Quantitative and Subjective Evaluation of Latency and Packet Loss Effects on Video Streaming Quality Using Controlled Network Emulation

Anthony Nwohiri[1,*], Adetomiwa Aribisala[2], Al-Bashir Muhammad[3], Oluwatosin Mofikoya[4], Korede Jacob[5]
[1]Department of Computer Science, Faculty of Computing and Informatics, University of Lagos, Nigeria
[2]Blacks In Technology Foundation, Cleves, Ohio 4500, USA
[3]Department of Computer Science, Colorado State University, Fort Collins, Colorado 80523, USA
[4]Amazon (Evi Technologies), London, UK
[5]Meta Platforms, London, UK
E-mails: anwohiri@unilag.edu.ng, adetomiwaaribisala@blacksintechnology.org, al-bashir.muhammad@colostate.edu, tosinmof@amazon.com, korede@meta.com
[*]Corresponding author

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With the rapid growth of high-speed internet and increasingly advanced smart devices, the way we consume media has changed dramatically, with video streaming now becoming the dominant form of digital content delivery. Despite this shift, the quality of experience (QoE) still depends heavily on network conditions, especially latency (LT) and packet loss (PL). In this study, we explore the individual and combined effects of LT and PL on video quality (VQ) using a mix of objective and subjective metrics. We built a controlled experimental testbed using media player VLC to stream videos, Clumsy to simulate network impairments, and FFmpeg to compute the peak signal-to-noise ratio (PSNR). Video streams (240p-480p resolution, 128-512 kbps bitrate, 25 fps) were delivered via a wireless network (UDP) at varying LT levels (0-200 milliseconds) and PL (0-10%). Subjective quality was assessed using the mean opinion score (MOS) from 30 participants in a randomized video-viewing condition. Results show that LT had only a small effect on objective VQ, with PSNR dropping slightly (e.g., from 36.8 dB to 36.0 dB at 128 kbps as LT increased from 0 to 200 ms), but had a noticeable effect on user perception, with MOS reducing from ~4.5-4.9 to 2.8-3.5. On the other hand, PL had a much stronger impact on both measured and perceived quality. Even a 1% PL dropped PSNR by up to 3.6 dB (e.g., from 36.8 dB to 33.2 dB at 128 kbps) and noticeably lowered MOS. At higher loss rates (7-10%), PSNR significantly decreased to around 24 dB, and MOS fell below 2.0, indicating poor to unacceptable quality. The findings reveal that PL is much more detrimental to VQ than LT, although higher bitrates can offer some resilience under adverse network conditions. These results provide quantitative guidelines and practical insights for enhancing video streaming systems and improving QoE in real-world networks.

Povzetek: Študija ugotavlja, da izguba paketov bistveno bolj poslabša kakovost pretočnega videa in uporabniško izkušnjo kot omrežna zakasnitev.

1 Introduction

Based on industry reports, video streaming has become the dominant driver of internet usage [1]. In 2024, it accounted for over 60% of global internet traffic and 50% of total mobile traffic worldwide [2]. Due to its economic diversity, Internet traffic has evolved over time, moving from multimedia applications such as video-on-demand services to social media platforms like Facebook, Instagram, YouTube, Twitch, Netflix, and Amazon Prime Video, as well as live streaming and broadcasting. New services like Disney+, Apple TV+, and HBO Max, which offer a one-stop streaming experience, compete with these well-known streaming platforms. In addition, the COVID-19 lockdown increased demand for real-time video conferencing apps like Zoom, Google Meet, and Microsoft Teams.

In contrast, interactive video applications in real time typically use peer-to-peer technologies and incorporate congestion control algorithms to handle dynamic network conditions. These multimedia platforms rely on the Hypertext Transfer Protocol (HTTP) to deliver video content efficiently to audiences around the world. Content Delivery Networks (CDNs) and HTTP Adaptive Streaming (HAS) control the distribution and adaptively change visual quality (VQ) in real time. Adaptive bitrate algorithms on the client side react to network property changes, resulting in continuous video streaming, even when there are changes in bandwidth and connectivity [3].

Unlike video-on-demand services, video streaming is real-time and imposes strict requirements for timely, uninterrupted data delivery. The properties of video streaming services include high time requirements and high bandwidth. Therefore, changes to network parameters have a significant impact, indicating that video streaming quality is susceptible to time-varying network properties, including substantial bandwidth requirements, sensitivity to LT, jitter, and PL. LT and PL are two network requirements for video streaming.

A more complex understanding of HTTP adaptive streaming LT requires examining multiple contributing factors, including client-side buffering, asynchronous media segment fetching, HTTP download time, and segmentation delay. LT represents a strict constraint on how quickly video data can be delivered and consumed. In practical terms, it reflects the amount of video information transmitted per unit time, typically measured in bits per second. In live-streaming environments, end-to-end LT is the total time it takes for content to move from capture to playback. This includes recording the video, encoding and encrypting it, transmitting it over the network, decrypting and decoding it on the user’s device, and finally rendering it for viewing.

PL is a measure of lost video data packets that fail to reach their destination. PL in a video streaming network is caused by insufficient queue capacity, network congestion, and wireless interference, among other factors. These drops affect VQ conveyance, causing high LT and resource waste.

Video streaming encompasses video ingestion/contribution, processing/encoding, and distribution/transmission. To ensure continuous playback, the transmission rate must be equal to the consumption rate; that is, the client must not run out of data (a condition known as buffer overflow), in which case the playback would rebuffer or accept more data than it can store in its buffer, discarding any extra data; Second, the bandwidth availability and real-time constraints—that is, the client's inability to retrieve or the server's inability to push media that has not yet been recorded, encoded, and packaged—limit the client's consumption rate.

LT and PL have their impact across the entire video streaming pipeline. Both parameters cause significant VQ degradation, which falls under two concepts: quality of service (QoS) and quality of experience (QoE). The former includes the latter. QoE is an end-to-end attribute that focuses on a single user's streaming experience and indicates whether the network provides an adequate end-user experience. Based on network measures such as LT, PL ratio, packet size, response time, and throughput, QoS is a network-centric quality [4].

The scientific community has accepted QoE as the best method for assessing the performance of video streaming services because it encompasses a wider range of metrics, including rate of buffering (ROB), buffering percentage over video session (BPOVS), rate of fluctuation (ROF), average playback bitrate (APB), frame video quality (FVQ), and more [5]. Even a very small percentage of PL can result in a significant drop in perceived VQ; as bit rate increases, so does the quality of video sequences affected by the PL ratio.

The client buffer is the primary source of LT in adaptive streaming over HTTP. This buffer holds fetched video segments that are queued for playback; its size needs to be large enough for an Adaptive Bitrate Streaming algorithm to adapt to and measure network conditions, and to change VQ before any rebuffering occurs.

The growing demand for high-quality streaming video has placed extreme strain on the currently available network infrastructure. Though current streaming technologies, especially adaptive bitrate (ABR) mechanisms on the client side, should dynamically adapt to changing network conditions, the resilience and resistance to certain and sustained network impairments, such as LT and PL, remain an issue.

