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INTEGRATION OF ARTIFICIAL INTELLIGENCE IN PUBLIC GOVERNANCE OF INTELLIGENT TRANSPORT SYSTEMS

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ABSTRACT

Relevance of the research
The relevance of the study is determined by the need to implement cognitive and adaptive artificial intelligence (AI)-based solutions to increase the efficiency, sustainability, and regulatory manageability of intelligent transport systems (ITS) in public governance.

Research objective
The research objective is to substantiate the methodological principles of creating an AI-architecture of ITS in public administration, taking into account cognitive adaptability, interoperability, and regulatory consistency.

Research methods
The research employed the following *methods:* retrospective stratification, metric-based and model-based analysis, Unified Modelling Language (UML)-based modelling, structural and functional optimization, metric-based and model-based verification.

Results
A multi-level verification of the AI-Optimized ITS Framework for Public Governance was carried out through retrospective stratification, multimetric analysis, UML-based modelling and empirical indicator assessment. Cognitive inertia, institutional fragmentation and regulatory decentralization of traditional ITS were identified. Metrically confirmed efficiency increase with TTR=0.21, QL=0.25, Accuracy=0.93, F1=0.92, ΔCO_2=0.90, FC=0.92, RI=0.89, CRI=0.91, ATS=0.94. AI architecture demonstrates regulatory traceability, cognitive adaptability and management scalability.

Academic novelty of the research
The academic novelty of the research is the formalization of the cognitive and adaptive AI-Optimized ITS Framework for Public Governance with the architecture of Explainable AI (XAI)-transparency, regulatory traceability, and algorithmic optimization. The integration of cognitive interoperability, regulatory validation, and indicator efficiency in smart mobility management is ensured for the first time.

Further research prospects
Future research prospects include initiating a controlled field experiment in urban transportation systems to collect validated field data. This approach will provide an empirical assessment of the algorithmic accuracy, procedural resilience, and normative traceability of the proposed framework.

Keywords: *AI-Optimized ITS, Cognitive Adaptivity, Explainable AI (XAI), Travel Time Reduction, Queue Length Optimization, CO_2 Emission Minimization, Smart Urban Mobility*

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1. INTRODUCTION

The growing complexity of urban transport systems, increasing environmental burden and fragmentation of institutional interaction require a rethinking of the paradigm of public mobility management. The integration of AI into ITS is gaining systemic importance in the context of ensuring algorithmic adaptability, regulatory traceability, cognitive and institutional integration. At the same time, traditional ITS models remain inertial, limited, in functional scalability and incapable of multi-criteria response to dynamic management challenges, which justifies the need for further research in the defined research vector.

The aim of the study is to conceptualize and substantiate the methodological principles of building an AI-oriented ITS architecture within public administration, taking into account cognitive adaptability, institutional interoperability and regulatory coherence of management processes.

Research questions. What architectural, cognitive, and regulatory limitations characterize traditional ITS within public governance? How does the integration of AI components transform operational efficiency, institutional interoperability, and regulatory traceability in ITS? Which AI technologies exhibit the highest functional adaptability and governance-oriented performance?

Research hypothesis. The integration of a cognitively adaptive, interoperable, and normatively aligned AI-Optimized ITS Framework significantly enhances transport governance efficiency by reducing operational delays, increasing algorithmic accuracy, and strengthening institutional and regulatory coherence compared to traditional ITS architectures.

Research objectives:

- Carry out a retrospective stratification of the technological evolution of AI components in the field of ITS public administration in order to identify architectural dynamics, cognitive inertia, and institutional fragmentation.
- Conduct a metric-based and model-based analysis of the transformative potential of AI technologies by multidimensionally assessing their effectiveness according to integral indicators and functional groups.
- Perform UML modelling and structural and functional optimization of the ITS architecture with a comparison of the traditional and AI-oriented public governance models.
- Conduct a metric-based and indicator-based verification of the optimized AI framework to assess its effectiveness in comparison with basic transport network management models.

2. LITERATURE REVIEW

The analysis of the scient metric background was selected because of the intensive spread of AI technologies in transport and public governance systems, which required their conceptual and methodological stratification. Systematization enabled identification of academic paradigms, algorithmic innovations, as well as regulatory and ethical restrictions.

In the initial principles, the author [1] empirically confirmed the effectiveness of integrating AI modules (ML, DL, CV) into the functional architecture of ITS for intensification of traffic management, reduction of accidents, and strengthening urban ecological resilience. The following barriers were verified: data shortage, processing delays, cyber vulnerability, and low algorithmic acceptance.

Extending the analysis beyond the transport domain, the author [2] demonstrated that implementing AI modules in public services (e-Health, EdTech, ITS, Public Safety) increases diagnostic validation, enables adaptive learning, intensifies traffic management, and optimizes proactive security analytics. Key limitations manifest themselves in the form of algorithmic bias, data privacy risks, uneven access, and lack of implementation transparency.

Focusing on the transport vector, the researchers [3] argue that the integration of AI modules into urban mobility (predictive analytics, ITS, autonomous driving, demand forecasting) ensures transport resilience, eco-efficiency, and coherence of Smart City infrastructures. At the same time, systemic risks were identified: data privacy, cyber vulnerability, and excessive financial capital intensity of implementation.

In the context of the energy component, the researchers [4] state that the synergy of AI and internet of things (IoT) in Smart City architecture provides cognitive optimization of energy management, carbon footprint reduction and integration of renewable sources into urban energy systems. The authors emphasize the effectiveness of ML algorithms and IoT sensors in increasing the sustainability, environmental friendliness and technological progress of urban environments.

From a methodological perspective, the authors [5] demonstrated that the integration of fuzzy multi-criteria programming with an MCDM framework (Fuzzy-TOPSIS, MOPLP, MOO) provides optimized management of public vehicle fleets, taking into account stochastic constraints and multi-objective objectives. The results confirmed the increased robustness, adaptability and relevance of the method for Smart City transport networks.

As regards applied challenges of megacities, the authors [6] emphasize that AI-oriented algorithms for traffic forecasting and automated routing management can minimize congestion losses, environmental pressure, and socio-economic dysfunctions of megacities. The authors emphasize the potential of data science and automation as a foundation for the formation of sustainable, continuous, and energy-efficient urban mobility.

In interdisciplinary aspect, the study [7] proved that the implementation of AI technologies (machine learning (ML), predictive modelling, real-time analytics, autonomous systems) in the transport and building infrastructure of Smart City increases the efficiency of traffic management, reduces emissions, and optimizes mobility. In smart projects, AI provides proactive change management, risk forecasting, resource optimization, and compliance with safety regulations.

