

Quality of Service-Based Analysis of Internet Network Performance and the Reliability of Digital Learning Services in Higher Education

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Article Info	Abstract
E-ISSN : 3026-6874 Vol: 4 No: 10 October 2026 Pages : 10-25	<i>Digital learning in higher education depends on reliable networks, yet campus network evaluations in Indonesia usually stop at Quality of Service (QoS) categories without testing their effect on service access. This study evaluates how QoS parameters affect the reliability of access to digital learning services through a controlled emulation experiment. The testbed comprised a client, a packet-level network emulator, and an LMS-like server. Sixteen scenarios varying bandwidth, delay, jitter, and packet loss were each repeated 15 times (240 trials). Each trial measured QoS, LMS page loading (10-second limit), and a 2 MiB learning-material download (30-second limit). Data were analysed using descriptive statistics, Kruskal-Wallis tests, and Spearman correlation. Page access succeeded in 90.4% of trials and material downloads in 81.7%. Throughput correlated most strongly with download time ($\rho = -0.95$), followed by packet loss ($\rho = 0.61$). Packet loss of 8.5%, still rated "good" under TIPHON, slowed material downloads to a median of 17.3 seconds. A composite profile rated "good" caused 93.3% of downloads to fail. BBR congestion control at the server sustained download success at 15% packet loss, where CUBIC failed completely. The findings indicate that TIPHON categories alone do not guarantee reliable access to learning services. Campus administrators should adopt service-based thresholds, prioritise packet-loss control, and evaluate the TCP configuration of LMS servers.</i>
Keywords: Quality of Service Access Reliability Digital Learning	

Abstrak

Pembelajaran digital di perguruan tinggi bergantung pada jaringan yang andal, tetapi evaluasi jaringan kampus di Indonesia umumnya berhenti pada kategori *Quality of Service* (QoS) tanpa menguji dampaknya terhadap akses layanan. Penelitian ini bertujuan mengevaluasi pengaruh parameter QoS terhadap keandalan akses layanan pembelajaran digital melalui eksperimen emulasi terkendali. Lingkungan uji terdiri atas klien, emulator jaringan tingkat paket, dan server tiruan LMS. Enam belas skenario yang memvariasikan *bandwidth*, *delay*, *jitter*, dan *packet loss* masing-masing diulang 15 kali (240 percobaan). Setiap percobaan mengukur QoS, keberhasilan pemuatan halaman LMS (batas 10 detik), dan unduhan materi 2 MiB (batas 30 detik). Data dianalisis dengan statistik deskriptif, uji Kruskal-Wallis, dan korelasi Spearman. Keberhasilan akses halaman mencapai 90,4% dan unduhan materi 81,7%. *Throughput* berkorelasi paling kuat dengan waktu unduh ($\rho = -0,95$), diikuti *packet loss* ($\rho = 0,61$). *Packet loss* 8,5%, yang masih berkategori "bagus" menurut TIPHON, memperlambat unduhan materi menjadi median 17,3 detik. Profil gabungan berkategori "bagus" menggagalkan 93,3% unduhan. Algoritme BBR di sisi server mempertahankan keberhasilan unduhan pada *packet loss* 15% yang gagal total dengan CUBIC. Temuan ini menunjukkan bahwa kategori TIPHON belum cukup menjamin k

keandalan akses layanan pembelajaran. Pengelola kampus perlu menetapkan ambang berbasis layanan, memprioritaskan pengendalian *packet loss*, dan mengevaluasi konfigurasi TCP server LMS.

Kata Kunci : *Quality of Service*; Keandalan Akses; Pembelajaran Digital

INTRODUCTION

Higher education institutions now deliver most of their academic services through online platforms, ranging from learning management systems (LMS) and material repositories to video conferencing for synchronous lectures. The large-scale shift to online learning during the COVID-19 pandemic accelerated this dependence and turned network infrastructure into an operational prerequisite for learning activities (Dhawan, 2020; Mishra et al., 2020; Pokhrel & Chhetri, 2021). Institutions that had previously treated e-learning as a supplement had to reorganise their services, policies, and technological capacity within a short time (Turnbull et al., 2021; Rapanta et al., 2020). The post-pandemic period has not fully restored the old patterns; many campuses have retained hybrid models, so the demand for reliable online access remains high (Adedoyin & Soykan, 2023; Ferri et al., 2020).

Weak connectivity has repeatedly emerged as a major barrier to online learning. A global survey of higher education students reported internet connection problems as one of the most frequently experienced obstacles (Aristovnik et al., 2020). Similar findings were reported in Romania (Coman et al., 2020), the Philippines (Barrot et al., 2021), and India (Kapasias et al., 2020; Muthuprasad et al., 2021), as well as in a cross-country study on the quality of distance learning (Lassoued et al., 2020). Studies in Indonesia show a consistent pattern: students faced unstable connections and burdensome data costs during emergency remote learning (Rahiem, 2020), while unequal internet access hindered the implementation of distance learning (Azhari & Fajri, 2022). A systematic review of the online component of blended learning also identified technological issues as one of the groups of challenges faced by both students and lecturers (Rasheed et al., 2020).

