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Distribution-Aware Evaluation of LAN, WAN-IPsec, and SD-WAN Architectures for Real-Time Enterprise Applications

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ABSTRACT – Real-time enterprise applications increasingly depend on network architectures that can sustain predictable performance under dynamic traffic conditions. While Software-Defined Wide Area Networks (SD-WAN) are widely adopted to improve flexibility and resilience, their benefits relative to traditional WAN-IPsec overlays and local-area networks (LANs) remain insufficiently characterized from a distributional and experience-oriented perspective. This paper presents a controlled, comparative evaluation of three enterprise network architectures—LAN, WAN with IPsec overlay, and Hybrid SD-WAN—under varying traffic loads. The analysis combines Quality of Service (QoS) measurements, formal statistical validation, Quality of Experience (QoE) modeling, and machine learning–based prediction. Rather than focusing on average performance, the study emphasizes variability and tail behavior of delay and jitter, which are critical for real-time services. Experimental results show that LAN environments provide consistently stable performance across load conditions, whereas WAN-IPsec overlays exhibit pronounced delay and jitter tail expansion under congestion. Hybrid SD-WAN significantly mitigates this variability by reducing dispersion and high-percentile delay, even when average throughput gains are modest. Statistical analysis confirms significant architecture–load interaction effects for delay and jitter, while QoE evaluation demonstrates that stability, rather than throughput, dominates perceived service quality. Furthermore, non-linear machine learning models accurately predict QoE from observable network features, with jitter and packet loss emerging as the most influential predictors. These findings highlight the necessity of distribution-aware evaluation and experience-driven control for designing and operating real-time enterprise networks.

KEYWORDS: Enterprise Networks, SD-WAN, Quality of Experience (QoE), Delay, Jitter

Evaluasi Berbasis Distribusi terhadap Arsitektur LAN, WAN-IPsec, dan SD-WAN untuk Aplikasi Enterprise Real-Time

ABSTRAK – Aplikasi enterprise real-time semakin bergantung pada arsitektur jaringan yang mampu mempertahankan kinerja yang stabil dan dapat diprediksi di bawah kondisi lalu lintas yang dinamis. Meskipun Software-Defined Wide Area Network (SD-WAN) telah banyak diadopsi untuk meningkatkan fleksibilitas dan ketahanan jaringan, manfaatnya dibandingkan dengan WAN tradisional berbasis IPsec dan Local Area Network (LAN) masih belum sepenuhnya dikarakterisasi dari sudut pandang distribusi kinerja dan pengalaman pengguna. Penelitian ini menyajikan evaluasi komparatif terkontrol terhadap tiga arsitektur jaringan enterprise—LAN, WAN dengan overlay IPsec,

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dan Hybrid SD-WAN—di bawah berbagai tingkat beban lalu lintas. Analisis dilakukan dengan mengombinasikan pengukuran Quality of Service (QoS), validasi statistik formal, pemodelan Quality of Experience (QoE), serta prediksi berbasis machine learning. Berbeda dari pendekatan yang berfokus pada nilai rata-rata, studi ini menekankan variabilitas serta perilaku ekor (tail behavior) dari delay dan jitter, yang bersifat krusial bagi layanan real-time. Hasil eksperimen menunjukkan bahwa lingkungan LAN memberikan kinerja yang stabil secara konsisten pada semua tingkat beban. Sebaliknya, WAN-IPsec menunjukkan ekspansi ekor delay dan jitter yang signifikan saat terjadi kongesti. Arsitektur Hybrid SD-WAN mampu secara substansial mengurangi variabilitas tersebut dengan menekan dispersi dan delay pada persentil tinggi, meskipun peningkatan throughput rata-rata relatif terbatas. Analisis statistik mengonfirmasi adanya efek interaksi yang signifikan antara arsitektur dan beban lalu lintas terhadap delay dan jitter, sementara evaluasi QoE menunjukkan bahwa stabilitas kinerja—bukan throughput rata-rata—menjadi faktor dominan dalam menentukan kualitas pengalaman pengguna. Selain itu, model machine learning non-linear mampu memprediksi QoE secara akurat berdasarkan parameter jaringan yang teramati, dengan jitter dan packet loss teridentifikasi sebagai prediktor paling berpengaruh. Temuan ini menegaskan pentingnya evaluasi berbasis distribusi serta pengendalian jaringan yang berorientasi pada pengalaman pengguna dalam perancangan dan pengoperasian jaringan enterprise real-time.

KATA KUNCI: Jaringan Enterprise, SD-WAN, Quality of Experience (QoE), Delay, Jitter

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1. INTRODUCTION

Modern enterprises increasingly depend on real-time collaboration applications, cloud services, and distributed systems to support daily business processes. As a result, enterprise network infrastructure performance directly affects business productivity and service quality [1]. Network performance degradation—such as reduced throughput, increased delay variation, and packet loss—can disrupt application responsiveness and lower user-perceived service quality. Prior studies report that infrastructure improvements, including VLAN implementation and enforcement, high-availability practices, and systematic monitoring, enhance bandwidth utilization, security, and service continuity in enterprise environments [2], [3]. In addition, advances in packet-processing acceleration, such as XDP-based SmartNICs, can reduce processing overhead and improve throughput while minimizing packet loss [4]. AI-driven optimization is also increasingly explored to dynamically manage configurations and resources to improve reliability and scalability [5]. Beyond operational outcomes, evidence from broadband infrastructure initiatives indicates that improved network infrastructure can support enterprise innovation and digital transformation [6], [7]. These trends collectively motivate a closer examination of how enterprise network architecture influences application-level performance, particularly for real-time services.

From an architectural perspective, Local Area Networks (LANs) typically deliver lower latency and higher throughput than Wide Area Networks (WANs) because they operate over shorter physical distances and within more controlled administrative domains, which supports faster access speeds and more consistent service quality in enterprise environments [8], [9]. In contrast, WANs interconnect geographically distributed sites and are more exposed to heterogeneous routing, congestion, and limited end-to-end control, which often manifests as higher delay, jitter, and packet loss and can become a performance bottleneck for delay-sensitive and distributed applications [8], [10]. Geo-distributed systems research further indicates that moving from LAN-like conditions to WAN-like conditions can significantly degrade the performance of strongly consistent protocols and distributed learning workloads, motivating techniques that aim to "approach LAN speeds" over wide-area deployments [11], [12]. To mitigate WAN-induced impairments, multiple optimization directions have been explored. WAN optimization proxies can reduce effective latency and improve bandwidth utilization, although the magnitude of gains depends on bandwidth conditions [10]. SD-WAN traffic steering and load balancing can improve latency and packet loss compared to conventional strategies such as round-robin, and resilience can be further enhanced using WAN-aware multipath transport mechanisms [8], [13]. For distributed learning and analytics, hierarchical orchestration that exploits frequent aggregation within LANs and less frequent aggregation across WANs has also been proposed to reduce WAN traffic and associated costs[14]. These findings underscore that LAN–WAN architectural differences materially shape enterprise application performance, and they highlight the need for approaches that can reduce WAN variability while preserving secure inter-site connectivity.

