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Communication-Aware Design of Mobile Learning Systems for Seamless Content Delivery

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Abstract

The high rate of mobile learning has increased the pressure regarding the smooth and secure delivery of content in dynamic wireless networks. Nonetheless, variable bandwidth, latency, and disruptions caused by mobility have a serious negative effect on the quality of experience (QoE) experienced by learners when traditional adaptive streaming techniques are used. The paper introduces a design concept of mobile learning environment that is communication-aware and jointly addresses both network-level quality of service (QoS) parameters and human-centric quality of experience (QoE) demands to support continuous provision of content. The recommendation is an QoS/QoE conscious adaptive streaming system, whereby real-time network supply, such as available bandwidth, end-to-end delay, jitter, and buffer use are used to make judicious bitrate change decisions. It is also through the proposed approach that extensive simulation of the scheme is evaluated in different network load and mobility conditions as compared to representative throughput-based and buffer-based adaptive streaming schemes. Performance indicates that the proposed design greatly minimises start up delay and rebuffing occurrences and that the proposed design enhances the average delivered bitrate and the stability of the bitrate. Moreover, there are significant improvements in the network performance measured by the element of lower latency, higher percentage of packet delivery, and efficiency of throughputs. This result indicates that by integrating adaptation strategies that are communication-sensitive, mobile learning systems that run on heterogeneous wireless networks can be significantly improved in regard to reliability and scalability.

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Introduction

The fast development of mobile communication technologies and the popularisation of smart devices influenced the situation in the digital education sphere greatly, which contributed to the increased usage of mobile learning systems. Wireless networks are becoming increasingly popular as learners are able to use them to deliver video-based lectures, interactive tutorials, and real-time collaborative learning materials. But, introducing such lavish multimedia state of affairs throughout a wireless environment is intrinsically touched by the influence of dynamic channel conditions, variable bandwidth, and mobility of the user that may significantly deter the quality of experience (QoE) unless its success is effectively attended to.[1, 2] Such problems lead to the need to come up with communication conscious mechanisms that have the potential to achieve reliability and smooth delivery of content in mobile learning applications.

The mobile learning environments are especially hard to provide seamless content delivery because of the cumulative impact of latency, jitter, network performance, and mobility induced handovers. The difference in the end-to-end delay and the loss of packets may result in a gap in playback and video resolution, which interrupts the learning process and decreases the interest demonstrated by the learner. These effects are magnified in cellular and heterogeneous wireless networks, which experience conception to more users and limited network resources overload.[9, 11] Recent research has emphasised the fact that traditional network-agnostic streaming systems can effectively keep operating in these scenarios whereas the need to try and incorporate network performance awareness into content delivery systems is pertinent.[12, 13]

Bitrate streaming techniques have extensively been adopted in dynamic adjustments in video quality depending on the observed bandwidth and the buffer occupancy to adapt to network variability. The latest studies have investigated reinforcement learning, federated learning-based paradigms to reinforce bitrate modification and QoE optimization.[2, 3, 7, 8, 10] Even though these solutions prove significant advancements to be made in the overall video streaming contexts, they are to the largest extent, tailored to entertainments-driven services and are not quite responsive to the demands of mobile learning. In applications where the learning is the focal point, not only the viewing satisfaction suffers, but also the knowledge retention and continuity during the learning process, necessitating the inadequacy of conventional adaptive streaming technologies.[5, 6]

To address these limitations, this paper proposes a communication-aware design of mobile learning systems, which both addresses network level quality of service (QoS) measures and requirements that relate to the quality of experience (QoE) of learners. The suggested architecture integrates real-time monitoring of the network states of available bandwidth, latency, jitter, and performance in delivering packets to a network to propel intelligent adaptive streaming control mechanism based on QoS/QoE consideration. The proposed approach will ensure that the video quality can be kept constant, and service interruptions reduced even in the conditions of extreme network congestion and high variability of wireless dynamics and mobility due to noticeable variation.

The first contribution of this work is that it shows that mobile learning systems can be very reliable and scaled in terms of adaptation through communication-aware enhancement. The proposed design is demonstrated to reduce the latency, better the throughput, increase the ratio of the packet delivery and improve the QoE than the representative baseline streaming schemes in the view of comprehensive network- level performance evaluation. These findings support the significance of incorporating the use of communication-layer intelligence in mobile learning systems and the given outcomes of the study can be useful in the designing of future wireless learning systems to work in the heterogeneous networking environments.

