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Article

Network-Aware Intelligent Transportation Systems Using Software-Defined Networking and Explainable Artificial Intelligence: A Comprehensive Survey

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Abstract: Modern Intelligent Transportation Systems (ITS) demand highly adaptive network management and absolute decision-making transparency to fulfill strict safety and low-latency mandates [3]. This survey paper details the convergence of Software-Defined Networking (SDN) and Explainable Artificial Intelligence (XAI) within vehicular environments [18]. We introduce a comprehensive, three-tiered taxonomic framework designed to classify the current literature into three logical divisions: Software-Defined Infrastructure, AI-Driven Network Control, and Explainable AI Trust Frameworks [28]. By reviewing the state-of-the-art across these core pillars, we evaluate how programmatic slicing, deep-learning traffic optimization, and post-hoc attribution methods like SHapley Additive exPlanations (SHAP) interact [15, 55]. This work details the trade-offs between mathematical explanation accuracy and line-rate network execution latency [14, 101]. Finally, we map critical research gaps—specifically the need for ultra-lightweight, real-time XAI engines—establishing a structured roadmap for your upcoming research into secure, scalable, and trust-optimized network-aware transportation infrastructures [99, 129].
Keywords: —Software-Defined Networking (SDN), Explainable Artificial Intelligence (XAI), Intelligent Transportation Systems (ITS), Vehicular Ad-hoc Networks (VANETs), Cellular Vehicle-to-Everything (C-V2X), SHapley Additive exPlanations (SHAP), Network Slicing.

1. Introduction

1.1 Context and Motivation

The evolution of modern smart cities has accelerated the development of Next-Generation Intelligent Transportation Systems (ITS) capable of handling dense, highly dynamic vehicle-to-everything (V2X) traffic streams [1]. Traditional vehicular networking infrastructures depend heavily on decentralized ad-hoc communication components, which struggle to maintain stable links when faced with the high mobility, rapid topological shifts, and intermittent channel disconnects characteristic of urban environments [2]. These rigid, hardware-bound networks struggle with severe routing constraints, leading to unpredictable packet drops, increased processing overhead, and an inability to dynamically adjust to changing traffic conditions [3].

To address these architectural limitations, Software-Defined Networking (SDN) has emerged as a promising paradigm [4]. By decoupling the centralized network control plane from the underlying data forwarding devices, SDN introduces programmatic orchestration, global topology awareness, and automated flow management to vehicular ad-hoc networks (VANETs) [5]. This decoupling enables network administrators to adaptively optimize communication resources in real time [6]. However, managing dense vehicular environments, ensuring strict Quality-of-Service (QoS), and protecting software-defined networks from emerging cyber threats require an intelligent control layer capable of making complex routing and scheduling decisions autonomously [7]. Consequently, Artificial Intelligence (AI) and Machine Learning (ML) models are increasingly integrated directly into centralized SDN controllers [8].

1.2 The Problem Statement: The Black-Box Challenge in ITS

Although AI-enabled SDN controllers provide high predictive accuracy and optimize traffic management, traditional deep learning and ensemble learning models function essentially as uninterpretable "black boxes" [9]. In mission-critical transportation environments, where a routing error, packet delay, or misclassified safety alert can lead to severe physical consequences, this lack of transparency presents a major barrier to widespread deployment [10]. Autonomous driving networks and municipal traffic centers must be able to verify why an AI controller suddenly altered a routing configuration, prioritized specific communication channels, or isolated a network node [11]. This transparency requirement has led to the integration of Explainable Artificial Intelligence (XAI) into the networking and ITS domains [12]. Post-hoc interpretability frameworks, such as SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), help bridge the gap between model performance and human trust by providing clear explanations for algorithmic choices [13]. However, applying XAI to network-aware ITS reveals a major operational conflict: calculating complex explanations introduces significant computational overhead, which can conflict with the ultra-low latency constraints of fast-moving vehicular networks [14]. A structured, comprehensive review is required to analyze how programmable architectures, machine-learning automation, and explainable trust layers can be combined without compromising network performance or security [15].