For streaming services, network quality is a genuine concern. If the network is slow or drops packets, it can cause problems with the VQ. The two main issues affecting VQ are LT and PL. LT can cause videos to take an excessive amount of time to start playing and can also delay the start of interactive videos. On the other hand, PL can cause serious problems, including video distortion, frame loss, video resolution degradation or failure to play the video. These issues can be annoying and cause a poor video viewing experience.

While these issues are widely recognized, there are currently no quantitative, detailed studies on the effect of LT and PL on objective and subjective VQ. This limits network optimization approaches.

This research paper examines the relationship between network performance and user experience in greater detail. It attempts to determine how issues such as buffering, poor resolution, and visual artifacts affect not only our subjective perception of the video's appearance, but also the video's quality. With this correlation, we are better positioned to understand what makes video streaming good or bad, and what can be done to improve it.

For companies that provide visual content, low quality can result in customer loss and financial losses. The research seeks to provide useful information that would enhance network performance, video transmission, and the apps that play them, so that people would always enjoy a wonderful and reliable video experience.

To determine the influence of various network conditions on VQ, a special test environment was set up. The effects of LT and PL on VQ in actual terms, as well as how people perceive it, were investigated. To quantify the VQ, we emja daployed a special tool known as PSNR and experimented with various LT times (from 0 to 200 ms) and PL rates (from 0 to 10%) in the video. We also asked people to indicate how they thought the video looked, which we call the MOS score. By comparing these two measurements, we could observe the impact of network issues on video streaming. Based on our findings, we developed workable solutions to enhance video streaming and user experience.

1.1 Research questions and objectives

Although a lot of research has been done before on video streaming quality, the exact quantitative relationship between network degradations and both objective and subjective VQ is still not clear. Specifically, there is a lack of controlled experimental studies that jointly assess LT and PL across a range of bitrate levels, and also relate technical metrics to subjective user experience. As such, the aim of this study is to answer the following questions:

- What is the impact of increasing LT on objective and subjective VQ across different bitrates?
- What is the quantitative relationship between PL and VQ?
- Are there bitrate-dependent thresholds at which perceptual VQ significantly deteriorates?

There are three intended outcomes of this: to quantify the relationship between LT, PL and VQ metrics; to determine practical threshold values for network impairments that impact user perception; and to offer actionable insights on how to best configure networks, streaming protocols and applications in order to enhance overall QoE.

2 Related work

Video streaming quality has been the focus of many studies, especially amid the ever-increasing demand for high-resolution, real-time video streaming [6]. Previous research has investigated the impact of network impairments (LT and PL) on the technical performance and user experience of streaming services [7].

The objective quality measures researched include PSNR, as well as subjective measures such as MOS, to better understand how network behavior relates to QoE. This section covers the literature on the effects of LT and PL on video transmission, the methodological techniques used in past research, and the gaps that drive the current research.

2.1 Impact of LT on streaming quality

The viewer's QoE is greatly affected by end-to-end LT, rebuffering, and playback speed. From an HTTP adaptive streaming perspective, the delivery of a video segment consists of an HTTP request from the client and an HTTP response from the server in HTTP/1.1-based streaming, which introduces at least one round-trip time (RTT). Thus, the bandwidth utilization in HTTP.1.1 is significantly reduced, especially when the is higher than the segment duration. Secondly, when network conditions degrade, the chosen bitrate cannot be changed until a full video segment is received by the client, introducing a segment delay. As a result, HAS, based on HTTP/1.1, cannot react quickly to network jitter, which may cause buffer underflow and thus worse QoE [8].

From the time a video scene starts until the user sees it on their screen, users are sensitive to End-to-end (E2E) LT while streaming videos. E2E LT often includes several delay components encountered during the uploading, encoding, packaging, downloading, decoding, and rendering of videos. All the parts must work together to optimize the live video reproduction process to achieve reduced end-to-end LT.

Segment-based encoding/packaging can be pipelined to reduce the LT for preparing a video frame for transmission on the encoding/packaging side [9]. Each segment must be downloaded or rendered within a brief window after it is generated to complete the download, decode, and render. This results in a very narrow error margin for video rate adaptation; if the chosen video rates for segments exceed the available bandwidth, the video buffer will rapidly empty, and there is a high risk of video freezes. The future video segments' playback LT will increase with each freeze. The streaming session must be resynchronized by skipping video segments that are behind their playback dates to keep up with the continuous live event [10].

2.2 Impact of PL on video streaming quality

Loss adaptation is a more significant issue in real-time streaming scenarios; even a small proportion of lost packets can result in a significant drop in the perceived VQ [11], [12]. Although a high PL rate will result in a deterioration in VQ, from the standpoint of delay (LT), a certain percentage of PL rate can be accepted without retransmitting the incorrect packet, which can save an average amount of time and improve the overall quality of output. Bitrate is determined by bandwidth; more bandwidth can be used for redundancy coding and subsequent PL correction, minimizing streaming LT by preventing retransmission (an additional bandwidth is sufficient to offset the impact of loss) [12]. Sending rates will momentarily exceed available bandwidth when bandwidth decreases, leading to congestion, PL, and longer frame delays for resending or waiting for delayed packets [13], [14].

When video data is lost due to PL, the video decoder pipeline is halted until either the video decoder state is reset using IDR frames (which results in lower VQ for a given bandwidth) or the missing packets are retransmitted (which causes shutters and longer delays). Without requiring receiver feedback, techniques that prevent or conceal data loss (forward erasure correction, partial decoding, error concealment, scalable coding) allow PL mitigation without incurring an RTT for loss recovery. However, while these techniques can reduce the frequency of video data loss at the cost of some bandwidth and compute overhead, they break down when PL exceeds a certain threshold and offer no guarantees [15].

Bienik et al. [16] studied the impact of PL on full HD and ultra-HD video encoded with H.264/AVC and H.265/HEVC. Their research showed that VQ steadily decreased as PL increased, no matter the resolution, codec or bitrate of the video. Although higher bitrates generally increased the quality for videos unaffected by PL, videos with PL sometimes had a more rapid decrease in quality as bitrate increased. This is because larger files must be broken down into more UDP packets, increasing the chance of losing some data and making the video appear even worse. When participants rated the quality of different videos, it was found that even very low levels of PL, such as 0.1%, can have a greater impact on VQ than the artifacts caused by compression. This implies that beyond a certain bitrate, VQ can decrease under lossy network conditions.

2.3 Existing research and related work

These days, a big part of the internet is used for video streaming. With advanced devices and high-speed internet, people demand high-quality video for important activities like online learning and video conferences. The underlying network infrastructure, however, is essential to deliver this content to users seamlessly. It is like the foundation that ensures videos load quickly and play without interruption.

A poor network may lower the quality of video and that is an issue for uses like remote education and video conferencing, where clear communication is essential. Hence, a reliable network infrastructure is needed to meet the increasing requirement for video streams and guarantee the user the reliable experience.

