



## RESEARCH ARTICLE

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# PREDICTIVE QUALITY OF SERVICE IN VEHICULAR COMMUNICATION SYSTEMS: MODELS, DATASETS, AND OPEN CHALLENGES

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## ARTICLE INFO

**Article History**

Received on: March 08, 2026

Reviewed on: April 08, 2026

Accepted on: July 01, 2026

Published on: July 31, 2026

**Keywords:**

Vehicle-to-Everything (V2X),  
Quality of Service (QoS),  
Predictive QoS,  
Machine Learning,  
Intelligent Transportation  
Systems (ITS).

## ABSTRACT

Reliable Quality of Service (QoS) prediction is fundamental to the performance of next-generation Vehicle-to-Everything (V2X) communication, particularly in 5G-enabled cloud and edge environments that support autonomous driving, cooperative safety, and time-critical mobility services. This survey provides a structured review of QoS prediction approaches spanning machine learning, deep learning, reinforcement learning, protocol-level evaluation, and security-trust mechanisms. Existing methods are analyzed with respect to their modeling strategies, required datasets, spatio-temporal dependencies, and scalability under high-mobility conditions. A comprehensive dataset survey synthesizes real-world, open-access, and simulation-based resources, highlighting key variables such as SINR, RSRP/RSRQ, mobility patterns, traffic density, delay, and throughput that influence predictive accuracy. The review identifies persistent challenges, including limited multi-modal datasets, poor cross-scenario generalization, computational overhead, weak interpretability, and the absence of unified multi-metric prediction frameworks. Based on these insights, the paper outlines promising research directions for developing adaptive, explainable, and privacy-preserving QoS prediction models for emerging 5G/6G V2X systems.



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## I. INTRODUCTION

The rapid evolution of vehicular communication systems, supported by 5G and emerging 6G infrastructures, has accelerated the development of Cooperative Intelligent Transportation Systems (C-ITS). Vehicle-to-Everything (V2X) communication enables continuous information exchange among vehicles, roadside infrastructure, pedestrians, and cloud-edge platforms to support safety-critical applications such as collision avoidance, cooperative lane change, platooning, and tele-operated mobility [1] [2]. These applications impose stringent Quality of Service (QoS) requirements involving ultra-low latency, high reliability, controlled jitter, and stable throughput. Global deployment of V2X technologies remains uneven. As illustrated in Figure 1, regions such as Europe, the USA, China, and Japan show more mature VANET and C-V2X implementations compared to other regions; this heterogeneity stems from differences in spectrum allocation, regulatory readiness, infrastructure investment, and industry adoption [3]. Such diversity complicates the design of QoS prediction models that must generalize across different operational environments and mobility patterns. The integration of 5G New Radio (NR) and Multi-access Edge Computing (MEC) provides foundational support for meeting V2X QoS targets by enabling ultra-reliable low-latency communication (URLLC), high-capacity links, and distributed computation near vehicles [4], [5]. Nonetheless, wireless channels and topologies in vehicular settings remain highly dynamic due to mobility, obstruction dynamics, multi-path fading, and network load fluctuations [6], [7]. As a result, traditional reactive QoS mechanisms are often inadequate for many safety-critical V2X services.

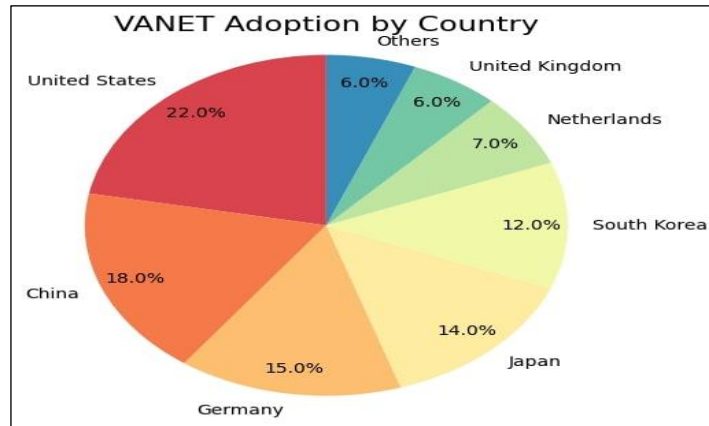


Figure 1: Global adoption of VANET/C-V2X deployments by region.  
Source: Authors, (2026).

Predictive QoS (PQoS) methods forecast future network behavior (e.g., latency, throughput, packet loss, signal quality) so systems can proactively allocate resources, schedule traffic, or adapt application behavior. Data-driven paradigms such as machine learning (ML), deep learning (DL), and reinforcement learning (RL) have been widely adopted for PQoS because they can capture nonlinear spatio-temporal relationships between mobility traces, radio KPIs (SINR, RSRP/RSRQ, CQI), traffic density, and application demand [6], [7], [8], [9], [10]. Complementary protocol-and simulation-based studies provide system-level insights into routing, scheduling, channel coding, and cross-layer interactions that affect end-to-end QoS [11], [12], [13]. Security- and trust-oriented frameworks (e.g., blockchain, federated learning, reputation systems) address adversarial and privacy concerns that can critically impact QoS in distributed V2X settings [14], [15]. Despite considerable progress, key challenges persist: (i) scarcity of large-scale, multi-modal, and geographically diverse datasets that combine radio, mobility, and application-level traces [16], [17]; (ii) limited cross-scenario generalization when models are trained on region-specific traces; (iii) computational and energy constraints that limit on-board deployment of complex DL/RL models; and (iv) lack of standardized multi-metric benchmarks and limited interpretability of many black-box models [7], [18], [19]. These gaps motivate a structured survey that consolidates techniques, datasets, and open issues to guide future research. The primary contributions of this research work are summarized as follows:

- This survey presents a comprehensive and structured analysis of Perceived Quality of Service (PQoS) evaluation approaches. First, it introduces a unified taxonomy that categorizes PQoS techniques into ML and DL based methods, protocol and simulation-based approaches, as well as security and trust-oriented frameworks.
- Second, the study provides a critical synthesis of these approaches by examining algorithmic trade-offs, model complexities, and feature dependencies that influence PQoS prediction and assessment.
- Third, a dataset-centric review is conducted to identify commonly used datasets, highlight key variables utilized for PQoS modeling, and discuss the inherent limitations and gaps present in existing datasets.
- Fourth, the survey consolidates major research challenges, including issues related to model generalization, interpretability, real-time feasibility, and system security.
- Finally, the paper outlines a roadmap for future research, emphasizing the need for multi-metric evaluation frameworks, explainable PQoS prediction models, and privacy-preserving intelligent systems for next-generation network environments.

#### A. Intended Audience

This survey is intended to support academic researchers, industry practitioners, and graduate students working in the domains of vehicular communication, wireless networking, and QoS prediction. By providing a comprehensive review of Predictive QoS (PQoS) techniques for V2X communication, the survey aims to offer valuable insights for network engineers, data scientists, and system designers who seek to develop efficient and reliable vehicular communication systems. The contributions presented in this survey will also benefit researchers from interdisciplinary fields, including intelligent transportation systems, edge computing, machine learning, and 5G/6G system design, by helping them understand the evolving landscape of dataset-driven, learning-based PQoS models. Furthermore, the challenges and future research directions discussed in this paper are expected to guide prospective researchers in identifying open issues and establishing meaningful technical objectives to advance the field and address existing research gaps.