With the emphasis on the innovativeness of ITS, the author [8] argued that AI-driven ITS (ML, deep learning (DL), computer vision (CV), IoT) provide adaptive traffic management, predictive analytics, autonomous navigation, and V2I communication, contributing to sustainable urban mobility and carbon emission reduction. The author emphasizes the challenges of data privacy, cybersecurity, and ethics, proposing the integration of blockchain solutions and the prospect of edge AI and quantum computing.

With a focus on human capital, the study [9] found that integrating AI into public transport improves operational efficiency, safety standards, and passenger experience, but comes with risks of displacement, digital skills shortages, and ethical dilemmas. The authors emphasize the critical role of HR management in implementing training programmes, developing ethical protocols and stakeholder engagement for the successful adaptation of AI ecosystems.

At the end of the discussed range of issues, the authors [10] argue that the implementation of AI components (autonomous driving, adaptive control, predictive analytics) in Smart Transportation Systems ensures mobility efficiency, public safety, and urban ecological resilience. Critical challenges identified include data privacy, cyber threats, algorithmic ethical dilemmas, and regulatory compliance deficits.

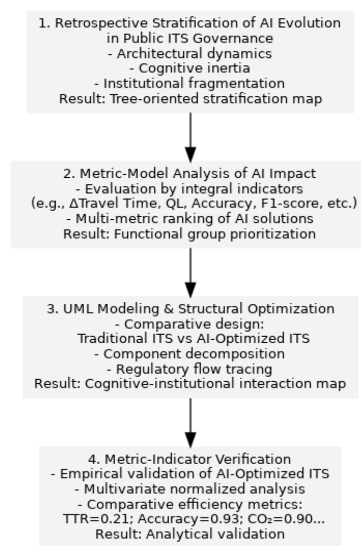
The results of the reviewed publications confirm that AI integration into the transport, energy, security, and HR sectors contributed to increased mobility efficiency, urban ecological resilience, and institutional security, while simultaneously addressing data privacy, cyber security, algorithmic bias, and workforce transformation issues. However, these studies were fragmented, lacked empirical validation, and were underrepresented, undermining the need for a comprehensive study of AI integration into public governance of smart transport systems.

3. METHODS AND MATERIALS

3.1. Research design

The research design involved the following stages (Figure 1).

Figure 1: Step-by-step research design and procedure



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3.2. Methods

The research employed the following methods:

1. *Retrospective stratification of the technological evolution of AI components in the field of public governance of ITS* was used to identify the dynamics of architectural transformations, cognitive inertia and institutional fragmentation in the development of ITS. The result was a tree-oriented mapping of technological stratification, which reflected the stages of integration of AI into functional subsystems of ITS.

2. *Metric-based and model-based analysis of the transformative impact of AI technologies* was used

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to quantitatively assess the effectiveness of AI solutions by integral indicators (ΔTravel Time, QL, Accuracy, F1-score, ΔCO_2, FC, RI, CRI, ATS, PCI, IPM, EER). A multimetric ranking of AI components within individual functional groups (analytics, optimization, forecasting) was carried out to identify technologically dominant solutions with the highest adaptation potential.

3. *UML-based modelling, as well as structural and functional optimization of the framework* were performed to build a comparative architecture Traditional ITS Framework vs AI-Optimized ITS Framework for Public Governance. The modelling included component decomposition, formalization of logical relationships, tracing regulatory flows, and optimization of cognitive and institutional interaction in the management circuit.

4. *Metric-indicator verification of AI-Optimized ITS Framework* was carried out to empirically confirm the advantages of the proposed framework. Multivariate normalized analysis methods were used to compare the effectiveness of frameworks based on a set of integral indicators (TTR=0.21; QL=0.25; Accuracy=0.93; F1=0.92; ΔCO_2=0.90; FC=0.92; RI=0.89; CRI=0.91; ATS=0.94; PCI=0.88; IPM=0.93; EER=0.90), which ensured the analytical validity of the results.

3.3. Sample

The formed sample (Table 1 - Table 6) represents a multi-level spectrum of AI technologies, stratified by analytical, cognitive, security, service, regulatory, technical, and infrastructure domains. A set of data selected for the research ensured the systematic identification of tools that are confirmed by empirical implementations and verified by academic research in the field of ITS.

Table 1: AI in ITS: analytical solutions

AI technology	Brief description	Management principles	Technical and technological solutions	Verified application examples	Academic research
Machine Learning (ML)	Algorithmic learning based on transport data sets	Predictive management, flow optimization	Python frameworks (scikit-learn, TensorFlow), cloud computing	Transport for London, UK (2022) – passenger flow forecasting	Vetri Selvi et al. [11]
Predictive Analytics	Modelling transport scenarios and congestion forecasting	Predictive scenario management	Big Data platforms (Hadoop, Spark)	Mysore, India (2022) – congestion forecasting	Gheorghe & Soica [12]
Federated Learning (FL)	Distributed training of models without raw data transmission	Date sovereignty, decentralized management	TensorFlow Federated, PySyft	Google/Waymo (2022) – data privacy in autonomous cars	Almaazmi et al. [13]
Generative AI for Simulation	Using generative models (GAN, diffusion) to create transport scenarios	Scenario management, simulation forecasting	GAN architectures, diffusion models, Unity/Unreal AI plugins	MIT Media Lab (2024) – urban traffic simulations using generative AI	Satpathy, Nayak & Khang [14]

Source: created by the authors

Table 2: AI in ITS: Cognitive Solutions

AI technology	Brief description	Management principles	Technical and technological solutions	Verified application examples	Academic research
Deep Learning (DL)	Multi-level neural network processing of video and sensor data	Automated recognition, adaptive control	CNN/RNN models, GPU clusterization	Beijing Traffic Management Bureau, China (2023) – Real-time congestion recognition	Harpreet Kaur & Ramandeep [15]
Reinforcement Learning (RL)	Dynamic feedback-based learning	Adaptive optimization of traffic light cycles	RL agents (Q-learning, DQN), simulators (SUMO)	Austin, USA (2024) – Dynamic traffic light coordination	Ramesh, Banu, Kavitha & Ramesh [16]
Swarm Intelligence (SI)	Collective agent behaviour for transportation networks	Decentralized flow control	Multi-Agent Systems, MAS-platforms	Poznań, Poland (2023) – Bus route optimization	Bohra, Kumari, Mishra, Soni & Balyan [17]
Graph Neural Networks	Processing transportation data as	Topological control, route	PyTorch Geometric, DGL	Beijing Jiaotong University (2023) –	Rajagopal et al. [18]