Related Work

Adaptive bitrate (ABR) streaming has received a lot of research as one of the core mechanisms of providing video contents across dynamic wireless networks. The classical ABR techniques use the estimation of throughput or occupancy at the buffering phase to control it to the desired video rates but they fail frequently at dynamically changing network conditions. Learning-based methods have also been embraced by recent studies in an attempt to overcome this weakness. It has been suggested that reinforcement learning and meta-learning methods can be used to allow smarter selection of the bitrate, which can change with time-varying and heterogeneous network conditions.[2, 3] These schemes prove to have better adaptability and QoE stability over heuristic based schemes, especially in the demanding wireless conditions.

In addition to the bitrate adaptation, there is a considerable amount of literature addressing the inclusion of quality of service (QoS) and quality of experience (QoE) awareness in the systems of delivering multimedia. QoE-conscious streaming systems attempt to explicitly optimise the apparent performance measured by concurrently accounting for user-perceivable variables like startup delay, rebuffing instances and bitrate consistency and network variables.[5, 11] The last takes the form of Edge-assisted and cloud-edge collaborative solutions which have helped to improve QoE by minimising latency and optimization of resource usage via smart aggregation and scheduling processes.[4, 13] Scalable QoE optimization with user privacy and reduced centralised training overhead has also been experimented with federated and distributed learning methods.[1, 8, 10]

The mobile learning systems further complicate multimedia delivery since it requires wireless connectivity, movement of the learners and continuous access to the content. Although video streaming technologies have been used extensively on the educational platform, most of the current mobile learning solutions have assumed content delivery to be a generic multimedia service offered without considering or taking cognizance of the communication-layer dynamics. Also, low-latency interactive streaming is a subject of studies that emphasise the significance of network-aware designs in real-time applications and which, in the context of mobile learning, are of great actuality.[9, 12] These works, however, are directed more at entertainment or conferencing applications than at learning-oriented settings, where service interruptions may have a direct impact on the interest of the learners and the learning platforms.

In spite of significant progress, there are still a number of gaps in the literature. The vast majority

Table 1: Comparison of Existing Mobile Learning and Adaptive Streaming Approaches

Ref.	Approach Type	Key Objective	QoS/QoE Awareness	Mobility Support
[2]	Meta-RL-based ABR	Adaptive bitrate selection	QoE-aware	Limited
[3]	Buffer-aware ABR	Buffer stability	Partial QoE	No
[5]	Edge-assisted streaming	QoE optimization	QoS-QoE	Limited
[1]	Federated RL ABR	Scalable adaptation	QoE-aware	No
[8]	Federated DRL ABR	Privacy-preserving streaming	Partial QoE	No
[9]	Low-latency live streaming	Delay reduction	QoS-focused	Partial
[11]	Cellular QoE optimization	Jitter mitigation	QoS-QoE	Yes
[13]	Cloud-edge scheduling	Resource efficiency	QoS-aware	Limited

of QoE optimization methods are developed without any reference to the background context of the communication and do not consider the application of QoS and QoE goals that are specific to mobile learning apparatus. Moreover, there has been minimal focus on the effects of mobility on the network performance and loss of learning performance in a large scale learning environment. Table 1 presents the summary of the representative works on the topic of adaptive streaming and QoE-aware delivery which provide its scope and limitations. Such gaps have stimulated the desire to adopt a communication conscious design that combines network level intelligence and QoS/QoE motivated adaptive streaming to achieve smooth content delivery of mobile learning in heterogeneous wireless network.

System Model and Problem Formulation

The mobile learning system that is being taken into account in this paper is made up of a group of learners who can use the multimedia education content via mobile communication device on heterogeneous wireless networks. Wireless access technologies are used to connect learners through Wi-Fi, LTE, and 5G access technology, but each has various coverage ranges, data rates, and latency profiles. Videos lectures and other interactive learning materials spare the educational content is stored in cloud servers, which can be reused in edge servers that are closer to the access network to minimise the access delay and to the backhaul traffic. A streaming controller (adaptive) works together with the learner devices and content servers in order to dynamically control the delivery of the content depending on current network conditions. A continuous feedback loop thus is created as shown in Figure 1 whereby real-time network state data is being gathered on the wireless links and input into the streaming controller to be able to communicateically adapt the content bitrate and delivery behaviour.