2.3.1 Key findings from previous studies. When it comes to VQ, a few key things can really make or break the experience. LT and PL are significant factors behind video degradation. This may be observed when the video begins buffering, becomes completely pixelated or the connection simply fails. Low VQ is greatly caused by high PL. With PL, higher bitrate may, in fact, worsen the VQ. This is because larger files require more packets to be transferred, which increases the likelihood of lost packets. Indeed, it has been demonstrated that a minute loss of packets, as little as 0.1 percent can cause more significant change in the way we experience VQ than anything else, such as compression artifacts in either H.264 or H.265. These have been noted by researchers like Bienik et al. [16], and Gbigbidje et al. [17], who have studied the impact of LT and PL on VQ.

In the same manner, end-to-end LT, which is the time gap between video capture and playback, has a tremendous effect on a viewer's QoE. In HAS terms, the primary contributor to LT is the client buffer [18], [19], [20]. This buffer must be large enough to allow the ABR algorithm to adapt to changing network conditions before rebuffering occurs.

2.3.2 Methodologies and tools. VQ is evaluated by subjective and objective methods. Objective measurements e.g. PSNR apply mathematical models to measure quality. Subjective evaluation is used where a group of users are asked to watch a video and to offer their opinion, which is averaged to obtain a score referred to as an MOS. A controlled network emulation environment is a standard methodology. A Windows network emulation tool, Clumsy is designed to emulate network impairments and control their behavior to achieve repeatable results.

2.3.3 Research gaps and aims. Adaptive bitrate algorithms reduce certain network variability, although they are not effective against persistent impairments such as LT and PL. Despite widespread awareness of these issues, there is a lack of comprehensive, quantitative studies examining how varying levels of LT and PL affect both objective and perceived VQ. Our study bridges this gap by comparing and estimating the cumulative and separate effects of these impairments. This can be used as actionable insights to optimize network infrastructure, streaming protocols and client applications.

Table 1 synthesizes the selected studies, highlighting their methodologies, datasets, metrics, and main findings.

Table 1: Summary of prior studies on the impact of LT and PL on video streaming quality

Study	**Methodology**	**Dataset / scenario**	**Metrics used**	**Key results**
Wu et al. [8]	Analytical survey of end-to-end streaming pipeline	General streaming architectures (HTTP-based)	Throughput, delay, QoE indicators	Identified RTT and segment delays as major contributors to LT; highlighted inefficiencies in HTTP/1.1 adaptive streaming
Su et al. [9]	Experimental and optimization-based pipeline design	Live video streaming systems	LT, buffering delay	Demonstrated that pipelining reduces encoding and delivery LT in live streaming
Vogel et al. [10]	Runtime adaptation in streaming systems	Multicore streaming applications	LT, system efficiency	Showed that adaptive scheduling improves LT but requires synchronization under real-time constraints
Timmerer et al. [11]	Comprehensive review of HTTP adaptive streaming (HAS)	Adaptive streaming scenarios	QoE, buffering, bitrate adaptation	Highlighted buffer size and adaptation delays as key QoE determinants
Raman et al. [15]	Experimental system for handling PL	Ultra-low LT video streaming	LT, packet recovery rate	Demonstrated trade-offs between retransmission delay and video continuity under PL
Bienik et al. [16]	Experimental analysis of PL effects	High-resolution compressed videos	PSNR	Confirmed strong negative correlation between PL and VQ across codecs and resolutions

Gbigbidje et al. [17]	Empirical network measurements (direct vs hotspot connections)	Real-world internet connections	LT, PL, QoS metrics	Demonstrated that both LT and PL significantly affect QoS and network selection
Shuai and Herfet [18]	Experimental adaptive streaming optimization	Live streaming scenarios	LT, buffering delay	Proposed mechanisms to reduce LT in adaptive streaming
Lyko et al. [19]	QoE optimization study with adaptive buffering	Low-LT live streaming systems	MOS, rebuffering rate	Showed buffer size trade-offs between LT reduction and playback stability
Hussain et al. [20]	System design for adaptive bitrate streaming	Streaming architectures	QoE, bitrate adaptation	Demonstrated improved QoE through efficient ABR mechanisms under varying conditions

While the extensive literature discussed above has provided a rich understanding of LT and PL, there remain key gaps in the state of the art. First, while many prior works focus on either objective (e.g., PSNR) or subjective (e.g., MOS) metrics, few attempt to jointly examine and correlate both under controlled settings. Second, although network impairments are extensively investigated, there is a dearth of comprehensive, detailed analysis of LT and PL across a range of impairment levels and bitrates, making it difficult to derive precise performance limits. Third, while some studies use analytical modelling or uncontrolled real-world measurements, there are fewer studies that use controlled network emulation to provide reproducible and realistic impairment scenarios. Finally, while previous studies offer descriptive analyses, few provide concrete thresholds (e.g., specific LT or PL levels at which QoE becomes unacceptable), which are important for system design, implementation and optimization. Such gaps motivate the current work, which seeks to offer a holistic, controlled and quantitative analysis of both objective and subjective metrics across varied impairment levels.

3 Methodology

The present study takes a two-pronged approach -- quantitative and qualitative methods -- to observe the impact of LT and PL on video streaming quality. For this, we designed a special setup that could control network conditions. This enabled us to measure not only the impact of network conditions on objective measures of the VQ but also on the actual experience of viewers.

3.1 Experimental setup design

The experiment uses a three-component network topology in a controlled environment to isolate and manipulate key variables.

Video server: A special local machine runs an open-source media player (VLC version 3.0.23). This player can send pre-encoded videos to a video client. It supports multiple protocols (such as HTTP and UDP) and formats, and provides socket-based communication for client-server interactions. VLC can compress videos using H.264, an industry-standard video compression codec. This improves bitrate efficiency by about 50%. To ensure seamless server-client communication, Windows Defender Firewall is disabled.

Network emulator: Clumsy simulates network conditions by introducing controlled LT and PL on the client side. This allows for accurate evaluation of streaming performance under impaired conditions.

Video client: Just as with the video server, there is a dedicated client machine running VLC (version 3.0.23) and Clumsy (version 0.3). It receives the streamed video while experiencing simulated network impairments. Firewalls are turned off to avoid interference.

Network: The video is delivered over a wireless UDP connection. UDP is commonly used for real-time multimedia streaming because it offers low LT. However, since it does not provide built-in error correction, additional mechanisms for packet-loss recovery must be implemented to maintain VQ.

The network environment was setup in such a way that it provided controlled and repeatable conditions. Experiments were carried out by isolating the wireless connection to external traffic and preventing background applications and competing network flows. This ensured that all observed impairments were introduced solely by the emulator.

Clumsy (version 0.3) was configured to introduce impairments in a controlled and reproducible manner. PL was applied using a uniform random distribution, where each packet had an independent probability of being dropped according to the specified loss rate (0-10%). Burst loss patterns were not enabled, in order to isolate the effect of steady-state PL. LT was introduced as a fixed delay applied uniformly to all packets within each experimental condition.