Most of this evidence derives from user perceptions. Questionnaires can capture students' experiences, but they cannot show which network parameters cause disruptions or at what level the disruptions begin to be felt. E-learning system success models position system quality as a factor that influences use and satisfaction (Al-Fraihat et al., 2020; Almaiah et al., 2020), yet the measures of system quality in these models are generally perception-based as well. The gap between user complaints and technical network data makes it difficult for infrastructure managers to determine well-targeted interventions.

Quality of Service (QoS) provides a technical framework for measuring network performance through the parameters of throughput, delay, jitter, and packet loss. These parameters determine whether a network can serve traffic with different characteristics; interactive traffic such as video conferencing is more sensitive to delay and jitter, whereas material downloads are more affected by throughput (ITU-T, 2001). QoS can also be managed actively at the network device level; for example, static routing combined with QoS has been implemented on Cisco routers to optimise network traffic management (Hermansyah et al., 2025). Measurements of popular video conferencing applications show that video quality and network utilisation change markedly when link capacity is constrained or network conditions fluctuate (Chang et al., 2021; MacMillan et al., 2021). Tests of v

ideo calls in instant messaging applications provide a similar picture of the sensitivity of real-time services to network conditions (Grote et al., 2023). The concept of Quality of Experience (QoE) complements QoS by assessing quality from the user's perspective, so the relationship between the two cannot be assumed to be linear (Barakabitze et al., 2020).

Changes in traffic patterns during online learning reinforce the urgency of such studies. An analysis of campus traffic at Politecnico di Torino showed drastic shifts in traffic volume and direction when lectures moved to online platforms (Favale et al., 2020). Data from multiple internet exchange points showed that social restrictions significantly increased internet traffic volume and changed daily usage patterns (Feldmann et al., 2020). These two studies indicate that the load on educational networks is dynamic, so the QoS conditions experienced by users can change sharply within a short period.

Studies of campus network QoS in Indonesia are numerous and generally use the TIPHOON framework. Measurements at Universitas Islam Negeri Sultan Syarif Kasim Riau placed network quality in the good category (Zikri et al., 2022), and measurements at Universitas Muhammadiyah Gorontalo also fell into the good category even though packet loss was recorded at about 9% (Hasyim et al., 2024). Different results were reported at Universitas Dayanu Ikhsanuddin, with a moderate category (Nur et al., 2023), and on the Wi-Fi network of Unjaya Campus 1, which obtained an overall moderate index even though several individual parameters were classified as good (Nisa et al., 2024). Peak-hour measurements in the Faculty of Engineering building of Universitas Perjuangan Republik Indonesia recorded a throughput of about 950 kbps, packet loss of 26.5%, delay of 485 ms, and jitter of 165 ms (Basmar & Yusuf, 2026). Other studies measured QoS per access point within a campus (Sula et al., 2022) and compared measurement software that yielded different sets of parameters (Saputra et al., 2023).

A comparison of previous studies reveals three limitations. First, campus QoS studies generally stop at categorising network indices without testing whether academic services can actually be accessed under those conditions. Second, field measurements record combinations of parameters that occur simultaneously, so the effect of each parameter cannot be isolated; a condition such as 9% packet loss can be rated "good" by the TIPHOON index without its impact on material downloads or LMS page loading being known. Third, studies that combine QoS with user perceptions, for example on cellular wireless internet services (Zulkarnain et al., 2025), have not tested network performance thresholds for learning services. The literature search in this study found no Indonesian study that tested, under controlled conditions, the relationship between QoS parameters and the reliability of access to digital learning services, although the possibility of similar unindexed studies remains open.

Network emulation allows each QoS parameter to be set in a controlled and repeatable manner, so its effect on services can be observed separately from other factors. This approach complements field measurement: field measurement describes the actual conditions of a campus, whereas emulation explains the consequences of those conditions for services. Transport protocol behaviour also needs to be considered, because loss-based TCP congestion control algorithms such as CUBIC (Xu et al., 2023) respond to packet loss differently from model-based algorithms such as BBR (Cardwell et al., 2016; Cao et al., 2019).

This study aims to evaluate the effect of internet network performance, expressed through QoS parameters, on the reliability of access to digital learning services through a controlled emulation experiment. Four research questions were formulated: (1) how do the success rate and access time of LMS pages and material downloads change under variations in delay, jitter, packet loss, and bandwidth; (2) which QoS parameters are most strongly associated with access reliability; (3) do TIPHON categories reflect the reliability of access to learning services; and (4) how does the server-side TCP congestion control algorithm affect access reliability under packet loss? The contributions of this study are a test design that combines packet-level QoS measurement with service-level access testing, controlled evidence on network performance thresholds for learning services, and practical recommendations for network and LMS server administrators in higher education.

METHOD

Research Design

This study used a quantitative approach with a network emulation experiment design. The independent variable was the network condition, controlled through four parameters: bandwidth capacity, one-way delay, jitter, and packet loss. The dependent variable was the reliability of access to digital learning services, measured through the success and loading time of LMS pages and the success and download time of learning materials. QoS parameters were also re-measured in every trial, so the analysis used measured values rather than configured values alone. The study did not involve human participants; user experience and learning outcomes were outside the scope of measurement.

