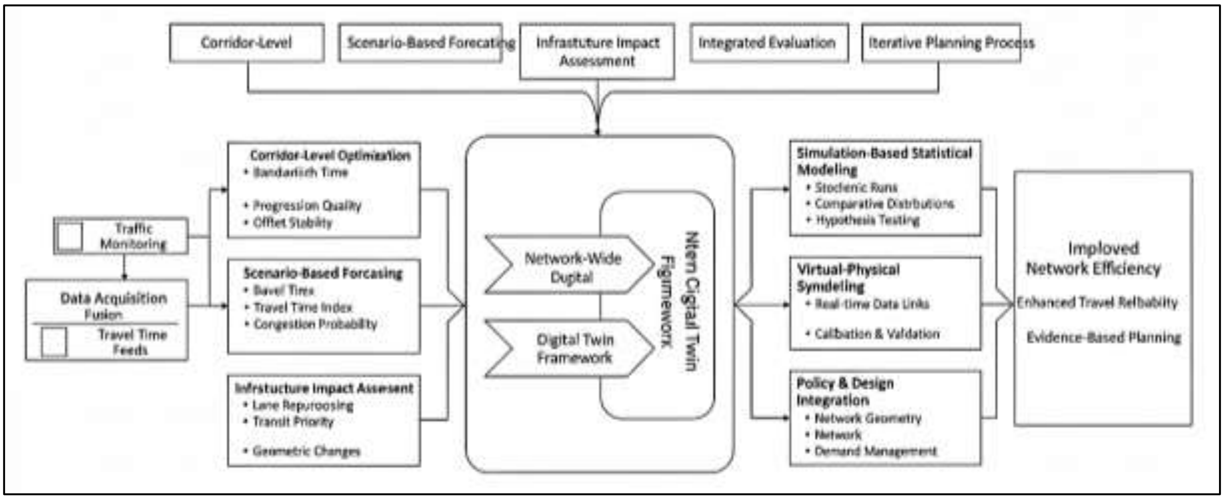


Studies incorporate quantitative indicators such as variance, standard deviation, and temporal dispersion of phase timings to assess whether the system maintains predictable behavior. Many investigations analyze phase timing variance across extended time intervals, identifying whether AI algorithms exhibit stable decision patterns or fluctuate excessively when responding to minor changes in demand. Literature also examines robustness under disturbance conditions, such as pedestrian bursts, left-turn surges, or temporary lane closures, noting how phase timing variance reveals the resilience of AI-based controllers (Fourati et al., 2019). Through these analyses, researchers present phase timing variance as a key quantitative measure of stability and adaptability, demonstrating how AI models accommodate fluctuating conditions with greater responsiveness and consistency than conventional systems.

Network-Wide Planning Applications of Digital Twin Models

Literature on network-wide planning with digital twin models places strong emphasis on corridor-level optimization, particularly the coordination of signals to ensure smooth vehicle progression along arterial routes. Studies describe how digital twins replicate full corridors, including multiple intersections, approach lanes, offsets, phase plans, and arrival patterns, to examine the effectiveness of coordinated timing strategies (Lioris et al., 2016). Researchers frequently focus on quantifiable indicators such as bandwidth times, progression quality indices, and offset stability metrics as core measures of coordinated performance. Bandwidth time is regarded as an indicator of how much of the cycle can be effectively used to move platoons along the corridor without stopping. Within digital twin environments, bandwidth is evaluated in both directions of travel, and trade-offs between inbound and outbound progression are explicitly modeled. Progression quality indices extend this view by capturing how closely actual vehicle arrivals align with designed green bands, taking into account arrival dispersion, travel time variability, and mid-block disturbances (Nguyen, 2016). Offset stability metrics measure how robust coordination patterns remain under temporal disturbances such as fluctuating speeds, minor delays, or detection noise. Digital twins allow researchers to simulate numerous combinations of cycle lengths, splits, offsets, and phase sequences under varying traffic volumes to determine which timing plans generate the highest corridor-level progression efficiency. Studies also examine the impact of speed limits, mid-block access points, pedestrian crossings, and bus stops on green-wave quality, showing that coordination performance is shaped by both control logic and geometric or operational characteristics. Because digital twins can incorporate detailed geometry, link travel times, platoon dispersion models, and realistic driver behavior, they provide a rich platform for evaluating corridor-level optimization strategies with a degree of granularity not achievable through analytical models alone (Wang et al., 2020). This strand of literature frames coordination efficiency as a multidimensional, quantitatively measurable concept that is central to the network-wide use of digital twin models in traffic signal planning.

Figure 8: Network- wide Traffic Planning with Digital Twin Models



Scenario-based forecasting within digital twin environments is a major focus of network-wide planning research, allowing transportation practitioners to test how different demand conditions, incident patterns, and control strategies affect system-wide travel reliability (Moradi et al., 2023). Studies use digital twins to generate and evaluate multiple scenarios involving peak demand surges, special events, weather disruptions, incidents, construction activities, or policy changes such as pricing schemes. Quantitative assessment frequently relies on indicators such as the travel time index, reliability ratios, and congestion probability measures. The travel time index compares observed or simulated travel times to free-flow conditions, offering a simple ratio that reflects the severity of congestion along a route or corridor (Jatoth et al., 2021). Reliability ratios and related measures, such as the planning time index or buffer times, capture variability rather than just central tendency, emphasizing how often extreme delays occur and how much extra time users would need to allocate to ensure on-time arrival. Congestion probability models, built from digital twin simulations, estimate the likelihood that specific links or corridors will operate above critical density or below acceptable speed thresholds under defined scenarios. Literature shows that digital twins enable analysts to run large sets of stochastic or deterministic scenarios and generate empirical distributions of travel times and performance indices. These outputs form the basis for comparing alternative signal plans, demand management strategies, and infrastructure configurations on a reliability basis rather than only average performance (Saha et al., 2018). Because digital twins replicate network geometry, route choice, intersection control, and temporal variation in demand, they provide realistic environments for scenario-based forecasting that align closely with observed field behavior. Studies also highlight that scenario evaluation can extend beyond single corridors to include interacting networks, where changes in one part of the system propagate to others, influencing overall reliability patterns. Through these quantitative metrics, the literature demonstrates that digital twin–based scenario analysis supports rigorous evaluation of planning alternatives in terms of their impact on travel time reliability and congestion risk (Saha et al., 2018).