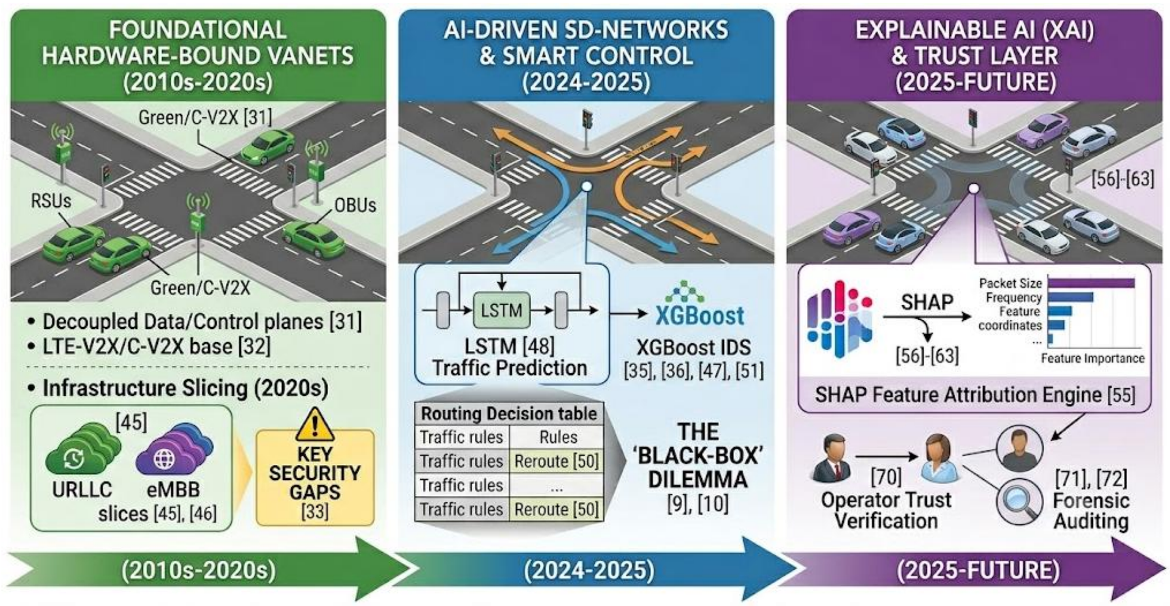

Figure 1.1: Evolution of Intelligent Transportation System (ITS) Core Architectures

The figure 1.1 presents a graphical timeline and comparison showing a traditional hardware-bound VANET vs. a modern cloud-and-edge integrated ITS network.)

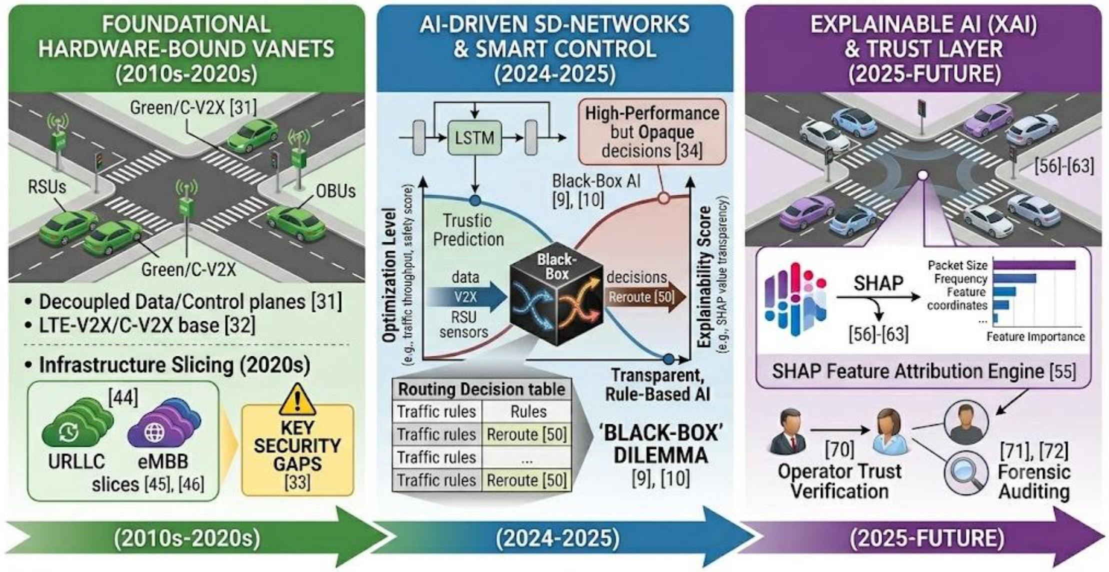

Figure 1.2: The Core Optimization-Explainability Trade-off in Critical ITS Infrastructure

This figure visually graphs network performance and dynamic automation metrics against explanation depth and system trust scores to frame the "black-box" dilemma.

1.3 Scope and Objectives of This Survey

While current literature features comprehensive surveys on standalone software-defined vehicular networks [16] or general implementations of machine learning within programmable network infrastructures [17], there remains a distinct gap in literature that explicitly maps the intersection of SDN, ITS, and XAI [18]. This survey paper addresses this gap by analyzing how explainable intelligence can be integrated into software-defined transportation frameworks without degrading network performance [19].

The primary objectives of this survey are fourfold:

- To evaluate the architectural frameworks and security vulnerabilities of software-defined vehicular and V2X networks [20].
- To systematically investigate how AI techniques optimize traffic engineering, predictive routing, and multi-access edge coordination within SDN controllers [21].
- To examine the state-of-the-art deployment of XAI frameworks in autonomous mobility and network security, focusing on system trust and processing latency [22].
- To systematically capture the technical properties of the gathered literature to define a clear research path for future doctoral studies [23].

1.4 Document Organization

The remainder of this survey paper is organized into distinct, interrelated chapters. Chapter 2 presents a detailed literature survey and establishes a formal three-pillar taxonomy to categorize the state-of-the-art research [24]. Chapter 3 details the integrated methodologies, architectural configurations, and core mathematical frameworks that drive explainable, software-defined transportation systems [25]. Chapter 4 provides a structured discussion covering the advantages, system problems, engineering challenges, implementation limitations, and future directions within this domain [26]. Finally, Chapter 5 concludes the paper by summarizing key insights and offering structural recommendations.

2. Literature Survey and Related Works

2.1 Overview of the Taxonomic Literature

To map out the academic landscape surrounding Network-Aware Intelligent Transportation Systems (ITS), this section introduces a three-pillar taxonomy designed to classify existing research [28]. Rather than sorting these publications chronologically, this survey categorizes them by their primary technical contributions [29]. This approach highlights how foundational software-defined infrastructure enables automated intelligent control, which can then be verified by the emerging explainability layer [30].