Testbed

All experiments were run on a single Linux host (kernel 6.18, 2 vCPUs, 8 GB RAM) divided into two network namespaces, a client namespace and a server namespace, as shown in Figure 1. The two namespaces were connected through TUN interfaces and an IP packet-level network emulator developed by the authors in Python 3.13. The emulator was developed in-house because the netem module was not available in the kernel of the test environment. The emulator applied three mechanisms in each traffic direction: (a) rate limiting through packet serialisation on a FIFO queue with a capacity of 150 KB and a drop-tail policy, (b) constant one-way delay plus normally distributed jitter with packet order preserved, and (c) random packet loss following a Bernoulli distribution. The same parameters were applied symmetrically in the uplink and downlink directions.

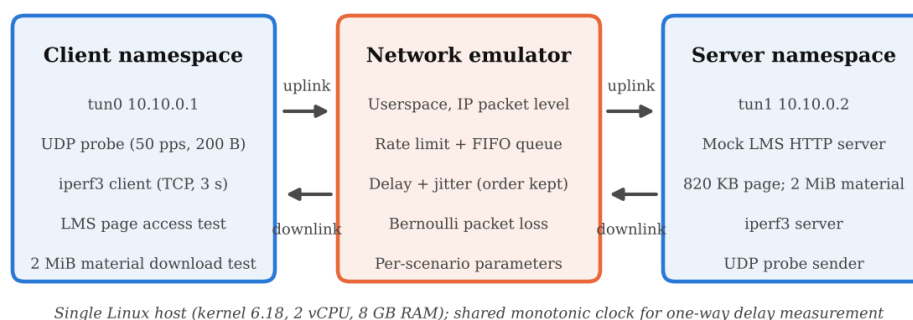


Figure 1. Architecture of the Emulation Testbed

The server namespace ran an HTTP/1.1 server that mimicked an LMS page. A single page load consisted of a 41 KB HTML document and four static assets (150 KB CSS, two JavaScript files of 350 KB and 200 KB, and an 80 KB image), giving a total payload of about 820 KB. Course material was represented by a single 2 MiB file. File contents were generated randomly so that they could not be compressed. The server also ran iperf3 version 3.16 and a UDP probe-stream sender. The server-side TCP congestion control algorithm was set to CUBIC (Xu et al., 2023) through the TCP_CONGESTION socket option, because CUBIC is the default algorithm in many Linux server distributions.

Experimental Scenarios

Sixteen scenarios were constructed as listed in Table 1. Scenario S01 is the baseline condition (20 Mbps, 10 ms delay, no jitter and no packet loss). Scenarios S02-S14 change one parameter from the baseline, whereas S15 and S16 are composite profiles. Profile S16 follows the peak-hour values reported by Basmar & Yusuf (2026) to test a condition that has been observed on an Indonesian campus network. The packet loss range of S08-S11 spans the TIPHON categories from "very good" to "moderate", including the 9% value equivalent to the finding of Hasyim et al. (2024).

Table 1. Emulation Scenarios (Configured Values per Direction)

Code	Group	Bandwidth (Mbps)	Delay (ms)	Jitter (ms)	Packet loss (%)
S01	Baseline	20	10	0	0
S02	Delay	20	50	0	0
S03	Delay	20	150	0	0
S04	Delay	20	300	0	0
S05	Jitter	20	50	10	0
S06	Jitter	20	50	30	0
S07	Jitter	20	50	75	0
S08	Packet loss	20	10	0	1
S09	Packet loss	20	10	0	3
S10	Packet loss	20	10	0	9
S11	Packet loss	20	10	0	15
S12	Bandwidth	5	10	0	0
S13	Bandwidth	2	10	0	0
S14	Bandwidth	1	10	0	0
S15	Composite: moderate load	5	75	20	3
S16	Composite: extreme peak hour	0.95	485	165	26.5

Each scenario was repeated 15 times, giving a total of 240 trials. The scenario order was randomised in each replication round (seed 20261013) to reduce order effects and the influence of host conditions. After the emulator configuration was changed, the system was given a 1.5-second pause before the trial began.

Measurement Procedure per Trial

Each trial consisted of four stages run sequentially from the client namespace. The first stage sent a UDP probe stream of 250 packets of 200 bytes from the server to the client at 20 ms intervals (50 packets per second), representing low-rate interactive traffic. Because the client and server shared the same monotonic clock, one-way delay could be measured directly from the difference between the receive time and the send time stamp. The second stage measured downlink TCP throughput using iperf3 for 3 seconds. The third stage tested LMS page access: the client retrieved the HTML document and then d

downloaded the four assets in parallel over four TCP connections. Access was considered successful if all objects were received completely with HTTP status code 200 within a 10-second limit. The fourth stage downloaded the 2 MiB material file with a 30-second limit. Failures were classified as timeouts, connection errors, HTTP errors, and incomplete downloads.