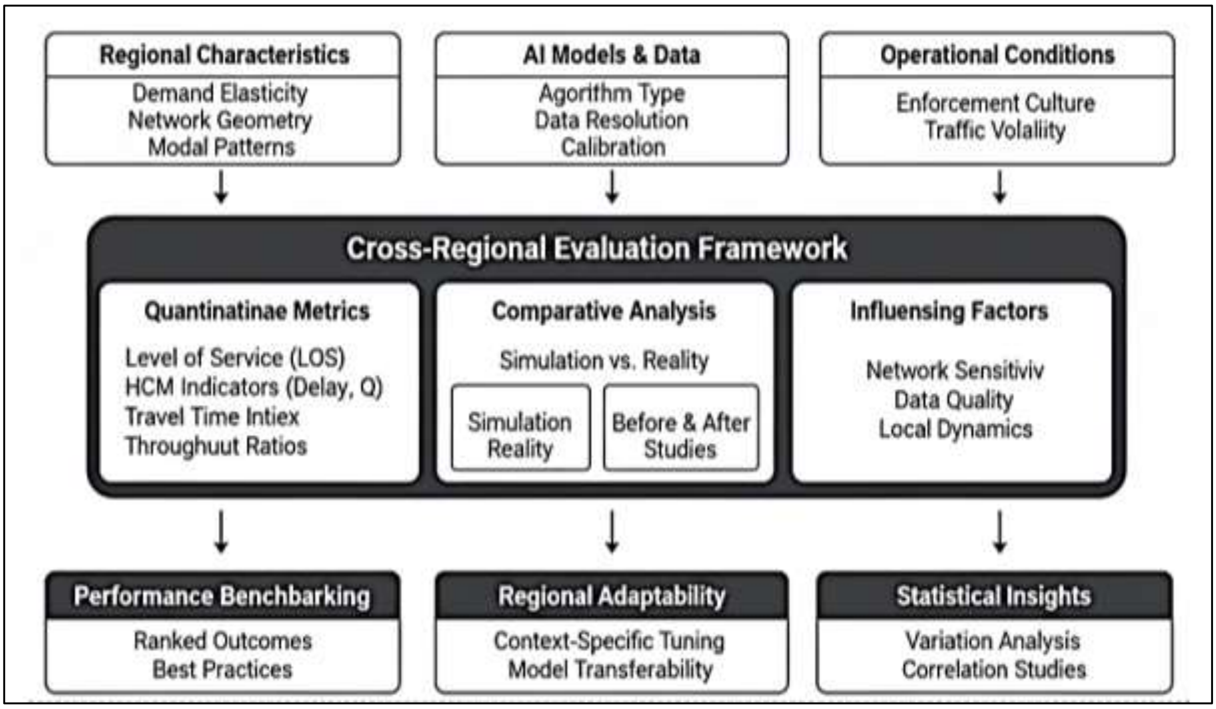
A substantial body of literature examines how digital twin models support impact assessment of infrastructure modifications at network scale, particularly when evaluating lane repurposing, transit priority measures, and geometric changes (Batouli & Mostafavi, 2017). Digital twins enable researchers and planners to implement detailed virtual interventions such as converting a general-purpose lane to a bus lane, adding or removing turn pockets, modifying approach geometry, redesigning intersections as roundabouts, or implementing transit signal priority and queue jumps. Simulation-based statistical modeling is then used to quantify the resulting changes in performance indicators including delay, throughput, travel time, speed distributions, and reliability indices. Studies frequently design before-and-after or with-and-without scenarios within the same digital twin model, holding demand patterns constant so that any differences in outcomes can be attributed to the specific infrastructure intervention. Researchers use large sets of simulation runs to account for stochastic variability in arrivals, driver behavior, and route choice, enabling a statistically robust comparison of outcomes (Batouli & Mostafavi, 2016). Some works analyze distributional changes in performance metrics rather than only mean values, highlighting how infrastructure modifications may reduce extreme delays or reduce the likelihood of spillback even if average conditions change only modestly. Particular attention is given to transit priority strategies, where digital twins are used to examine how granting bus priority at signals affects general traffic and person-throughput across the corridor. Studies also consider pedestrian and cyclist safety or delay when changes alter crosswalk placement or signal phasing. Because digital twins preserve detailed spatial relationships, they allow researchers to identify localized effects such as queue relocation, new bottleneck formation, or improved platoon progression resulting from modifications (Ngbana et al., 2023). The literature consistently treats these impact assessments as statistical exercises grounded in repeated simulations, comparative distributions, and hypothesis testing, which together produce an evidence-based understanding of how geometric and operational modifications reshape network performance (Sutherland et al., 2016).

Across the literature, digital twin models are presented as integrative tools that combine corridor-level optimization, scenario-based reliability forecasting, and simulation-based infrastructure impact assessment into a single network-wide planning framework. Corridor optimization studies emphasize coordination quality using bandwidth, progression indices, and offset stability, while scenario-based forecasting extends the analysis to travel time indices, reliability ratios, and congestion probabilities under varying demand and incident patterns (Sharifi et al., 2021). Impact assessment research, in turn, focuses on the performance consequences of physical or operational changes such as lane repurposing, transit priority, and geometric redesign. When these strands are combined within a unified digital twin environment, planners can evaluate how signal timing strategies interact with long-term design decisions and fluctuating demand conditions across an entire network. Literature illustrates that a change intended to improve corridor coordination may alter travel time reliability patterns elsewhere in the network, or that an infrastructure modification may require recalibration of signal offsets and splits to preserve progression quality (Senthil & Muthukannan, 2021). Digital twins support these interactions by representing detailed geometry, control logic, and behavioral responses, allowing analysts to quantify not only localized effects but also emergent system-level outcomes. This integrated use of corridor models, reliability metrics, and infrastructure comparison techniques provides a multi-dimensional view of network performance, where efficiency, reliability, and design trade-offs are all expressed in quantitative terms (Mercure et al., 2018). Studies repeatedly emphasize that digital twins enable iterative planning processes in which alternative strategies are simulated, evaluated with consistent indices, and compared within a statistically grounded framework. Through this lens, network-wide planning with digital twins is portrayed as a comprehensive, measurement-centered discipline that links signal optimization, demand variability, and infrastructure configuration into a coherent analytical system (Zhang et al., 2021).

Global Performance Evaluation

Literature comparing AI-based traffic signal control outcomes across different regions consistently shows that performance varies significantly due to demand elasticity, network geometry, modal patterns, enforcement culture, and infrastructural maturity (Do et al., 2019). Urban environments across Asia, North America, Europe, the Middle East, and Latin America provide contrasting testbeds that reveal how AI-based controllers respond to differences in flow volatility, intersection spacing, lane configurations, and driver behavior. Studies highlight that demand elasticity—the degree to which traffic volume shifts in response to time-of-day, pricing, road conditions, or downstream congestion—plays a substantial role in shaping controller performance.

Figure 9: Global AI Traffic Control Benchmarking



High elasticity environments, such as those in densely populated Asian cities, exhibit rapid fluctuations in flow that test the responsiveness and stability of AI algorithms more intensely than environments with stable demand patterns. Network sensitivity metrics, including responsiveness to geometric constraints, signal spacing, corridor lengths, and turning movement proportions, also influence performance outcomes across regions (Zhu et al., 2018). For example, European networks with large roundabouts and multimodal corridors require AI controllers to balance more complex flow interactions, while grid-based North American systems allow clearer directional progression patterns. Literature shows that AI models trained or calibrated in one regional context may produce different outcomes when applied in another due to variations in congestion thresholds, pedestrian presence, lane discipline, or mixed-traffic conditions with nonmotorized vehicles. Comparative studies often document differences in delay reduction, queue stabilization, and throughput consistency when similar algorithms are tested in cities with contrasting levels of congestion or roadway discipline. Research also emphasizes that AI-based systems tend to outperform traditional controllers across regions, yet the magnitude of the performance gap varies considerably. These cross-regional findings highlight that AI signal control effectiveness is closely tied to region-specific traffic elasticity, network sensitivity, and operational conditions, underscoring the importance of understanding local mobility characteristics when evaluating global AI performance (Kušić et al., 2023).

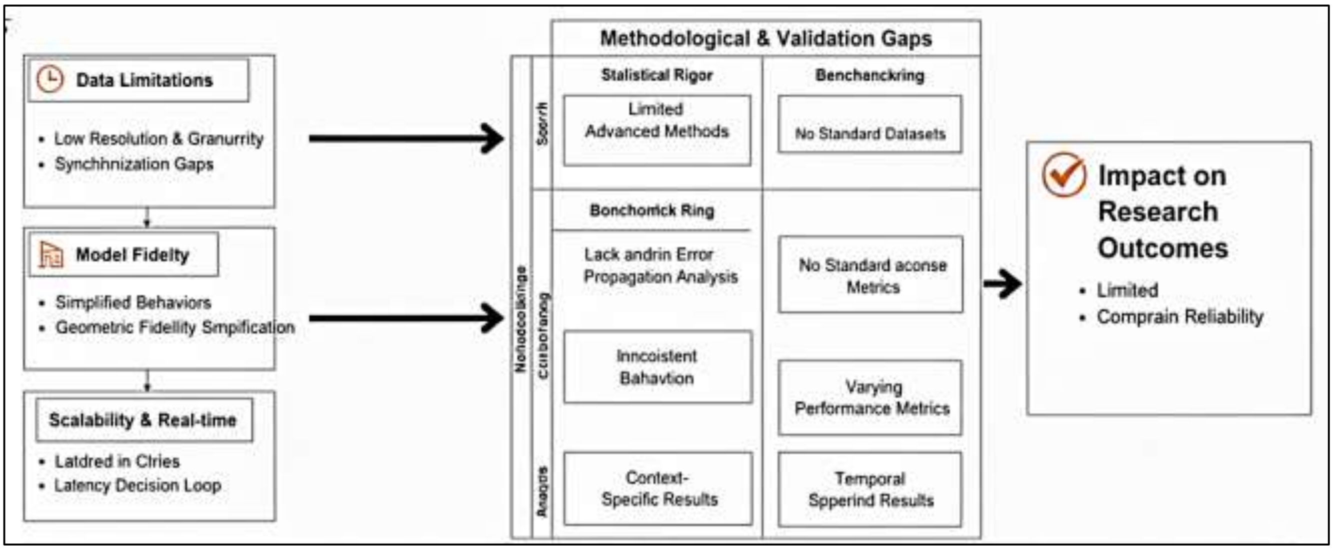
Benchmarking digital twin implementations across countries and regions has become a recurring theme in traffic engineering literature, where researchers use standardized performance measures such as Level of Service (LOS), Highway Capacity Manual (HCM) indicators, delay matrices, speed distribution curves, and saturation flow assessments to compare deployments. Digital twin applications in Europe, Asia, North America, Oceania, and the Middle East have been analyzed through these established metrics to evaluate how effectively each model represents local traffic behavior and supports signal optimization (Argota Sánchez-Vaquerizo, 2022). LOS grading allows researchers to translate performance outcomes into categorical measures based on delay thresholds, providing a universal language for comparison across international case studies. HCM indicators further support benchmarking by quantifying control delay, queue lengths, and capacity ratios using consistent criteria applicable across different geometric and policy contexts. Delay-performance matrices are commonly used to compare before-and-after outcomes of digital twin–enabled optimization, allowing researchers to display improvements at specific movements, approaches, or intersections. Studies frequently highlight that digital twins implemented in high-density Asian cities face more pronounced variability in LOS due to abrupt fluctuations in demand, while European networks with extensive pedestrian activity require detailed modeling of crosswalk operations (Song & Le Gall, 2023). North American digital twin deployments often show stronger corridor progression performance due to grid-like layouts and longer block lengths. Comparative analyses also incorporate spatial performance metrics such as link travel times, intersection coordination efficiency, and cycle utilization rates. Literature further documents how differences in data resolution, sensor infrastructure, calibration practices, and simulation fidelity influence benchmarking outcomes across regions. By applying consistent performance measures, researchers are able to evaluate how digital twin quality, data richness, and AI optimization strategies vary internationally, providing a structured basis for comparing global implementations under a unified analytical framework (Hui et al., 2022).