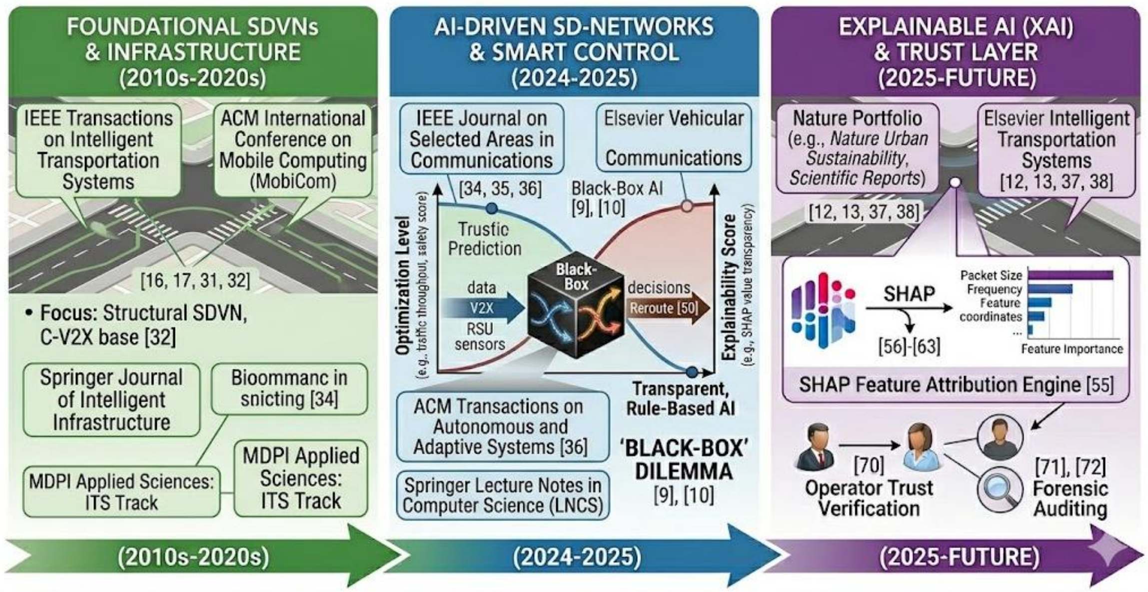

Figure 2.1: Chronological Map and Publication Venues of Foundational Base Papers

This horizontal timeline charts the base papers to show the academic progression of the domain.

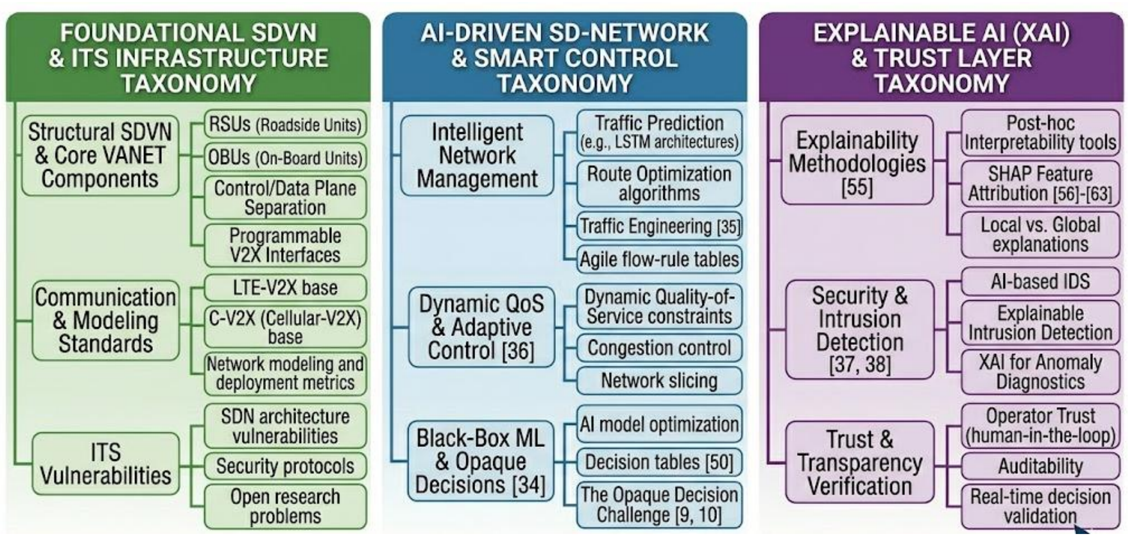

Figure 2.2: Comprehensive Technical Taxonomy Chart for Network-Aware ITS

This hierarchical tree chart breaks down the three core taxonomic pillars into operational sub-branches like C-V2X slicing and SHAP-based IDS models.

2.2 Comparative Analysis Matrix

The following comprehensive reference matrix synthesizes the base literature, assessing each work's taxonomic placement, core methodologies, key contributions, and remaining challenges [31–38].