Operational Definitions and Parameter Formulas

Throughput is the TCP data rate received by the client during the iperf3 test, calculated using Equation (1).

$$\text{Throughput (Mbps)} = \text{Amount of data received (bits)} / \text{Observation time (s)} \times 10^{-6} \quad (1)$$

Delay is the mean one-way travel time of the received probe packets, calculated using Equation (2), where D_i is the delay of the i -th packet and N is the number of packets received. The 95th percentile of delay was also recorded to capture spikes.

$$\text{Delay (ms)} = \sum D_i / N \quad (2)$$

Jitter is the mean absolute difference in delay between consecutive received packets, calculated using Equation (3). The jitter estimator defined in RFC 3550 (Schulzrinne et al., 2003) was calculated for comparison.

$$\text{Jitter (ms)} = \sum |D_i - D_{i-1}| / (N - 1) \quad (3)$$

Packet loss is the percentage of probe packets that were not received, calculated using Equation (4).

$$\text{Packet loss (\%)} = (\text{Packets sent} - \text{Packets received}) / \text{Packets sent} \times 100\% \quad (4)$$

Access reliability is expressed as the access success rate in each scenario, calculated using Equation (5), and is complemented by page loading time and material download time. The proportion of probe packets arriving within 150 ms was also calculated as an indicator of suitability for interactive services, referring to the one-way delay limit recommended for conversational communication in ITU-T G.1010 (ITU-T, 2001).

$$\text{Access success rate (\%)} = \text{Successful trials} / \text{Total trials} \times 100\% \quad (5)$$

Evaluation Criteria and Data Analysis

The measured delay, jitter, and packet loss values in each scenario were categorized using the TIPPHON categories (ETSI, 1999), which are commonly used in campus QoS studies in Indonesia (Basmar & Yusuf, 2026; Nisa et al., 2024), as presented in Table 2. These categories were then compared with the access success rate to answer the third research question.

Table 2. QoS Index Categories Based on TIPPHON

Category	Index	Delay (ms)	Jitter (ms)	Packet loss (%)
Very good	4	< 150	0	0-2
Good	3	150-300	0-75	3-14
Moderate	2	300-450	75-125	15-24
Poor	1	> 450	125-225	≥ 25

Source: ETSI (1999), as adopted in QoS studies in Indonesia.

Data analysis comprised three stages. The first stage calculated descriptive statistics for each scenario, namely the mean and standard deviation of the QoS parameters, the access success rate, and the median access time. The second stage tested differences in page loading time and material download time across parameter levels using the Kruskal-Wallis test, because the distribution of access times was not assumed to be normal. The

he tests were conducted separately for each parameter group with S01 as the reference level, and effect sizes were reported as epsilon squared (ϵ^2). The third stage analysed the relationship between the measured QoS parameters and the access reliability indicators across all trials using Spearman rank correlation. The significance level was set at 0.05. The analysis was performed in Python with the SciPy library.

An additional test was conducted to answer the fourth research question. Scenarios S01 and S08-S11 were repeated 15 times with the BBR congestion control algorithm on the server side (Cardwell et al., 2016) and then compared with the CUBIC results using the Mann-Whitney U test for each scenario.

RESULTS AND DISCUSSION

Results

Emulator Validation and Measured QoS Performance

All 240 trials ran successfully and produced complete data. Table 3 presents the measured QoS values for each scenario. The baseline condition produced a measured delay of 10.7 ms against a configured 10 ms, so the emulator added less than 1 ms of processing overhead. The measured packet loss in S08-S11 (0.9%, 3.1%, 8.5%, and 15.1%) was close to the configured values. Measured jitter was lower than the configured standard deviation, and the mean delay increased (S07: 109.5 ms), because the emulator preserved packet order. Bandwidth limiting produced TCP throughputs of 4.54, 1.75, and 0.70 Mbps for capacities of 5, 2, and 1 Mbps. The difference reflects protocol overhead and the TCP slow-start phase within the 3-second measurement.

Table 3. Measured QoS Parameters and TIPHON Categories per Scenario

Code	Delay (ms)	Jitter (ms)	Packet loss (%)	Throughput (Mbps)	Packets $\leq$ 150 ms (%)	TIPHON category (D/J/L)
S01	10.7	0.2	0.0	18.87	100	4/4/4
S02	50.8	0.3	0.0	17.10	100	4/4/4
S03	150.8	0.3	0.0	7.59	0	3/4/4
S04	300.8	0.4	0.0	1.05	0	2/4/4
S05	51.3	10.6	0.0	12.95	100	4/3/4
S06	62.2	20.5	0.0	4.89	100	4/3/4
S07	109.5	27.7	0.0	2.07	79	4/3/4
S08	10.7	0.3	0.9	7.13	99	4/4/4
S09	10.7	0.3	3.1	3.47	97	4/4/3
S10	10.7	0.3	8.5	1.02	91	4/4/3
S11	10.7	0.3	15.1	0.47	85	4/4/2
S12	11.0	0.2	0.0	4.54	100	4/4/4
S13	11.6	0.3	0.0	1.75	100	4/4/4
S14	12.5	0.4	0.0	0.70	100	4/4/4
S15	80.5	16.4	2.9	0.47	97	4/3/3
S16	646.1	43.7	28.2	0.00	0	1/3/1

Note: values are means of 15 trials. D/J/L = TIPHON index for delay, jitter, and packet loss (4 = very good, 3 = good, 2 = moderate, 1 = poor).