#### B. Survey Methodology

Over the past several years, numerous studies have explored QoS optimization and performance modeling in vehicular communication systems. However, many of these works primarily emphasize traditional QoS management, statistical models, or protocol-level enhancements, while only a limited number examine predictive QoS (PQoS) using machine learning, deep learning, or reinforcement learning techniques. Furthermore, recent PQoS contributions, particularly those incorporating mobility-aware prediction, cross-layer metrics, and 5G/6G edge intelligence, were excluded from earlier surveys. As a result, it is essential to include updated studies to accurately assess the current state of PQoS research. Additionally, previous surveys often focus on narrow aspects of V2X communication, such as routing, channel modeling, or general QoS analysis, without providing a unified overview of learning-based prediction frameworks. In this context, the literature was examined to address the following research questions:

1. *What is the current understanding of QoS requirements in V2X communication, and why is predictive QoS necessary?* This question aims to clarify the motivation for PQoS in highly dynamic vehicular environments. The corresponding discussion appears in the section titled “QoS Fundamentals and Motivation for Predictive QoS.”

2. Which machine learning, deep learning, reinforcement learning, and protocol-based models have been developed for QoS prediction in V2X networks? This survey provides a detailed overview of PQoS methodologies developed over the past decade.
3. What datasets support PQoS prediction research in V2X systems? The section “Dataset Survey and Variable Mapping” summarizes available real-world, simulation-based, and open-access datasets along with their relevance to prediction tasks.
4. What metrics and indicators are used to evaluate PQoS models? The section “Analysis and Discussion” presents commonly used evaluation metrics such as RMSE, MAE, MAPE, accuracy, and latency prediction error.
5. What limitations and research gaps exist in current PQoS studies? These issues are highlighted in the “Challenges and Future Directions” section.

By addressing these questions, this survey provides a holistic understanding of the state-of-the-art in predictive QoS for V2X communication and highlights key gaps that offer opportunities for future research.

### C. Search Strategy

The databases listed in Table 1 were used to identify relevant journal articles and conference papers published by top publishers

Table 1: Academic databases used for the literature search.

| Academic Database        | Link                                                                            |
|--------------------------|---------------------------------------------------------------------------------|
| IEEE Xplore              | <a href="https://ieeexplore.ieee.org/">https://ieeexplore.ieee.org/</a>         |
| ACM Digital Library      | <a href="https://dl.acm.org/">https://dl.acm.org/</a>                           |
| ScienceDirect (Elsevier) | <a href="https://www.sciencedirect.com/">https://www.sciencedirect.com/</a>     |
| SpringerLink             | <a href="https://link.springer.com/">https://link.springer.com/</a>             |
| Wiley Online Library     | <a href="https://onlinelibrary.wiley.com/">https://onlinelibrary.wiley.com/</a> |
| MDPI                     | <a href="https://www.mdpi.com/">https://www.mdpi.com/</a>                       |
| Taylor & Francis Online  | <a href="https://tandfonline.com/">https://tandfonline.com/</a>                 |
| Scopus                   | <a href="https://www.scopus.com/">https://www.scopus.com/</a>                   |
| Google Scholar           | <a href="https://scholar.google.com/">https://scholar.google.com/</a>           |

Source: Authors, (2026).

The initial search keywords were carefully selected to align with the research objectives of this survey. Following a preliminary exploratory search, multiple terms identified in several related PQoS and V2X research papers were analyzed to generate a broader list of candidate keywords. These terms were gradually refined and narrowed to ensure consistency with the core theme of predictive QoS modeling in vehicular communication systems. The final keywords used in this survey include “predictive QoS,” “V2X communication,” “QoS prediction vehicular networks,” “latency prediction V2X,” “machine learning QoS prediction,” “deep learning QoS modeling,” “reinforcement learning QoS optimization,” “5G/6G QoS prediction,” and “vehicular communication performance prediction.”

### D. Article Filtering and Selection Methodology

To ensure a rigorous and comprehensive survey of PQoS research in V2X communication, all retrieved publications were systematically screened through a multi-stage filtering process. The initial pool of studies identified from IEEE Xplore, ACM Digital Library, Elsevier, Springer, and Google Scholar was examined by reviewing their titles, abstracts, introductions, and conclusions. Papers that aligned with the core themes of predictive QoS, V2X communication, ML/DL-based prediction, protocol-level QoS mechanisms, dataset development, or security–trust frameworks were included, while studies that fell outside these domains were excluded.

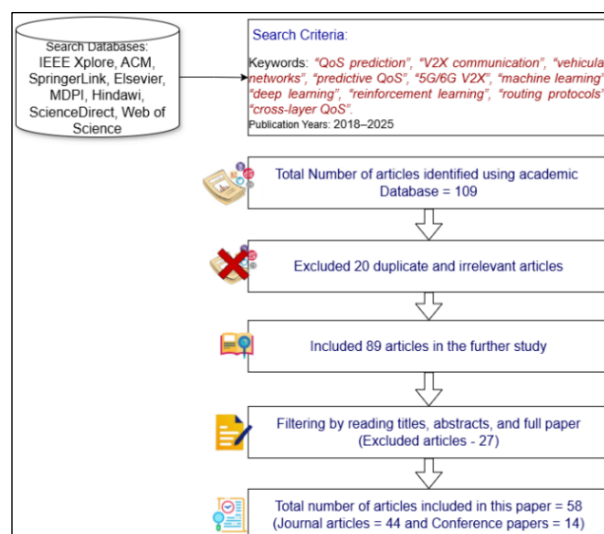


Figure 2: Paper selection procedure.

Source: Authors, (2026).

Figure 2 illustrates the overall article filtering workflow, including identification, screening, eligibility assessment, and final inclusion. To ensure consistency, objective inclusion and exclusion criteria were applied throughout the process. These criteria, summarized in Table 2, guided the evaluation of study relevance, methodological rigor, and applicability to PQoS prediction in vehicular communication systems. This structured filtering ensured that the final set of reviewed papers represents a balanced and comprehensive overview of state-of-the-art PQoS techniques across machine learning, deep learning, reinforcement learning, protocol design, dataset development, and security.

Table 2: Inclusion and exclusion criteria used for paper selection in this survey.

| Inclusion criteria                                                                                                                                                | Exclusion criteria                                                                      |
|-------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------|
| Studies published between 2018 and 2025, reflecting modern 5G/6G-era V2X research.                                                                                | Papers lacking methodology, experimental setup, QoS metrics, or performance evaluation. |
| Research focused on V2X/VANET communication, QoS or PQoS prediction, or network performance modeling.                                                             | Outdated pre-2018 VANET studies or works unrelated to QoS prediction.                   |
| Peer-reviewed studies using ML/DL-based QoS prediction, RL-based resource optimization, routing/protocol QoS enhancement, or cross-layer QoS modeling frameworks. | Security-only papers (cryptography/privacy) without analysis of QoS impact.             |

Source: Authors, (2026).

## 1.1 V2X COMMUNICATION FRAMEWORK

The Vehicle-to-Everything (V2X) communication framework provides the foundational architecture required for cooperative intelligent transportation systems by enabling continuous information exchange among vehicles, roadside infrastructure, pedestrians, and cloud or edge networks. V2X consists of four primary communication modalities: Vehicle-to-Vehicle (V2V), which supports distributed safety messaging and localized situational awareness; Vehicle-to-Infrastructure (V2I), where Road-Side Units (RSUs) disseminate traffic, control, and connectivity information [4], [5]; Vehicle-to-Network (V2N), which leverages cellular Uu connectivity and MEC/cloud services for large-scale orchestration and computation [20], [21]; and Vehicle-to-Pedestrian (V2P), which enhances the safety of vulnerable road users through device-assisted communication [22]. These modalities operate across heterogeneous communication technologies, including IEEE 802.11p/802.11bd, LTE-V2X PC5 sidelink, and cellular Uu interfaces, each offering distinct trade-offs in reliability, latency, and communication range. Prior studies emphasize that hybrid architectures combining PC5 for low-latency direct communication with Uu-based wide-area coordination achieve higher robustness and reliability under dense mobility conditions [5], [23]. RSUs serve as critical components within this framework, functioning not only as connectivity anchors but also as MEC-enabled units capable of supporting real-time QoS prediction, traffic analytics, security enforcement, and localized decision-making [19].