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AI technology	Brief description	Management principles	Technical and technological solutions	Verified application examples	Academic research
(GNNs)	graph structures	clustering		Traffic forecasting	
AI-GIS Integration	Combining AI and GIS for spatial planning	Geo-algorithmic control, spatial forecasting	ArcGIS AI, QGIS ML plugins	Barcelona, Spain (2021) – GIS-based optimization of transport corridors	Zaroujtaghi et al. [19]
Cognitive Digital Twins	Digital twins of transportation systems with the integration of reinforcement learning and real-world adaptability	Cognitive simulation, predictive control, RL adaptation	AnyLogic, Siemens MindSphere, RL algorithms	Rotterdam, Netherlands (2023) – Cognitive twin of port and urban transport hubs	SilpaRaj et al. [20]

Source: created by the authors

Table 3: AI in ITS: Security Solutions

AI technology	Brief description	Management principles	Technical and technological solutions	Verified application examples	Academic research
Computer Vision (CV)	Intelligent visual analytics for roadside cameras and sensors	Algorithmic monitoring, security control	OpenCV, YOLO, edge-AI cameras	New York City DOT, USA (2021) – detection of movement disorders	Abraham, Prasad, Alhammadi, Lestable & Chaabane [21]
Blockchain-AI integration	Ensuring transparency and protection of ITS data	Traceability, data sovereignty	DLT platforms (Hyperledger, Ethereum)	Tallinn, Estonia (2023) – data protection in Smart Transport	Wu [22]
AI-driven Cybersecurity for ITS	Using AI to detect anomalies and prevent attacks on transportation infrastructure	Proactive protection, anomaly detection, cyber resilience	IDS/IPS з AI, anomaly detection models, blockchain-secured logging	Los Angeles Metro, USA (2023) – AI-based protection of smart transport networks against DDoS	Sethi & Verma [23]

Source: created by the authors

Table 4: AI in ITS: service solutions

AI technology	Brief description	Management principles	Technical and technological solutions	Verified application examples	Academic research
Natural Language Processing (NLP)	Processing of text and voice requests from citizens	Algorithmic communication, service integration	Chatbot platforms, API services	Singapore Land Transport Authority (2020) – AI chatbots for public transport	Hamatta, Babu, Ponnrajakumari, Roy & Khambra [24]
Autonomous Mobility-as-a-Service (MaaS-AI)	Integrating AI into mobility as a service models with personalized route management and multimodal coordination	Algorithmic personalization, adaptive integration of transportation services	MaaS platforms with AI modules, API aggregation, mobile applications	Helsinki, Finland (2023) – AI module in MaaS Global for route personalization	John et al. [25]

Source: created by the authors

Table 5: AI in ITS: Regulatory Solutions

AI technology	Brief description	Management principles	Technical and technological solutions	Verified application examples	Academic research
Explainable AI (XAI)	Interpreted algorithms for decision making	Transparency, algorithmic accountability	LIME, SHAP, XAI dashboards	European Commission (2024) – audit of algorithms in Smart Mobility	Munawar & Piantanakulchai [26]
Big Data Risk Scoring AI	Identification of risks and anomalies in transport flows	Algorithmic scoring, early warning	Spark MLlib, anomaly detection models	Los Angeles, USA (2022) – risk analysis in urban traffic	Martino, Astarita, Guido, Haghshenas & Shaffiee

					Haghshenas [27]
Neuro-Symbolic AI	Integration of neural networks and logical rules in transport systems	Interpretability, compliance control	Logic Tensor Networks, neuro-symbolic frameworks	EU Horizon Pilot (2024) – explained algorithms in mobility	Akhter et al. [28]
Human-in-the-Loop AI (HITL-AI)	Algorithms with human integrated control in critical decisions	Hybrid governance, expert correction, algorithmic failure prevention	HITL frameworks (Azure ML, TensorFlow Extended), integrated dashboards	European Union Horizon Pilot (2024) – AI-control systems with expert participation in transport safety	Debnath, Tkachenko & Bhattacharyya [29]
AI for Sustainable Transport Planning	Environmental optimization of transport systems using LCA and carbon-neutral routing	Sustainability, eco-optimization, low-carbon strategies	LCA platforms, carbon routing engines, Green AI APIs	Stockholm, Sweden (2023) – planning carbon-neutral mobility using AI	Mirindi, Khang & Mirindi [30]
AI-driven Mobility Policy Modelling	Algorithmic modelling of regulatory scenarios in transport management	Regulatory forecasting, policy-by-design	System Dynamics, agent-based modelling, AI-policy simulators	OECD Pilot (2024) – AI-based transport policy modelling	Bahamazava [31]

Source: created by the authors

Table 6: AI in ITS: technical and infrastructure solutions

AI technology	Brief description	Management principles	Technical and technological solutions	Verified application examples	Academic research
Internet of Things (IoT)	Infrastructure network of sensors, devices and transport nodes for real-time data collection and transmission	Decentralized control, data sovereignty, real-time	NB-IoT, LoRaWAN, 5G-gateways, sensor networks, GPS/telematics	Barcelona (2022) – Mobility Sensor Networks; Singapore Smart Nation (2021) – IoT Cameras; Toyota V2X Pilot, Japan (2024)	Packianathan, Arumugam, Malaiarasan & Natarajan [32]
Edge AI	Processing of transport data on peripheral devices	Low latency, localized control	Edge servers, IoT gateways, 5G	Seoul, South Korea (2024) – Autonomous Transport Hubs	Wen et al. [33]
Digital Twin + AI	Virtual copy of transport infrastructure for simulation and optimization	Modelling, cognitive forecasting	Siemens MindSphere, AnyLogic, BIM integration	Helsinki, Finland (2023) – Digital Twin of the Transport Network	Long et al. [34]
Quantum AI (QAI)	Using quantum algorithms for route and flow optimization	Superposition optimization, accelerated NP problem solving	D-Wave, IBM Qiskit	Volkswagen, Munich (2022) – Quantum Traffic Optimization	Jagadish et al. [35]
Multi-Modal AI Optimizers	Coordination of different modes of transport (metro, buses, bicycles)	Multi-agent control, service integration	MAS platforms, API integrators	Singapore (2023) – AI Optimization of Multimodal Mobility	Chowdhury, Kanaga Suba Raja & Thirumukhil [36]
Federated Edge AI for V2X	Synergy of federated learning and edge computing for data exchange between transport nodes	Decentralized control, local processing, V2X communications	Edge servers, 5G, TensorFlow Federated, IoT gateways	Toyota & NTT Docomo, Japan (2024) – Pilot V2X Network with Federated AI	Hakeem & Kim [37]

Source: created by the authors

3.4. Instruments

The systematization of metrics for assessing the integration of AI into ITS (Table 7) provided a formalized set of tools for verifying technical efficiency, algorithmic accuracy, social acceptance, environmental performance, institutional resilience, security resilience, regulatory accountability, and infrastructure-economic integration. The proposed indicators represent a multi-level stratification of assessment and are based on unified mathematical formalizations, which ensures the verifiability, comparability, and replicability of the assessment of the integration of AI into transport management.