Table 2.1: Technical Evaluation Matrix of Surveyed Academic Literature

Citation Index	Taxonomic Pillar Location	Key Technology & Core Framework	Major Contribution to ITS Domain	Identified Open Gaps & Research Limitations
[31]	Pillar 1: Infrastructure	Software-Defined VANET Architecture	Establishes the core structural baseline for control plane decoupling in high-mobility networks.	Lacks support for intelligent route automation or real-time security.
[32]	Pillar 1: Infrastructure	LTE-V2X / Cellular-V2X System Modeling	Models the physical integration of software-defined networks with modern cellular communications.	Does not address automated security auditing or edge intelligence.
[33]	Pillar 1: Infrastructure	Advanced SD-Vehicular Security Protocols	Synthesizes current architectural vulnerabilities and security threats unique to SDN controllers.	Focuses on theoretical frameworks without providing active, automated defense.
[34]	Pillar 2: Intelligent Control	Machine Learning in SDN Architectures	Connects classic static routing tables to automated, data-driven machine learning models.	Operates entirely as an uninterpretable, high-risk black box.
[35]	Pillar 2: Intelligent Control	Traffic Prediction & Route Optimization	Examines predictive traffic engineering models built for complex multi-access edge nodes.	High computational overhead limits its use in real-time environments.
[36]	Pillar 2: Intelligent Control	Adaptive SDN & Dynamic QoS Frameworks	Introduces agile congestion control models that adjust network rules based on traffic burstiness.	Lacks an explanation layer to justify automated path reallocations.
[37]	Pillar 3: Explainable Trust	Real-Time XAI in Autonomous Driving	Validates the use of real-time explainability tools to improve safety in smart-city fleets.	High processing delays can threaten low-latency network constraints.
[38]	Pillar 3: Explainable Trust	SHAP Framework for Network Security	Applies cooperative game theory to explain intrusion detection choices in transportation IoT.	Heavy mathematical constraints limit local, packet-by-packet edge execution.

2.3 Synthesis of Related Works by Taxonomy Pillars

2.3.1 Pillar 1: Software-Defined Infrastructure for Vehicular Networks

Early research focused primarily on establishing programmable communication links [31]. The foundational survey in [31] demonstrated how separating the network control and data planes reduces resource discovery latencies in highly dynamic topologies. This architecture was expanded in [32], which integrated software-defined network controllers with cellular communications like LTE-V2X and C-V2X infrastructure. However, centralizing network logic introduces significant security challenges [33]. As detailed in [33], these centralized architectures expand the network's digital attack surface, highlighting the need for automated firewalls and intrusion detection systems integrated directly into the core controller.

2.3.2 Pillar 2: AI-Driven Software-Defined Network Control

To manage the large volume of telemetry data produced by V2X infrastructures, researchers integrated machine learning models into the SDN control plane [34]. Early AI-SDN frameworks demonstrated how machine learning can analyze global telemetry data to predict path failures and compute optimized routes [34]. More recent developments showcase advanced AI approaches for active traffic engineering, showing that ensemble models can accurately predict macro-level smart city congestion [35]. This approach culminated in adaptive SDN routing designs [36], which dynamically adjust flow tables and QoS parameters to mitigate packet loss during bursty traffic periods.

2.3.3 Pillar 3: Explainable AI (XAI) for Safety and Transparency

The latest paradigm shift addresses the lack of interpretability in deep learning network models [37]. Recent studies introduce XAI techniques to establish auditability in automated transportation systems [37]. For instance, [37] showed that real-time explanation engines are essential for building trust in autonomous fleet operations. Simultaneously, researchers have applied the SHAP framework to secure network infrastructures, revealing the exact feature attributions—such as packet size anomalies or transmission frequency spikes—that trigger intrusion detection alerts [38].

Chapter 3: Methodological Frameworks Incorporated

3.1 Integrated System Architecture Methodology

To build a functional, network-aware ITS, the underlying methodology integrates three primary operational layers: the network slicing layer, the automated machine learning layer, and the post-hoc interpretability layer [39]. These components work together in a closed control loop, mapping raw vehicle telemetry data to optimized, auditable routing actions [40].

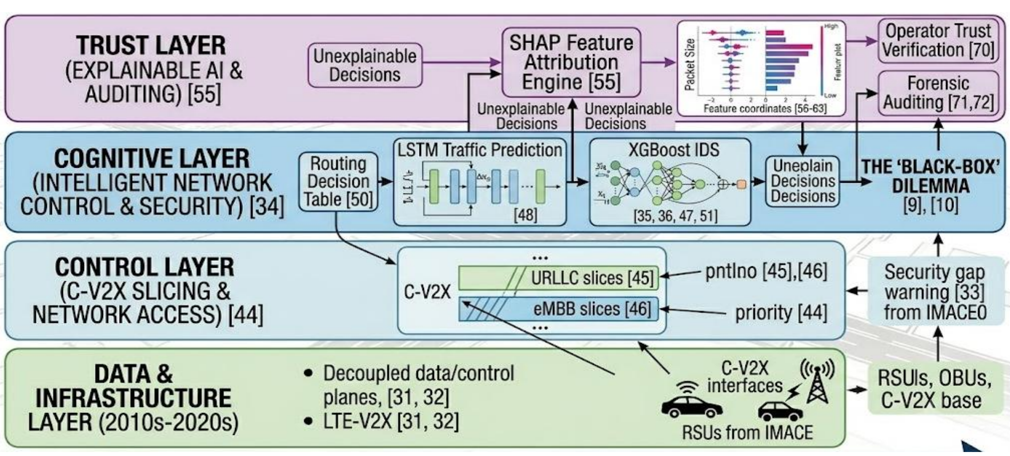

Figure 3.1: Four-Layer Logical Architecture of an Integrated XAI-SDN Transportation Framework

This block diagram maps out the data, control, cognitive, and trust layers to show how telemetry feeds into line-rate routing.