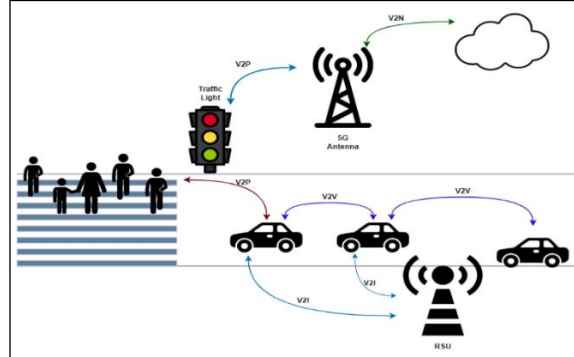


Figure 3: Illustration of the V2X communication framework showing V2V, V2I, V2N, and V2P interactions.

Source: Authors, (2026).

Meanwhile, cloud platforms handle long-term learning, federated model aggregation, and cross-region orchestration to support large-scale V2X intelligence [20]. The integration of emerging 5G and future 6G capabilities—such as URLLC, network slicing, and distributed edge intelligence—further strengthens the V2X communication ecosystem and enables predictive, QoS-driven communication essential for next-generation vehicular networks. Figure 3 demonstrate the framework for V2X communication.

## 1.2 QUALITY OF SERVICE (QOS) IN V2X COMMUNICATION

Quality of Service (QoS) in vehicular communication refers to the network's ability to deliver predictable, reliable, and efficient performance under highly dynamic mobility and radio conditions. Since V2X applications operate across diverse environments ranging from dense urban intersections to high-speed highways, QoS becomes a fundamental requirement for ensuring safe, stable, and delay-sensitive information exchange. Each V2X modality, including Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Network (V2N), and Vehicle-to-Pedestrian (V2P), imposes distinct performance constraints based on latency, reliability, throughput, and service continuity [4], [5], [20]. V2X QoS is typically quantified using a set of measurable performance indicators:

- **Latency:** The end-to-end delay between message generation and reception. Safety-critical applications such as collision avoidance demand sub-10 ms latency for reliable execution.
- **Throughput:** The volume of successfully transmitted data per unit time, essential for applications involving high-rate sensor streams, cooperative perception, and teleoperation.
- **Reliability:** The probability of error-free packet delivery, often exceeding 99.999% for mission-critical V2X scenarios.

- *Jitter*: The variation in inter-packet arrival time, which affects the stability of real-time control and cooperative driving applications.
- *Packet Loss Rate*: The fraction of packets lost due to channel impairments, congestion, or mobility; a key metric influencing application stability.
- *Availability*: The percentage of time the communication link remains operational and satisfies service-level requirements.

RSUs, cellular infrastructure, and cloud services collaborate to support low-latency and reliable vehicular communication. Adapted from Mendes et al. [24]. These QoS indicators are strongly influenced by dynamic vehicular environments where mobility, traffic density, propagation conditions, and infrastructure placement rapidly evolve. For example, high user density and mobility degrade SINR, RSRP, RSRQ, and other radio-link quality parameters, directly affecting throughput and latency [6] [7]. Consequently, ensuring stable QoS requires not only reactive adaptation but also predictive intelligence capable of forecasting link performance before degradation occurs. The emergence of 5G NR and Multi-access Edge Computing (MEC) enhances QoS provisioning by enabling Ultra-Reliable Low-Latency Communication (URLLC), network slicing, and localized computation. These advancements allow V2X systems to dynamically allocate resources based on predicted network states and application requirements. Overall, QoS in V2X communication serves as the foundational performance requirement underlying all cooperative transportation services. As vehicular networks transition toward fully autonomous and connected mobility, the role of accurate, multi-metric QoS prediction becomes indispensable for enabling real-time decision-making and ensuring communication reliability in next-generation 5G/6G V2X ecosystems.

### I.3 MOTIVATION

The rapid evolution of V2X communication systems, supported by 5G and emerging 6G technologies, has intensified the demand for reliable and predictive Quality of Service (QoS) to enable safety-critical and latency-sensitive vehicular applications. Although existing V2X communication modalities V2V, V2I, V2N, and V2P collectively provide the foundation for cooperative awareness and real-time information exchange, their performance is fundamentally challenged by high mobility, dynamic topology changes, intermittent connectivity, and heterogeneous wireless conditions [25], [22]. These characteristics lead to rapid fluctuations in latency, throughput, packet delivery ratio (PDR), SINR, and other link-quality indicators, making conventional reactive QoS mechanisms inadequate for next-generation vehicular services. Predictive QoS (PQoS) has therefore emerged as a critical capability for enabling proactive resource allocation, congestion control, handover optimization, and service continuity in V2X systems. Recent studies demonstrate that ML, DL, and RL models can capture hidden spatio-temporal dependencies in vehicular mobility patterns, radio metrics, and network behaviors, allowing more accurate forecasting of communication performance [6], [7], [16]. Such predictions are particularly essential for applications such as cooperative perception, tele-operated driving, platooning, and emergency message dissemination, where even millisecond-level QoS degradation can compromise safety and reliability [10], [19]. Furthermore, the proliferation of RSUs, MEC nodes, and cloud services introduces new opportunities for distributed learning, edge-level inference, and hierarchical decision-making. RSUs equipped with MEC capabilities can support real-time QoS estimation and localized control actions, while cloud platforms enable long-term model training, cross-region knowledge transfer, and federated learning strategies [25], [24]. However, the effectiveness of such architectures depends on understanding the limitations of current communication technologies, including IEEE 802.11p/802.11bd, LTE-V2X PC5 sidelink, and 5G NR Uu, each of which exhibits distinct performance bottlenecks under dense traffic, high mobility, and varying propagation environments [22], [26], [27]. These challenges highlight the need for a comprehensive survey that unifies advances in PQoS prediction, analyzes emerging communication technologies, synthesizes ML/DL/RL developments, and examines dataset limitations, security constraints, and cross-layer performance issues. By integrating insights from predictive intelligence, communication protocols, and real-world measurement studies, this survey aims to provide a structured foundation for the design of scalable, explainable, and context-aware PQoS solutions for future V2X networks.

## II. THEORETICAL REFERENCE

### II.1 TAXONOMY AND METHODOLOGICAL CLASSIFICATION

The existing research on QoS prediction in V2X communication exhibits a broad methodological diversity, reflecting the interdisciplinary nature of vehicular networking, wireless communication, and intelligent systems. To provide a structured view of these developments, this survey categorizes state-of-the-art approaches into five distinct methodological domains: (i) protocol- and simulation-based models, (ii) supervised machine learning approaches, (iii) deep learning architectures, (iv) reinforcement learning frameworks, and (v) hybrid or cross-layer solutions. These categories capture the progression from traditional analytical and optimization-driven communication models toward data-driven, predictive, and autonomous decision-making paradigms. The proposed taxonomy also enables systematic comparison of modeling assumptions, feature dependencies, prediction objectives, and performance trade-offs across different V2X scenarios. Figure 4 illustrates the full taxonomy used throughout this survey. A comparative analysis of these methodological categories, supported by the evidence aggregated from existing studies, reveals clear distinctions in their underlying assumptions, feature dependencies, and operational constraints.