All scenarios except S16 obtained a TIPHON index of 3 or 4 for delay, whereas the packet loss of S09, S10, and S15 fell into the "good" category and that of S11 into the "moderate" category. The proportion of probe packets arriving within 150 ms remained 100% in all bandwidth scenarios and at 10-30 ms jitter, but dropped to 79% at 75 ms jitter and to 0% at delays of 150 ms and above. The 0% value in S03 occurred because the measured delay (150.8 ms) slightly exceeded the 150 ms limit.

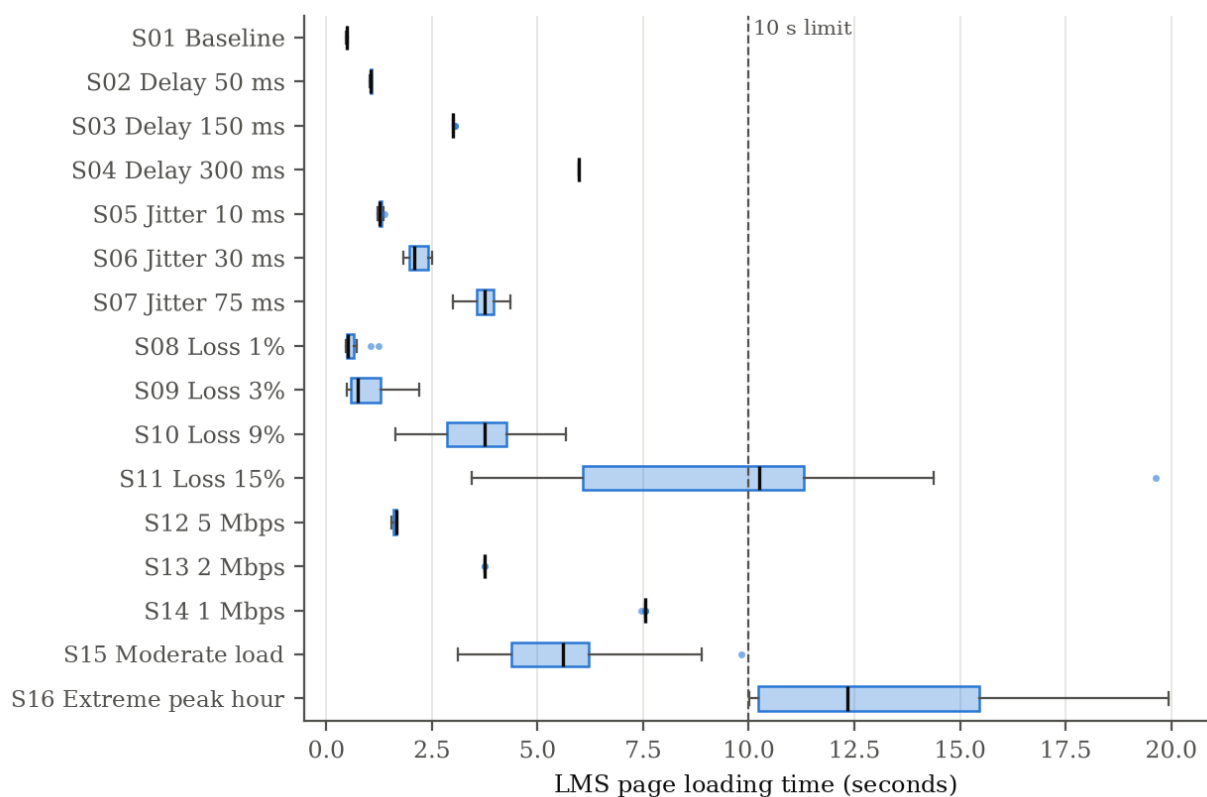
Reliability of Access to Digital Learning Services

Table 4 summarises access success and access time for each scenario, while the distributions of access times are shown in Figure 2 and Figure 3. Overall, LMS page access succeeded in 90.4% of trials and material downloads in 81.7% of trials. All failures were timeouts; no connection errors or HTTP errors were found.

Table 4. Service Access Success and Time per Scenario

Code	LMS page success (%)	Median load time (s)	Material download success (%)	Median download time (s)
S01	100.0	0.49	100.0	0.95
S02	100.0	1.05	100.0	1.39
S03	100.0	3.00	100.0	3.02
S04	100.0	5.97	100.0	5.52
S05	100.0	1.27	100.0	2.06
S06	100.0	2.08	100.0	3.08
S07	100.0	3.75	100.0	6.79
S08	100.0	0.52	100.0	2.10
S09	100.0	0.75	100.0	5.61
S10	100.0	3.76	100.0	17.27
S11	46.7	10.26	0.0	30.76
S12	100.0	1.65	100.0	3.52
S13	100.0	3.74	100.0	8.73
S14	100.0	7.55	100.0	17.43
S15	100.0	5.59	6.7	30.71
S16	0.0	12.34	0.0	51.91

Note: medians were calculated from all trials; for failed trials, the recorded time is the time until the request was terminated.