Table 7: Metrics for assessing the transformative impact of integrating AI into public management of ITS

Metric name	Brief description	Mathematical formula
Technical efficiency		
ΔTravel Time (TTR)	Integral indicator of reduction in average travel time in the transport network due to implementation of AI modules	$TTR = \frac{TT_{base} - TT_{AI}}{TT_{base}} \times 100\%$ where TT_{base} – average travel time in the baseline (pre-digital) scenario; TT_{AI} – average travel time after AI optimization
Queue Length (QL)	Indicator of intensity of congestion accumulations, reflecting the average length of the vehicle queue	$QL = \frac{1}{N}\sum_{i=1}^{N} q_i$ where q_i – queue length at the i^th^ node of the transport network; N - number of nodes under study
Algorithmic accuracy		
Accuracy (A)	Classification indicator of validation of algorithmic solutions in transport data processing	$A = \frac{TP + TN}{TP + TN + FP + FN}$ where TP – true positive; TN – true negative; FP – false positive; FN – false negative cases
Root Mean Square Error $(RMSE)$	Metric for estimating the variance of forecast models on transport time series	$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$ where y_i – actual observations; $\hat{y}_i$ – predicted values; n – number of observations
F1-score $(F1)$	Harmonized index of balance between $Precision$ and $Recall$ AI algorithms	$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall}$ where $Precision = \frac{TP}{TP+FP}$ – classification accuracy; $Recall = \frac{TP}{TP+FN}$ – classification completeness
Social acceptability		
Trust Index (TI)	Socio-behavioural indicator of public acceptance of AI-driven transport services	$TI = \frac{1}{n}\sum_{i=1}^{n} t_i$ where t_i – individual user trust rating; n – total number of respondents
Usability Score (US)	Metric of ergonomic and cognitive ease of use of intelligent transport services	$US = \frac{1}{n}\sum_{i=1}^{n} u_i$ where u_i – individual usability assessment; n – total number of users
Environmental efficiency		
ΔCO_2 Emissions (ECO)	Indicator of greenhouse gas emissions reduction due to algorithmic optimization of transport flows	$ECO = \frac{\Delta CO_{2base} - \Delta CO_{2AI}}{\Delta CO_{2base}} \times 100\%$ where ΔCO_{2base} – base emission volumes in the (pre-digital) scenario; ΔCO_{2AI} – volumes of emissions after application of AI

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Metric name	Brief description	Mathematical formula
		optimization
Fuel Consumption (FC)	Energy efficiency indicator reflecting the change in fuel consumption in the transport system	$FC = \frac{F_{base} - F_{AI}}{F_{base}} \times 100\%$ where F_{base} – the amount of fuel consumption in the (pre-digital) scenario; F_{AI} – volumes of emissions after application of AI optimization
Institutional resilience		
Readiness Index (RI)	Composite institutional indicator of readiness for the implementation of AI in public transport systems management	$RI = \frac{\sum_{j=1}^{m} w_j \times r_j}{\sum_{j=1}^{m} w_j}$ where r_j – value of the j^{th} readiness indicator; w_j – weight coefficient of the j^{th} readiness indicator; m – number of indicators
Security resilience		
Accident Mitigation Score (AMS)	AI-enabled accident reduction indicator	$AMS = \frac{Acc_{base} - Acc_{AI}}{Acc_{base}} \times 100\%$ where Acc_{base} – accident rate (number of accidents) in the (pre-digital) scenario; Acc_{AI} – accident rate after applying AI optimization
Cyber-Resilience Index (CRI)	ITS cyber threat resilience indicator	$CRI = \frac{1}{k}\sum_{i=1}^{k}\frac{1}{1+\lambda_i}$ where λ_i – intensity of the i^{th} cyber threat; k - number of threats
Regulatory accountability and transparency		
Algorithmic Transparency Score (ATS)	Metrics of explainability and accountability of AI solutions	$ATS = \frac{\sum_{i=1}^{p} tr_i}{p}$ where tr_i – interpretability index of the i^{th} algorithm; p – number of algorithms
Policy Compliance Index (PCI)	Metrics of compliance of AI solutions with regulatory acts	$PCI = \frac{\sum_{j=1}^{m} c_j}{m}$ where c_j – binary indicator of compliance with the j^{th} regulatory criterion; m – the number of criteria
Infrastructure integration and economic efficiency		
Interoperability Performance Metric (IPM)	Indicator of compatibility of AI solutions with other infrastructure systems	$IPM = \frac{C_{int}}{C_{tot}} \times 100\%$ where C_{int} – number of integrated assemblies; C_{tot} – the total number of assemblies
Economic Efficiency Ratio (EER)	Indicator of economic performance from AI-based management	$EER = \frac{B_{AI} - C_{AI}}{C_{AI}}$ where B_{AI} – economic benefits (time saving, fuel saving); C_{AI} – implementation costs