Traditional ML-based QoS prediction methods rely heavily on handcrafted features such as SINR, RSRP, RSRQ, vehicle speed, mobility patterns, and traffic density [6], [28], [29]. These models are computationally lightweight and enable fast inference, making them suitable for RSU-level or on-board prediction; however, their performance often degrades across heterogeneous environments due to scenario dependence, feature-engineering bottlenecks, and limited adaptability to nonlinear spatio-temporal variations [30], [31]. Deep learning approaches overcome these limitations by automatically learning complex hierarchical and temporal relationships using architectures such as LSTM, Bi-LSTM, GRU, CNN, and hybrid DNN models [18], [32], [33]. These models achieve superior accuracy and long-range QoS forecasting, particularly under rapidly changing mobility or channel conditions, but require large annotated datasets and MEC/GPU-based inference due to their high computational cost [9], [34]. Reinforcement learning (RL) and deep RL extend predictive capabilities by enabling sequential, adaptive decision-making for resource allocation, routing, slicing, and teleoperation [19], [35], [36]. While RL provides strong robustness in dynamic environments, its practicality is often limited by unstable convergence, intensive training requirements, and dependence on realistic simulation environments [37], [38].

In contrast, routing- and protocol-based approaches remain computation-efficient and well-suited for real-time deployment but lack predictive intelligence and often struggle under high-density or high-mobility scenarios [11], [39], [40]. Security- and trust-oriented frameworks strengthen resilience by incorporating authentication, trust scores, and anomaly detection [14], [41], [42], though these mechanisms introduce additional signaling overhead, authentication delay, and processing load, making them less suitable for strict real-time QoS prediction. Collectively, these observations highlight fundamental trade-offs between predictive accuracy, interpretability, computational complexity, scalability, and real-time feasibility across the methodological spectrum in V2X QoS prediction research.

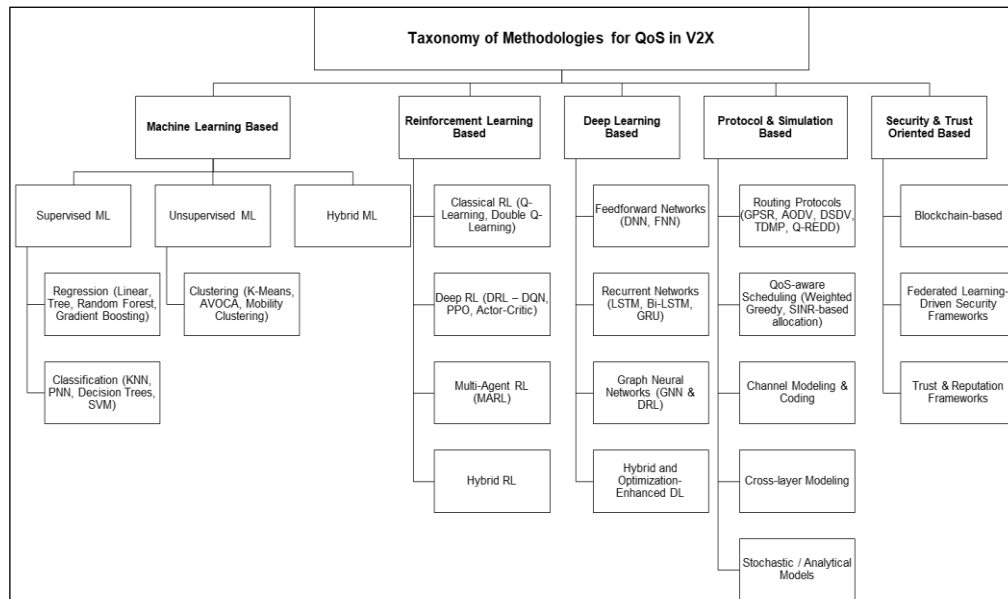


Figure 4: Taxonomy of methodological approaches in QoS prediction for V2X communication.  
Source: Authors, (2026).

The framework categorizes existing literature into protocol-based, machine learning, deep learning, reinforcement learning, and hybrid cross-layer techniques, supporting structured performance and applicability analysis.

### II.1.1 Machine Learning-Based QoS Prediction Techniques

Machine learning (ML) has been extensively explored for QoS prediction in V2X communication due to its relatively low computational overhead, interpretability, and suitability for deployment on RSUs and OBUs. ML approaches generally rely on handcrafted feature sets that capture radio conditions, mobility patterns, and traffic descriptors, many of which have been identified as dominant predictors of latency, throughput, and packet delivery ratios. A consolidated overview of commonly used variables is provided in Table 3. Compared to deep or reinforcement learning, ML techniques offer faster inference and reduced model complexity, making them suitable for real-time PQoS estimation; however, these advantages come at the cost of limited representational capacity and reduced generalizability in heterogeneous environments. Across the literature, supervised regression and classification models such as random forests, gradient-boosted trees, SVMs, and linear models have shown strong performance for near-term QoS forecasting when trained on a combination of PHY-layer metrics (e.g., SINR, RSRP, CQI) and mobility indicators (e.g., speed, heading, inter-vehicle distance) [28] [29], [30], [33]. These works consistently demonstrate that radio KPIs are necessary but insufficient without mobility and contextual features, particularly in highly dynamic V2I and V2V links. Models such as random forests provide robust prediction performance with low inference latency, making them practical for RSU-level deployment in online prediction systems [28].

However, the heavy reliance on feature engineering limits adaptability: ML models trained in urban environments often degrade when applied to highway or mixed mobility scenarios, revealing dataset bias and poor cross-environment generalization [31], [43]. Unsupervised learning and clustering have been introduced to mitigate these generalization issues by partitioning heterogeneous data into more homogeneous behavioral regimes before prediction. Studies leveraging K-means clustering and fuzzy-rule grouping demonstrate that per-cluster prediction improves model stability under varying LOS/NLOS propagation states and traffic densities [29-44]. This approach enables ML models to operate as context-aware predictors rather than global regressors. While effective, clustering-based schemes increase system complexity and require continuous reclassification of vehicles or channel states, which may be challenging under stringent latency constraints. Hybrid ML methods further extend predictive capabilities by combining supervised models with clustering, fuzzy logic, or rule-based components. These frameworks have been shown to improve resilience to noise, measurement sparsity, and abrupt mobility transitions, especially in scenarios where deep learning solutions may be computationally infeasible [45], [46].

Table 3: Overview of Variables Used in Machine Learning-Based Papers.

| Variable       | [10] | [16] | [17] | [44] | [29] | [8] | [47] | [30] | [31] | [48] | [29] | [44] | [49] | [45] | [46] |
|----------------|------|------|------|------|------|-----|------|------|------|------|------|------|------|------|------|
| Latency        | ✓    | -    | ✓    | -    | ✓    | ✓   | ✓    | -    | -    | ✓    | ✓    | ✓    | ✓    | ✓    | ✓    |
| Jitter         | ✓    | -    | -    | -    | ✓    | ✓   | ✓    | -    | -    | -    | -    | -    | -    | -    | -    |
| Throughput     | ✓    | -    | ✓    | ✓    | ✓    | ✓   | ✓    | ✓    | -    | -    | -    | ✓    | ✓    | ✓    | ✓    |
| RTT            | -    | ✓    | -    | -    | -    | -   | -    | -    | -    | -    | -    | -    | -    | -    | -    |
| UE-RSU Latency | -    | ✓    | -    | -    | -    | -   | -    | -    | ✓    | -    | -    | ✓    | -    | -    | -    |
| Packet Delay   | -    | -    | ✓    | -    | ✓    | ✓   | ✓    | -    | -    | ✓    | ✓    | ✓    | ✓    | ✓    | ✓    |

|                   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |
|-------------------|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PHY Features      | - | - | - | ✓ | ✓ | ✓ | ✓ | - | - | - | - | - | - | - | - |
| Speed             | - | - | - | ✓ | - | - | - | - | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| GPS               | - | - | - | ✓ | - | - | - | - | ✓ | - | - | - | - | - | - |
| Leading Vehicle   | - | - | - | ✓ | - | - | - | - | - | ✓ | - | - | - | - | - |
| RSRP              | - | - | - | - | ✓ | ✓ | - | ✓ | - | - | - | ✓ | - | - | - |
| RSRQ              | - | - | - | - | ✓ | ✓ | - | ✓ | - | - | - | ✓ | - | - | - |
| SINR              | - | - | - | - | ✓ | ✓ | - | ✓ | - | - | - | ✓ | - | - | - |
| Mobility Patterns | - | - | - | - | - | - | - | - | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Source: Authors, (2026).