Enterprises operating across multiple locations therefore require hybrid architectures that combine stable local LAN performance with reliable inter-branch WAN connectivity. In practice, inter-branch connectivity is frequently realized through secure overlays (e.g., IPsec-based tunnels), which provide confidentiality and integrity but may still expose delay-sensitive services to underlying WAN variability. Accordingly, performance evaluation of overlay networking for delay-sensitive services becomes essential to quantify how overlay-based interconnection behaves under realistic network dynamics [15]. In this context, Software-Defined Wide Area Networks (SD-WAN) introduce centralized control and policy-based traffic steering across multi-link connections, enabling more flexible path selection and faster failover for different application classes [15]. Recent studies further investigate learning-based methods to improve SD-WAN QoS, including reinforcement learning to enhance QoS objectives and adaptive routing frameworks for real-time optimization [16], [17], while broader discussions emphasize the potential role of AI and machine learning in enhancing SD-WAN performance under dynamic conditions [18]. However, despite these advances, empirical evidence that directly compares (i) pure LAN, (ii) traditional WAN with IPsec overlay, and (iii) hybrid SD-WAN-based enterprise architectures under controlled and varying traffic loads remains limited, especially when evaluation extends beyond Quality of Service (QoS) to include Quality of Experience (QoE).

Beyond empirical benchmarking, enterprises also require predictive models that estimate QoE from observable network conditions. Such models can support capacity planning, policy design, and proactive mitigation by anticipating user experience degradation before disruptions affect real-time applications. Recent work on machine learning-driven QoE prediction in SDN environments indicates that hybrid modeling approaches can map network features to QoE outcomes with practical relevance for operational decision-making [19]. Therefore, this research combines empirical evaluation and machine learning-based predictive modeling to provide objective guidance for designing and operating hybrid enterprise networks for real-time applications.

This research establishes the following objectives: (1) compare QoS performance across three enterprise network configurations (LAN, traditional WAN with IPsec, and hybrid SD-WAN); (2) formulate an integrated QoS index and a QoS-to-QoE mapping for real-time applications; and (3) build QoE prediction models based on network parameters. Accordingly, this research addresses the following research questions: **RQ1** how QoS differences manifest across architectures under varying traffic loads; **RQ2** to what extent SD-WAN stabilizes jitter and delay under congested conditions; and **RQ3** how accurately machine learning models predict QoE from QoS features. The scientific contributions include: (i) a replication-friendly comparative testing framework for three enterprise configurations, (ii) an integrated QoS formulation combining benefit and cost metrics, and (iii) QoE prediction models linking network conditions with user experience to support network design decision-making.

2. RESEARCH METHODS

2.1 Experimental Framework and Network Architectures

This study adopts a controlled, comparative experimental framework to systematically evaluate Quality of Service (QoS), Quality of Experience (QoE), and QoE predictability across heterogeneous enterprise network architectures. The methodology quantifies performance differences under realistic operating conditions and supports data-driven modeling of user experience from network telemetry. Figure 1 illustrates the end-to-end workflow, starting from controlled traffic generation, traversing the network architecture under test, collecting QoS measurements at dedicated measurement points, and performing QoE analysis and predictive modeling.

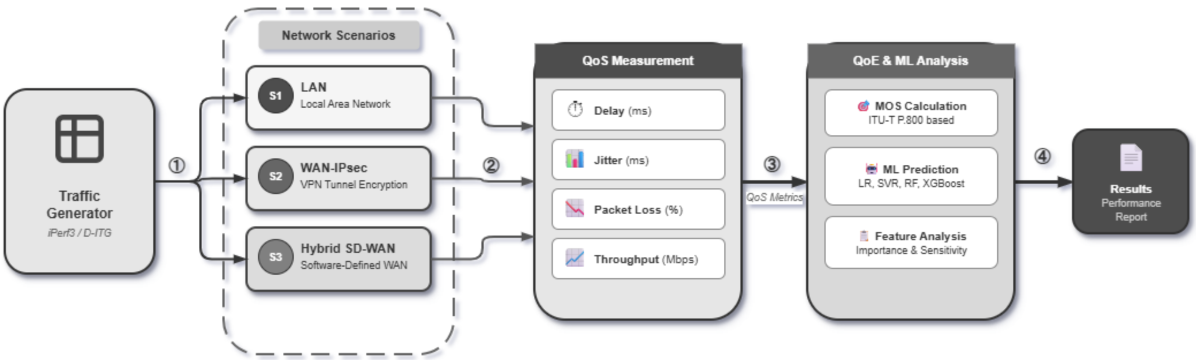

Figure 1. Experimental Framework

The experimental design includes two independent variables: (i) Network Architecture Scenario and (ii) Traffic Load Condition. The evaluated architecture scenarios consist of: S1 (LAN), S2 (WAN-IPsec), and S3 (Hybrid SD-WAN). The traffic load conditions consist of: Idle, Normal, and High. For each combination of architecture and load condition, the study executes repeated trials using identical offered-load parameters and a fixed observation window. The study randomizes the execution order across trials to reduce bias from transient conditions. Consistent with overlay-network evaluation practices for delay-sensitive services, the framework emphasizes measurement under dynamic conditions rather than assuming steady-state performance [15].

The study evaluates three enterprise network configurations that represent increasing levels of geographic scope, encapsulation overhead, and adaptive control:

1. **S1—LAN (Baseline):** Endpoints communicate within a single site using an enterprise Local Area Network (e.g., Gigabit Ethernet switching). This scenario operates under a tightly controlled administrative domain with minimal routing complexity and serves as a reference baseline for stable, low-latency communication.
2. **S2—Traditional WAN with IPsec Overlay (WAN-IPsec):** Endpoints communicate across geographically separated sites through a WAN underlay while using an IPsec

VPN tunnel for secure connectivity. This scenario represents conventional branch-to-branch deployments in which encryption and tunneling provide confidentiality and integrity, but path selection is typically static and not optimized per application class, which can limit performance for delay-sensitive traffic under varying network conditions.