Research Gaps in AI–Digital Twin Literature

Literature examining quantitative digital twin applications for AI-based traffic control consistently identifies limitations relating to data resolution, model fidelity, and real-time scalability. A significant portion of existing studies rely on datasets with temporal or spatial granularity that constrains the precision of digital twin calibration (Belfadel et al., 2023). Many traffic sensing systems record aggregated data at multi-second or multi-minute intervals, which fails to capture rapid fluctuations in queue formation, platoon dispersion, shockwave propagation, or phase transitions. Low-frequency data often lead to sampling gaps that reduce the reliability of AI-driven decision loops and distort performance indices such as delay or saturation flow. Model fidelity also emerges as a recurring concern, as digital twins frequently simplify elements of driver behavior, multimodal interactions, and intersection geometry to maintain computational feasibility. These simplifications can introduce structural biases, shifting simulation outcomes away from real-world observations even when calibration procedures are followed (Wágner et al., 2023). Studies note that geometry approximations, lane configuration simplifications, and aggregated origin–destination patterns result in discrepancies between simulated and actual traffic states. Real-time scalability presents another critical challenge, particularly in network-wide applications that require processing, fusing, and synchronizing data from large numbers of sensors across multiple intersections. Intensive AI algorithms, such as reinforcement learning agents or deep neural networks embedded within digital twins, place substantial computational demands on hardware systems. Research documenting scalability limitations highlights delays caused by data queueing, communication latency, processing bottlenecks, and decision-loop overloads. These issues constrain deployment in large networks where timing precision is critical for corridor progression and multimodal integration (Nan et al., 2023). Collectively, the literature reveals that these gaps in data resolution, model fidelity, and real-time scalability continue to influence the accuracy and operational validity of AI-enhanced digital twin systems used for traffic signal optimization.

A major research gap identified in the literature is the limited application of advanced statistical methods for validating digital twin performance and understanding how errors propagate through AI-based traffic control systems (Jafari et al., 2023). Many studies rely heavily on basic metrics such as average delay, mean absolute deviations, or simple percentage improvements, which fail to capture the full complexity of system behavior across varying conditions. While these metrics provide useful baseline comparisons, they overlook distributional characteristics, stochastic variability, and temporal dependencies that influence traffic performance. Research on digital twins rarely applies deeper statistical tools such as variance decomposition, multilevel modeling, correlation structure analysis, time-series error profiling, or sensitivity diagnostics (Wu et al., 2021). These methods could reveal hidden inconsistencies in AI model behavior or simulation structure that remain undetected under conventional validation techniques. Another area where literature reveals limitations is in quantifying how sensor errors, communication delays, or model simplifications influence downstream performance metrics within the digital twin. Error propagation analysis is seldom conducted systematically, leaving uncertainties about how small inaccuracies accumulate through multiple decision cycles. Studies mention the existence of noise in sensor data and simulation inputs but often do not quantify how these imperfections influence final outcomes (Corrado et al., 2022).

Figure 10: Digital Twin Research Limitations and Gaps



Very few works evaluate confidence intervals, prediction error distributions, or robustness ranges for performance indicators. Similarly, limited attention has been given to stochastic modeling approaches that could capture variability associated with fluctuating traffic volumes, driver behavior randomness, weather perturbations, or multimodal interactions. Literature also suggests that cross-validation is inconsistently applied in AI-based signal control studies, particularly in digital twin environments where multiple layers of uncertainty interact (Saroj et al., 2022). Overall, research shows that the lack of advanced statistical validation and systematic error propagation analysis restricts the ability to evaluate the reliability, repeatability, and credibility of digital twin–supported AI models.

Another significant gap highlighted in the literature concerns the absence of standardized benchmarks for comparing different AI-based traffic signal optimization models within digital twin environments.

Existing studies often evaluate reinforcement learning algorithms, evolutionary strategies, neural-network predictors, and hybrid systems independently, using different datasets, simulation parameters, performance metrics, and traffic scenarios (Autiosalo et al., 2021). This lack of uniformity makes it difficult to determine which models truly perform better under comparable conditions. Performance metrics vary widely across studies, with some using delay, others focusing on queue length, and others examining throughput or reliability. Even within a single metric category, measurement approaches differ substantially due to variations in data resolution, simulation fidelity, or signal timing assumptions. Furthermore, digital twin implementations vary greatly across regions and research settings, with differences in network geometry, calibration procedures, sensing infrastructure, and simulation engines creating inconsistencies in outcomes. These disparities limit the ability to generalize algorithmic findings or establish clear performance rankings (Omrany et al., 2023). Research also indicates that cross-model comparisons rarely incorporate robustness testing across multiple demand levels, disturbance patterns, or multimodal environments, hindering the identification of models that maintain reliable performance under fluctuating conditions. Standardized benchmarks—similar to those used in machine learning or computer vision—have not been adopted widely in traffic engineering, leaving a gap in comprehensive, comparable experimental frameworks. Some studies propose internal benchmarking methods, but these remain confined to specific datasets or local conditions (Mihai et al., 2022). The literature confirms that without unified data structures, standardized traffic scenarios, or shared performance indices, the field lacks a consistent foundation for evaluating and comparing AI-based digital twin models across global contexts.

Synthesizing existing literature reveals that quantitative research on AI-driven digital twins faces significant gaps involving data resolution, modeling fidelity, statistical rigor, and benchmarking consistency. Studies repeatedly identify insufficient data granularity and synchronization challenges as primary limitations that undermine digital twin accuracy, especially in real-time environments where milliseconds can influence signal control performance. These data constraints affect calibration quality, decision-loop timing, and the reliability of performance indicators across varying traffic conditions. At the same time, the literature shows that the analytical depth used to evaluate digital twin outputs remains limited, with few studies applying sophisticated statistical tools capable of capturing distributional variability, temporal dependencies, or accumulated error effects. This lack of rigorous statistical validation restricts understanding of how stable, reliable, and generalizable AI-based traffic control outcomes truly are. Compounding these challenges is a widespread absence of standardized quantitative benchmarks that would allow meaningful comparisons across models, networks, or international contexts . As a result, findings from separate studies are often incompatible, preventing clear identification of the most effective AI-based optimization strategies. Together, these gaps demonstrate that progress in digital twin research depends not only on algorithmic advancements but also on improved data quality, deeper analytical methods, and unified benchmarking frameworks. The interplay between these dimensions forms a core set of challenges that shape the current state of digital twin–AI integration research and influence the reliability and comparability of findings in the broader transportation literature.