A comparative analysis of ML-based PQoS studies reveals several overarching trends. First, multi-domain feature integration combining physical-layer indicators with mobility and traffic information consistently outperforms single-domain predictors [6] [28]. Second, the scarcity of large-scale, diverse, real-world V2X datasets limits generalizability and contributes to the overfitting observed in many ML-based models [16], [44]. Third, validation protocols vary significantly across studies, with some relying on random shuffling rather than route-based or temporal holdout strategies, leading to optimistic performance reporting [30]. Finally, while ML offers favorable computational efficiency and is well-suited for real-time inference, its inability to model long-range temporal dependencies and nonlinear interactions reduces accuracy relative to deep learning techniques, particularly under rapidly changing network dynamics.

### II.1.2 Deep Learning-Based QoS Prediction Techniques

Deep learning (DL) has gained significant traction in V2X QoS prediction because of its ability to automatically learn hierarchical spatial and temporal representations from high-dimensional communication and mobility data. Unlike traditional ML methods, which depend heavily on engineered features and perform well only under stable or moderately dynamic conditions, DL models can capture non-linear interactions between radio KPIs, mobility patterns, traffic states, and environmental factor properties essential for highly dynamic V2X environments [7], [33]. A prominent research direction focuses on deep neural networks (DNNs) for throughput and latency forecasting, where models consistently outperform linear and ensemble-based ML approaches by learning latent correlations not explicitly visible in handcrafted features [7]. Recurrent neural networks (RNNs), particularly LSTM, Bi-LSTM, and GRU architectures, extend these benefits by modeling longer-term temporal dependencies in vehicular mobility and communication traces [18], [50]. These models demonstrate superior performance in predicting fluctuating QoS under high-speed mobility, where future states depend on extended historical sequences. More recent approaches integrate attention mechanisms, GAN-based data augmentation, and multi-task learning to enhance robustness and reduce sensitivity to noise [32], [51]. Table 4 summarizes common input variables used across DL-based studies.

Table 4: Variable usage across selected V2X predictions using deep learning and QoS papers.

| Variable          | [7] | [33] | [9] | [18] | [32] | [52] | [50] | [34] | [53] | [51] | [54] |
|-------------------|-----|------|-----|------|------|------|------|------|------|------|------|
| SINR              | ✓   | ✓    | -   | -    | -    | -    | -    | -    | -    | -    | -    |
| Location          | ✓   | -    | -   | -    | -    | -    | -    | -    | -    | -    | -    |
| Throughput        | ✓   | ✓    | -   | -    | ✓    | -    | -    | -    | -    | ✓    | -    |
| Mobility          | -   | ✓    | -   | -    | -    | -    | -    | -    | -    | -    | ✓    |
| Vehicle Velocity  | -   | -    | ✓   | -    | -    | -    | -    | -    | -    | -    | -    |
| Density           | -   | -    | ✓   | -    | -    | -    | -    | -    | -    | -    | -    |
| Distribution      | -   | -    | ✓   | -    | -    | -    | -    | -    | -    | -    | -    |
| Signal Quality    | -   | -    | ✓   | -    | -    | -    | -    | -    | -    | -    | -    |
| Traffic Volume    | -   | -    | -   | ✓    | -    | -    | -    | -    | -    | -    | -    |
| Latency           | -   | -    | -   | -    | ✓    | ✓    | -    | -    | -    | ✓    | ✓    |
| BER               | -   | -    | -   | -    | ✓    | -    | -    | -    | -    | ✓    | -    |
| MSE               | -   | -    | -   | -    | ✓    | -    | -    | -    | -    | ✓    | -    |
| Packets/sec       | -   | -    | -   | -    | -    | -    | ✓    | -    | -    | -    | -    |
| RMSE              | -   | -    | -   | -    | -    | -    | ✓    | -    | -    | -    | -    |
| MAPE              | -   | -    | -   | -    | -    | -    | ✓    | -    | -    | -    | -    |
| Processing Time   | -   | -    | -   | -    | -    | -    | ✓    | -    | -    | -    | -    |
| Position          | -   | -    | -   | -    | -    | -    | -    | ✓    | -    | -    | -    |
| Speed             | -   | -    | -   | -    | -    | -    | -    | ✓    | -    | -    | -    |
| Heading           | -   | -    | -   | -    | -    | -    | -    | ✓    | -    | -    | -    |
| Trajectory        | -   | -    | -   | -    | -    | -    | -    | -    | ✓    | -    | -    |
| Acceleration      | -   | -    | -   | -    | -    | -    | -    | -    | ✓    | -    | -    |
| Relative Position | -   | -    | -   | -    | -    | -    | -    | -    | ✓    | -    | -    |
| Traffic Type      | -   | -    | -   | -    | -    | ✓    | -    | -    | -    | -    | -    |
| Reliability       | -   | -    | -   | -    | -    | ✓    | -    | -    | -    | -    | -    |
| Recourse Utilize  | -   | -    | -   | -    | -    | ✓    | -    | -    | -    | -    | -    |
| User Mobility     | -   | -    | -   | -    | -    | -    | -    | -    | -    | -    | ✓    |
| Bandwidth         | -   | -    | -   | -    | -    | -    | -    | -    | -    | -    | ✓    |

Source: Authors, (2026).

DL has also advanced spatial modeling in V2X networks. Graph neural networks (GNNs) represent vehicles as graph nodes, enabling the learning of inter-vehicle spatial dependencies relevant for collision risk assessment and link-quality prediction [53]. Hybrid DL–RL models leverage DL as function approximators to optimize resource allocation or routing with improved predictive QoS awareness [54]. Collectively, these approaches highlight DL’s ability to fuse heterogeneous mobility, radio, and contextual input capabilities beyond the scope of conventional ML. Despite these advantages, DL-based QoS prediction faces several practical limitations. First, DL models typically require large-scale, diverse, labeled datasets; however, publicly available V2X datasets remain limited, geographically biased, or collected under controlled conditions [33]. [55] As a result, models often overfit and fail to generalize to new traffic densities, weather conditions, or propagation environments. Second, DL models impose significant computational and memory overhead, making them less suitable for real-time deployment on resource-constrained RSUs or OBUs without model compression or edge offloading. Third, DL operates as a “black box,” offering limited interpretability, an issue particularly problematic for safety-critical ITS applications where prediction rationale must be auditable. Finally, variations in evaluation methodologies across studies (windowing strategies, train–test splits, and scenario coverage) contribute to inconsistent reporting of performance gains. Overall, DL-based QoS prediction provides substantial improvements over traditional ML by capturing complex spatio-temporal dependencies and multi-modal interactions inherent in V2X systems. However, the practical utility of DL remains constrained by dataset scarcity, computational costs, and limited generalization. These shortcomings motivate current research directions involving hybrid DL–RL architectures, domain adaptation, transfer learning, and model compression to improve scalability and real-time applicability in 5G/6G vehicular networks.