3.2 Video content

The videos were carefully chosen and prepared to be consistent and pertinent to the literature. The videos were from a public source and were the same for all tests. The video clips varied in terms of motion and color. This was done to provide a good evaluation of VQ. The videos were recorded at varying resolutions 240p, 360p and 480p, at 25 frames per second (fps). We focused on low-bitrate scenarios to better observe how quality falls under distortion. Two 10-second videos, covering news and soccer scenes, were selected to balance viewers' interest and ensure a reliable subjective assessment. Longer video sequences might be tedious for participants, and shorter sequences may not allow sufficient time for subjects to make a correct subjective evaluation. All videos were encoded in MP4 format using H.264, with bitrates set at 128 kbps, 256 kbps, and 512 kbps. These parameters remained constant throughout the experiments to maintain a controlled testing environment.

3.3 Variables

This study measures the effects of literature-aligned, controlled inputs on a set of quantifiable outputs. Table 2 presents the variables.

.Table 2: Summary of independent and dependent variables

Variable name	Variable type	Description	Range / Levels	Rationale for inclusion
Latency (LT)	Independent (manipulated)	End-to-end delay between packet transmission and reception, measured in milliseconds (ms).	0 ms (baseline), 30 ms, 60 ms, 90 ms, 120 ms, 150 ms, 200 ms	Selected to represent realistic network delay conditions reported in literature and to evaluate its effect on playback smoothness and user-perceived quality.
Packet loss (PL)	Independent (manipulated)	Ratio of lost packets to total transmitted packets, expressed as a percentage.	0% (baseline), 1%, 3%, 5%, 7%, 9%, 10%	Chosen to simulate varying degrees of network degradation and assess its direct impact on video fidelity and playback reliability.
Objective video quality (PSNR)	Dependent (measured)	Peak Signal-to-Noise Ratio (PSNR), measuring distortion between original and received video frames.	Continuous (dB scale): <30 dB (poor), 30-35 dB (acceptable), >35 dB (high quality)	Provides a quantitative, frame-level assessment of visual degradation due to LT and PL.
Subjective video quality (MOS)	Dependent (measured)	Mean Opinion Score (MOS), representing users' perceived VQ on a 5-point scale.	1 (very poor) to 5 (excellent); n = 30 participants	Captures user-perceived QoE, complementing objective metrics with human evaluation.

3.4 Data collection

Objective and subjective data were collected for a comprehensive analysis. For the objective data, we compared video sequences from each experiment with the original video to compute the PSNR. These calculations were performed under various LT and PL conditions using FFmpeg (version 8.1), a free and open-source utility. The entire data was categorized and saved in tabular form to be analyzed.

For the subjective data, we have administered a controlled viewing test to 30 individuals. They had to view video clips featuring various types of impairments. Subsequently, they were asked to rate the VQ on a five-point MOS scale (a 5-point Absolute Category Rating [ACR] scale). We randomized the order of the clips and impairment levels for each person to minimize bias. Objective data provides figures and facts, whereas subjective data narrates what people actually think and feel.

All responses were checked for consistency, and no significant outliers were identified; therefore, all ratings were included in the analysis.

For the subjective evaluation, the presentation order of video clips and impairment conditions was randomized for each participant using a balanced randomization approach to minimize ordering and learning effects. While a full Latin square design was not implemented, care was taken to ensure that no single condition consistently appeared in the same position across participants.

The participants had diverse demographic backgrounds. They were aged 20-35 years, featuring male and female respondents with varying levels of technical familiarity. Most of them were generally familiar with video streaming apps, and none were VQ evaluation experts. They were informally screened before the experiment to make sure they had normal or corrected-to-normal vision, and were given brief instructions on how to interpret the MOS scale.

All viewing tests were conducted on a standard display device. The screen size was 14-15 inches with a resolution of 1920 x 1080 pixels. The default display settings were not professionally calibrated, and brightness and viewing conditions were held consistent throughout the sessions to reduce variability.

3.5 Data analysis and visualization

The data obtained was analyzed using correlation analysis and data visualization tools to identify patterns or trends. The correlation analysis was used to determine the interrelation between the objective (PSNR) and subjective (MOS) measures. Trends were expressed in line graphs. This helped visualize the effects of LT and PL impairments.

Correlation analysis was done in addition to descriptive analysis to measure the relationship between PSNR and MOS. All conditions were calculated with basic statistical summaries (mean values). Although the emphasis was not on formal hypothesis testing, variability among observations was evaluated, and trends were analyzed for consistent patterns across several levels of bitrate and impairment. The findings are thus shown as indicative trends rather than inferential statistical conclusions.

4 Experiments, results, and discussion

4.1 Experiment design

4.1.2 Experimental setup. The video material that was used in this experiment was carefully prepared, so as to support the goals of the study. Classic, standard test sequences, such as Foreman, Soccer, and Anchor (see Table 3), were chosen for their diverse characteristics, including different motion levels, color variations, and scene complexity. These sequences are widely recognized and commonly used in various studies involving VQ assessment, hence making them suitable for reliable evaluation [21] [22].

Table 3: Video information across resolution, length, frame rate, frames, and bitrate

VS	R (p)	L (s)	FR (fps)	F	BR (kbps)
Foreman	240	10	25	250	128
Soccer	360	10	25	250	256
Anchor	480	10	25	250	512

Abbreviations: *VS*, video sequences; *R*, resolution; *L*, Length, *FR*, frame rate; *F*, frames; *BR*, bitrate.

The video sequences were prepared at a base resolution of 240p with a frame rate of 24 fps, as shown in Figure 1. H.264 codec (current industry standard) was used for video compression. Raw video was encoded by the video server with this codec, and the client-side also used H.264 to decode the compressed stream. Using this popular codec ensured that our experimental results were applicable to current video streaming practices.

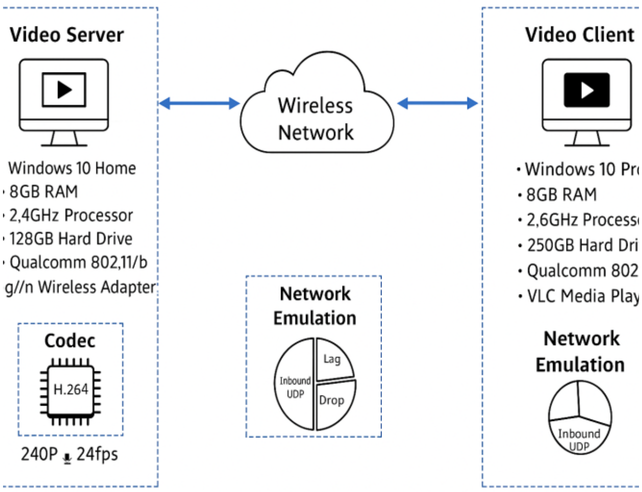

Figure 1: Experimental setup comprising video server, client, and network emulation

The original video sequences are shown in Figure 2.