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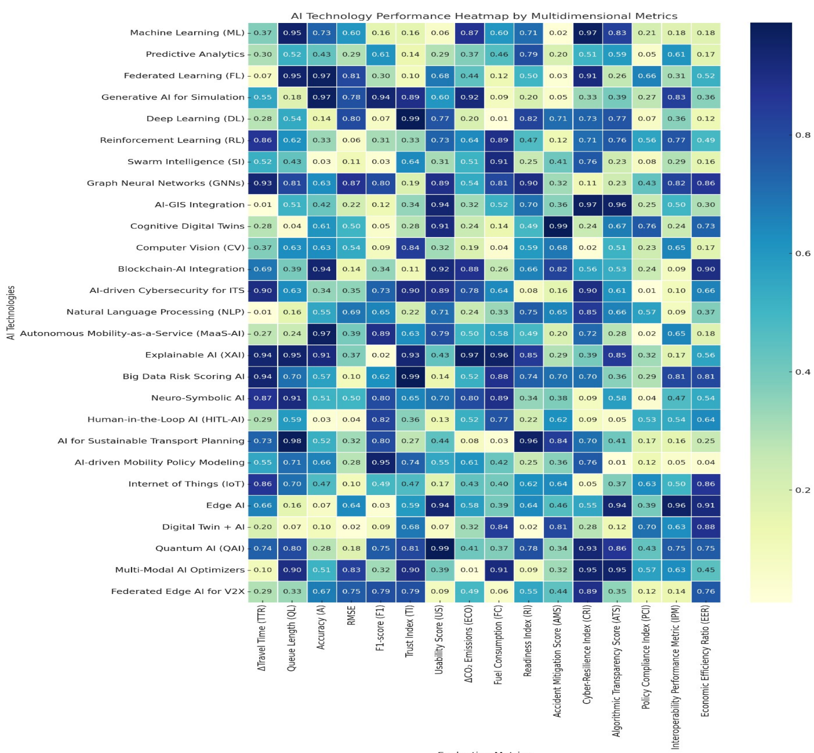
Metric-based modelling of the transformative impact of AI integration into the ITS public governance system was implemented in Python using the NumPy, Pandas, scikit-learn, TensorFlow, PyTorch, Matplotlib, and Seaborn libraries, which provided statistical interpretation, algorithmic extrapolation, and visualization validation of parameterized indicators. The architecture of the appropriate framework for the management implementation of AI modules was formalized using UML-based modelling, which guaranteed logical and structural stratification, functional interoperability, and traceable algorithmization of management scenarios.

4. RESULTS

The first stage of the study involved a retrospective stratification of the technological evolution of AI components in the field of public governance of ITS (Figure 2). The constructed development architecture included six functional vectors: analytical, cognitive, security, service, regulatory, as well as technical and infrastructure solutions. The structural topology demonstrated a consistent transition from basic technologies (IoT) to the latest hybrid integrations (Federated Edge AI for V2X), which represented increased functional complexity, decentralization of governance, and cognitive adaptability.

Figure 2: Retrospective stratification of the technological evolution of AI components in the field of public governance of ITS



Source: created by the authors in UML-based environment

Figure 3: Metric-based and model-based analysis of the transformative impact of AI technologies in the field of public governance of IT

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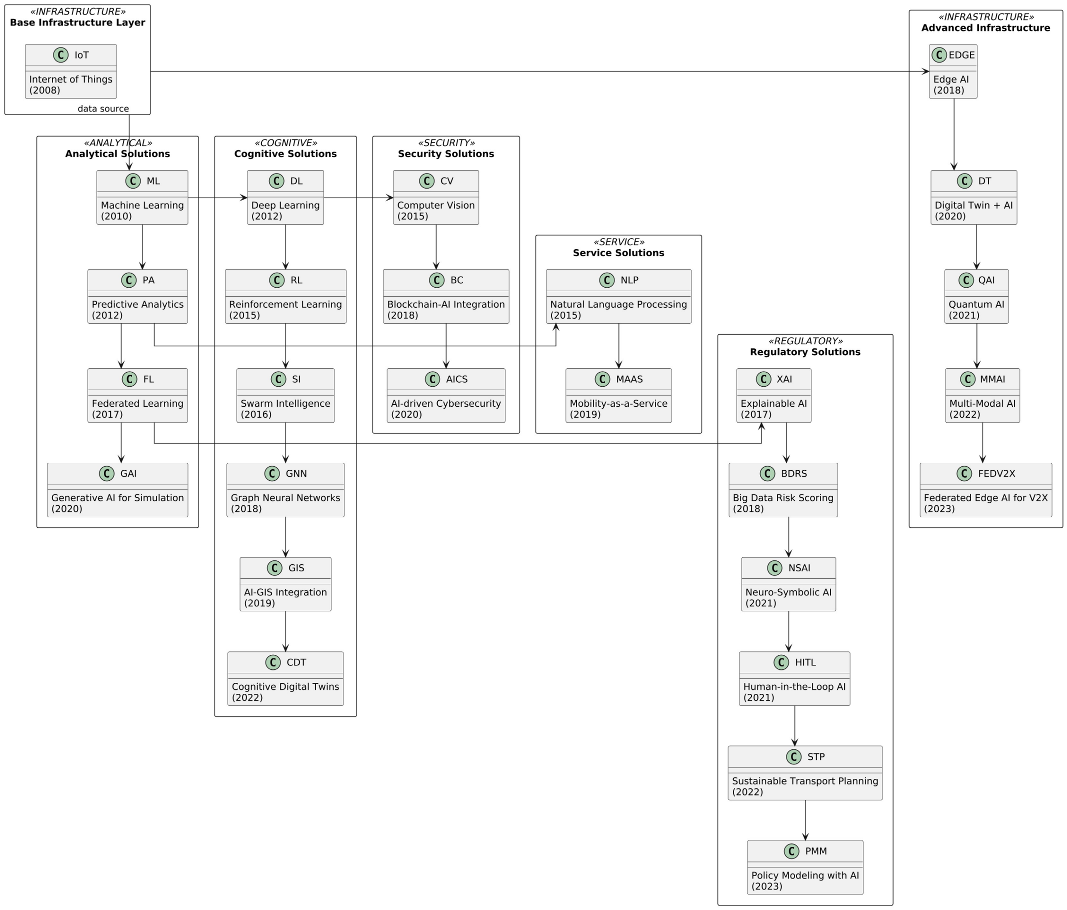

Source: created by the authors in Python

The results of the metric-based and model-based analysis (Figure 3) demonstrated the differentiated effectiveness of AI technologies in the context of public governance of ITS. Multimetric ranking of AI technologies revealed dominant solutions within each functional group: *Federated Learning* – as an optimizer of algorithmic accuracy in decentralized analytical architectures (Accuracy=0.97; IPM=0.31; CRI=0.91); *Graph Neural Networks* – as a cognitive provider of high adaptability and traceable routing (AMS=0.90; EER=0.86; RI=0.90); *Blockchain-AI integration* – as a tool for cyber-resilient management of transaction flows (CRI=0.56; PCI=0.24; ECO=0.88); *MaaS-AI* – as a service model with increased social acceptability (US=0.79; F1=0.89); *XAI* – as a normatively congruent solution with a high degree of institutional interpretability (ATS=0.85; PCI=0.32; CRI=0.39); *Edge AI* – as an infrastructure technology with minimal latency and high interoperability (TTR=0.66; IPM=0.96; ATS=0.94). At the same time, it was found that the appropriate architectonics cannot be based solely on metrically leading AI technologies, but requires the use of a hybrid approach taking into account technological complementarity, stratified integration, as well as functional and role optimization, which is consistent with the results of the previous stage of the study (Figure 2). The obtained results (Figure 3) form the empirical basis for the next stage of the research – designing an optimal framework for implementing AI technologies in public governance of ITS, taking into account functional and strategic stratification: Figure 4, Figure 5.