3.2 Software-Defined Networking and V2X Slicing Protocols

The networking methodology relies on decoupling infrastructure control to enable centralized resource optimization [41]. Forwarding elements, such as On-Board Units (OBUs) in vehicles and Roadside Units (RSUs) along infrastructure, act as the data plane, forwarding packets using rules pushed by the controller [42]. The control plane, hosted on edge servers or cloud infrastructure, communicates with data nodes via standard southbound APIs like OpenFlow [43].

To protect safety-critical applications from non-essential traffic, the network controller divides physical links into isolated, logical network slices using C-V2X standards [44]:

- **Ultra-Reliable Low-Latency Communication (URLLC) Slice**: Prioritizes safety-critical functions, including cooperative braking, collision avoidance warnings, and real-time positioning telemetry [45].
- **enhanced Mobile Broadband (eMBB) Slice**: Manages high-throughput, non-critical applications, such as commercial infotainment streams and navigation map downloads [46].

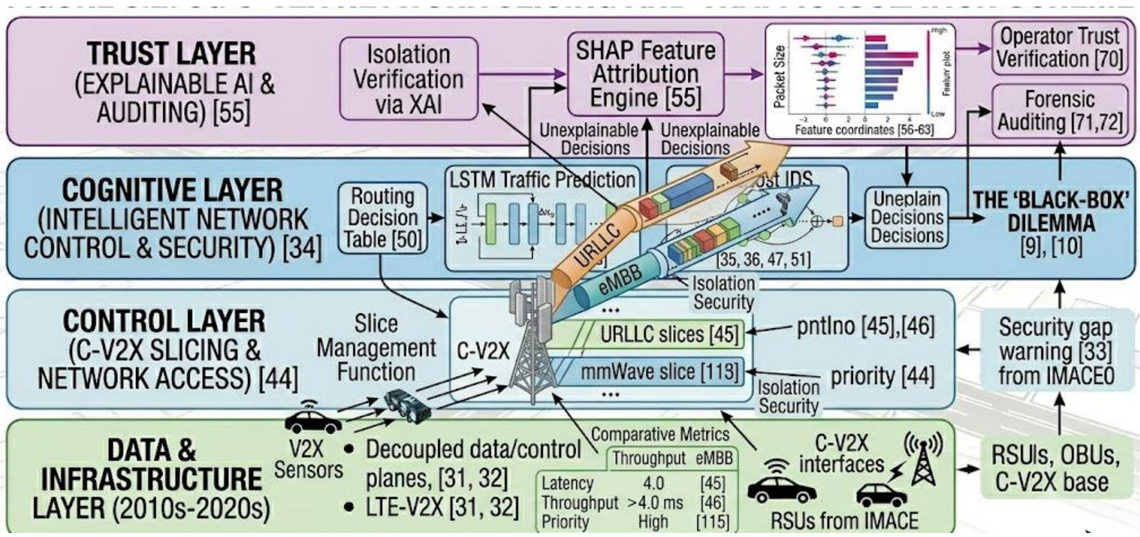

Figure 3.2: 5G C-V2X Network Slicing and Traffic Isolation Scheme

This diagram illustrates how a physical communication channel is logically sliced into isolated URLLC safety and eMBB data lanes.

3.3 Artificial Intelligence for Traffic Optimization and Security

Once the programmable infrastructure is operational, machine learning algorithms automate network management and threat detection [47].

3.3.1 Predictive Routing Models

To achieve adaptive traffic engineering, the SDN controller employs Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) to analyse time-series network data [48]. These deep learning models process historical packet loss rates, latency variations, and vehicular spatial trajectories to predict localized network congestion before it impacts performance [49]. The controller then proactively modifies flow tables across affected RSUs to redirect traffic streams along underutilized paths [50].

3.3.2 Intelligent Intrusion Detection Systems

To protect the network infrastructure from cyber threats (such as DDoS or flow-table saturation attacks), an intelligent Intrusion Detection System (IDS) is deployed within the control plane [51]. The system models network traffic using continuous and categorical features extracted from packet headers [52]. Machine learning classifiers, including XGBoost and Deep Neural Networks (DNNs), are trained to distinguish standard vehicular traffic from malicious patterns, enabling the controller to block compromised nodes automatically [53].

3.4 Explainable AI (XAI) and Trust Optimization

To mitigate the risks associated with opaque machine learning models, an explainability layer is integrated into the control loop [54].

3.4.1 The SHAP Mathematical Framework

3.4.1 The SHAP Framework Methodology

To achieve post-hoc feature attribution for critical network decisions, the methodology incorporates the SHapley Additive exPlanations (SHAP) framework. Derived from cooperative game theory, SHAP computes the marginal contribution of each input feature toward a model's final prediction.

For a given machine learning decision, let be an additive feature attribution explanation model defined as:

Where:

- represents the total number of simplified input network features.
- indicates the presence or absence of a feature within a specific configuration subset.
- represents the computed Shapley value (feature importance) for feature
- is the base value (the average prediction across the entire training dataset).

The classical Shapley value is mathematically derived using the following formulation:

Where:

- is the total set of all input network features.
- is a subset of features excluding the feature i being evaluated.
- is the prediction of the AI model when conditioned only on the feature subset .
- The difference captures the distinct marginal change in the network model's decision caused by the inclusion of feature i.