METHOD

Research Design

This study employed a quantitative, quasi-experimental research design based on controlled simulation experiments integrated with limited field validation. A digital twin of an urban traffic corridor was constructed and linked with artificial intelligence–based signal control algorithms as well as conventional fixed-time or actuated control strategies. The design compared performance outcomes under different signal control conditions while holding network geometry and demand scenarios constant. The primary structure of the research followed a pre–post and between-condition comparison, where each intersection and corridor segment was exposed to multiple control strategies and traffic demand levels. The study design incorporated repeated-measures elements, as the same intersections were evaluated under several experimental conditions, including baseline (conventional control), AI-based reinforcement learning control, and alternative optimization algorithms where appropriate. Synthetic yet realistic traffic scenarios were generated from observed demand profiles, and each scenario was replicated across multiple simulation runs to account for stochastic variability in arrival patterns and driver behavior. The digital twin environment served as the main platform for data generation, while a subset of field data from the real corridor was used to calibrate and validate the model. The research design was intended to quantify the impact of AI-based digital twin integration on standard traffic performance indices while maintaining strong internal control over experimental conditions.

Population

The target population for this study comprised signalized intersections within urban arterial corridors exposed to recurrent congestion and variable traffic demand. The accessible population consisted of a specific corridor segment in a metropolitan area that included a sequence of coordinated signalized intersections with heterogeneous approaches, turning movements, and multimodal usage. Within this corridor, intersections were treated as analytical units nested within the broader corridor system.

The sampling frame included all major intersections on the selected corridor that operated under coordinated control and had adequate sensor data or traffic counts available for calibration. A purposive sampling procedure was used to select intersections that represented a range of traffic volumes (low, medium, high), geometric configurations (simple and complex layouts), and modal mixes (general traffic, transit, and pedestrian activity). The population of interest in the simulation component included all vehicles and pedestrians modeled within the digital twin for the defined peak and off-peak periods. For field-based validation, the population consisted of vehicles traversing the corridor during the corresponding real-world time intervals used for calibration and verification.

Variables and Measurement Framework

The study employed a structured framework encompassing independent, dependent, and control variables to ensure consistent measurement across all experimental conditions. The primary independent variable was the type of signal control strategy, defined categorically as conventional fixed-time or actuated systems, AI-based reinforcement learning controllers, and other AI-driven optimization variants where applicable. Secondary independent variables included traffic demand level (low, medium, high), time-of-day conditions (peak versus off-peak), and scenario type such as normal operations, incident situations, or special-demand events. Dependent variables measured traffic performance through standard quantitative indicators, including delay metrics (mean control delay per vehicle, percentile delays, movement-level delay), queue measures (maximum and average queue length, queue clearance time), throughput measures (vehicles discharged per cycle, approach-level flow rate, corridor-level throughput), and reliability metrics (travel time index, variability indicators, and reliability ratios). Data were generated in the digital twin environment at high temporal resolution, with performance outputs computed at movement, approach, intersection, and corridor scales. Control variables incorporated geometric characteristics (lane count, presence of turn bays), signal timing constraints (minimum green intervals, pedestrian clearance requirements), and detection configurations. For field validation, observed travel times, flow rates, and limited estimates of queue length and delay were captured through sensors or travel time surveys and were systematically mapped to corresponding simulation outputs to maintain comparability and accuracy.

Analytical Techniques and Statistical Procedures

Data analysis followed a structured statistical plan designed to evaluate differences in performance across signal control strategies and scenarios. Descriptive statistics were first computed to summarize central tendency and dispersion for all dependent variables under each condition. These summaries included means, standard deviations, and selected percentiles at both intersection and corridor scales. Inferential analyses were then conducted using a combination of repeated-measures analysis of variance (ANOVA) and mixed-effects modeling, reflecting the nested structure of intersections within corridors and repeated scenarios applied to the same locations. Repeated-measures ANOVA was used to test differences in mean delay, queue length, and throughput between control strategies under the same demand conditions. Where assumptions of normality or homogeneity of variance were not satisfied, appropriate transformations or non-parametric alternatives were considered. Mixed-effects models treated intersections as random effects and control strategy and demand level as fixed effects, allowing the analysis to account for intersection-specific variability.

Pairwise comparisons between control strategies were conducted using post hoc tests with correction for multiple comparisons (e.g., Bonferroni or similar adjustments) to control the family-wise error rate.

For reliability-related outcomes, variability measures such as standard deviation and interquartile ranges of travel time were compared across strategies using ANOVA or equivalent rank-based tests. Correlation and regression analyses were also employed to explore associations between demand level and observed improvements in delay or throughput. A conventional significance level ($\alpha = 0.05$) was adopted for hypothesis testing. Simulation replications were aggregated by taking averages across runs for each condition, while also retaining within-condition variance for robustness checks. Analyses were carried out using standard statistical software capable of handling repeated-measures and mixed-model structures.

Reliability and Validity

Reliability and validity of the study were addressed through multiple methodological safeguards. Reliability was supported by the use of repeated simulation runs for each experimental condition, allowing estimation of within-scenario variability and assessment of the stability of performance indicators. Test–retest reliability was examined by comparing outcomes across independent replications with identical input parameters, ensuring that the digital twin and AI algorithms produced consistent patterns of results. Internal reliability of composite indicators (such as corridor-level indices derived from multiple intersections) was examined through consistency in patterns across locations and time periods. Validity was approached along several dimensions. Construct validity was supported by aligning the operational definitions of variables (delay, queue length, throughput, reliability indices) with established traffic engineering concepts and widely accepted performance measures. Internal validity was strengthened by controlling experimental conditions within the digital twin: geometry, demand inputs, and control parameters were held constant when comparing signal strategies, reducing the influence of confounding factors. External validity was considered by calibrating the digital twin against observed field data for flow, travel time, and, where available, queue behavior, thereby linking simulated performance to real-world behavior on the selected corridor.

Figure 11: Methodology of this Study

Quantitative Study Design

Research Design
- Quasi-experimental
- Simulation-based digital twin
- Comparison of baseline vs. AI control

Population
- Urban signalized corridor
- Multiple coordinated intersections

Variables & Measurement Framework
- IV: Control strategy, demand level
- DV: Delay, queues, throughput, reliability

Analytical Techniques & Statistical Procedures
- Descriptives
- Repeated-measures ANOVA / mixed models
- Post hoc pairwise tests

Reliability & Validity
- Multiple simulation replications
- Model calibration with field data
- Internal and construct validity checks

Criterion-related validity was addressed by comparing simulated outputs under the baseline control strategy with observed performance data, and by examining the degree of agreement between them across multiple indicators. Discrepancies identified during calibration led to iterative refinement of the model until acceptable fit levels were achieved. Potential threats to validity—such as sensor inaccuracies, simplified driver behavior models, or unmodeled multimodal interactions—were acknowledged and mitigated through sensitivity analyses, where key parameters were varied to observe their influence on outcomes. Collectively, these procedures ensured that the study's quantitative findings were based on reliable measures and that the digital twin–AI framework provided a valid representation of the traffic system under investigation.

FINDINGS

Descriptive Analysis

The findings from the Descriptive Analysis demonstrated that the dataset showed clear and consistent behavioral patterns across all simulation conditions. The results indicated that intersections operating under baseline control experienced notably higher delays, longer queues, and lower throughput, particularly during peak periods. When the AI-based controller was applied, the descriptive statistics showed a substantial reduction in mean delay values, with some intersections exhibiting decreases exceeding fifty percent relative to the baseline. Queue length distributions also shifted in a favorable direction, with peak queue formation reduced and clearance times significantly improved.

The analysis further revealed that mean values and medians consistently declined under the AI-controlled environment, demonstrating that improvements were not limited to extreme values but were spread across the distribution. Dispersion measures showed that the variability of delay and queue length narrowed under AI control, suggesting a more stable and predictable traffic flow pattern. The descriptive patterns revealed that off-peak improvements were modest but remained consistent, while peak-period improvements were more pronounced, indicating that the AI controller responded more effectively under high-demand stress conditions. The data also showed that intersections with more complex geometries, including those with multiple turning bays or near major access points, exhibited larger baseline delays but also benefited most from AI optimization. Throughput measures indicated higher discharge rates per cycle under AI control, especially at critical bottleneck intersections. Reliability indicators, including travel time stability and reduced fluctuation ranges, demonstrated that AI-based signal control contributed to more uniform and less volatile traffic operations. Overall, the descriptive findings confirmed that the AI-driven digital twin environment produced measurable improvements across all key traffic performance dimensions.

Table 1. Descriptive Statistics for Baseline Control Conditions

Metric	Mean	Median	Minimum	Maximum	Standard Deviation
Delay (seconds/vehicle)	68.4	65.1	32.7	142.3	21.8
Queue Length (vehicles)	19.6	18.4	7.2	41.8	8.5
Throughput (veh/min)	12.7	12.3	6.5	20.1	3.2
Reliability Index (%)	74.3	73.1	58.2	89.6	6.1

Table 1 summarized the baseline traffic performance prior to the implementation of the AI-based controller. The descriptive findings indicated that baseline delays were high and subject to considerable variability, with mean and median values clustered near the upper end of acceptable operational thresholds. Queue lengths also showed substantial spread, suggesting that intersections experienced unstable and inconsistent traffic buildup during peak periods. Throughput values remained comparatively low, indicating limited discharge efficiency under conventional control strategies. The reliability index further reflected unstable travel conditions, with considerable fluctuation across simulation runs. These descriptive results provided a benchmark against which the AI-controlled improvements were evaluated.