Figure 2: Original video sequences

The video server was configured on a Windows 10 Home computer (8 GB of RAM, 2.40 GHz x64 processor, 128 GB of storage, and a Qualcomm 802.11b/g/n adapter). The video server was connected to the same wireless network as the client device. The server was equipped with VLC Media Player to stream video content. It was necessary to ensure that the server and the client were connected before each experiment. This was achieved by configuring IP addresses and running ping tests to ensure there was no PL. Similar checks were also done on the client side. The original video files were stored on the server, from which they were streamed to the client using the UDP protocol via VLC. In order to configure streaming, the "Media → Stream" option was selected in VLC, the video file to be streamed was added, and UDP (legacy) was chosen as the destination. The streaming format profile of Video - H.264 + MP3 was selected and the IP address of the client inputted, the default port of 1234 was used, and the streaming format was set to the Video - H.264 + MP3 profile. The codec settings were configured to adjust the bitrate and frame rate and then the stream was started. This setup was helpful because it enabled us to stream video material from the server to the client over the wireless network, allowing the experiments to be conducted under controlled conditions.

The video client was a computer with Windows 10 Pro (8GB RAM, 2.60 GHz x64 processor, 250GB storage and a Qualcomm 802.11b/g/n adapter). It was also equipped with VLC, which was used to receive the video stream. We also added the Clumsy, which was also installed in this machine, to simulate LT and PL. To commence the experiment, we opened VLC and in the Media tab, typed the URL udp://0:1234 to receive a stream from the server. We captured the video in real time as it was playing in VLC. FFmpeg (which includes a built-in PSNR filter that provides a quantitative measure of the extent to which the VQ had degraded) was then used to compare the recorded video with the original. It was this process that enabled us to observe the difference in VQ as it streamed across the network and to better understand how various factors, such as LT and PL, can influence video streaming.

Network simulator: Clumsy was installed on the client machine as a network impairment simulator used in the experiment. For each test, the application was launched using administrator privileges. A traffic filter was configured as “inbound and udp and ip.SrcAddr == Host IP Address”. This would guarantee that only inbound UDP traffic originating from the video server is interfered with.

No preset profiles were used. Instead, under the Functions section, either Lag or drop was activated to simulate an LT or PL, respectively. The Inbound setting was selected, and the appropriate delay (in milliseconds) or loss rate (in percentage) was specified to impair the arrival of packets into the system. At the end of each test run, Clumsy was stopped and reconfigured to suit the next experimental scenario.

4.2 Measurement procedures

Measurement of objective quality: PSNR was used to measure objective VQ. PSNR uses mathematical computations to measure video degradation by comparing the received (impaired) video stream to the original source video. This was assessed at the end of each experiment to provide a direct, objective measure of quality. The decoded video parts were recorded after each test run. The frame-by-frame comparison was carried out using FFmpeg's built-in PSNR filter, which compared the reconstructed video to the original source. The result of this process is the PSNR value for each frame. These per-frame values are then averaged to produce a single overall PSNR for the entire video stream, which serves as a definitive measure of each test condition.

Even though objective measures give numerical outcomes, they do not necessarily go hand in hand with human perceptions. This is why we conducted a subjective evaluation to gather MOS ratings under the various network conditions. We used 30 persons in line with the recommendation ITU-R BT.500-15 [23], which indicates that to enhance reliability and statistical validity, a minimum of 15 observers is required. All tests were performed under controlled conditions. The lighting, display settings and viewing distance were all consistent. Each person was seated directly in front of the screen with a 4-6H distance, where H is the height of the video display. To minimize bias, the videos (representing various network scenarios) were presented at random. Having watched every clip, the participants rated the perceived quality of the video on an MOS scale between 1 and 5 (5 [Excellent, no noticeable impairment], 4 [Good, noticeable impairment but not annoying], 3 [Fair, slightly annoying impairment], 2 [Poor, annoying impairment], 1 [Bad, very annoying impairment]).

4.3 Results

Results are provided against known literature findings (Section 2 and Table 1), especially on perceptual thresholds and the interaction between LT and PL, and bitrate.

4.3.1 Effects of LT on quality of video streams (objective findings): The results showed that LT was not a critical factor influencing objective VQ. PSNR remained largely constant across LT levels (Table 4). For example, it changed little at 128 kbps, decreasing slightly from 36.8 dB at 0 ms to 36.0 dB at 200 ms; at 512 kbps, it dropped from 42.0 dB to 41.4 dB. This consistency implies that LT does not significantly degrade the visual fidelity of the decoded frames. Instead, the findings indicate that bitrate is a critical factor of PSNR -- higher bitrates invariably resulted in better quality regardless of delay. LT had the greatest effect on QoE by introducing timing impairments, including longer startup delay and possible interruptions during playback. This small reduction in PSNR at higher LT could indicate small adaptive rate changes during streaming. Comprehensively, the results indicate that LT has a bigger impact on playback smoothness than on how good the video looks.

Table 4: Objective performance results under varying LT conditions at 128 kbps, 256 kbps, and 512 kbps bitrates

Scenario	LT (ms)	Avg. PSNR (dB)
Bitrate = 128 kbps		
Test 1	0	36.8
Test 2	30	36.7
Test 3	60	36.6
Test 4	90	36.5
Test 5	120	36.3
Test 6	150	36.2
Test 7	200	36.0
Bitrate = 256 kbps		
Test 1	0	39.2
Test 2	30	39.1
Test 3	60	39.0
Test 4	90	38.9
Test 5	120	38.8
Test 6	150	38.6
Test 7	200	38.5
Bitrate = 512 kbps		
Test 1	0	39.2
Test 2	30	39.1
Test 3	60	39.0
Test 4	90	38.9
Test 5	120	38.8
Test 6	150	38.6
Test 7	200	38.5

These findings confirm that, although PSNR is largely unaffected by network delay, LT remains crucial in real-world streaming by influencing initial buffer times and rebuffering frequency (factors not captured directly by PSNR). Figure 3 shows that a minimal reduction in PSNR at higher LT probably indicates adjustments made in adaptive bitrate during streaming.

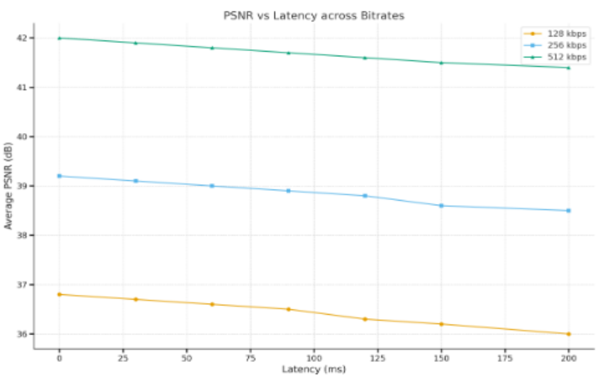

Figure 3: Impact of LT on PSNR for video sequences at different bitrates

4.3.2 Effect of LT on the quality of video streaming (subjective results): According to subjective assessment results, it is observed that there is a downward trend as LT increases, which remains the same irrespective of the three bitrate rates. MOS falls steadily as LT worsens. At baseline (0 ms LT), viewers reported their QoE as very high, and the MOS scores were close to the highest, Excellent (4.5 at 128 kbps, 4.7 at 256 kbps, and 4.9 at 512 kbps). This means that with no network delays, the viewers were generally content with the quality of the video, especially at higher bitrates. At higher LT (60-90 ms), viewers reported an increase in startup time and occasional stalling. Although VQ was unaffected, playback smoothness was reduced. Thus, MOS was in the Good-Fair range.