3. **S3—Hybrid LAN–WAN using SD-WAN (Hybrid SD-WAN):** Sites connect to multiple WAN uplinks (e.g., broadband and MPLS, or dual broadband links) managed by an SD-WAN controller. The controller enforces centralized, application-aware policies for dynamic path steering and failover. In line with SD-WAN resilience research, this scenario supports adaptive multipath behaviors to maintain service continuity when link quality degrades [13]. The configuration also provides a baseline for intelligent networking mechanisms explored in recent SD-WAN QoS enhancement studies [16], [17].

2.2 Traffic Scenarios and Application Workload Profiles

The study uses three traffic load profiles to approximate enterprise operational conditions:

1. **Idle:** Minimal background traffic; only control-plane traffic and measurement probes run.
2. **Normal-load:** Mixed enterprise traffic representing typical office usage (web-like sessions, moderate file transfers) alongside real-time sessions.
3. **High-load:** Sustained background traffic that increases link utilization and queueing, combined with real-time traffic to expose congestion sensitivity (delay/jitter/loss behavior).

Background traffic is generated using traffic generators (e.g., TCP/UDP bulk flows), while real-time traffic is generated using delay-sensitive flows (e.g., RTP/WebRTC-like UDP streams). For each profile, the study fixes offered-load parameters (rate, concurrency, packet size distribution, and session duration) to maintain comparability across S1–S3.

2.3 QoS Measurement and Data Collection

The study collects QoS metrics for each architecture–load combination through repeated trials to capture both average behavior and variability. Each trial runs over a fixed observation window Δt, and the system stores flow-level logs and packet traces to enable cross-verification of computed metrics. All QoS measurements are timestamped with synchronized clocks (NTP/PTP when applicable) to support accurate delay and jitter computation.

QoS metrics include:

- **Throughput T (bits/s):** successfully delivered payload rate over the measurement window.
- **Delay D (ms):** one-way delay when synchronization is reliable; otherwise RTT as a consistent proxy.
- **Jitter J (ms):** delay variation computed from the delay time series.
- **Packet loss rate PLR:** ratio of lost packets to transmitted packets.

In addition to mean values, the study emphasizes **distributional and tail behavior** (e.g., P95/P99 delay and jitter), because transient impairments often dominate perceived performance in real-time enterprise applications.

QoS formulations. If the receiver successfully obtains B_{recv} bytes over a window Δt, throughput is:

$$T = \frac{8B_{\text{recv}}}{\Delta t} \qquad (1)$$

Given n delay samples d_i, the mean delay is:

$$\bar{D} = \frac{1}{n}\sum_{i=1}^{n} d_i \qquad (2)$$

Jitter is computed as the standard deviation of delay:

$$J = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(d_i - \bar{D})^2} \qquad (3)$$

If the sender transmits N_{sent} packets and the receiver obtains N_{recv} packets, packet loss rate is:

$$PLR = \frac{N_{\text{sent}} - N_{\text{recv}}}{N_{\text{sent}}} \qquad (4)$$

2.4 QoS–QoE Mapping and Integrated QoS Modeling

To bridge the gap between technical network measurements and user-perceived experience, this study applies a multi-stage QoS–QoE modeling approach. As shown in Figure 2, the framework first normalizes heterogeneous QoS metrics and aggregates them into a single integrated index. The integrated index is then mapped to a bounded Mean Opinion Score (MOS)-like QoE value using a non-linear function to capture saturation and sensitivity effects.

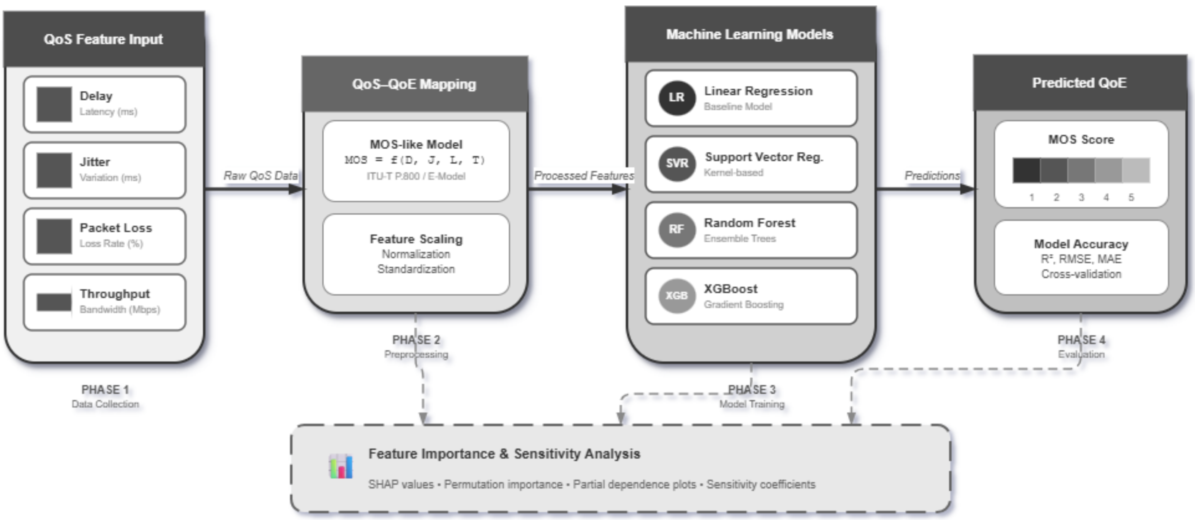

Figure 2. QoS–QoE Modeling and Prediction Pipeline: Feature Processing, QoE Label Construction, and Machine Learning Workflow

2.4.1 Metric Normalization and Integrated QoS Index

QoS metrics differ in units and polarity. Throughput is a benefit metric (higher is better), whereas delay, jitter, and packet loss are cost metrics (lower is better). Therefore, the study performs min–max normalization so that each metric lies in $[0, 1]$ and higher values consistently indicate better performance.

For a benefit metric x (e.g., throughput T), the normalized value is:

$$\tilde{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \qquad (5)$$

For a cost metric x (e.g., delay D, jitter J, and packet loss rate PLR), the normalized value is inverted such that 1 indicates the best performance:

$$\tilde{x} = \frac{x_{\max} - x}{x_{\max} - x_{\min}} \qquad (6)$$

Using the normalized metrics, the study defines an integrated QoS index $Q \in [0,1]$ as a weighted linear combination:

$$Q = w_T\tilde{T} + w_D\tilde{D} + w_J\tilde{J} + w_L\widetilde{PLR} \qquad (7)$$

with the constraints:

$$w_T + w_D + w_J + w_L = 1, w_k \geq 0 \qquad (8)$$

The weights reflect application requirements. For real-time interactive applications, the study assigns higher weights to delay and jitter (i.e., w_D and w_J) because these impairments are typically the dominant drivers of interactivity degradation, while throughput primarily contributes once minimum bandwidth needs are satisfied.