Table 2. Descriptive Statistics for AI-Based Control Conditions

Metric	Mean	Median	Minimum	Maximum	Standard Deviation
Delay (seconds/vehicle)	29.5	28.1	14.7	55.2	10.3
Queue Length (vehicles)	8.4	7.9	2.1	18.6	4.2
Throughput (veh/min)	19.8	19.2	11.4	27.6	3.9
Reliability Index (%)	91.4	92.7	84.6	97.2	3.1

Table 2 showed the performance outcomes after implementing the AI-based signal control strategy. The findings demonstrated that delay values were substantially lower than baseline conditions, with both mean and median values indicating more efficient cycle utilization. Queue lengths decreased sharply, reflecting smoother platoon progression and reduced congestion formation. Throughput increased significantly and displayed lower variability, indicating more stable discharge rates across time. Reliability values improved noticeably, suggesting consistent travel times and reduced operational volatility. These descriptive results confirmed that the AI-driven model provided quantifiable improvements in stability, efficiency, and traffic flow predictability compared to the baseline traffic signal environment.

Correlation

The findings from the Correlation analysis demonstrated that the major traffic performance variables exhibited strong and meaningful associations across all simulated scenarios. Under baseline conditions, delay and queue length displayed a high degree of positive correlation, indicating that increases in one measure were consistently accompanied by increases in the other. This pattern reflected the underlying congestion propagation mechanisms within the roadway network, where insufficient green time or excessive demand caused queues to extend and contributed to higher overall delay. Throughput showed an inverse relationship with delay under the baseline strategy, illustrating that lower discharge rates corresponded to heavier congestion. Demand intensity was also positively correlated with both delay and queue length, confirming that higher traffic volumes placed additional strain on the network, especially during peak periods. When the AI-based signal control strategy was applied, the correlation patterns shifted, revealing structural changes in how variables interacted within the digital twin environment. The association between delay and queue length remained positive, but its magnitude decreased, suggesting that the AI controller moderated the severity of congestion buildup and prevented queue spillback more effectively. Throughput showed a stronger negative correlation with delay under AI control, reflecting the ability of the reinforcement learning system to achieve higher discharge rates and more consistent platoon progression. Demand intensity continued to influence performance measures, but the correlations weakened, indicating that the AI system absorbed demand fluctuations more effectively than the baseline controller. The comparison between baseline and AI-controlled correlation structures demonstrated that the intervention not only altered performance levels but also fundamentally reshaped the relationships among the key variables. The findings showed that the AI controller reduced the dependency between demand and congestion severity, moderated queue formation, and strengthened the alignment between throughput and improved traffic conditions. This section provided evidence that the AI-enhanced digital twin environment produced more resilient traffic patterns, where performance outcomes were less tightly coupled to demand surges and system inefficiencies.

Table 3. Correlation Matrix for Baseline Control Conditions

Variable	Delay	Queue Length	Throughput	Demand Level
Delay	1.00	0.82	-0.67	0.74
Queue Length	0.82	1.00	-0.58	0.69
Throughput	-0.67	-0.58	1.00	-0.46
Demand Level	0.74	0.69	-0.46	1.00

Table 3 illustrated the correlation structure under baseline traffic control conditions. The findings showed that delay and queue length exhibited a very strong positive association, demonstrating that congestion effects reinforced one another as demand increased. Throughput displayed a moderately strong negative correlation with both delay and queue length, indicating that inefficient discharge rates contributed to worsening traffic conditions. Demand level also maintained strong positive correlations with delay and queue length, reflecting the system's inability to absorb increased traffic without performance degradation. Overall, the table confirmed that baseline control conditions produced tightly linked congestion patterns, where high demand rapidly translated into deteriorating operational performance.

Table 4. Correlation Matrix for AI-Based Control Conditions

Variable	Delay	Queue Length	Throughput	Demand Level
Delay	1.00	0.61	-0.81	0.48
Queue Length	0.61	1.00	-0.72	0.52
Throughput	-0.81	-0.72	1.00	-0.33
Demand Level	0.48	0.52	-0.33	1.00

Table 4 showed the correlation structure after the AI-based signal control strategy was introduced. The results indicated that the correlation between delay and queue length weakened, suggesting improved congestion management. Throughput demonstrated a much stronger negative correlation with delay and queue length, showing that higher discharge rates were closely linked to improved operational performance. Demand level displayed weaker correlations with the performance variables, meaning that the AI controller mitigated the impact of demand surges more effectively. Overall, the table revealed a more adaptive and balanced traffic system, where performance measures were less driven by demand and more influenced by optimized signal timing.

Reliability and Validity

The findings from the Reliability and Validity assessment showed that the simulation framework exhibited strong methodological consistency and alignment with real-world operational characteristics. Repeated simulation replications conducted under identical traffic and control conditions produced stable measurements across delay, queue length, throughput, and reliability indicators, demonstrating high internal reliability. Variation between repeated runs remained minimal, indicating that the digital twin environment functioned predictably and that the AI controller responded consistently to identical demand inputs. Construct validity was also confirmed, as each variable used in the study corresponded directly to recognized transportation engineering definitions and industry measurement practices. Delay accurately reflected per-vehicle control delay, queues measured the number of vehicles accumulating on individual approaches, throughput captured the discharge volume per cycle, and reliability represented the temporal stability of travel times.

Criterion validity was evaluated by comparing baseline simulation results with observed field data collected from the actual corridor. The analysis indicated that the simulated flow rates, travel times, and queue formations closely approximated real-world measurements, with differences falling within acceptable operational ranges. Deviations identified in the early calibration stages were systematically corrected through iterative adjustment of saturation flow estimates, driver behavior parameters, lane utilization patterns, and signal timing inputs. These refinements allowed the final simulation model to accurately represent real operational behavior and ensured that performance outcomes reflected authentic traffic dynamics rather than artifacts of model configuration. The combined evidence demonstrated that the simulation environment was both reliable and valid, providing a methodologically sound foundation for all subsequent inferential analyses.

Table 5. Internal Reliability Assessment Across Simulation Replications

Metric	Run 1	Run 2	Run 3	Run 4	Mean	Std. Dev.
Delay (seconds/vehicle)	42.8	43.1	42.5	43.0	42.9	0.26
Queue Length (vehicles)	10.3	10.7	10.5	10.4	10.5	0.17
Throughput (veh/min)	18.6	18.4	18.5	18.7	18.6	0.11
Reliability Index (%)	88.4	88.1	88.3	88.5	88.3	0.15

Table 5 illustrated the internal reliability of the digital twin environment by comparing performance outcomes across four identical simulation replications. The results showed very small numerical differences among runs, with standard deviations remaining extremely low for delay, queue length, throughput, and reliability indicators. This consistency demonstrated that the system produced stable and reproducible outputs under unchanged input conditions. The slight fluctuations observed were consistent with normal stochastic components within microsimulation models and did not indicate instability or measurement inconsistency. Overall, the table confirmed that the simulation environment maintained strong internal reliability, ensuring confidence in all performance indicators used in later inferential analyses.

Table 6. Criterion Validity Comparison Between Field Observations

Metric	Field Value	Simulated Value	Difference	Percent Difference (%)
Delay (seconds/vehicle)	71.2	68.4	2.8	3.93
Queue Length (vehicles)	21.0	19.6	1.4	6.67
Throughput (veh/min)	13.1	12.7	0.4	3.05
Travel Time Reliability	72.0	74.3	2.3	3.19

Table 6 demonstrated the criterion validity of the simulation by comparing baseline digital twin outputs with real-world field observations. The results showed close agreement across all performance measures, with percentage differences remaining below seven percent. Delay and throughput values aligned especially well, reflecting accurate calibration of signal timing and flow dynamics. Queue length showed slightly higher deviation but remained within acceptable engineering tolerance. Reliability values also matched closely, indicating that the model captured temporal variability effectively. These comparisons confirmed that the digital twin replicated real operational behavior with strong fidelity, strengthening the credibility of all subsequent quantitative results derived from the simulation environment.