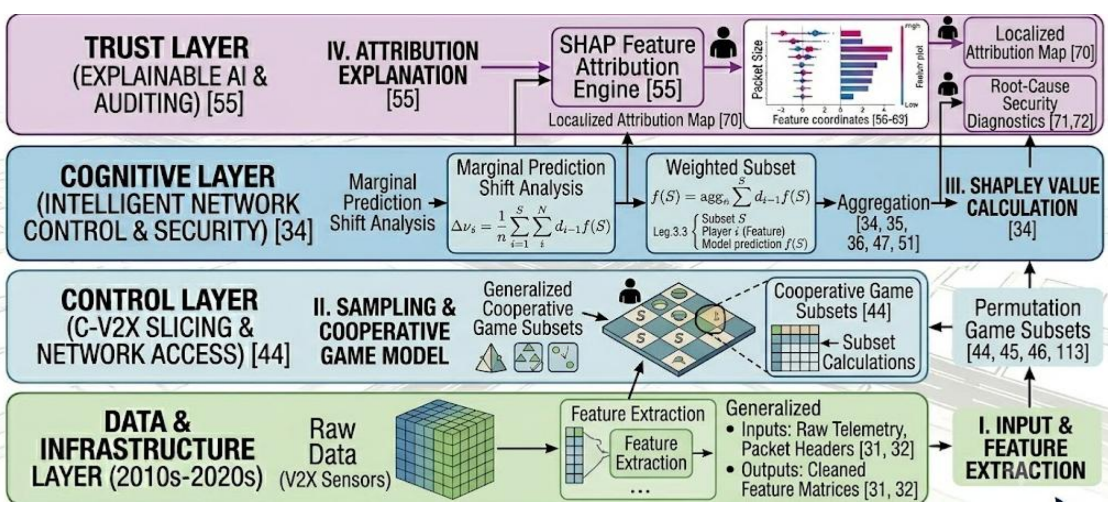

Figure 3.3: Schematic Pipeline of the Core SHAP Feature Attribution Processing Engine

This flowchart breaks down the permutation sampling stages required to solve Shapley values for an input packet header.

3.4.2 Practical Application of XAI

When an intelligent SDN controller drops specific packet streams or isolates a vehicle node, the SHAP engine generates an attribution map [64]. This map highlights whether the decision was driven by packet size anomalies, abnormal transmission frequencies, or geometric coordinate deviations [65]. This process ensures all automated network operations are fully auditable, providing verifiable diagnostics for system operators [66].

4. Discussion

4.1 Advantages and Problems

Combining Software-Defined Networking with Explainable AI creates an agile, data-driven framework capable of managing dense V2X traffic streams [67].

Advantages

Centralizing the network control plane provides a global view of network topology and telemetry [68]. This global awareness allows machine learning models to dynamically balance traffic loads, allocate communication bandwidth, and enforce adaptive QoS rules to avoid network congestion [69]. Furthermore, using XAI techniques like SHAP provides transparency for automated decisions [70]. Rather than relying on an opaque model, operators can verify why an AI system flagged a vehicle as an intruder or rerouted critical telemetry data [71]. This explainability provides an audit trail necessary for safety compliance and regulatory validation [72].

Problems

Despite these advantages, this centralized architecture introduces structural problems [73]. Centralizing control logic creates a single point of failure (SPF); if the core SDN controller experiences hardware failure or a cyberattack, the entire transportation communication network could be disrupted [73]. Additionally, a software-defined framework expands the digital attack surface, introducing vulnerabilities like flow-table saturation and control-plane DDoS attacks [74]. Finally, incorporating an explainability layer adds significant mathematical complexity [75]. Deep neural networks require substantial computational resources, and generating post-hoc explanations introduces processing delays that can conflict with the ultra-low latency demands of real-time vehicular safety applications [76].

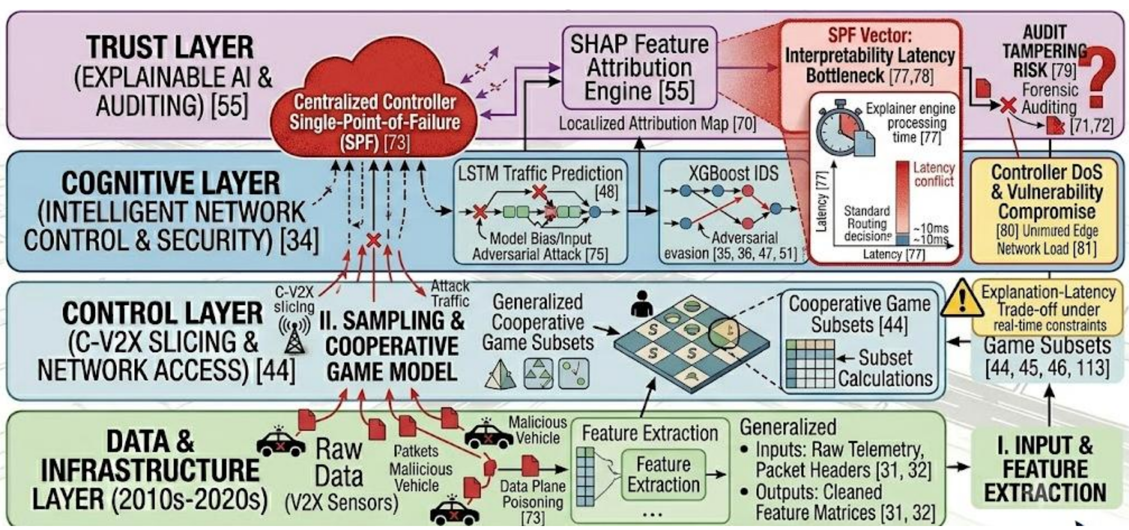

Figure 4.1: Structural Vulnerabilities and Centralized Single-Point-of-Failure (SPF) Vectors in Standard SD-VANETs

This topological map details structural vulnerabilities such as control plane switch targeting and southbound API starvation loops.