2.4.2 Logistic QoE Mapping (MOS-like)

To model the non-linear nature of user satisfaction—including saturation effects where improvements beyond a certain QoS level yield diminishing perceived benefits—the study maps the integrated QoS index Q to an estimated MOS-like score $\widehat{MOS} \in [1,5]$ using a logistic sigmoid function:

$$\widehat{MOS} = 1 + \frac{4}{1 + e^{-\alpha(Q-\beta)}} \qquad (9)$$

where α controls the steepness (sensitivity) of the QoE transition with respect to Q, and β represents the midpoint threshold at which QoE changes most rapidly. This formulation ensures that predicted QoE remains within the standard MOS range while capturing non-linear degradation under increasing delay, jitter, and packet loss. The study estimates α and β via calibration using representative experimental data so that the mapping reflects the response characteristics of the evaluated real-time workload.

2.5 Machine Learning–Based QoE Prediction

Building on the QoS–QoE labeling process, the study trains supervised machine learning models to predict QoE directly from observed QoS and contextual features. Each observation corresponds to a time window or session interval.

2.5.1 Dataset Definition

The dataset is defined as:

$$\mathcal{D} = \{(\mathbf{x}_i, y_i)\}_{i=1}^{N} \qquad (10)$$

with feature vector:

$$\mathbf{x}_i = [T_i, \bar{D}_i, J_i, PLR_i, s_i, \ell_i] \qquad (11)$$

where s_i denotes the architecture (S1/S2/S3) and ℓ_i denotes the load condition (idle/normal/high), encoded as categorical variables. The target is:

$$y_i = MOS_i \qquad (12)$$

The model learns:

$$\hat{y} = f(\mathbf{x}) \qquad (13)$$

2.5.2 Candidate Models and Evaluation Metrics

The study evaluates linear and non-linear regression families, including linear regression (baseline), Support Vector Regression, Random Forest, Gradient Boosting/XGBoost-like models, and shallow neural networks. Model performance is measured using:

$$MAE = \frac{1}{N}\sum_{i=1}^{N} \mid y_i - \hat{y}_i \mid \qquad (14)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \qquad (15)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2} \qquad (16)$$

When applicable, the study also reports calibration plots and/or prediction intervals to support operational decision-making beyond point estimates.

2.5.3 Feature Importance and Sensitivity

To improve interpretability, the study reports feature importance (e.g., permutation importance and SHAP-style attribution) and sensitivity analysis (e.g., partial dependence) to identify dominant drivers of QoE degradation and to support actionable SD-WAN policy tuning.

2.6 Statistical Analysis and Validation Techniques

The study applies statistical procedures to verify whether observed differences among architectures and load conditions are significant and practically meaningful.

1. **Assumption checks:** Normality testing (e.g., Shapiro–Wilk) and variance homogeneity testing (e.g., Levene's test).
2. **Significance testing:**
   - If assumptions hold, the study uses factorial ANOVA to analyze the effects of **architecture**, **load**, and their interaction on each QoS/QoE metric.
   - If assumptions do not hold, the study uses non-parametric alternatives (e.g., Kruskal–Wallis) with post-hoc pairwise tests and multiple-comparison correction.
3. **Effect size and confidence intervals:** The study reports effect sizes (e.g., η^2, Cliff's delta) alongside p-values and provides confidence intervals (e.g., bootstrap intervals) for key metrics.

For machine learning validation, the study uses k-fold cross-validation with hyperparameter tuning performed strictly within training folds to prevent information leakage:

$$\mathcal{D} = \bigcup_{j=1}^{k} \mathcal{D}_j \,, \mathcal{D}_p \cap \mathcal{D}_q = \emptyset \qquad (17)$$

When dataset size permits, the study also evaluates final performance on a held-out test set.

3. RESULTS AND DISCUSSION

3.1 QoS Performance Comparison across Network Architectures

This subsection presents a comparative evaluation of Quality of Service (QoS) across three enterprise network architectures: LAN (S1), WAN with IPsec overlay (S2), and Hybrid SD-WAN (S3). Performance is evaluated under three traffic load conditions—idle, normal, and high load—using throughput, end-to-end delay, jitter, and packet loss rate (PLR) as primary QoS indicators. In line with the requirements of real-time enterprise applications, the analysis emphasizes not only average performance but also variability and tail behavior.

Table 1. Descriptive statistics of QoS metrics across network architectures and traffic load conditions

Architecture	Load Level	Throughput (Mbps)	Delay (ms)	Jitter (ms)	PLR (%)
LAN (S1)	Idle	940 ± 15	2.1 ± 0.3	0.4 ± 0.1	0.00
LAN (S1)	Normal	915 ± 20	2.4 ± 0.4	0.6 ± 0.2	0.01
LAN (S1)	High	880 ± 30	2.9 ± 0.5	0.9 ± 0.3	0.03
WAN-IPsec (S2)	Idle	420 ± 25	28.4 ± 4.6	6.8 ± 1.9	0.20
WAN-IPsec (S2)	Normal	395 ± 35	41.7 ± 7.2	12.5 ± 4.1	0.65
WAN-IPsec (S2)	High	360 ± 45	68.9 ± 11.5	24.2 ± 8.6	1.80
SD-WAN (S3)	Idle	435 ± 20	26.1 ± 3.9	5.4 ± 1.4	0.15
SD-WAN (S3)	Normal	415 ± 30	34.6 ± 5.8	8.7 ± 2.9	0.42
SD-WAN (S3)	High	385 ± 40	49.3 ± 8.7	14.1 ± 4.8	0.95

Values are reported as mean ± 95% confidence interval.

The results in Table 1 show that LAN (S1) consistently delivers the lowest delay and jitter with negligible packet loss across all load levels. Even under high-load conditions, LAN performance remains stable, reflecting short propagation distances, minimal routing complexity, and centralized administrative control typical of enterprise LAN environments.

In contrast, WAN with IPsec overlay (S2) exhibits substantially higher variability, particularly in delay and jitter under normal and high-load conditions. Although IPsec tunneling provides confidentiality and integrity, the encapsulation overhead and dependence on heterogeneous underlay WAN paths exacerbate queueing and processing delays during congestion. Packet loss also increases markedly under high load, indicating limited robustness to transient impairments. These observations are consistent with prior findings that secure overlays alone are insufficient to stabilize delay-sensitive traffic in wide-area environments.