**Figure 2. Distribution of LMS Page Loading Time per Scenario**

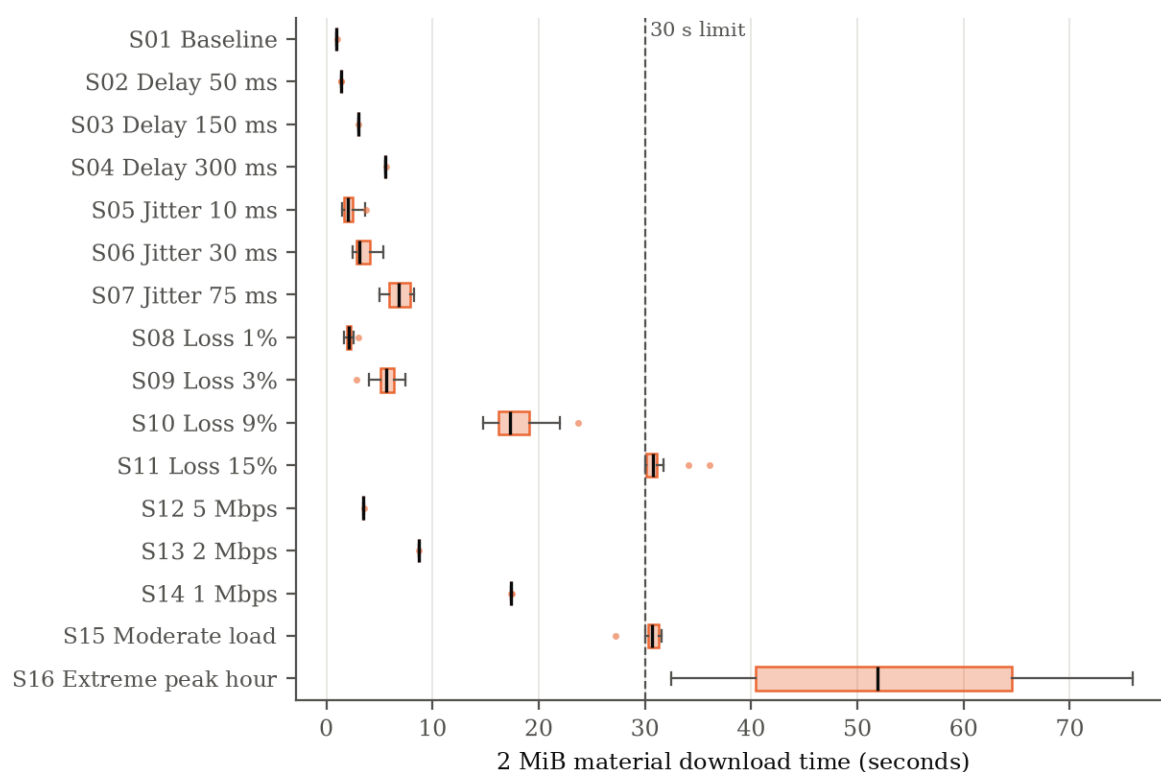


Figure 3. Distribution of 2 MiB Material Download Time per Scenario

Delay did not cause access failures within the tested range, but it progressively lengthened page loading time from a median of 0.49 seconds under the baseline condition to 5.97 seconds at 300 ms delay. A similar pattern was observed for jitter and bandwidth limiting: all access attempts remained successful, but material download time increased to 6.79 seconds at 75 ms jitter and to 17.43 seconds at 1 Mbps capacity.

Packet loss had the sharpest effect on material downloads. The median download time increased from 0.95 seconds under the baseline condition to 5.61 seconds at 3% packet loss and 17.27 seconds at 9%. Packet loss of 15% caused all downloads to fail within the 30-second limit, and only 46.7% of page loads succeeded. The composite profile S15, all of whose parameters were rated "good" or "very good", still allowed pages to load (100%), but only 6.7% of material downloads succeeded. Profile S16, which reflects campus peak-hour conditions, caused all page access and downloads to fail.

Tests of Differences and Relationships between QoS Parameters and Access Reliability

The Kruskal-Wallis test results in Table 5 show that page loading time and material download time differed significantly across parameter levels in all groups ($p < 0.001$), with large effect sizes ($\epsilon^2 \geq 0.86$). The identical H values in several groups occurred because the access time distributions of the different levels did not overlap, so the ranks were perfectly separated.