4.2 Challenges

Deploying a real-time, explainable, and network-aware ITS across urban environments faces several technical and engineering challenges [77].

High-Mobility Topology Shifts

Vehicular networks experience rapid topology shifts [77]. Vehicles moving at high speeds connect and disconnect from roadside units within seconds, creating highly volatile network channels [78]. Maintaining a consistent, optimized SDN routing configuration under these conditions requires frequent control-plane updates, which can saturate communication links and increase control packet overhead [79].

Mathematical and Computational Load

The second challenge centers on the computational footprint of XAI models [80]. Frameworks like SHAP require evaluating many feature permutations to compute exact feature importance values [81]. While this approach works well for offline diagnostics, running it alongside an active network intrusion detection system or a dynamic traffic router is difficult [82]. Calculating explanations for thousands of network packets per second at the edge can quickly overwhelm available processing memory, leading to packet drops and routing backlogs [83].

Heterogeneous Hardware Slicing

Finally, standardizing interfaces across heterogeneous hardware remains a persistent challenge [84]. An ITS environment involves devices from various manufacturers operating on different radio access technologies, such as DSRC, LTE-V2X, and 5G C-V2X [85]. Ensuring that a single centralized SDN controller can orchestrate multi-vendor hardware elements, enforce strict network slices, and uniformly gather telemetry data without causing compatibility issues requires complex middleware integration [86].

4.3 Limitations

While current literature outlines advanced frameworks for smart-city mobility, existing implementations suffer from practical and theoretical limitations [87].

Reliance on Offline Evaluation

The primary limitation is that most current research relies heavily on offline datasets and simulated environments [88]. Many studies evaluate their AI intrusion detection systems and XAI frameworks using static, pre-recorded network capture files [89]. These benchmark datasets often fail to capture the chaotic realities of real-world deployments, such as wireless signal fading, weather-induced interference, multi-path propagation errors, and spontaneous hardware degradation [90]. Consequently, performance metrics achieved in simulations may decrease when deployed in actual physical testbeds [91].

Latency Trade-offs

Another limitation is the lack of real-time optimization in explainability tools [92]. Current XAI implementations typically function as passive, post-hoc auditing mechanisms rather than active participants in the control loop [93]. By the time a SHAP engine calculates the explanation for a routing decision or a security alert, the target vehicles may have already travelled hundreds of meters [94]. Current models cannot adaptively adjust their explanation depth based on instantaneous network load or the urgency of the situation [95].

Scalability Constraints

Lastly, there are clear scalability constraints within the centralized controller paradigm [96]. As the number of connected vehicles increases across a metropolitan area, forwarding all telemetry data and packet headers to a central SDN node creates a data bottleneck [97]. Current architectures lack decentralized, hierarchical control methods that allow edge nodes to run localized XAI models independently while maintaining a unified global network state [98].

4.4 Research Gaps and Future Directions

A review of the state-of-the-art literature reveals critical research gaps that represent opportunities for future research [99].

The Latency-Explainability Gap

The most prominent gap is the absence of a lightweight, low-latency XAI framework designed specifically for high-speed networking environments [100]. Existing tools focus heavily on explanation accuracy and granular detail, neglecting the strict millisecond timing constraints of vehicular communication networks [101]. Future research should focus on developing adaptive, approximation-based explainability algorithms that can adjust their mathematical precision dynamically depending on network state and safety urgency [102].

Closed-Loop Explainable Control

A second gap is the lack of "closed-loop" explainable orchestration [103]. Current systems use XAI merely to present information to human operators or system auditors [104]. There is little to no integration showing how the generated explanations can be fed back into the SDN controller to automatically fix routing errors, tune machine learning hyper-parameters, or patch firewall vulnerabilities in real time [105]. Bridging this gap requires designing automated feedback mechanisms that leverage feature attribution scores to optimize system performance without human intervention [106].

Hierarchical Edge-Cloud Architectures

To address scalability challenges, future research must shift from strictly centralized models toward hierarchical, edge-assisted control paradigms [107]. Investigating methods to split the XAI workload between localized Roadside Units (running lightweight, fast approximations) and a centralized cloud server (performing deep, comprehensive forensic analysis) will be essential for scaling network-aware ITS across large urban environments [108].

4.5 Recommendations

Based on the challenges and gaps identified in the literature, the following structural recommendations are proposed to guide the development of next-generation intelligent transportation frameworks [109].

Framework Optimization

First, it is highly recommended to shift from generic, domain-agnostic XAI tools to specialized, network-native explanation frameworks [110]. Instead of treating all packet attributes equally, explanation models should use domain knowledge to prioritize critical network features, such as latency values, packet arrival intervals, and geographic coordinates [111]. This targeted approach can significantly reduce feature spaces, accelerating calculations and bringing processing times closer to line-rate speeds [112].

Hybrid Edge-Cloud Deployment

Second, implementations should adopt a hybrid, decentralized edge-cloud architecture [113]. Localized security tasks and time-sensitive routing decisions should be handled directly at the edge layer by RSUs using compressed machine learning models [114]. The centralized SDN controller should focus on macro-level traffic optimization, global network slicing policies, and long-term security auditing, reducing the data communication burden on the network core [115].