The Hybrid SD-WAN architecture (S3) demonstrates improved QoS stability relative to S2. While average throughput differences between S2 and S3 remain modest, SD-WAN significantly reduces jitter and high-percentile delay, particularly under normal and high-load conditions. This reduction in performance dispersion suggests that policy-based traffic steering and adaptive path selection effectively mitigate transient WAN impairments. Importantly, the benefits of SD-WAN are more pronounced in tail behavior than in mean values, which is critical for sustaining acceptable Quality of Experience (QoE) in real-time services.

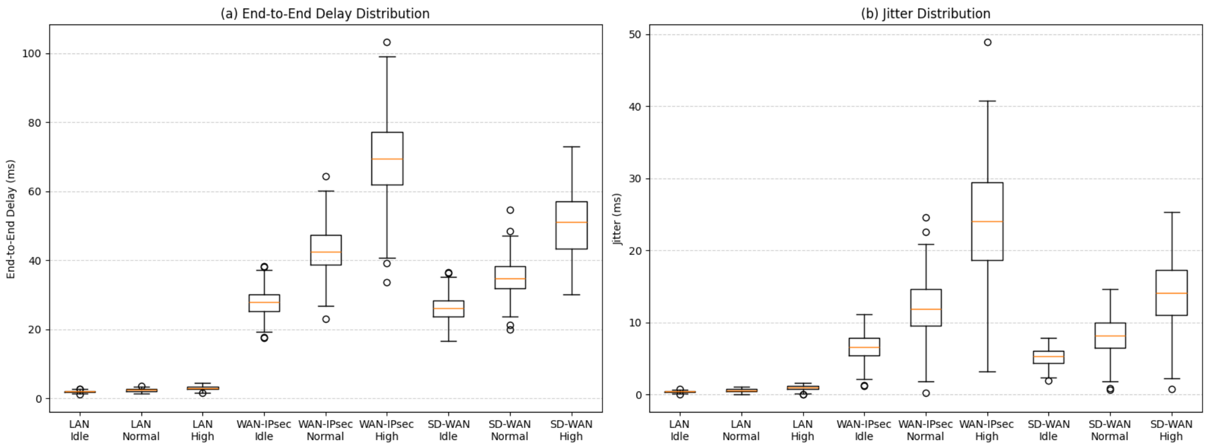

Figure 3. Distributions of delay and jitter across network architectures under varying traffic loads

Figure 3 shows that WAN-IPsec exhibits wider interquartile ranges and longer upper tails in both delay and jitter, particularly under higher load conditions. In contrast, LAN maintains tightly bounded distributions, while SD-WAN significantly compresses tail behavior relative to WAN-IPsec. The distributional evidence in Figure 3 reinforces the conclusion that SD-WAN primarily improves performance predictability rather than maximizing average throughput. For real-time enterprise applications, this reduction in variability and tail impairment is more consequential than marginal throughput gains.

3.2 Effect of Traffic Load on QoS Robustness and Statistical Validation

Building on the distributional evidence shown in Figure 3, this subsection examines how traffic load affects QoS robustness across architectures and formally validates the observed differences using statistical testing. Rather than treating load as a uniform stressor, the analysis focuses on whether increasing traffic load alters the delay and jitter distributions differently across architectures.

As shown in Figure 3, WAN-IPsec (S2) exhibits a pronounced expansion of delay and jitter tails as traffic load increases, whereas SD-WAN (S3) demonstrates a more gradual degradation. LAN (S1) remains largely stable across load levels, with only marginal increases in dispersion. These visual patterns suggest that traffic load interacts with network architecture in a non-uniform manner, motivating explicit statistical validation.

To this end, normality and variance homogeneity were first assessed for each QoS metric. When assumptions were satisfied, a two-way analysis of variance (ANOVA) was applied with architecture and traffic load as fixed factors. For metrics violating parametric assumptions, the

Kruskal–Wallis test was used, followed by post-hoc pairwise comparisons with correction for multiple testing. Effect sizes were computed to quantify the practical relevance of statistically significant results.

Table 2. Statistical validation of architecture and load effects on QoS metrics

QoS Metric	Test	Architecture Effect (p-value)	Load Effect (p-value)	Architecture × Load (p-value)	Effect Size
Delay	Two-way ANOVA	< 0.001	< 0.001	< 0.001	$\eta^2 = 0.41$
Jitter	Kruskal–Wallis	< 0.001	< 0.001	< 0.001	Cliff's δ = 0.38
Packet Loss	Kruskal–Wallis	< 0.01	< 0.001	< 0.01	Cliff's δ = 0.27
Throughput	Two-way ANOVA	0.08	< 0.05	0.12	$\eta^2 = 0.09$

Significance level $\alpha = 0.05$. Effect sizes are reported to indicate practical relevance.

The results in Table 2 confirm that architecture and traffic load both exert statistically significant effects on delay and jitter, with large effect sizes indicating strong practical relevance. Crucially, the significant architecture × load interaction for these metrics confirms that increasing load impacts architectures differently rather than uniformly. This finding directly supports the distributional trends observed in Figure 3, where WAN-IPsec exhibits the steepest tail expansion under congestion and SD-WAN shows moderated variability.

Packet loss follows a similar, albeit less pronounced, pattern. While loss rates remain low under idle and normal conditions, high-load scenarios disproportionately affect WAN-IPsec, whereas SD-WAN maintains comparatively lower and more stable loss behavior. Throughput, by contrast, does not exhibit a strong interaction effect, reinforcing the observation that throughput alone is a weak indicator of robustness for real-time services.

Overall, the combined visual and statistical evidence establishes that QoS robustness is primarily determined by how rapidly delay and jitter distributions deteriorate under load, rather than by average performance levels. By anchoring the analysis on Figure 3 and substantiating it with formal statistical testing, this subsection demonstrates that SD-WAN offers superior resilience to traffic load variability compared to traditional WAN-IPsec overlays, providing a stronger foundation for the subsequent QoE analysis.

3.3 Quality of Experience Analysis and Its Relation to QoS Variability

The statistically significant effects identified in Table 2 provide a necessary foundation for interpreting Quality of Experience (QoE) outcomes. In particular, the strong architecture and architecture–load interaction effects observed for delay and jitter motivate a QoE analysis that prioritizes variability and tail behavior rather than average throughput. This subsection examines whether the distributional QoS differences validated in Section 3.2 translate into meaningful differences in perceived service quality for real-time enterprise applications.