Table 5. Kruskal-Wallis Test Results for Access Time across Parameter Levels

Parameter group	Scenarios	H (load time)	ϵ^2 (load time)	H (download time)	ϵ^2 (download time)	df
Delay	S01-S04	55.33	0.94	55.33	0.94	3

Parameter group	Scenarios	H (load time)	ϵ^2 (load time)	H (download time)	ϵ^2 (download time)	df
Jitter	S01, S05-S07	55.33	0.94	52.48	0.89	3
Packet loss	S01, S08-S11	63.76	0.86	70.99	0.96	4
Bandwidth	S01, S12-S14	55.33	0.94	55.33	0.94	3
Composite	S01, S15, S16	39.13	0.89	39.13	0.89	2

The Spearman correlations in Table 6 were calculated from 240 trials. Throughput had the strongest relationship with page loading time ($\rho = -0.861$) and material download time ($\rho = -0.951$). Packet loss was the network parameter with the strongest relationship to download success ($\rho = -0.704$) and page loading success ($\rho = -0.581$). Delay correlated moderately with page loading time ($\rho = 0.478$) but weakly with material download time ($\rho = 0.197$).

Table 6. Spearman Correlation Coefficients between QoS Parameters and Access Reliability Indicators (n = 240)

Parameter	Page load time	Material download time	Page success	Download success
Delay	0.478**	0.197*	-0.226**	-0.191*
Jitter	0.261**	0.234**	-0.315**	-0.327**
Packet loss	0.320**	0.612**	-0.581**	-0.704**
Throughput	-0.861**	-0.951**	0.487**	0.658**

Effect of the TCP Congestion Control Algorithm

Table 7 and Figure 4 compare the CUBIC and BBR results under the baseline condition and the packet loss scenarios. With BBR, throughput at 9% packet loss reached 16.68 Mbps, compared with only 1.02 Mbps for CUBIC. BBR also achieved download success at 15% packet loss, namely 100.0% with a median of 1.41 seconds, whereas all downloads with CUBIC failed. The difference in download time between the two algorithms was significant in scenarios S01, S08, S09, S10, and S11 (Mann-Whitney U test, $p < 0.05$). The difference under the baseline condition S01 was statistically significant but practically negligible (median 0.95 seconds versus 0.94 seconds), whereas the differences in S10 and S11 amounted to approximately 16 and 29 seconds, respectively.

Table 7. Comparison of CUBIC and BBR in the Packet Loss Scenarios

Code	Loss (%)	Throughput CUBIC (Mbps)	Throughput BBR (Mbps)	Download success CUBIC / BBR (%)	Median download time CUBIC / BBR (s)	p (Mann-Whitney)
S01	0	18.87	18.64	100 / 100	0.95 / 0.94	$p < 0.001$
S08	1	7.13	18.75	100 / 100	2.10 / 0.95	$p < 0.001$
S09	3	3.47	18.45	100 / 100	5.61 / 0.97	$p < 0.001$
S10	9	1.02	16.68	100 / 100	17.27 / 1.26	$p < 0.001$
S11	15	0.47	12.67	0 / 100	30.76 / 1.41	$p < 0.001$

Note: two-sided Mann-Whitney U test on material download time (n = 15 per group).

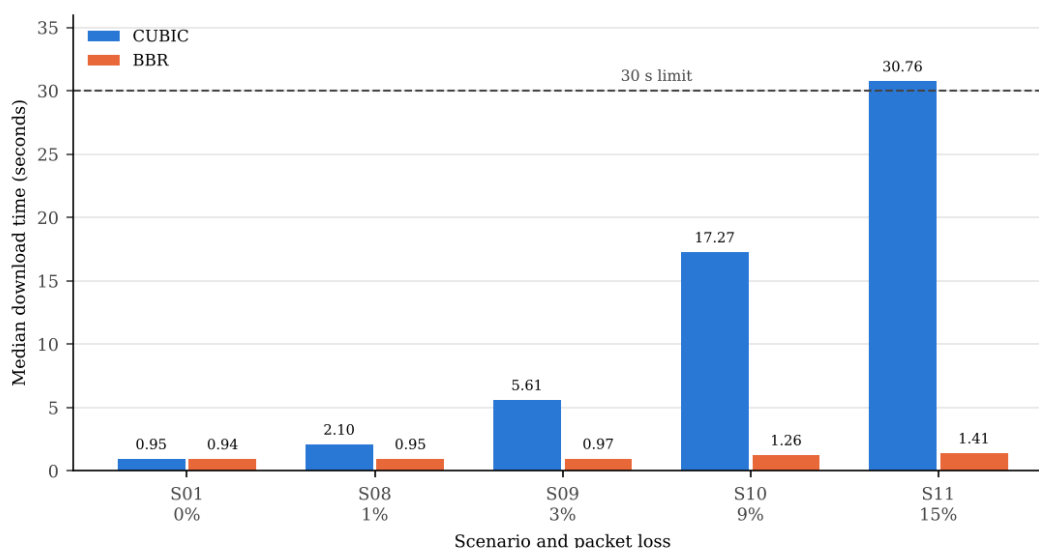


Figure 4. Median Material Download Time under the CUBIC and BBR Algorithms

Discussion

The main finding of this study is the mismatch between QoS categories and the reliability of service access. A packet loss of 8.5% is rated "good" by TIPHON, yet it lengthened the median material download time from 0.95 to 17.27 seconds, roughly an 18-fold increase. Profile S15, all of whose parameters were rated "good" or "very good", caused 93.3% of downloads to fail. These results provide a technical explanation for field findings that appear contradictory, for example the Universitas Muhammadiyah Gorontalo network, which was rated good despite packet loss of about 9% (Hasyim et al., 2024), and the Unjaya network, whose individual parameters were good but whose overall index was moderate (Nisa et al., 2024). TIPHON was originally developed for the harmonisation of telecommunication services, particularly voice, over IP networks (ETSI, 1999), so its categories cannot be read directly as a guarantee that TCP-based learning services are accessible.