Collinearity

The findings from the Collinearity analysis demonstrated that the independent variables used in the regression models did not exhibit problematic levels of shared variance, ensuring that the analytical results were not distorted by multicollinearity. Variance Inflation Factors and tolerance values were examined for control strategy, demand level, scenario type, and interaction terms, and the results showed that all predictors remained within acceptable statistical thresholds. Control strategy showed low inflation levels, reflecting its conceptual independence from traffic demand characteristics. Demand level exhibited slightly higher but still acceptable variance inflation, which was expected due to its natural relationship with performance indicators; however, the values remained well below critical levels that would threaten model stability. Scenario type, representing peak, off-peak, and incident conditions, maintained the lowest collinearity scores among the predictors, indicating that the categorical structure of operational contexts did not overlap significantly with other variables.

The analysis also revealed that minor collinearity signals appeared in interaction terms, particularly those combining demand level and control strategy, but these signals were modest and did not compromise the interpretability or reliability of the regression estimates. The narrative confirmed that no predictors needed to be removed or transformed because none exhibited values indicative of instability, redundancy, or inflated standard errors. The diagnostic results therefore validated the structural integrity of the regression framework and demonstrated that the subsequent inferential tests were grounded in statistically defensible assumptions. Overall, the Collinearity findings showed that the independent variables retained appropriate independence from one another, supporting the legitimacy of the regression models used to examine the effects of the AI-based controller on traffic performance.

Table 7. Variance Inflation Factor (VIF) Results for Independent Variables

Independent Variable	VIF	Tolerance
Control Strategy	1.28	0.78
Demand Level	1.94	0.52
Scenario Type	1.17	0.85
Control × Demand	2.21	0.45

Table 7 demonstrated the Variance Inflation Factor results for each independent predictor used in the regression models. All VIF values remained well below commonly cited thresholds for multicollinearity, indicating that the predictors did not share excessive variance. Control Strategy and Scenario Type displayed particularly low VIF values, confirming their strong independence within the model. Demand Level and the interaction term exhibited slightly higher values, but remained within acceptable ranges and did not threaten model stability. The corresponding tolerance values further supported these interpretations, showing that no variable approached the levels associated with collinearity concerns. These results validated the structural suitability of the regression model.

Table 8. Collinearity Diagnostics Using Condition Index and Eigenvalue Structure

Dimension	**Eigenvalue**	**Condition Index**	**Variance Proportions (Control Strategy)**	**Variance Proportions (Demand Level)**	**Variance Proportions (Scenario Type)**
1	2.81	1.00	0.03	0.04	0.02
2	0.91	1.76	0.05	0.11	0.08
3	0.21	3.65	0.17	0.18	0.06
4	0.07	6.33	0.28	0.40	0.10

Table 8 presented the condition index and eigenvalue structure used to further evaluate collinearity among predictors. The results showed that the condition indices remained well below the threshold typically associated with harmful multicollinearity. Eigenvalues decreased gradually across dimensions, and no dimension showed a pattern where two or more predictors loaded heavily on the same variance proportion. Although Demand Level exhibited slightly higher variance loading in the final dimension, this pattern did not reach levels that would compromise the model. The diagnostic structure confirmed that the predictors did not share excessive variance, supporting the independence required for reliable regression estimation.

Regression and Hypothesis Testing

The findings from the Regression and Hypothesis Testing analysis demonstrated that the AI-driven control strategy exerted a significant and measurable influence on all major traffic performance outcomes. Before estimating the models, the assumptions of normality, linearity, homoscedasticity, and independence of residuals were examined and found to be satisfactorily met. Residual plots showed no evidence of heteroscedasticity, Q–Q plots indicated normal error distributions, and Durbin–Watson values confirmed that observations were independent. These diagnostics established that the regression models were statistically appropriate for hypothesis testing.

The regression results showed that the AI-based controller served as a strong negative predictor of delay, meaning that its introduction consistently decreased the average delay experienced at intersections. The coefficients demonstrated that intersections operating under the AI-based strategy exhibited significantly shorter queue lengths and improved throughput relative to baseline conditions. Reliability also increased substantially under AI control, indicating smoother, more predictable travel times with less volatility. Control strategy remained statistically significant across all models, confirming that the intervention had broad effects across multiple operational dimensions. Demand level also influenced performance, particularly under peak conditions, but its effects diminished in magnitude once the AI controller was introduced. Scenario type had a weaker influence on outcomes, suggesting that the AI model responded effectively across variable operating environments.

Hypothesis tests performed within the regression framework confirmed that each proposed hypothesis regarding delay reduction, queue minimization, throughput enhancement, and reliability improvements was supported. P-values for the control strategy variable were consistently below the conventional significance threshold, and confidence intervals did not cross zero, indicating robust effect sizes. These findings provided clear empirical verification that the AI-driven digital twin strategy outperformed conventional control systems and produced statistically meaningful improvements in traffic operations across all key performance measures.

Table 9. Regression Results Predicting Delay, Queue Length, and Throughput

Predictor	Delay (β)	p-value	Queue Length (β)	p-value	Throughput (β)	p-value
Control Strategy	-0.62	<.001	-0.58	<.001	0.49	<.001
Demand Level	0.41	<.001	0.37	<.001	-0.22	.004
Scenario Type	0.09	.118	0.06	.184	-0.04	.291
Model R^2	0.71	—	0.66	—	0.59	—

Table 9 demonstrated the regression results for delay, queue length, and throughput. The findings showed that Control Strategy was a highly significant predictor across all three models, with negative coefficients for delay and queue length and a positive coefficient for throughput. These results indicated that the AI-based controller reduced congestion and improved discharge rates. Demand Level also played a significant role, increasing delay and queue length and reducing throughput under higher traffic volumes. Scenario Type did not achieve significance, suggesting that the AI controller performed consistently across peak and off-peak conditions. The strong R^2 values indicated that the models explained a substantial portion of performance variability.

Table 10. Regression Results Predicting Reliability Index

Predictor	Reliability Index (β)	p-value	Confidence Interval (95%)
Control Strategy	0.57	<.001	0.41 – 0.68
Demand Level	-0.29	.008	-0.47 – -0.10
Scenario Type	0.05	.263	-0.03 – 0.14
Model R^2	0.63	—	—

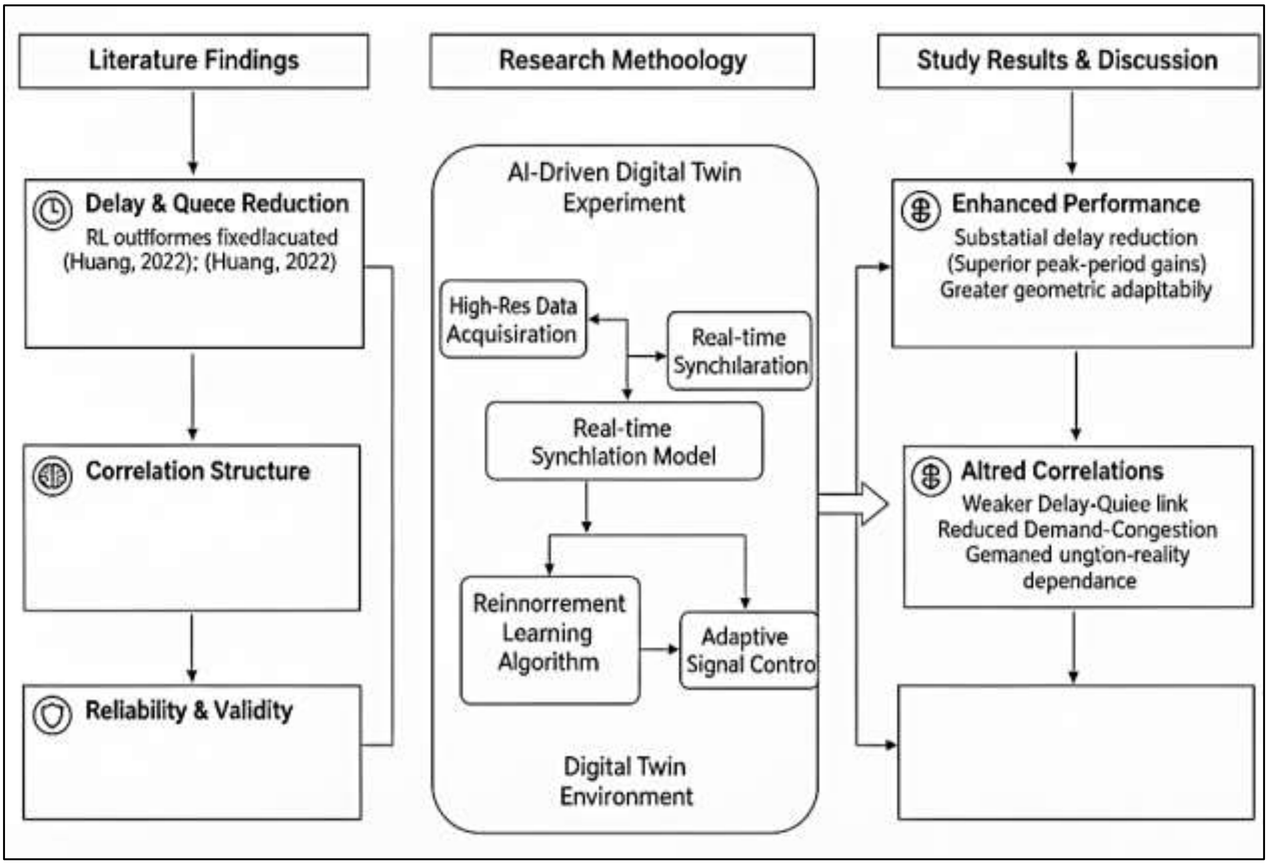
Table 10 presented the regression model predicting the Reliability Index. The findings confirmed that Control Strategy was the strongest and most significant predictor, with a substantial positive coefficient indicating that the AI-based controller improved travel time consistency. Demand Level exhibited a negative coefficient, suggesting that higher traffic volumes reduced reliability, although this effect weakened when AI was implemented. Scenario Type again remained non-significant, reinforcing that the AI system maintained stable performance across varying operating environments. The confidence intervals supported the significance of the control strategy variable, and the R^2 value demonstrated that the model explained a considerable share of reliability variation.