The negative impact was more prominent at higher LT (120-200 ms). As shown in Table 5 and Figure 4, MOS decreased sharply to 2.8 at 128 kbps, 3.1 at 256 kbps and 3.5 at 512 kbps under 200 ms LT. An important finding is that increased bitrates helped partially compensate for the impact of LT. MOS remained above 3.5 at 512 kbps and 200 ms LT, and below 3.0 at 128 kbps and 200 ms LT. This suggests that although the increased bitrate cannot completely compensate the negative effect of LT, it can reduce the impact on user-perceived VQ.

These findings indicate perceptual thresholds in line with previous literature: an LT below ~50-60 ms does not cause significant effects on perceived quality; degradation becomes noticeable above ~90 ms, and severe degradation above 120-150 ms. This falls in line with quality QoE research, where LT was found to be a key driver of playback-related dissatisfaction rather than visual distortion.

Table 5: Subjective evaluation results under varying LT conditions at 128 kbps, 256 kbps, and 512 kbps bitrates

Number of participants (n)	LT (ms)	Mean opinion score (mean)
Bitrate = 128 kbps		
30	0	4.5
30	30	4.3
30	60	4.0
30	90	3.7
30	120	3.4
30	150	3.1
30	200	2.8
Bitrate = 256 kbps		
30	0	4.7
30	30	4.5
30	60	4.3
30	90	4.0
30	120	3.7
30	150	3.4
30	200	3.1
Bitrate = 512 kbps		
30	0	4.9
30	30	4.7
30	60	4.5
30	90	4.3
30	120	4.1
30	150	3.8
30	200	3.5

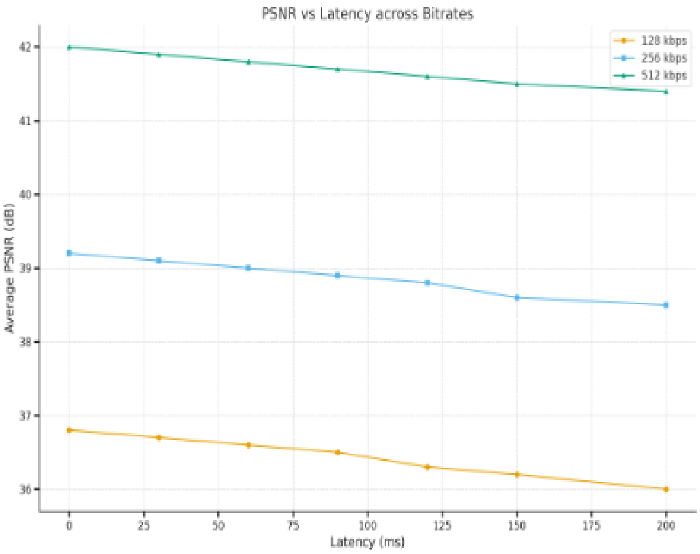

Figure 4: Impact of LT on MOS for video sequences at different bitrates

4.3.3 Impact of PL on video streaming quality (objective results): The experimental results show that PL has a severe and direct impact on objective VQ. VQ is more affected by PL than LT, which mainly influences playback timing. PL is equivalent to discarding valuable video information, and the result is evident video distortions. As Table 6 indicates, even a small 1% loss rate makes a big difference in VQ across all bitrates. For example, at 128 kbps, PSNR decreases from 36.8 dB (no loss) to 33.2 dB (1% loss). On the same note, at a higher bitrate (512 kbps), the drop is from 42.0 dB to 38.8 dB. This behavior aligns with previous research (e.g., Bieńik et al. [16]; Gbigbidje et al. [17]) showing that compressed video streams are highly sensitive to even the slightest PL.

Table 6: Objective performance results under varying PL rates at 128 kbps, 256 kbps, and 512 kbps bitrates

Scenario	PL (%)	PSNR (dB)
Bitrate = 128 kbps		
Test 1	0%	36.8
Test 2	1%	33.2
Test 3	3%	30.1
Test 4	5%	28.0
Test 5	7%	26.5
Test 6	9%	25.0
Test 7	10%	24.2
Bitrate = 256 kbps		
Test 1	0%	39.2
Test 2	1%	36.0
Test 3	3%	33.4
Test 4	5%	31.2
Test 5	7%	29.7

Test 6	9%	28.1
Test 7	10%	27.3
Bitrate = 512 kbps		
Test 1	0%	42.0
Test 2	1%	38.8
Test 3	3%	36.1
Test 4	5%	34.0
Test 5	7%	32.3
Test 6	9%	30.8
Test 7	10%	29.5

This demonstrates that the decoder cannot fully conceal the impact of missing packets, leading to visible artifacts such as macroblocking, pixelation, and frozen frames. This shows just how sensitive VQ is to PL, and how even a small amount of loss can have a significant impact. Figure 5 indicates that at 10% loss, PSNR dropped to approximately 24 dB at 128 kbps and 29 dB at 512 kbps, i.e. low perceptual quality. Even though higher bitrates tolerate loss better than lower ones, all streams exhibit a gradual reduction in objective quality as PL increases.

Besides visual fidelity, playback smoothness is also influenced. Lost packets delay the delivery of segments on time. This leads to a faster depletion of the client's playback buffer than it can be refilled. Consequently, the video freezes more often while buffering. As PL rate increases, the frequency of interruptions and the duration of each pause increase significantly, and users' QoE is observed to decrease significantly.

In general, the findings show that a PL is more detrimental than LT. Whereas LT primarily affects timing and responsiveness, PL has a direct negative effect on video content, causing playback to be disrupted, making its impact more severe for viewers.

Notably, the results show clear degradation limits: at least 1% PL leads to a measurable decrease in PSNR, and higher values (>3-5%) lead to significant degradation in quality, consistent with previous codec-level research on error propagation.