### II.1.3 Routing and Protocol-Based Approaches

Routing and protocol-level techniques play a central role in determining how reliably and efficiently V2X messages are propagated under high mobility. Classical routing protocols such as GPSR, AODV, and DSDV are frequently used as baselines to assess delay, packet delivery ratio, and robustness; however, their performance degrades in dense or fast-changing topologies [11]. Recent QoS-aware routing schemes attempt to address these limitations by incorporating mobility prediction, SINR estimation, and relay selection, with approaches such as TDMP and C-V2X-assisted D2D forwarding demonstrating improved reliability and reduced route breaks [39], [56]. Nonetheless, these methods remain sensitive to wireless channel fluctuations, indicating that routing alone cannot guarantee end-to-end QoS. Scheduling and resource-allocation strategies complement routing by prioritizing transmissions based on queue states, predicted link stability, or latency requirements. Mobility-aware schedulers and weighted-greedy allocation methods achieve measurable reductions in delay and congestion [12], although their performance is constrained by the accuracy of channel state estimation. At the physical layer, studies of channel coding and propagation models show that coding schemes such as turbo and LDPC significantly influence link reliability and retransmission behavior under varying mobility and fading conditions [13], [57]. These findings underscore the tight coupling between PHY-layer characteristics and protocol-layer performance. Cross-layer QoS modeling integrates routing, scheduling, and PHY-level parameters to provide more realistic analyses of end-to-end reliability and latency. Such models capture the combined effects of queuing delays, MAC contention, retransmissions, and route dynamics, offering insights that single-layer evaluations cannot [58]. Analytical and stochastic models further complement empirical results by characterizing multi-hop connectivity, interference, and dissemination delay in large-scale V2X settings [59]. Table 5 provides the variable-to-study mapping covering routing, scheduling, PHY, and cross-layer QoS methods.

Table 5: Mapping of QoS-Relevant Variables to Representative Routing, Scheduling, and PHY-Layer Studies.

| Variable      | [7] | [33] | [9] | [18] | [32] | [52] | [50] | [35] | [53] | [54] |
|---------------|-----|------|-----|------|------|------|------|------|------|------|
| Throughput    | ✓   | ✓    | -   | ✓    | ✓    | -    | ✓    | -    | -    | ✓    |
| Latency/Delay | -   | ✓    | ✓   | ✓    | -    | ✓    | ✓    | -    | ✓    | -    |
| Reliability   | -   | ✓    | -   | ✓    | ✓    | -    | ✓    | ✓    | -    | -    |
| Mobility Data | ✓   | -    | ✓   | -    | ✓    | ✓    | -    | ✓    | ✓    | -    |
| SINR/Channel  | ✓   | -    | ✓   | ✓    | -    | ✓    | ✓    | -    | ✓    | ✓    |

Source: Authors, (2026).

Overall, protocol-level research highlights that no individual layer can ensure stable QoS in vehicular networks. Routing depends on efficient scheduling, scheduling depends on predictable channel behavior, and PHY-layer gains require upper-layer coordination. Consequently, the most effective solutions emphasize cross-layer design, mobility awareness, and adaptive protocol mechanisms to maintain QoS under realistic vehicular mobility and channel variability.

### II.1.4 Security and Trust-Based Approaches

Security- and trust-oriented frameworks have become integral to ensuring reliable QoS in V2X networks, particularly as message integrity, privacy, and misbehavior detection directly influence latency, throughput, and packet delivery. Existing solutions span blockchain-based architectures for tamper-resistant message dissemination [14], federated learning models for privacy-preserving QoE prediction [15], [41], and trust–reputation systems that evaluate forwarding behavior, PDR, and misbehavior rates [42]. As summarized in Table 6, these studies incorporate diverse variables such as latency, throughput, security metrics, and computational cost, highlighting the increasing convergence of security and performance requirements in modern V2X systems. A notable theme across the literature is the inherent security–QoS trade-off. Blockchain and distributed ledger mechanisms strengthen message integrity but introduce non-negligible processing delays and communication overhead, which may hinder time-critical V2X applications. Federated learning reduces privacy risks but increases model synchronization overhead, while trust-based systems depend heavily on continuous recommendation exchange, potentially increasing control traffic. These factors collectively impact QoS prediction accuracy by altering latency profiles, reliability guarantees, and resource consumption. Consequently, security mechanisms cannot be treated independently of QoS constraints and must be evaluated as part of an integrated design strategy.

Table 6: Overview of Variables in Security and Trust Frameworks for V2X.

| Variable                    | [14] | [15] | [42] | [43] | [60] |
|-----------------------------|------|------|------|------|------|
| Latency                     | -    | ✓    | ✓    | ✓    | -    |
| Throughput                  | -    | ✓    | ✓    | -    | -    |
| QoE                         | -    | ✓    | ✓    | -    | -    |
| Privacy / Security Metrics  | ✓    | ✓    | ✓    | ✓    | ✓    |
| Trust / Reputation          | -    | -    | -    | ✓    | -    |
| PDR (Packet Delivery Ratio) | -    | -    | -    | ✓    | -    |
| Misbehavior Detection       | -    | -    | -    | ✓    | -    |
| Channel / Network Features  | ✓    | -    | -    | -    | -    |
| Computing Requirements      | ✓    | -    | -    | -    | -    |

Source: Authors, (2026).

Despite progress, several gaps remain. Most existing frameworks rely on simulation-based datasets and lack large-scale real-world validation under diverse mobility and attack conditions. Current models also focus predominantly on single-aspect security (e.g., trust or privacy) rather than holistic, cross-layer protection. Furthermore, limited research has examined how security metrics can be directly incorporated into ML/DL-based QoS predictors to enhance robustness against adversarial behavior. Addressing these gaps will require standardized datasets, lightweight cryptographic and trust mechanisms compatible with 5G/6G latency budgets, and unified frameworks capable of jointly optimizing QoS, privacy, and security in future V2X systems.

### III. DATASET SURVEY FOR PQOS IN V2X COMMUNICATION

Datasets constitute the empirical foundation for Predictive QoS (PQoS) research, enabling systematic evaluation of ML-, DL-, and RL-based models under diverse mobility patterns, radio conditions, and network loads. Existing datasets are typically categorized into three groups: real-world drive-test datasets, public open-access datasets, and synthetic or simulation-based datasets. Each category offers distinct benefits in terms of realism, scalability, parameter control, and reproducibility.

#### III.1 REAL-WORLD DRIVE TEST DATASETS

Real-world measurements provide the most accurate representation of 5G and V2X communication behavior, capturing realistic mobility dynamics, channel impairments, and congestion conditions that directly impact QoS. Brehon et al. [10] conducted extensive 5G SA industrial experiments for tele-operated mobility, demonstrating that regression-based PQoS models reduced end-to-end latency by nearly 15%. Similarly, Muller et al. [28] collected urban mobility traces in 5G NSA and LTE networks and reported strong correlations between vehicle movement and uplink/downlink throughput, with typical latency ranges of 15–20 ms in dense environments. BandSeer [16] and Schwarz et al. [17] further evaluated short-term bandwidth and uplink throughput prediction, identifying SINR as a dominant variable for regression-based models. Although real-world datasets provide high-fidelity ground truth, they remain geographically limited and costly to scale and often lack synchronized multimodal measurements integrating mobility, PHY, and network-layer parameters.

#### III.2 PUBLIC OPEN-ACCESS DATASETS

Public datasets enable reproducible benchmarking across the research community. The Berlin V2X dataset [43] provides GPS-tagged multi-RAT measurements that support cross-layer analysis of mobility, channel quality, and application-layer performance. NordicDat [29] expands this scope by offering more than 90,000 annotated samples with SINR, RSRP, RSRQ, throughput, delay, and mobility metrics. Reported studies show that Random Forest models achieve  $R^2 > 0.85$  for throughput prediction and median latency errors below 8 ms, supporting research in federated and domain-adaptive PQoS modeling. While open datasets lower the entry barrier for ML-based experimentation, they often exhibit climatic, geographical, or environmental bias, limiting global generalizability.