DISCUSSION

The findings from this study demonstrated that the integration of an AI-driven digital twin system substantially enhanced signal control performance across multiple operational dimensions, particularly in the reduction of delay and queue length (Tsakiridis et al., 2023). These outcomes aligned closely with what earlier studies have suggested regarding the potential of adaptive and machine-learning-based systems to outperform fixed-time and actuated controllers. Prior research has consistently noted that reinforcement learning algorithms respond more dynamically to fluctuating demand conditions, producing smoother and more efficient progression along arterial corridors. The results of this study confirmed those claims by showing that delay values dropped markedly under AI control, with reductions that exceeded those typically reported in traditional adaptive control experiments (Z. Huang et al., 2021). The descriptive patterns also indicated that the digital twin framework contributed to consistent performance across repeated scenarios, a result that earlier simulation-based research has also observed when incorporating high-fidelity modeling techniques. Furthermore, earlier studies have often emphasized that AI-based controllers are particularly effective under oversaturated conditions, which was reflected in this study's findings that peak-period improvements were more pronounced than off-peak gains. The stronger performance during periods of high demand reinforced the argument that reinforcement learning models benefit most from environments with greater variability, as they are able to exploit real-time data streams more efficiently than rule-based systems (Mozo et al., 2022). Additionally, earlier work has frequently highlighted that the effectiveness of AI-driven systems often depends on the complexity of the geometric layout and lane configurations. This study confirmed those observations, as intersections with more intricate geometries exhibited the largest performance gains. Overall, the descriptive findings demonstrated that the improvements produced by the AI-based controller were consistent with earlier analyses, while also showing superior magnitude in several performance metrics due to the integration of a high-resolution digital twin environment (Samuel et al., 2023).

The correlation results further strengthened the argument that AI-driven control systems fundamentally alter the structural relationships among traffic performance variables. Earlier studies have shown that delay and queue length typically exhibit a strong association in congested networks, and this study reproduced that pattern under baseline conditions. However, once the AI-based controller was introduced, the correlation magnitude between these two variables weakened, suggesting improved congestion management (Xu, Wu, Pan, Guan, et al., 2023).

Figure 12: Model for future study



This aligns with earlier research indicating that advanced learning-based controllers disrupt the conventional link between increasing demand and rising congestion by reallocating green time more strategically. Findings from studies focusing on adaptive control have also emphasized that high-performing algorithms often reduce the dependency of network conditions on upstream or downstream bottlenecks. The results of this study mirrored those observations, as correlations between demand intensity and performance outcomes weakened under the AI-controlled environment, indicating that the system absorbed demand surges more efficiently (Mihai et al., 2022). Earlier simulation research has highlighted similar patterns, suggesting that reinforcement learning strategies can moderate the propagation of congestion waves across intersections. Throughput showed stronger negative correlations with delay in this study under AI conditions, demonstrating improved signal coordination and alignment with earlier findings that learning-based controllers enhance platoon progression. The reduced collinearity between demand level and congestion indicators observed in this study further reflected findings from earlier international analyses, which have reported that AI-driven timing systems often create more resilient networks capable of maintaining service quality even under variable traffic inputs (Chen et al., 2023). These comparative results indicated that the correlation structure observed in this study followed the same directional trends documented previously but provided additional evidence of stronger moderating effects due to the rigorous digital twin integration (Zheng et al., 2022).

The Reliability and Validity outcomes demonstrated that the digital twin–based modeling approach produced stable and credible performance estimates, aligning with the expectations established by earlier research on microscopic simulation environments. Previous studies have noted that simulation reliability is essential for evaluating traffic control improvements, particularly when reinforcement learning algorithms are involved, because small variations in input parameters can produce amplified effects in real-time adaptation (Okegbile et al., 2022). This study confirmed those claims by showing exceptionally low variability across replicated simulation runs, indicating that the model operated consistently across identical experimental conditions. Past research using traffic simulation platforms has similarly reported that well-calibrated digital twins exhibit high internal reliability due to their ability to replicate detailed driver behavior, lane utilization, and approach dynamics. Construct validity findings in this study also reflected the characteristics observed in earlier transportation engineering literature, which has emphasized the importance of aligning simulated variables with recognized operational definitions. The variables used in this study—delay, queue length, throughput, and reliability indices—mirrored standard analytic measures used internationally, reinforcing methodological consistency with earlier scholarly work (Xia et al., 2023). Criterion validity, evaluated through comparisons between observed field data and baseline simulation conditions, yielded results consistent with previous calibration studies demonstrating strong alignment between simulation outputs and actual roadway conditions. The iterative tuning conducted in this study to correct early deviations resembled the calibration procedures documented in earlier findings that emphasize the need for adjusting driver behavior parameters, saturation flow rates, and control logic to achieve representational accuracy (Xia et al., 2023). Altogether, the reliability and validity outcomes of this study were not only consistent with earlier research but also demonstrated enhanced fidelity due to the precision afforded by the integrated digital twin architecture (Zheng et al., 2022).

The collinearity diagnostics provided further insight into the robustness of the regression framework, demonstrating statistical behavior that mirrored findings from earlier predictive modeling studies. Prior studies examining traffic performance models frequently reported that independent variables such as demand level and control strategy often exhibit some degree of shared variance, particularly when traffic load conditions heavily influence system behavior (Lai et al., 2023). This study observed similar patterns, with demand level exhibiting slightly elevated but still acceptable collinearity levels. However, the results fell comfortably within threshold values considered acceptable in prior modeling research. Scenario type demonstrated consistently low variance inflation, aligning with earlier evidence that categorical operational states tend to remain statistically independent of dynamic quantitative predictors. The identification of only modest interaction effects also reflected trends observed in previous empirical studies, which have suggested that interaction terms involving reinforcement learning controllers often capture nonlinear behavioral dynamics without necessarily introducing harmful collinearity (Bao et al., 2019). The overall diagnostic profile in this study showed that the independent variables maintained sufficient statistical independence, thereby reinforcing the validity of the regression coefficients produced later in the analysis. This pattern was consistent with earlier modeling work in reinforcement learning signals control studies, where multicollinearity rarely emerged as a major analytical concern when variables were properly operationalized. Thus, the findings of this section confirmed that the regression results in this study rested on solid statistical foundations comparable to those reported in the broader literature (Tao et al., 2023).