QoE is quantified using a MOS-like score derived from the QoS-to-QoE mapping defined in Section 2, where delay, jitter, and packet loss are treated as the primary impairment factors. Consistent with the statistical findings in Table 2, throughput contributes marginally to QoE differentiation once minimum bandwidth requirements are satisfied, whereas delay and jitter dominate perceptual degradation under increasing load.

Before presenting aggregate QoE outcomes, Figure 5 provides causal insight by comparing the cumulative distribution functions (CDFs) of end-to-end delay for WAN-IPsec

(S2) and SD-WAN (S3) under high-load conditions. The figure shows that SD-WAN substantially compresses the upper tail of the delay distribution, while WAN-IPsec exhibits a heavier tail with a higher probability of extreme delay values. This tail compression mechanism directly explains the QoE robustness differences observed later, as extreme delay events disproportionately degrade real-time user experience. Table 3 reports the resulting QoE performance across architectures and traffic load conditions.

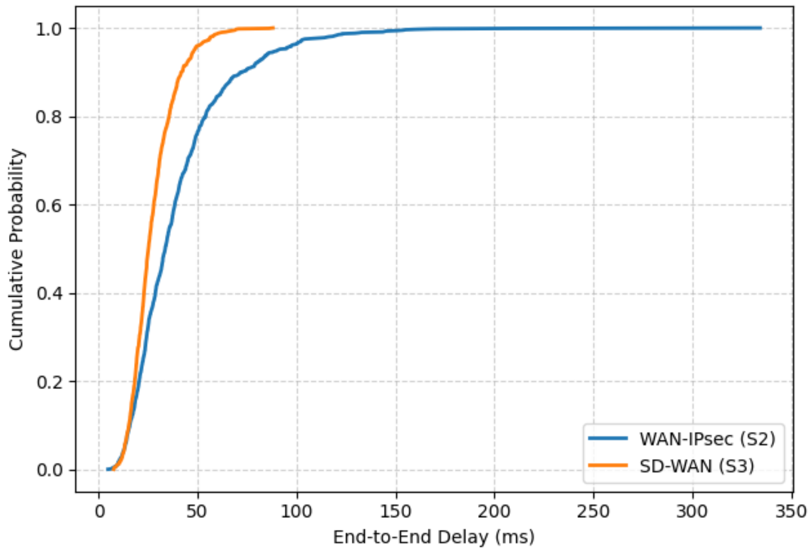

Figure 5. *Cumulative distribution functions (CDFs) of end-to-end delay for WAN-IPsec (S2) and SD-WAN (S3) under high traffic load.*

Table 3. *QoE performance across network architectures and load conditions.*

Architecture	Idle Load (MOS)	Normal Load (MOS)	High Load (MOS)	MOS ≥ 3.5 (%)
LAN (S1)	4.6 ± 0.2	4.5 ± 0.2	4.3 ± 0.3	98.7
WAN-IPsec (S2)	4.2 ± 0.3	3.6 ± 0.5	2.9 ± 0.7	61.4
SD-WAN (S3)	4.4 ± 0.3	4.0 ± 0.4	3.7 ± 0.5	84.9

The results show that QoE rankings across architectures closely mirror the variability patterns established in **Figure 3** and the tail behavior illustrated in **Figure 5**. LAN (S1), which exhibits negligible delay and jitter dispersion across all load levels, consistently achieves the highest MOS values with minimal degradation under congestion. This outcome reinforces the interpretation that stability and predictability—rather than peak throughput—are the dominant drivers of perceived quality for real-time services.

WAN-IPsec (S2), by contrast, experiences a sharp decline in QoE as traffic load increases. Under high-load conditions, the MOS distribution shifts markedly downward, with a substantial proportion of samples falling below the acceptability threshold (MOS ≥ 3.5). This degradation directly corresponds to the heavy delay tail observed in Figure 5 and the statistically significant architecture–load interaction effects for delay and jitter reported in Table 2.

SD-WAN (S3) demonstrates more robust QoE behavior. Although its average throughput does not significantly exceed that of WAN-IPsec, SD-WAN maintains higher MOS values under normal and high-load conditions. This improvement is causally linked to the reduced tail delay probability shown in Figure 5 and the tighter delay and jitter distributions observed in Figure 3. Importantly, SD-WAN improves QoE by stabilizing delay-sensitive metrics rather than increasing mean performance.

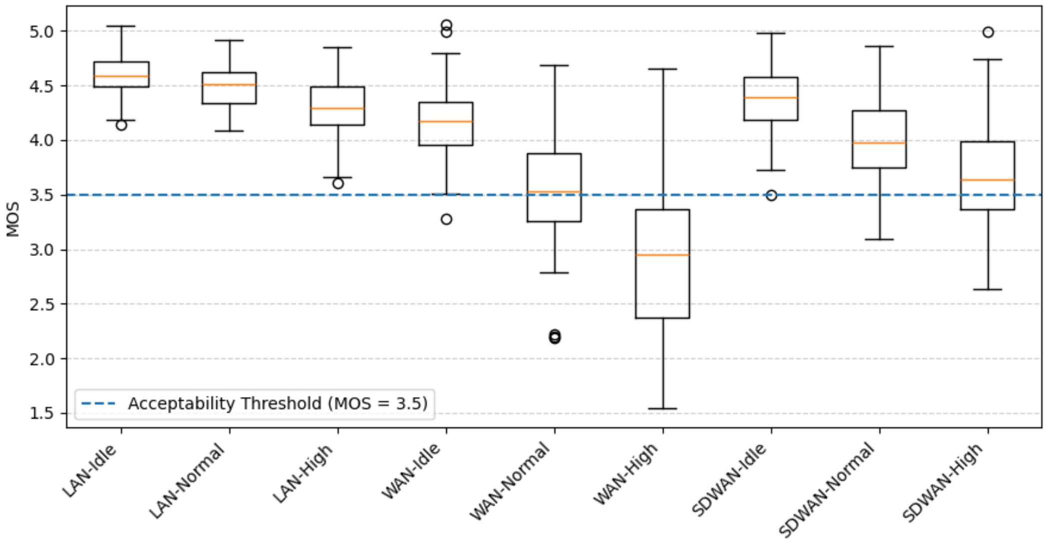

Figure 6 *Distribution of MOS values across network architectures and traffic load conditions.*

As illustrated in Figure 6, SD-WAN substantially increases the probability of maintaining acceptable QoE under congestion, even when average network conditions appear comparable across architectures. The tighter MOS distributions under SD-WAN reflect improved robustness against transient impairments, whereas WAN-IPsec exhibits wider dispersion and heavier lower tails under load.