#### III.2 SYNTHETIC AND SIMULATION-BASED DATASETS

Synthetic datasets generated through simulators such as ns-3, SUMO, and 3GPP PHY engines provide full control over mobility, density, radio models, and traffic patterns. They are particularly valuable for RL-based PQoS frameworks requiring interactive environments. The PRATA framework [19], for example, used ns-3 teleoperation simulations to train PPO agents, reporting a 20% prediction gain over Double Q-Learning. Additional synthetic datasets combine BiLSTM modeling with partially real mobility traces for traffic prediction [61], while 3GPP PHY-layer evaluations [30] compare Turbo, LDPC, and Polar codes, highlighting sub-10 ms latency for Turbo-coded V2X frames. Despite their scalability and flexibility, synthetic datasets may oversimplify fading, blockage, and interference, reducing their real-world transferability.

#### III.3 SUMMARY AND LIMITATIONS

The reviewed datasets collectively capture a wide spectrum of QoS-relevant variables: mobility traces, GPS coordinates, SINR, RSRP/RSRQ, throughput, delay, jitter, and CIR, enabling comprehensive benchmarking across ML, DL, and RL paradigms. Table 7 summarizes key characteristics of widely used datasets. However, a notable gap persists: the lack of synchronized datasets that jointly capture mobility, network KPIs, and PHY-layer signal measurements. Such multimodal datasets are essential for accurate end-to-end PQoS prediction, yet remain scarce across current literature. Developing standardized, cross-layer, and large-scale datasets represents a critical research direction for the next generation of V2X QoS prediction systems.

Table 7: Dataset-wise Variable Mapping with Authors.

| Dataset                 | GPS | Speed | SINR | RSRP | RSRQ | RSSI | CQI | Throughput | Delay | Jitter | CIR | Mobility |
|-------------------------|-----|-------|------|------|------|------|-----|------------|-------|--------|-----|----------|
| Aveiro WLAN & Cellular  | ✓   | ✓     | -    | ✓    | ✓    | ✓    | -   | ✓          | -     | ✓      | -   | -        |
| Munich Drive Test QoS   | ✓   | ✓     | ✓    | -    | -    | -    | -   | ✓          | -     | -      | -   | ✓        |
| Industrial D2D AGV      | -   | -     | -    | -    | -    | -    | -   | -          | -     | -      | ✓   | -        |
| Large-Scale Mobility    | ✓   | ✓     | -    | -    | -    | -    | -   | -          | -     | -      | -   | ✓        |
| Nuremberg Multi-Vehicle | -   | -     | ✓    | ✓    | ✓    | ✓    | -   | ✓          | -     | -      | -   | -        |
| Berlin V2X Multi-Rat    | ✓   | ✓     | ✓    | ✓    | ✓    | -    | ✓   | ✓          | -     | -      | -   | ✓        |
| IoV Delay – Wuxi        | -   | -     | -    | -    | -    | -    | -   | ✓          | ✓     | -      | -   | -        |
| V2X QoS (Munich+Brno)   | ✓   | -     | ✓    | ✓    | ✓    | -    | ✓   | ✓          | -     | -      | ✓   | -        |

Source: Authors, (2026).

#### IV. CHALLENGES AND OPEN ISSUES

The analysis presented in the previous sections, together with the comparative tables and dataset summaries, reveals several recurring limitations that continue to affect the reliability of V2X QoS prediction models. These observations indicate that, despite substantial progress in ML-, DL-, and RL-based methods, fundamental gaps persist in data availability, model robustness, real-time inference categories, (i) interpretability, and system-level integration. As depicted in Figure 5, these challenges can be broadly classified into two major categories: (i) Dataset and Generalization Issues and (ii) Methodology and Deployment Constraints. The flowchart illustrates how factors such as the lack of multi-modal real-world datasets, environment-specific model behavior, absence of cross-layer modeling, and limited explainability directly influence the accuracy and practicality of QoS prediction in V2X networks. Additionally, inconsistent KPI definitions, heterogeneous evaluation metrics, and various security vulnerabilities further complicate real-world adoption. Together, these insights highlight the need for more comprehensive datasets, interpretable and secure learning models, and unified cross-layer prediction frameworks to support robust and scalable V2X communication systems.

##### IV.1 STRUCTURAL RESEARCH GAPS IN EXISTING PQOS LITERATURE

Although substantial progress has been achieved in predictive QoS modeling for V2X systems, a critical synthesis of the reviewed literature reveals several structural limitations that constrain scalability, robustness, and deployment readiness.

- 1) *Absence of Spatial QoS Field Modeling*: Most ML- and DL-based approaches perform point-wise prediction using locally observed indicators such as SINR, RSRP, mobility traces, or traffic density [28], [30], [33]. While effective for short-term estimation, these models do not reconstruct QoS behavior across unmeasured road segments. Empirical drive-test studies confirm strong spatial variability of throughput and latency in dense urban scenarios [17], [28]. However, explicit spatial correlation modeling and network-wide QoS field reconstruction remain largely unexplored, limiting generalization across heterogeneous road networks.

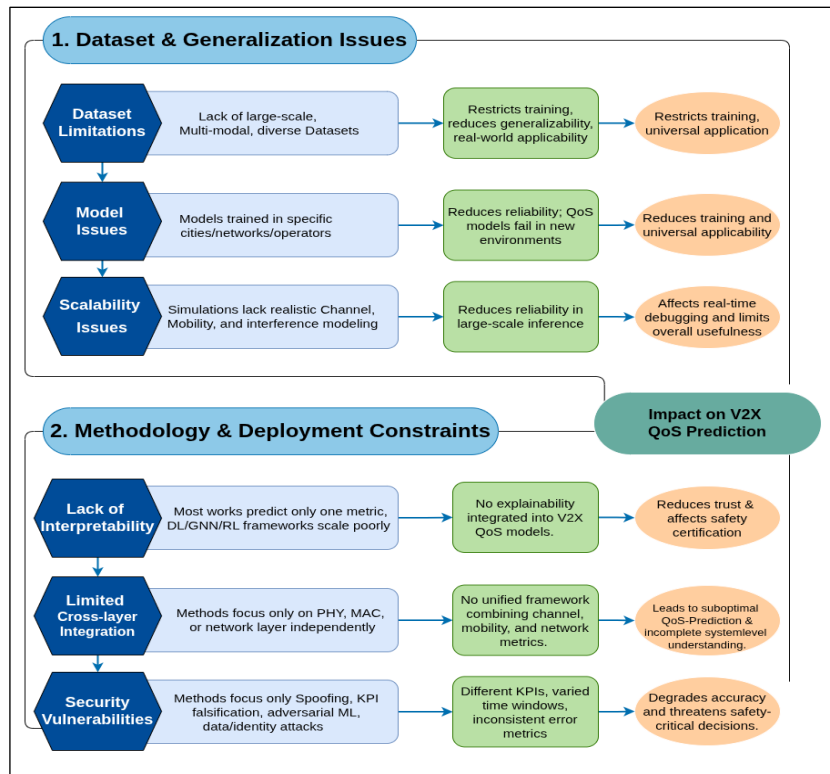


Figure 5: Diagram illustrating the key challenges and open issues in V2X QoS prediction.

Source: Authors, (2026).

- 2) *Single-Metric Prediction Dominance*: A significant portion of existing studies focuses on isolated metrics such as throughput or delay [7], [18]. In contrast, safety-critical V2X services require simultaneous guarantees on latency, reliability, jitter, and availability. The

absence of unified multi-metric prediction frameworks restricts cross-layer optimization and may lead to suboptimal system-level adaptation decisions.