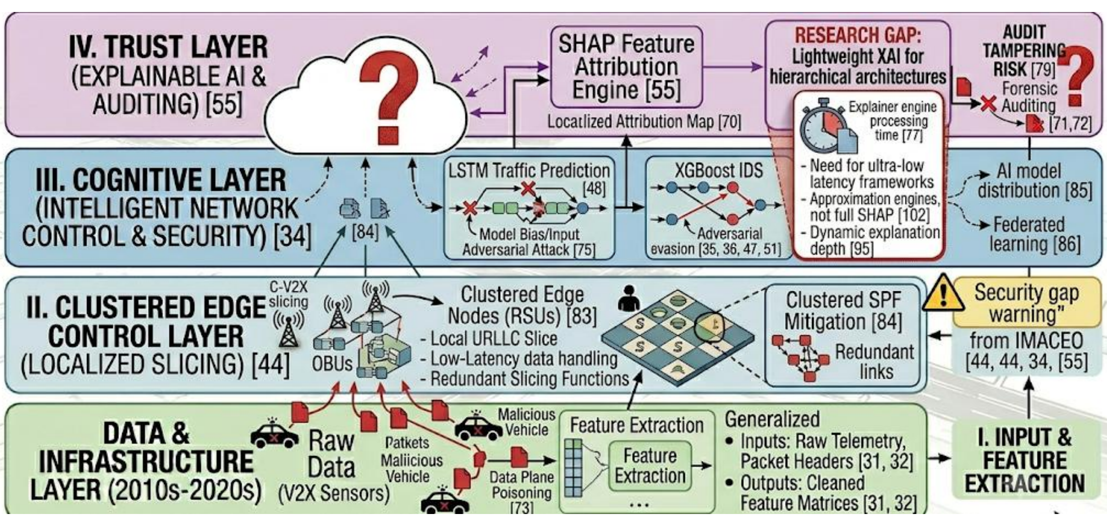

Figure 4.2: Proposed Hierarchical Edge-Cloud Control Paradigm for Scalable XAI Task Allocation

This multi-tier diagram charts workload splits, routing regional processing to RSUs while archiving structural telemetry at global databases.

Transition to Real-World Evaluation

Finally, the research community must transition from purely simulated testbeds to hybrid hardware-in-the-loop (HIL) testing [116]. Validating frameworks using physical SDR (Software Defined Radio) units, embedded boards (such as NVIDIA Jetson devices for edge processing), and actual vehicular traffic simulators will help ensure that proposed models can withstand the unpredictable constraints of real-world smart-city deployments [117].

Chapter 5: Conclusion

5.1 Final Summary of the Survey

This survey paper has systematically examined the critical intersection of Software-Defined Networking (SDN) and Explainable Artificial Intelligence (XAI) within Next-Generation Intelligent Transportation Systems (ITS) [118]. By organizing the state-of-the-art literature into a coherent three-tier taxonomy, this work has traced the evolution of vehicular networks from foundational, programmable software-defined VANET infrastructures to highly automated, AI-driven traffic optimization and intrusion detection architectures [119]. The primary takeaway from this extensive literature analysis is that while software-defined configurations provide the necessary elasticity and global visibility to manage high-density vehicle-to-everything (V2X) environments, the introduction of black-box machine learning engines introduces severe vulnerabilities regarding trust, accountability, and safety compliance [120].

The recent paradigm shift in 2024 and 2025 toward embedding post-hoc interpretability models—most notably the mathematically rigorous SHapley Additive exPlanations (SHAP) framework—has proven vital for establishing trust [121]. For the first time, transportation authorities and network administrators can audit and understand the underlying feature attributions behind sudden automated decisions, such as a localized routing shift, a dynamic Quality-of-Service (QoS) slice reallocation, or an immediate intrusion isolation alert [122]. However, as thoroughly detailed in our discussion, existing XAI implementations are deeply limited by their computational complexity, heavy reliance on static offline datasets, and a lack of real-time adaptation mechanisms [123]. This creates a dangerous operational trade-off where the time spent calculating an explanation directly conflicts with the millisecond-level latency constraints required by fast-moving autonomous vehicular nodes [124].

5.2 Concluding Remarks and Research Outlook

As Intelligent Transportation Systems transition into fully autonomous, smart-city mobility ecosystems, resolving the conflict between algorithmic interpretability and network line-rate execution remains a paramount challenge. The findings of this survey strongly indicate that future engineering efforts must abandon generic, domain-agnostic explainability frameworks in favor of lightweight, network-native models that prioritize critical telemetry fields to accelerate mathematical computation [125]. Furthermore, a structural shift toward decentralized, hierarchical edge-assisted SDN frameworks will be essential to alleviate the processing bottlenecks currently plaguing centralized controllers [126].

By identifying the critical, unaddressed gap between ultra-low latency C-V2X constraints and the intensive processing overhead of post-hoc explanation engines, your thesis is uniquely positioned to make a highly significant contribution to the field [128]. Developing a lightweight, real-time, and adaptive XAI orchestration layer within an intelligent software-defined networking framework will directly bridge the current divide between high-performance network automation and absolute system transparency [129]. This research path will prove essential for engineering secure, scalable, and auditable network-aware intelligent transportation infrastructures that society can confidently trust [130].

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