The wireless networks underpin mobile learning applications are dynamic and stochastic; this is the reason why communication environment is modelled. The channel bandwidth changes with time because of mobility, interference of the wire, and changing network loads. End-to-end delay is the delay due to combined transmission, propagation, queuing, and processing delay and the variation of packet arrival times with dynamic scheduling and congestion (on an occasional basis) is the packet jitter. Packet loss can be induced due to overflow of buffers or impairments of wireless channels, or even handover in cellular networks. The model of user mobility predicts movement between access points or base stations and thus can cause handover events leading to a temporary decrease in the quality of communication. These assumptions used in modelling are realistic learning situations where students constantly relocate and will undergo various wireless environments in the process of content reception.

A QoS-QoE mapping framework is embraced in order to connect network performance and the quality perceived by learners. Network quality of service indicators, like available bandwidth, latency, and jitter, and the ratio of the lost packets is directly related to quality of experience measures observed in learning sessions. Increased bandwidth allows delivery of increased video bitrates and longer latency and jitter result in increased start up delays and playback instability. Interruptions in learning and regular changes in the bitrate forbid continuity of learning and have an adverse impact on the engagement of the learners. QoE in this work is adopted as a utility function which combines the important perceptual variables through provided bitrate and buffering time and start up time. The adaptive streaming controller can map the observed QoS conditions onto bitrate selection decisions which are conscious of QoE using this mapping. The ensuing issue can thus be defined as maximisation of the learner QoE, as under varying conditions of dynamic wireless network, as the basis of the anticipated mechanism of communication-sensitive adaptive streaming.

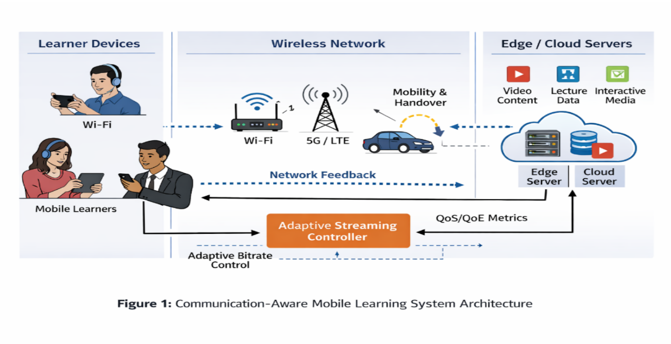

Figure 1: Communication-Aware Mobile Learning System Architecture

Fig. 1: Communication-aware mobile learning system architecture.

QoS/QoE-Aware Adaptive Streaming Algorithm

The proposed adaptive streaming algorithm will be designed based on the necessity to provide smooth content delivery of mobile learning application that would run across dynamic wireless networks. The proposed approach uses the communication-aware design, which employs real-time network feedback in the bitrate adaptation mechanism as opposed to the conventional adaptive mechanisms that use limited network indicators. The key challenge is to choose video bitrates that both accommodate real-time network capacity resources and also maintain video playback and continuity in educational systems when faced with changing wireless conditions. To this effect, the algorithm collaboratively mechanisms the network performance measures in conjunction with applications-level buffering behaviour to settle at a balanced trade off among quality, delay, and robustness.

The suggested adaptive streaming algorithm assumes that a collection of real-time measurements of the network and the client device, which consists of available bandwidth, end-to-end latency, packet jitter, and buffer occupancy, is passed into the algorithm. Available bandwidth estimation gives information on the sustainable transmission rate and latency and jitter give information on short-term network behaviour that can make the playback smooth. Buffer occupancy is considered as an important critical measurement of playback safety, which allows the algorithm to predict possible rebuffering. Due to these inputs, the streaming controller dynamically decides the correct bitrate level of videos to be applied to each content segment. The rationale behind the decisions is to maximise the stable bitrate selection chances so that it makes no attempts to aggressively add more quality during spikes in bandwidth, and it actively lowers quality when buffer underflow (or excessive delay) is observed. The algorithm causes the adaptive bitrate decisions to be made in real time as shown in Figure 2, inside a closed-loop control environment where the continuous feedback of the network and playback buffer give the adaptive decisions.