- 3) *Limited Cross-Scenario Generalization*: Many predictive models are validated using city-specific drive-test datasets or simulator-generated traces [16], [43]. Although high accuracy is often reported under controlled settings, performance frequently degrades when deployed in unseen environments. This suggests insufficient domain adaptation and limited robustness to distribution shifts across mobility regimes, propagation conditions, and infrastructure density.
- 4) *Simulation-Centric Reinforcement Learning*: Reinforcement learning approaches demonstrate adaptive capabilities in teleoperation, slicing, and multicast optimization [19], [54]. However, most frameworks rely heavily on synthetic environments such as ns-3 simulations. The realism gap between simulation assumptions and operational 5G/6G V2X conditions raises concerns regarding deployment safety, convergence stability, and policy transferability.
- 5) *Weak Integration of Security and QoS Prediction*: Security-oriented frameworks based on blockchain, federated learning, and trust management enhance resilience [14], [15], [42], yet they are typically evaluated independently of predictive QoS modeling. The direct impact of authentication latency, secure aggregation overhead, or adversarial interference on QoS prediction accuracy remains insufficiently quantified.
- 6) *Evaluation Methodology Inconsistencies*: Validation protocols vary widely across studies, including random train-test splits and metric selection differences [34], [50]. In mobility-correlated datasets, random splitting may introduce temporal and spatial leakage, artificially inflating reported accuracy. The absence of standardized benchmarking and route-based validation hinders fair comparison and reproducibility.

Collectively, these gaps indicate that current PQoS research remains predominantly point-based, dataset-constrained, and method-driven rather than system-driven. Addressing these limitations requires unified spatio-temporal modeling, multi-metric prediction, uncertainty quantification, and deployment-aware validation using large-scale real-world vehicular datasets.

## IV.2 FUTURE RESEARCH DIRECTIONS

Building upon the identified structural gaps, several forward-looking research directions emerge for advancing PQoS modeling toward reliable 5G/6G-enabled V2X systems.

### IV.2.1 Multimodal and Cross-Layer Dataset Development

Future progress in PQoS research depends on the availability of synchronized, large-scale datasets that jointly capture mobility patterns, PHY-layer indicators, MAC-layer statistics, and application-level performance metrics. Existing datasets typically isolate individual parameters, limiting their ability to model complex spatio-temporal dependencies. Future efforts should focus on developing multimodal benchmarking datasets with:

1. Fine-grained temporal resolution (sub-100 ms sampling),
2. Diverse urban, suburban, and highway scenarios,
3. Explicit support for 5G/6G features such as sidelink, beam management, RIS-assisted links, and ISAC.

Standardized open benchmarks would enable reproducibility and fair cross-model comparison across research communities.

### IV.2.2 Robust and Generalizable PQoS Models

ML/DL-based models often exhibit strong performance under training conditions but degrade under domain shifts. Future research should investigate domain adaptation, transfer learning, self-supervised representation learning, and distributionally robust optimization techniques capable of maintaining stable error bounds across heterogeneous deployments. A key objective is to design models whose prediction degradation remains within acceptable operational margins when transferred across cities, densities, or infrastructure configurations. Incorporating reliability scoring and uncertainty estimation into PQoS predictors can further improve decision confidence in safety-critical scenarios.

### IV.2.3 Uncertainty-Aware and Risk-Constrained PQoS Modeling

In safety-critical V2X environments, prediction confidence is as important as prediction accuracy. Future PQoS frameworks should integrate uncertainty-aware learning mechanisms such as Bayesian deep learning, Gaussian processes, conformal prediction, and risk-sensitive reinforcement learning. Uncertainty estimates can enable:

1. Confidence-aware resource allocation,
2. Risk-adaptive handover decisions,
3. Safe fallback strategies under prediction ambiguity.

Designing predictors that quantify epistemic and aleatoric uncertainty will be essential for trustworthy deployment in autonomous mobility systems.

### IV.2.4 Integration of Learning With Network Control and Protocol Design

Current approaches often treat learning models and networking protocols as independent components. A promising direction involves co-designing predictive models with routing, scheduling, slicing, and resource allocation mechanisms. Lightweight and stable RL or multi-agent RL frameworks operating under partial observability and tight latency constraints could enable closed-loop adaptation in dense vehicular scenarios. Hybrid learning—protocol architectures that directly embed predictive outputs into real-time control logic—represents a key step toward context-aware QoS guarantees.

#### IV.2.5 Secure, Privacy-Preserving, and Trust-Integrated PQoS Frameworks

As V2X ecosystems become increasingly interconnected, PQoS pipelines must integrate security and privacy constraints. Future research should explore federated PQoS learning, secure aggregation, blockchain-enabled trust verification, and adversarial robustness. A critical research question concerns balancing security overhead with latency budgets. Embedding trust metrics directly into QoS prediction models may enhance resilience against falsified measurements and adversarial manipulation.

#### IV.2.6 Toward 6G: Semantic, Predictive, and Edge-Intelligent V2X

The transition to 6G will shift PQoS modeling toward semantic-aware communication, AI-native network control, and distributed edge intelligence. Emerging technologies such as integrated sensing and communication (ISAC), reconfigurable intelligent surfaces (RIS), sub-THz links, and graph neural networks for network-wide coordination offer new opportunities for predictive QoS assurance. Future PQoS systems are expected to operate as distributed edge-intelligent agents capable of continuous learning, real-time adaptation, and proactive risk mitigation. Achieving this vision requires rethinking QoS prediction as a core architectural component of autonomous, self-optimizing V2X networks. Taken together, these research directions highlight a paradigm shift from isolated algorithmic improvements toward holistic, deployment-aware, uncertainty-conscious, and security-integrated PQoS intelligence suitable for large-scale autonomous mobility in 5G and beyond.

### V. CONCLUSIONS

This paper provided a critical review of predictive Quality of Service (PQoS) modeling for V2X communication systems, examining machine learning, deep learning, reinforcement learning, protocol-level, and security-aware approaches. While significant progress has been reported in metric-specific prediction accuracy, our analysis shows that current research remains largely point-based, single-metric focused, and heavily reliant on simulation or city-specific datasets. The absence of spatial QoS field reconstruction, limited cross-scenario generalization, weak integration of security and control mechanisms, and inconsistent evaluation methodologies collectively restrict the scalability and deployment readiness of existing solutions in real-world high-mobility environments. To meet the stringent reliability and latency demands of next-generation vehicular networks, PQoS research must evolve beyond incremental accuracy improvements toward unified spatio-temporal modeling, multi-metric and uncertainty-aware prediction, and tightly integrated learning-control architectures. As V2X systems transition toward AI-native 6G ecosystems, predictive QoS should be positioned as a foundational architectural component enabling proactive, resilient, and self-optimizing communication. Achieving this transformation will require deployment-aware design, standardized benchmarking, and system-level intelligence capable of sustaining trustworthy operation in large-scale autonomous mobility scenarios.

### VI. AUTHOR'S CONTRIBUTION

**Conceptualization:** Parita Patel and Mahesh Goyani.  
**Methodology:** Parita Patel and Mahesh Goyani.  
**Investigation:** Parita Patel and Mahesh Goyani.  
**Discussion of results:** Parita Patel and Mahesh Goyani.  
**Writing – Original Draft:** Parita Patel.  
**Writing – Review and Editing:** Mahesh Goyani.  
**Resources:** Parita Patel and Mahesh Goyani.  
**Supervision:** Parita Patel and Mahesh Goyani.  
**Approval of the final text:** Mahesh Goyani.

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