The dominance of packet loss in material downloads can be explained by the TCP congestion control mechanism. Loss-based algorithms such as CUBIC interpret every packet loss as a sign of congestion and reduce the sending window (Xu et al., 2023). Random packet loss that does not stem from congestion, for example loss caused by wireless interference, makes the sender keep lowering its rate even though link capacity is still available. This explanation is consistent with the finding that CUBIC throughput fell to 1.02 Mbps at 9% packet loss despite a link capacity of 20 Mbps, and with the critique of loss-based congestion control on networks with non-congestion packet loss (Cardwell et al., 2016). BBR, which models bandwidth and round-trip time, does not overreact to random packet loss and can therefore sustain high throughput. Cao et al. (2019) showed that the advantage of BBR depends on network conditions, including buffer depth, so this finding cannot be generalised to all conditions without further testing.

Delay plays a greater role in page loading than in file downloads. Page loading requires several exchange cycles, namely connection setup, the document request, and the asset requests, so every additional round-trip time accumulates. This relationship is reflected in the correlation coefficient between delay and page loading time ($\rho = 0.48$),

which is stronger than that between delay and material download time ($\rho = 0.20$). Delays of up to 300 ms did not cause LMS access to fail, but they already pushed interactive services beyond the 150 ms limit recommended for conversational communication (ITU-T, 2001). Video conferencing for synchronous lectures is therefore more vulnerable to increases in delay than asynchronous LMS access, in line with the sensitivity of video conferencing applications to network conditions reported by Chang et al. (2021) and MacMillan et al. (2021).

Profile S16 shows that the peak-hour conditions previously observed on an Indonesian campus network (Basmar & Yusuf, 2026) allow neither LMS access nor material downloads. This finding complements campus traffic studies during online learning that showed drastic changes in network load (Favale et al., 2020; Feldmann et al., 2020): load surges that degrade QoS to that level can halt service access, not merely slow it down. The connectivity complaints reported by students in various surveys (Aristovnik et al., 2020; Barrot et al., 2021; Rahiem, 2020) can be understood as a consequence of such network conditions, although this study did not measure user perceptions directly.

The findings have several implications for the management of higher education infrastructure. Network administrators need to complement the TIPHON index with service-based thresholds, for example limits on LMS page loading time and on the download time of standard materials. Packet loss should be prioritised in monitoring because its impact on TCP-based services far exceeds what its category implies. Adding access points and tuning wireless channels to reduce packet loss could deliver greater benefits than adding bandwidth alone, and router-level QoS policies that manage and prioritise traffic (Hermansyah et al., 2025) can support this effort. Monitoring can also be made predictive: Random Forest and Long Short-Term Memory models have been compared for predicting optical power degradation in FTTH networks (Hermansyah et al., 2026), and a similar approach could be used to anticipate degradation in campus access networks before it disrupts learning services. LMS server administrators can evaluate the use of BBR after first testing it in their own campus environment. E-learning success models position system quality as a prerequisite for use (Al-Fraihat et al., 2020; Almaiah et al., 2020); this study shows that such system quality can be translated into measurable technical thresholds.

This study has several limitations. The emulator ran on a single host and applied random packet loss following a Bernoulli distribution, whereas packet loss in wireless networks often occurs in bursts. Jitter was applied while preserving packet order, so the effective delay increased with jitter. The mock LMS server served only static content and did not model database load, TLS encryption, or real browser behaviour. The 3-second throughput measurement was affected by the TCP slow-start phase in the high-delay scenarios. User experience and learning outcomes were not measured. Future research can validate the findings through field measurements on campus networks, use bursty packet loss models, test real LMS and video conferencing platforms, and add QoE measurements using validated instruments.

CONCLUSION

This study shows that the reliability of access to digital learning services is not sufficiently explained by TIPHON QoS categories. Across 240 emulation trials, throughput and packet loss were the parameters that most strongly determined access time and success, whereas delay had a greater effect on page loading than on material downloads. P

packet loss of about 9%, still rated "good", slowed material downloads approximately 18-fold, a composite profile rated "good" caused most downloads to fail, and the peak-hour profile caused all access attempts to fail. The server-side BBR congestion control algorithm sustained access under high packet loss conditions that CUBIC could not handle.

These results imply that higher education network evaluations should be complemented by service-based performance thresholds, that packet loss monitoring should be prioritised, and that the TCP configuration of LMS servers should become part of learning service management policy. These findings were obtained in an emulation environment and therefore require validation through measurements on real campus networks before being widely applied.

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