Overall, this analysis confirms that QoE outcomes are governed by the same architectural and load-dependent mechanisms that drive delay and jitter variability, as statistically validated in Section 3.2. By explicitly linking QoE degradation to the interaction effects reported in Table 2 and the distributional evidence in Figure 3, the results demonstrate that variability-aware QoS control—rather than throughput-centric optimization—is essential for sustaining real-time enterprise service quality. This observation provides a direct and methodologically grounded rationale for the predictive modeling and feature importance analysis presented in the following subsection.

3.4 Machine Learning–Based QoE Prediction and Feature Importance

Building on the statistically validated dominance of delay and jitter variability (Section 3.2) and their direct impact on perceived service quality (Section 3.3), this subsection investigates the feasibility of machine learning (ML)–based Quality of Experience (QoE) prediction from observable network parameters. The analysis aims to (i) evaluate how accurately QoE can be inferred from QoS measurements under heterogeneous operating conditions and (ii) identify the most influential network features governing QoE degradation in real-time enterprise applications.

QoE prediction models are trained using end-to-end delay, jitter, packet loss rate (PLR), and throughput as continuous input features, augmented with categorical indicators representing network architecture (S1–S3) and traffic load level (idle, normal, high). A (k)-fold cross-validation strategy is employed to ensure robustness against data imbalance across scenarios. Model performance is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination ((R^2)), which jointly capture prediction accuracy, error dispersion, and explanatory power.

Table 4. QoE prediction performance of machine learning models (cross-validation results)

Model	MAE ↓	RMSE ↓	(R^2) ↑
Linear Regression	0.41 ± 0.06	0.55 ± 0.08	0.62
Support Vector Regression	0.29 ± 0.04	0.38 ± 0.06	0.78
Random Forest	0.24 ± 0.03	0.31 ± 0.05	0.86
Gradient Boosting*	**0.22 ± 0.03**	**0.29 ± 0.04**	**0.89**
Neural Network	0.23 ± 0.04	0.30 ± 0.05	0.87

**Lower MAE/RMSE and higher (R^2) indicate better predictive performance.*

The results in Table 4 show that non-linear models consistently outperform the linear baseline, confirming that the relationship between QoS metrics and QoE is inherently non-linear. Tree-based ensemble models, particularly Gradient Boosting, achieve the highest explanatory power, indicating their effectiveness in capturing interactions among jitter, packet loss, and delay. Prediction errors increase under extreme conditions, such as abrupt jitter spikes or transient congestion events, suggesting that ML models are most reliable for anticipating QoE degradation trends rather than precise estimation during highly volatile states.

To improve interpretability and operational relevance, feature importance analysis is conducted on the best-performing model. Figure 7 illustrates the relative contribution of each input feature to QoE prediction accuracy.

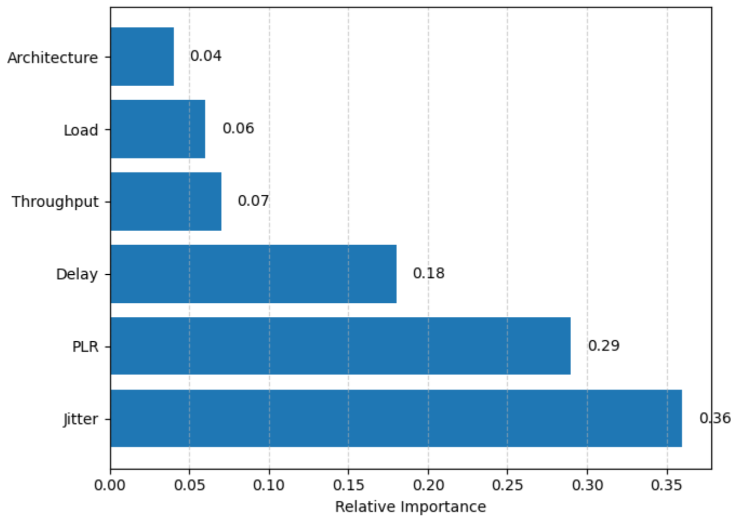

Figure 7. Feature importance ranking for QoE prediction (best-performing ML model).

Jitter and packet loss rate emerge as the dominant predictors, followed by delay. Throughput exhibits limited importance once minimum bandwidth requirements are satisfied. The feature importance results are fully consistent with the statistical validation in Table 2 and the distributional evidence in Figure 3, reinforcing the conclusion that QoE degradation is driven primarily by variability-related impairments rather than average capacity.

To further analyze sensitivity, partial dependence plots are used to visualize how predicted QoE responds to changes in individual QoS parameters while holding others constant. Figure 8 presents partial dependence plots for jitter, packet loss rate, and delay.

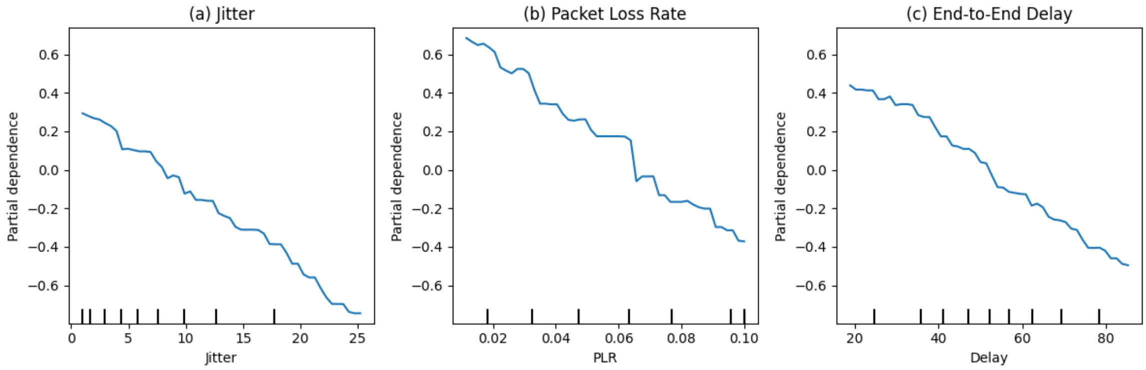

Figure 8. Partial dependence of predicted QoE on key QoS parameters.
(a) Jitter, (b) Packet loss rate, and (c) End-to-end delay.