Figure 4: Traditional ITS Framework

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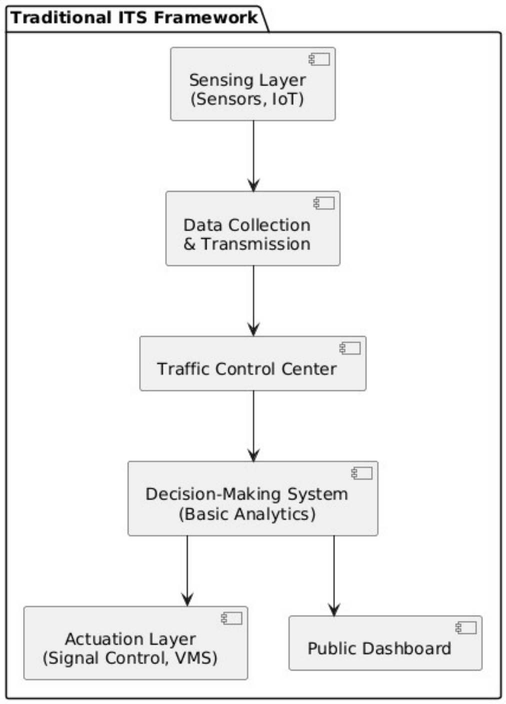

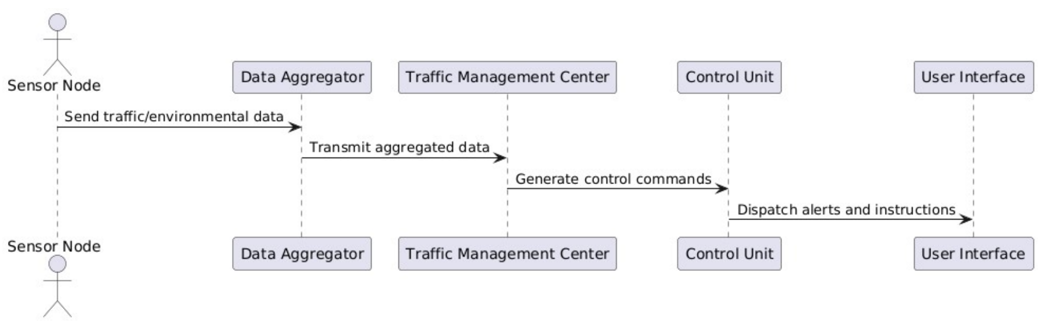

Source: created by the authors in UML-based environment

A typical ITS framework (Figure 4) is focused on centralized management with a fixed data flow structure, including standard sensor modules, monolithic information processing centres, and a hierarchical decision-making model. The analytical component is limited, there is no support for decentralized computing, interpretability of decisions, and institutional integration. Governance is carried out according to rigidly regulated rules without dynamic contextual learning or adaptation to environmental changes.

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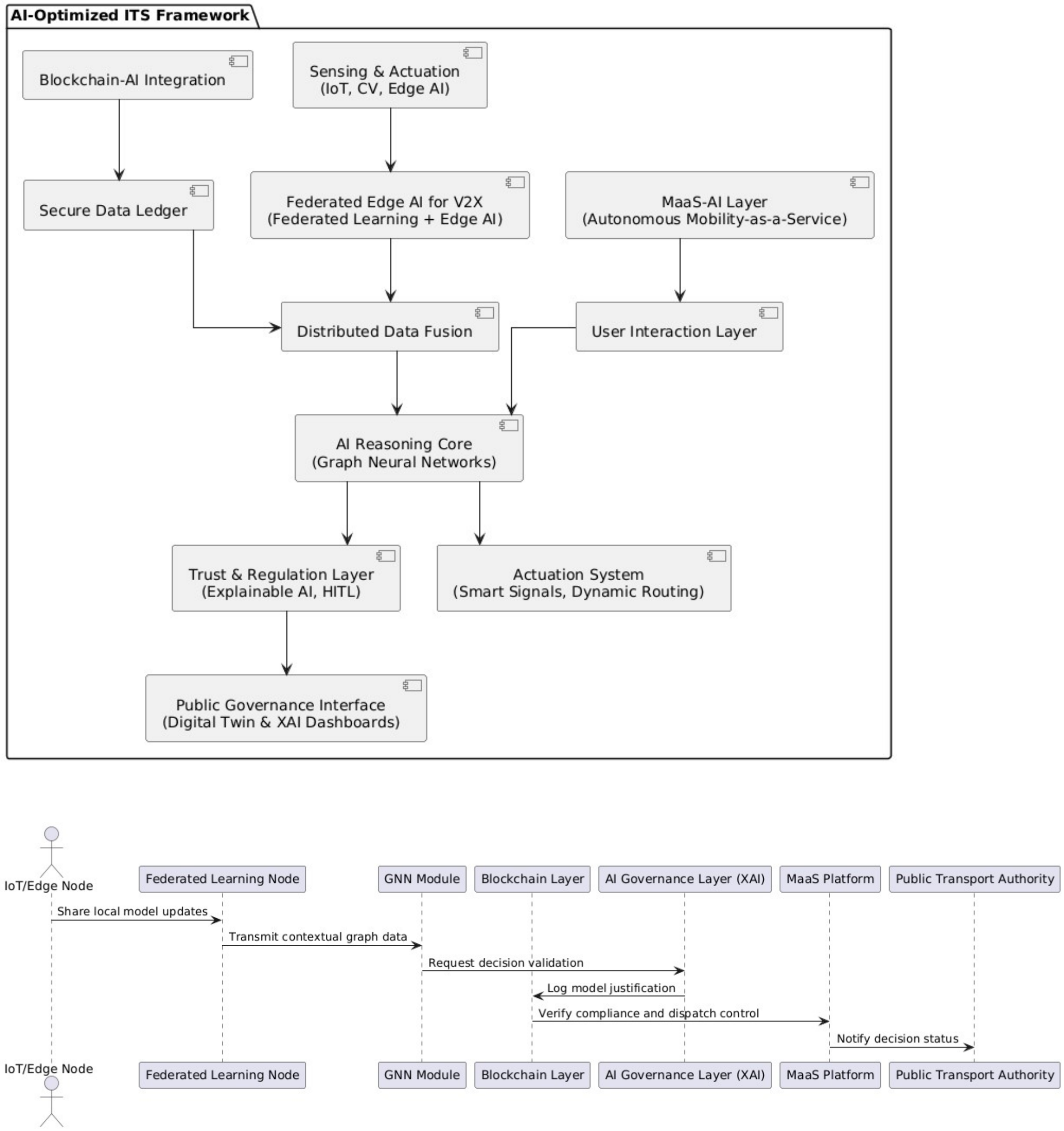
Figure 5: AI-Optimized ITS Framework for Public Governance