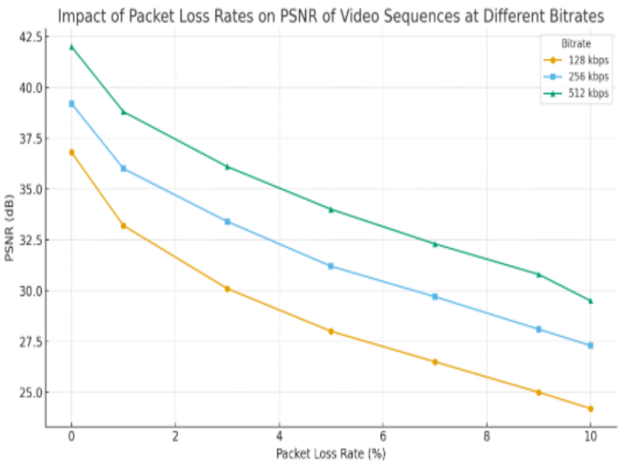

Figure 5: Impact of PL rates on PSNR for video sequences at different bitrates

4.3.4 Impact of PL on video streaming quality (subjective results): The subjective findings indicate that participants found PL to be a major disruptive factor compared to LT. Table 7 reveals a drastic reduction in MOS scores even at low loss rates. At baseline (0% loss), the streams were rated between Good and Excellent (MOS 4.5-4.9, depending on bitrate). Nevertheless, even at just 1% loss, MOS reduced significantly.

Table 7: Subjective evaluation results under varying PL rates at 128 kbps, 256 kbps, and 512 kbps bitrates

Number of participants (n)	PL (%)	Mean opinion score (mean)
Bitrate = 128 kbps		
30	0	4.5
30	30	3.7
30	60	3.0
30	90	2.3
30	120	1.8
30	150	1.5
30	200	1.3
Bitrate = 256 kbps		
30	0	4.7
30	30	4.0
30	60	3.3
30	90	2.7
30	120	2.2
30	150	1.9
30	200	1.6
Bitrate = 512 kbps		
30	0	4.9
30	30	4.7
30	60	4.5
30	90	4.3
30	120	4.1
30	150	3.8
30	200	3.5

Participants reported visible pixelation and occasional frame freezes, which immediately impacted their perception of quality. When the loss rate reached 3-5%, the video began to appear very poor, dropping into the Fair-to-Poor category (MOS 2.3-3.3). Respondents reported frequent macroblocking, flickering, and the video halting and resuming repeatedly. At higher loss rates (7-10 percent), MOS was below 2.0 for 128 kbps streams (Figure 9), indicating that the videos were essentially unwatchable.

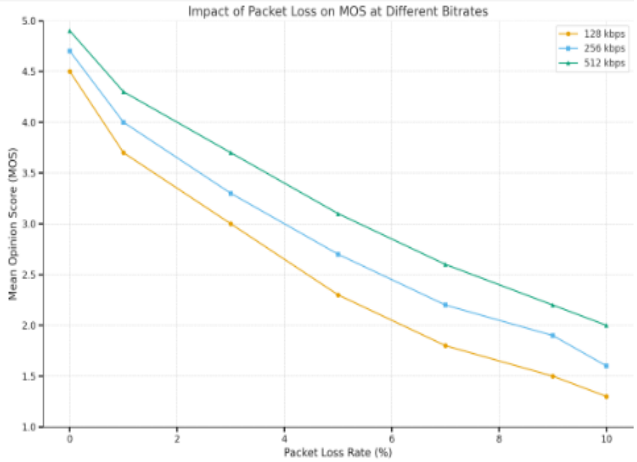

Figure 9: Impact of PL rates on MOS for video sequences at different bitrates

A notable trend is that bitrate provides some resilience. At a bitrate of 512 kbps and even a 5% PL rate, the stream maintained an MOS of 3.1 (Fair), as compared to only 2.3 (Poor) at 128 kbps. However, continuous deterioration was observed irrespective of bitrate, and quality eventually collapsed. These results support the fact that users consider PL as much more disruptive than LT. LT is the leading cause of delays and buffering, but PL directly corrupts the visual stream, resulting in artifacts that can be seen and are annoyingly distracting, an experience that was rated poorly by participants.

From a perceptual standpoint, the findings confirm that PL thresholds for acceptable quality are low: MOS drops below acceptable levels (~3.0) at approximately 3-5% loss, and streams become largely unwatchable beyond 7-10%, in agreement with prior QoE studies.

Across all experiments, bitrate plays a moderating, not compensatory, role. Higher bitrates improve baseline quality and provide partial resilience to both LT and PL; however, they do not eliminate degradation. In particular, while higher bitrates mitigate LT-induced QoE decline, they may increase sensitivity to PL due to larger data volumes and packetization. This interplay between bitrate, LT, and PL highlights the need for balanced adaptation strategies rather than isolated parameter optimization.

4.4 Discussion

This section relates the findings to the studies outlined in Table 1, indicating the shared aspects, discrepancies, and the new contributions of our work.

4.4.1 Analysis of LT effects: Objective results show that the effect of LT by itself on frame-by-frame fidelity is small. These minor variations show that the visual fidelity of the decoded video frames remains quite stable despite longer delay. However, subjective ratings tell a different story. Although PSNR was not dramatically affected, MOS decreased significantly as LT intensified. This indicates that users felt that their QoE was negatively impacted, despite a high objective quality measure.. The discrepancy between consistent PSNR and declining MOS indicates that users are more sensitive to image timeliness than to minor changes in image quality under LT-only conditions. These results align with previous research as described in Table 1 that indicate that LT is a significant variable influencing playback smoothness but not frame-level fidelity.

Bringing the objective and subjective findings together reveals two distinct effects of LT. Frame-level visual fidelity is typically not affected by delay. On the other hand, playback smoothness and perceived quality are highly sensitive to delays. We observe a threshold: user experience is highly impaired at low delays (50 ms), and is extremely bad at high delays (100-150 ms or more). This is due to longer start-up delays and more frequent buffering. These results indicate how adaptive bitrate clients and transport behavior correlate with RTT. Longer RTT delays delivery of segments and bitrate adaptation feedback. So, while codecs and decoders preserve per-frame VQ, user experience is degraded by timing issues (caused by LT) that PSNR alone cannot capture.

4.4.2 Analysis of PL impact: PL has a more direct impact on objective VQ than LT. Small increases in PL can result in a significant decrease in PSNR. This suggests that a small PL can lead to noticeable frame corruption and severely degraded decoded fidelity. This objective degradation translates into subjective quality loss, as MOS falls rapidly with PL, and has a strong correlation with PSNR. Artifacts caused by missing packet are highly visible to viewers. Hence, MOS dropped into the poor-bad category under moderate-to-high PL. This strong correlation between PSNR and MOS under PL is in contrast with the weak correlation under LT alone.

This aligns with experimental findings reported by Bieńik et al. [16] and Gbigbidje et al. [17] (Table 1), who also observed a strong degradation in VQ even at low PL rates.

A key point to note is that, although higher bitrates are typically associated with higher baseline PSNR, they can also lead to more absolute PSNR degradation when PL occurs. This is because higher-bitrate streams are split into more packets. Consequently, at the same PL rate, more video data is lost in higher-bitrate streams. In practice, higher bitrates improve baseline quality, but they do not eliminate the need for data-loss protection mechanisms. In a lossy network environment, a higher bitrate without error resilience mechanisms can cause a quality degradation for each unit of data lost.