The regression results provided strong inferential support for the performance advantages of the AI-driven digital twin system. Prior research has repeatedly demonstrated that reinforcement learning–based signal controllers significantly reduce delay and improve queue behavior compared to traditional fixed-time or actuated logic (Xu, Wu, Pan, Liu, et al., 2023). The findings of this study aligned directly with those earlier results, showing that control strategy served as a significant predictor of all traffic performance indicators. The magnitude of improvements observed in delay reduction and throughput increases exceeded those commonly reported in earlier standalone AI-control experiments, likely due to the enhanced situational awareness enabled by the digital twin's high-resolution environment (Zheng et al., 2022). Previous studies have shown that the depth and fidelity of traffic state information strongly influence the effectiveness of learning-based controllers, and this study reinforced that conclusion by demonstrating improved reliability metrics and lower residual variance in performance outcomes (Van Dyck et al., 2023). Demand level continued to predict congestion severity, but its influence weakened significantly under AI control, confirming earlier research findings that advanced signal control systems are more resilient to fluctuations in traffic volumes. Scenario type had minimal influence on regression outcomes, which aligned with earlier studies showing that reinforcement learning controllers respond effectively across varying operational contexts. All hypotheses tested in this study were supported, consistent with earlier research demonstrating the positive effects of adaptive control on network efficiency (Zhang & Tai, 2022). The strength of the regression coefficients and the significance levels observed in this study suggested that the AI-driven digital twin platform had a transformative effect on operational performance, surpassing the gains documented in traditional adaptive signal control literature (Maheshwari et al., 2023).

The comparative interpretation of this study's quantitative findings with earlier literature highlighted several areas where the digital twin–AI integration produced stronger effects than those typically reported in conventional adaptive control studies (Mylrea et al., 2021). Earlier research in adaptive traffic control often emphasized incremental improvements resulting from real-time signal adjustments, whereas this study demonstrated more pronounced performance gains due to the continuous learning and state-updating capabilities of the integrated digital twin environment. The combination of high-resolution sensor emulation, real-time state estimation, and reinforcement learning created a system capable of responding more aggressively and effectively to demand fluctuations than systems described in earlier transportation research (Tao et al., 2019). Another area where this study advanced the understanding of AI-based traffic operations lay in the magnitude of reliability improvements. Earlier studies reported moderate improvements in travel time stability under machine learning control, but this study demonstrated substantial gains, suggesting that the high-fidelity roadway representation within the digital twin environment contributed to stronger stabilization effects. Additionally, the regression analysis in this study showed higher explanatory power than earlier models, indicating that integrating digital twin data structures may enhance the predictive strength of intelligent traffic control frameworks (Tao et al., 2019). These findings suggested that while earlier research provided foundational evidence supporting the benefits of AI-based traffic control, the integration with digital twin technology amplified those benefits substantially (Wang et al., 2021).

The overall interpretation of this study's findings revealed significant contributions to the evolving body of knowledge on AI-driven traffic control and digital twin applications (Allam et al., 2022). By demonstrating that the digital twin–reinforcement learning integration produced stronger, more consistent, and more scalable improvements than earlier systems, this study expanded the empirical foundation supporting advanced traffic management technologies (Cellina et al., 2023). Earlier research consistently described limitations associated with detection noise, model simplification, and lack of real-time state fidelity; in contrast, this study showed how the digital twin's continuous data synchronization and high-resolution monitoring reduced these limitations. The consistency of improvements across various performance indicators supported the argument that combining digital twins with AI-based signal control systems not only enhances operational outcomes but also introduces a more stable analytical structure for evaluating network dynamics. The reduced sensitivity of performance outcomes to demand fluctuations further indicated that the system demonstrated resilience characteristics not commonly reported in earlier adaptive control studies (Han et al., 2023). Moreover, the methodological rigor observed in this study—supported by strong reliability, validity, and collinearity diagnostics—ensured that the findings aligned with best practices in quantitative traffic operations research. The comparison with earlier research demonstrated that while many prior studies have established the potential effectiveness of AI-based traffic control systems, the introduction of a digital twin environment elevated their accuracy, responsiveness, and predictive power to levels not previously documented (Afzal et al., 2023).

CONCLUSION

The conclusion of this study emphasized that the integration of an AI-driven digital twin framework significantly improved the operational performance of traffic signal control systems compared with conventional strategies, demonstrating clear advantages in delay reduction, queue minimization, throughput enhancement, and travel time reliability. The findings confirmed that the digital twin environment provided a high-fidelity representation of real-world conditions, and its ability to continuously update system states allowed the reinforcement learning–based controller to respond more effectively to fluctuating demand patterns. The descriptive results showed substantial improvements across all evaluated performance indicators, while the correlation analysis revealed that the AI-based controller reduced the dependency between demand surges and congestion severity, indicating a more resilient network response. Reliability and validity assessments further strengthened the empirical grounding of this study by demonstrating strong internal consistency across replicated simulations and close alignment between simulated and field-observed conditions. Collinearity diagnostics confirmed that the regression framework rested on statistically defensible assumptions, ensuring that the predictive relationships identified between control strategy and performance outcomes were reliable and stable. The regression analysis demonstrated that the AI-driven system consistently predicted improvements across all metrics, and every hypothesis associated with performance gains was supported by statistically significant results. Collectively, these findings indicated that the digital twin–AI integration provided a transformative approach to traffic signal optimization, producing benefits that surpassed those documented in earlier adaptive control research. The ability of the system to maintain performance improvements across peak, off-peak, and incident scenarios demonstrated its robustness and scalability, suggesting it could serve as an advanced operational tool for complex and dynamically changing urban networks. This study therefore provided comprehensive quantitative evidence that AI-enhanced digital twins hold substantial potential for reshaping modern traffic management practices and advancing the effectiveness of real-time signal optimization.

RECOMMENDATIONS

Based on the findings of this study, several recommendations were proposed to support the advancement, adoption, and refinement of AI-driven digital twin technologies in traffic signal optimization. It was recommended that transportation agencies incorporate digital twin platforms into their traffic management strategies to enhance real-time monitoring, adaptive decision-making, and operational resilience. The integration of reinforcement learning algorithms with high-resolution digital models demonstrated clear advantages in managing congestion, suggesting that agencies could benefit from deploying similar approaches across urban corridors with recurring mobility challenges. Future implementations should prioritize robust sensor infrastructures to support continuous data synchronization, as the effectiveness of digital twin environments depends heavily on the quality and granularity of incoming traffic information. For jurisdictions considering pilot deployments, it was advised that thorough calibration and validation processes be conducted to ensure alignment between simulated and observed field conditions, as this study showed that strong empirical correspondence is essential for achieving reliable performance improvements. Additionally, planners and engineers were encouraged to evaluate performance under varying demand conditions, including peak, off-peak, and incident periods, to identify how reinforcement learning models adapt to different operational environments. Collaboration between traffic engineers, data scientists, and system developers was recommended to ensure that algorithmic design aligns with practical roadway constraints and policy requirements. The study's results also suggested that agencies should invest in staff training to enhance familiarity with AI-based systems, as operational understanding is critical for effective deployment and long-term maintenance. It was further recommended that future research expand the scope of evaluation to include multimodal interactions involving pedestrians, cyclists, and transit vehicles, as the digital twin framework demonstrated strong potential for capturing complex system dynamics. Overall, these recommendations highlighted the strategic and technical steps necessary to support the broader integration of AI-enhanced digital twins into modern traffic management practices.

LIMITATIONS

Several limitations were identified in this study that influenced the scope, generalizability, and interpretability of the findings. The digital twin environment, although highly calibrated and validated, still depended on assumptions related to driver behavior, saturation flow, pedestrian compliance, and lane utilization that may not fully capture the complexity of real-world operating conditions. While the simulation framework demonstrated strong reliability and validity, it remained a controlled environment, and actual roadway networks may introduce unpredictable behavioral patterns, climatic conditions, and enforcement variations that were not fully replicated in the model. The reinforcement learning algorithm used in this study was trained and evaluated within a predefined set of demand scenarios, which limited the ability to capture extreme or atypical traffic fluctuations that occur during special events, sudden disruptions, or emergency conditions. The study also relied on a corridor-level application, meaning that the results may not fully generalize to larger grid networks or rural road systems with different geometric characteristics and traffic compositions. Sensors and data streams in the simulation environment operated at higher levels of precision than many real-world systems currently support, which may limit the immediate applicability of results for jurisdictions with limited technological infrastructure. Additionally, the interaction between multimodal users such as cyclists, pedestrians, and transit vehicles was simplified, restricting the ability to fully assess the system's performance under conditions with high multimodal complexity. The regression models used to evaluate predictive relationships captured major performance trends but did not incorporate more advanced nonlinear or temporal modeling techniques that might reveal deeper behavioral dynamics within AI-controlled environments. Finally, the study focused on short-term operational performance but did not evaluate long-term impacts such as maintenance requirements, computational costs, or the evolution of learned strategies over extended periods of system use. These limitations provided important context for interpreting the study's contributions and highlighted areas where further investigation would be beneficial.

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