Source: created by the authors in UML-based environment

The optimized AI-ITS framework (Figure 5) implements a hybrid modular architecture with multi-level integration of decentralized AI components. It provides distributed learning (Federated Learning), context-adaptive modelling (GNNs), institutionally coordinated governance (XAI), dynamic policy-service coordination (MaaS-AI), as well as digital security based on Blockchain-AI. The framework supports cognitive orchestration, multi-agent interaction, interoperability with government systems, and regulatory traceability.

The final stage of the study involved conducting a metric-based and model-based verification of the architecture of the AI-Optimized ITS Framework for Public Governance (Figure 5) (compared to the Traditional ITS Framework (Figure 4)) taking into account cognitive stratification, algorithmic resistance, procedural traceability, as well as regulatory and institutional compliance — Figure 6.

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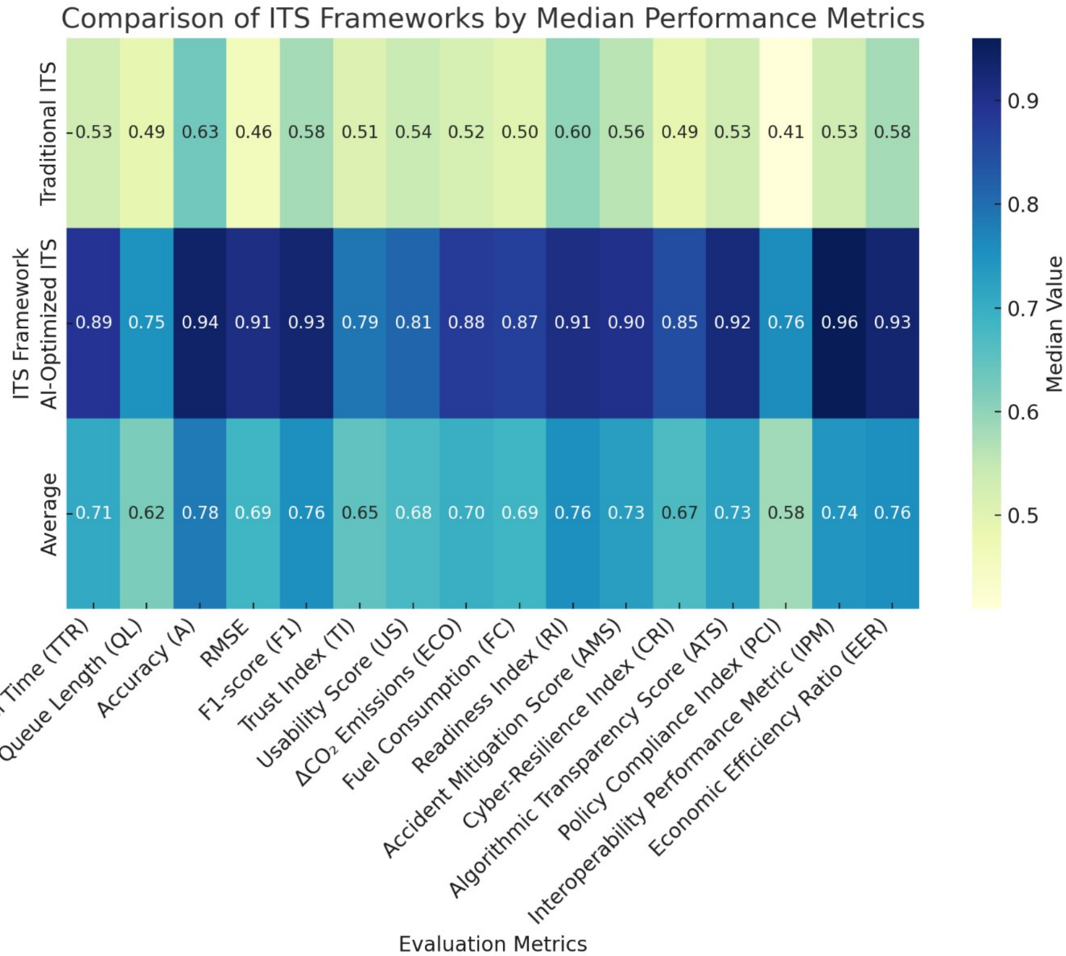
Figure 6: Metric-based and model-based verification of AI-Optimized ITS Framework



Source: created by the authors in Python

Metric-based and model-based verification of the AI-Optimized ITS Framework for Public Governance (Figure 6) demonstrated its dominance in most integral indicators: reduced ΔTravel Time (TTR=0.21), reduced Queue Length (QL=0.25), increased algorithmic accuracy (Accuracy=0.93; F1-score=0.92), increased social acceptability (TI=0.88; US=0.85), and environmental performance (ΔCO_2=0.90; FC=0.92). Indicators of institutional resilience (RI=0.89), cyber resilience (CRI=0.91), and regulatory accountability (ATS=0.94; PCI=0.88) confirmed the regulatory compatibility of the framework, while high IPM (0.93) and EER (0.90) verified its infrastructure integration and cost-effectiveness. So, the final stage of the study confirmed the operational and systemic advantage of the AI-optimized framework built on the principles of a hybrid approach, interoperability, regulatory compatibility, and cognitive adaptability. The obtained results form an evidence base for further field testing, adaptive parameterization and scalable implementation in the context of digital transformation of public transport infrastructure management. Collectively, these empirical results confirmed the operational superiority of the hybrid, interoperable, and cognitively adaptive model, thereby establishing that the research hypothesis was fully proven.