4.4.3 Subjective versus Objective Quality: Our experiments reveal that the relationship between subjective and objective quality depends on the type of network impairment. PSNR and MOS are closely aligned in the case of PL. When PSNR falls, viewers report poorer VQ. This renders PSNR to be a reliable predictor of visual degradation arising from corrupted or missing frame data. In LT-only impairments, the correlation is weak. PSNR remains relatively stable, whereas MOS falls as playback smoothness deteriorates. In LT conditions, playback continuity metrics (startup delay, rebuffer count/duration and bitrate adaptation) are better predictors of perceived quality (MOS) compared to PSNR. Such distinction suggests the need to use both metrics in a comprehensive QoE evaluation.

4.4.4 Comparison to Existing Literature: The results of this research confirm an established finding about streaming research: LT is a primary interruption to playback flow and perceived smoothness, whereas PL is an explicit harm to VQ at the frame level. Prior research has consistently shown that viewers are less sensitive to minor declines in visual acuity than to interruptions or long startup delays. Our results confirm that even when PSNR remains almost constant across added LT, MOS drops drastically. This supports earlier evidence that stalling may carry up to three times the perceptual impact of moderate visual degradation. That is, time-based impairments prevail in low-loss high-delay networks in terms of quality perception.

On the other hand, PL can lead to irreversible corruption of video frames. This results in blocking artifacts, freezing, or decoding errors, all of which have a direct detrimental effect on PSNR. Such behavior is consistent with the published literature on codec resilience, which indicates that compressed video streams are highly vulnerable to lost packets because frame dependencies (I/P/B structure) propagate errors forward in time. The significant drop in PSNR at just 1-3% PL is in line with what has been reported in the literature for H.264/AVC and H.265/HEVC. The other significant contribution of this study is the numerical values for the test cases: at 128 kbps, PSNR falls below 30 dB (commonly cited as the good-quality threshold) at only 3% PL, and subjective MOS scores drop below fair (3.0) at similar levels.

The other contribution of this study is that simply raising the bitrate will not compensate for the effect of PL. While high bitrate results in higher VQ (in terms of initial PSNR), the percentage decrease due to PL is substantial. This is consistent with previous studies on adaptive streaming, which suggest that higher-bitrate streams are split into more packets, making them more vulnerable to PL. This indicates that simply increasing the bitrate without employing loss-mitigation schemes (forward erasure correction, retransmission, redundancy), does not necessarily improve QoE under PL conditions.

Some differences between our results and those of previous research might be explained by the variations in experimental design, such as controlled network emulation (Clumsy), specific encoding parameters (H.264 at low bitrates), and the inclusion of both objective and subjective assessments using a specified group of participants. In contrast, a number of earlier studies have used simulations, analytical models or one-metric assessments, which might not be as representative of actual user perception.

This study has three main aspects of novelty. To begin with, it offers a combined analysis of objective (PSNR) and subjective (MOS) metrics under identical controlled experimental conditions. Second, it sets quantitative thresholds of perceptual degradation (e.g., MOS decrease to an unacceptable level at 100-150 ms LT and 1-3% PL). Third, it shows specific correlation patterns: weak PSNR-MOS correlation under LT-only conditions and strong correlation under PL. These findings provide actionable insights for optimizing streaming systems beyond what has been reported in the literature.

Although PSNR offers a more consistent, objective baseline, it cannot fully measure perceptual distortions; hence, in future research, perceptual metrics like SSIM (Structural Similarity Index Measure) and VMAF (Video Multi-Method Assessment Fusion) will be used to improve alignment with user experience.

4.5 Limitations and future work

There are a few limitations to this study that should be noted when interpreting the results. Firstly, the experiments involved only low-bitrate streams (128-512 kbps), and thus the results might not be entirely applicable to higher-resolution or high-bitrate streaming scenarios. Future work could extend this analysis to HD and 4K content to better reflect modern streaming conditions.

Only a small number of video clips were used. Although they were chosen to emulate various content types, they cannot cover the full spectrum of motion and visual complexity encountered in real-world streaming applications. Expanding the range of content in future studies would provide a more comprehensive evaluation..

All the videos were encoded with one codec (H.264/AVC). So, performance may vary with more recent codecs like HEVC, VP9 and AV1. Evaluating these newer codecs is an important direction for future research.

Subjective assessments relied on a rather small sample size (n = 30), which could restrict the extent to which the findings can be generalized. Larger and more diverse participant groups would help strengthen future findings.

Lastly, the experiment was based on controlled network emulation. This makes it feasible to isolate and study specific impairments in a consistent way; however, real-world networks are often more dynamic and unpredictable than what can be reproduced in a controlled setting. Future work could incorporate real network traces to better reflect practical deployment conditions.

Despite these limitations, the study employs a controlled design that enables a clear and focused analysis of the impact of LT and PL on objective and perceived video quality.

5 Conclusion

In this research, the effects of LT and PL on video streaming were investigated across 3 different bitrates. Our key findings are:

1) A minor packet loss (<1-2%) can severely degrade VQ.
2) Users have a low tolerance for LT. MOS begins to drop noticeably below 50-100 milliseconds of RTT, even though PSNR remains almost unchanged.
3) Adaptive bitrate algorithms keep videos playing without stalling by reducing quality when network conditions worsen. However, viewers still react negatively to frequent stalling or prolonged low quality.
4) Bitrate is related to the network conditions: a higher bitrate may result in higher quality if PL is low. For

moderate or high PL, increasing the bitrate alone offers little benefit. If the network is not protected against losses, higher-bitrate videos can degrade just as much.

5.1 Recommendations

Content providers: Minimizing startup delay is key. Users are very sensitive to how quickly a video begins playing, even if the VQ is technically good. Faster handshakes, better segmentation, and reduced initial buffers may make a difference. Adaptive bitrate strategies are also to be fine-tuned to user preferences.

Network operators: A key focus should be on reducing video RTT. Delays are evaluated very negatively, even with high objective VQ score. Reducing end-to-end LT by optimizing routing, edge caching and congestion control should be considered a priority.

Application developers: Video clients should log both playback-timing metrics and frame-fidelity metrics. PSNR alone does not reflect user frustration associated with delays. A complete playback QoE assessment would include startup delay, rebuffer count/duration, bitrate adaptations, and actual PL.

Data availability

The data used in this study can be made available upon reasonable request, and in line with institutional and ethical guidelines.

Ethical statement

This study used human subjects for subjective video quality assessment. All participants were informed about the purpose of the study and informed consent was obtained beforehand. The evaluation was conducted in accordance with standard ethical research practices, ensuring anonymity, voluntary participation, and the right to withdraw at any time.

Authors' contributions

- Anthony Nwohiri: Writing – review & editing, Supervision, Resources, Methodology, Investigation/Experiment, Conceptualization.
- Adetomiwa Aribisala: Writing – original draft, Validation, Methodology. Investigation/Experiment, Formal analysis
- Al-Bashir Muhammad: Visualization, Validation, Data curation.
- Oluwatosin Mofikoya: Visualization, Validation, Data curation.
- Korede Jacob: Visualization, Validation, Data curation.

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