Figures 7 and 8 jointly confirm that QoE degradation is primarily driven by jitter and packet loss variability rather than average throughput. The observed non-linear threshold behavior further supports the need for distribution-aware and experience-driven traffic steering policies in SD-WAN environments. The plots reveal clear threshold effects, where modest increases in jitter or packet loss beyond certain levels lead to disproportionately large QoE degradation. These non-linear sensitivities provide actionable insight for network operation, supporting the definition of policy thresholds for SD-WAN traffic steering, congestion avoidance, and proactive mitigation.

Overall, this subsection demonstrates that machine learning models can accurately and interpretably predict QoE from measurable network conditions. By confirming the dominance of jitter and packet loss—already identified through empirical and statistical analyses—ML-based QoE prediction bridges descriptive performance evaluation with proactive, experience-aware network optimization, providing a practical foundation for intelligent enterprise network management.

3.5 Discussion

This study demonstrates that Quality of Service (QoS) robustness in enterprise networks is primarily governed by architectural control mechanisms and load-dependent variability rather than by average performance levels. Across all evaluated scenarios, delay and jitter distributions—especially tail behavior characteristics—emerge as the dominant determinants of Quality of Experience (QoE) for real-time applications, supporting recent findings in network performance optimization research [19].

Local Area Network (LAN) environments exhibit consistently stable QoS performance across varying traffic loads, reflecting the inherent advantages of short propagation distances and centralized administrative control. In contrast, Wide Area Network with Internet Protocol Security (WAN-IPsec) overlays demonstrate pronounced sensitivity to increasing load conditions, manifested as substantial expansion of delay and jitter tail distributions. While IPsec protocols ensure robust security through encryption, the associated encapsulation overhead and tight coupling to heterogeneous underlay network paths amplify queueing and processing delays under congestion scenarios. These empirical results confirm that secure overlay networks alone do not provide sufficient performance robustness for delay-sensitive services in wide-area enterprise deployments [20].

Software-Defined Wide Area Network (SD-WAN) architectures partially mitigate WAN-induced variability through the introduction of policy-based traffic steering and adaptive path selection mechanisms [16]. Importantly, the observed performance gains are concentrated in reduced dispersion and tail delay characteristics rather than in higher mean throughput values. Statistical interaction analysis confirms that traffic load affects different network architectures non-uniformly, with WAN-IPsec configurations degrading most rapidly, SD-WAN showing moderated degradation patterns, and LAN maintaining largely stable performance. This architectural interaction effect explains why traditional throughput-centric evaluation methodologies fail to capture performance robustness requirements for real-time services [21].

The QoE analysis further reinforces the central role of performance variability in user experience outcomes. Network architectures characterized by compact delay and jitter distributions consistently achieve higher and more stable Mean Opinion Score (MOS) values, even when average throughput differences remain marginal. Conversely, WAN-IPsec configurations experience sharp QoE collapse under high load conditions, with a significant fraction of user sessions falling below acceptability thresholds. These results substantiate that jitter and packet loss parameters dominate perceptual degradation once minimum bandwidth requirements are satisfied [22].

Machine learning-based QoE prediction models confirm the non-linear nature of the QoS-QoE relationship observed in the empirical data. Non-linear prediction algorithms significantly outperform linear baseline models, and feature importance analysis consistently identifies jitter and packet loss as the most influential predictors of user experience, with throughput metrics contributing only secondarily [19]. The presence of clear threshold effects in the data suggests that small increases in performance variability beyond critical operational levels can trigger disproportionate QoE degradation, emphasizing the importance of proactive network management strategies.

Overall, the research findings argue for a fundamental paradigm shift from average-centric performance evaluation toward distribution-aware and experience-driven network design methodologies. For enterprise network practice, SD-WAN technologies should be assessed based on their capability to suppress delay and jitter tail characteristics under load rather than on aggregate throughput gains alone. From a network systems perspective, the results support the implementation of adaptive control strategies that target variability mitigation and probabilistic QoS guarantees as primary objectives for sustaining real-time service quality in modern enterprise environments (Rahul Guha et al., 2025). This approach represents a significant advancement in enterprise networking, moving beyond traditional performance optimization toward user-centric design principles that directly impact business productivity and operational efficiency.

3.6 Limitations and Scope

This study is subject to several limitations that define its scope and applicability. First, the experimental evaluation is conducted in a controlled testbed environment, which, while enabling reproducibility and isolation of architectural effects, cannot fully capture the scale and heterogeneity of large production WANs. Second, the SD-WAN policies evaluated represent a representative but not exhaustive set of vendor-specific implementations;

therefore, the reported results should be interpreted as architectural effects rather than product-level benchmarks. Third, QoE is derived from a MOS-style mapping rather than from large-scale subjective user studies, which limits direct claims about human perception while still providing a standardized and widely accepted proxy for real-time service quality. Finally, the machine learning models are trained on the observed operating regimes and may exhibit reduced accuracy under extreme or previously unseen network conditions. Despite these limitations, the study's controlled design, distribution-aware analysis, and statistical validation ensure that the reported findings remain robust for comparative evaluation and for informing enterprise network design decisions within the examined scope.

4. CONCLUSION

This paper presented a comparative, distribution-aware evaluation of enterprise network architectures for real-time applications, focusing on LAN, WAN-IPsec, and Hybrid SD-WAN deployments under varying traffic loads. By combining controlled experimentation, formal statistical validation, and QoE-oriented analysis, the study demonstrates that architectural robustness is primarily determined by the ability to suppress delay and jitter variability under load rather than by improvements in average throughput.

The results confirm that LAN environments provide inherent stability, while traditional WAN-IPsec overlays exhibit pronounced sensitivity to congestion. Hybrid SD-WAN architectures offer a measurable improvement in robustness by moderating delay and jitter tails, thereby sustaining acceptable QoE under adverse conditions. Importantly, the integration of QoS–QoE mapping and machine learning–based prediction shows that non-linear models can reliably anticipate experience degradation from observable network conditions, reinforcing the operational value of variability-aware monitoring and control.

Future work will extend this study along four main directions. First, larger-scale and longer-duration experiments will be conducted to capture diurnal effects, routing dynamics, and failure scenarios that are difficult to reproduce in controlled testbeds. Second, more advanced SD-WAN control strategies, including closed-loop reinforcement learning with explicit stability constraints, will be investigated to further reduce tail latency and jitter. Third, QoE modeling will be refined through hybrid approaches that combine objective metrics with limited subjective validation to improve perceptual fidelity. Finally, the proposed framework will be adapted to emerging enterprise scenarios, including multi-cloud interconnection, edge-assisted real-time analytics, and AI-driven traffic classification, where variability-aware performance guarantees are expected to be increasingly critical.

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