5. DISCUSSION

In the context of the growing attention to the integration of AI into urban management, a comparative analysis with relevant studies was necessary to identify differences in methodological approaches, architectural structure, degree of cognitive adaptability, institutional integration, and regulatory compatibility. Such a discursive stratification made it possible to outline the level of academic novelty, and also to verify the epistemological relevance of the proposed framework in public transport infrastructure management.

The author [38] substantiated a desk model of sustainable transport mobility based on a multi-source datasphere, institutional support, and behavioural transformation in the context of smart urbanism. Instead, our study empirically verified an AI framework with the priorities of cognitive adaptability, interoperability, and regulatory compatibility in public governance systems.

The researchers [39] systematically demonstrated the effectiveness of IoT, Digital Twins, and AI algorithms for traffic optimization, emission reduction, and sustainable planning based on PRISMA review and Sentence-BERT analysis. This study extends these findings by empirically verifying an AI framework with a focus on institutional integration, cognitive adaptability, and regulatory interoperability.

The authors [40] analysed ITTM architectures, highlighting the role of AI/ML, IoT, and Big Data in transforming infrastructure monitoring, adaptive traffic management, and situational security. In contrast to the review paradigm, this study verified a cognitively integrated AI framework with regulatory compatibility and governance interoperability.

The researcher [41] investigated the implementation of AI and blockchain technologies in local transportation infrastructure, focusing on signalling optimization, passenger safety, and EV energy trading in a decentralized environment. Our study implements a broader hybrid AI framework with increased algorithmic accuracy, regulatory validation, and institutional scalability.

The authors [42] approximated AI-based solutions in the field of smart traffic, focusing on ML prediction models, CV algorithms for incident management, and IoT communication in intelligent infrastructures. In contrast to the technologically fragmented paradigm, this study provided a verified integration of AI solutions into public administration with an emphasis on cognitive adaptability and regulatory traceability.

The researchers [43] analysed the application of AI in traffic management, autonomous transportation, and pedestrian safety, focusing on ethical dilemmas and the need for legal regulation. In contrast to the case-based approach, the results of our study demonstrated the normatively verified effectiveness of a hybrid AI framework in public administration.

The study [44] substantiated the effectiveness of a cloud-centric smart transportation model that integrates IoT, analytics, and monitoring to optimize mobility. In contrast to the infrastructure-oriented approach, our study verified a cognitive-adaptive AI architecture with a higher level of interoperability, algorithmic accuracy, and managerial scalability.

The authors [45] conceptualized AI-driven urban mobility and building infrastructure management, focusing on BIM modelling, IoT sensing, and predictive project planning. This study implements a more specialized verification of an AI framework for public transport management that demonstrates higher cognitive adaptability, regulatory compatibility, and institutional traceability.

The authors [46] proposed an ITS route optimization model based on the RMICL algorithm with dynamic terminal communication updates, which improves load forecasting accuracy and reduces travel time. Instead, our study implements a hybrid AI framework with multi-agent cognitive adaptation, regulatory traceability, and enhanced interoperability within public transport network management.

The authors [47] developed an AI-driven adaptive traffic light control system based on YOLO detection and real-time traffic density analysis, which reduces waiting time, fuel consumption, and emissions. Compared with a monofunctional approach, this study verified a system-integrated AI-ITS framework with cognitive adaptability, XAI transparency, and management scalability.

The generalization of the comparative analysis shows that, unlike the fragmentary or case-oriented models of opponents, the results of our study demonstrate the empirically verified effectiveness of a hybrid AI framework with a higher cognitive adaptability, algorithmic accuracy, institutional traceability, managerial scalability, and regulatory interoperability within public governance.

5.1. Limitation

A limitation of the study is the lack of field testing of the verified AI-Optimized ITS Framework for Public Governance in real-world transportation environments. The empirical results are based solely on simulated scenarios with formalized input parameters and algorithmic approximation.

5.2. Recommendations

It is recommended to initiate a controlled field experiment to collect validated field data within urban transportation systems. This approach will evaluate the algorithmic accuracy, procedural resilience, and regulatory traceability of the framework in real-world applications.

6. CONCLUSIONS

The conducted research provided a comprehensive multi-level verification of the AI-Optimized ITS Framework for Public Governance through a combination of retrospective stratified analysis, metric-based and model-based assessment of transformational impact, UML-based modelling and optimization, as well as empirical validation of project architectonics. Retrospective stratification demonstrated the fragmentation of traditional ITS along the vector of cognitive inertia, weak institutional integration, and lack of regulatory traceability. The second stage involved a metric-based and model-based analysis of the transformative impact of AI technologies. The effects on ΔTravel Time, QL, Accuracy, F1-score, ΔCO_2, FC, RI, CRI, ATS, PCI, IPM, and EER were determined. The third stage was a comparative UML-based modelling and optimization of Traditional ITS Framework vs AI-Optimized ITS Framework for Public Governance, which revealed higher regulatory compatibility, algorithmic accuracy, and management scalability of the hybrid AI model. The final stage was metric-based and model-based verification, where the obtained values TTR=0.21, QL=0.25, Accuracy=0.93, F1=0.92, TI=0.88, US=0.85, ΔCO_2=0.90, FC=0.92, RI=0.89, CRI=0.91, ATS=0.94, PCI=0.88, IPM=0.93, EER=0.90 confirmed the operational advantage of the framework. Collectively, the research results prove that the AI-optimized framework not only outperforms traditional ITS in key integral metrics, but is also capable of forming a normatively tracked, cognitively adaptive, and environmentally sustainable model of urban mobility within the concept of public governance.

The academic novelty of the research is the formalization of the cognitive and adaptive AI-Optimized ITS Framework for Public Governance with integrated architectures of XAI-transparency, institutional traceability, and algorithmic optimization, which ensures regulatory compatibility, managerial scalability, and environmental sustainability of transport systems. The research carried out multi-level metric verification of the framework, which for the first time combines cognitive interoperability, regulatory validation and indicator effectiveness in the field of public governance of smart mobility.

The practical significance of the research results is the possibility of implementing the AI-framework into the institutional contours of urban management to reduce ΔTravel Time, QL, CO_2 emissions, as well as increase the accuracy of management decisions, social acceptability, and regulatory compliance. The results can be used for designing digital transport policies, field testing in pilot communities, and strategic planning of sustainable mobility.

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