In order to improve playback stability even more, the algorithm adds anti-rebuffering and high bitrate alternate measures. An adaptation strategy that is buffer- and delay-sensitive is used where bit rate increments on a case-by-case basis are only allowed when a stable network condition and adequate headroom in the buffer are noted. On the other hand, when latency or jitter and packets loss are above predetermined thresholds, reductions in bitrate are immediately activated thus avoiding buffer underruns. Also, a smoothing constraint is instituted to narrow the frequency of the changes in bitrate to avoid visual quality swings that tend to distract a learner and lower QoE. Such design decisions allow the suggested algorithm to sustain the regular quality and surface of videos, in addition to reducing the service outages, regardless of the bandwidth variations associated with mobility and the network congestion.

To benchmark the performance, the adaptive streaming algorithm is compared to performances of representative base schemes used in the adaptive video delivery. A throughput-based ABR scheme picks bitrates using only an estimated available bandwidth hence very responsive yet easily subject to instability in fluctuating network conditions. ABR scheme using a buffer-based approach uses buffer occupied mainly to give bitrate control, providing a better stability but at the cost of responding

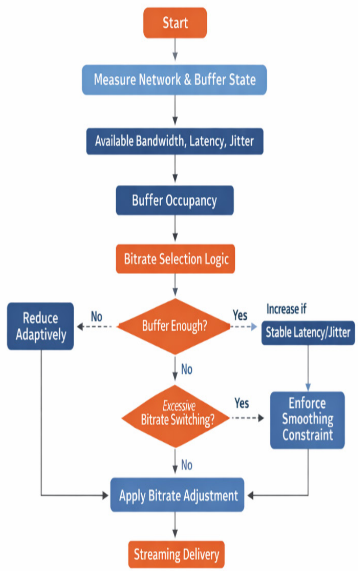

Fig. 2: Flowchart of the proposed QoS/QoE-aware adaptive streaming algorithm.

slowly to low-level network variations. Moreover, a fixed-bitrate streaming scheme is accounted as a reference point since it is a way of non-adaptive content delivery. These are the baseline methodologies, which offer a full-fledged comparison grid to determine the quality of the suggested QoS/QoE-conscious algorithm both in terms of network performance and quality as perceived by learners.

Performance Evaluation Setup

The effectiveness of the proposed communication-aware adaptive streaming framework is tested with the help of simulation-based environment that reflects real-life situation in mobile learning over wireless networks. A network simulation architecture is used to simulate heterogeneous wireless access technologies, such as Wi-Fi, cellular networks, and to simulate time-varying channel conditions, which are faced by mobile learners. To simulate realistic wireless communication behaviour the simulation environment includes stochastic bandwidth variability, queuing delay, the loss of packets and the impact of mobility induced handover effects. The video-based educational content is divided and delivered through adaptive-bitrate technology, and the duration of the learning sessions and segment lengths are set to reflect the common mobile learning consumption behaviours.

The parameters of wireless networks are taken so that realistic evaluation conditions will be established. Channel bandwidth is described as dynamic process and depends on mobility of users, background traffic and load of the network. The delay and jitter at the edges is brought in by changing queuing and scheduling of variable calls at access networks and core networks. The predefined movement patterns with varying speed profiles are used to model the mobility of the learners, allowing the assessment of the handover effects and temporary performance impairment in the course of content delivery. All of the major parameters of the simulation, such as network settings, video bitrate rates, buffer, and mobility were also summarised in Table 2 to make sure that the evaluation setup could be reproduced and its parameters understood.

In an attempt to evaluate the performance of the system systematically, various evaluation scenarios are addressed. The count of concurrent learners on the mobile learning platform is also diverse to study the scalability and resource contention conditions as the network load is increased. The effectiveness of the suggested adaptive streaming algorithm is tested with different motion speeds to determine its stability in different stationary or pedestrian and vehicle motion systems. Besides, the background traffic can also be tuned to different performance levels, thus the performance degradation under limited bandwidth can be studied. All the previous scenarios allow effectively assessing the network-level performance indicators as well as the perceived quality of the learners, which will form a substantial basis of comparison against the suggested approach with baseline streaming schemes assessments in the following results and discussion section.

Table 2: Simulation Parameters and Network Configuration

Parameter	Setting
Network type	Wi-Fi / LTE / 5G
Number of learners	10-100
Mobility speed	0-30 km/h
Channel bandwidth	2-50 Mbps
End-to-end latency	10-150 ms
Packet loss rate	0-3%
Video segment duration	2 s
Available bitrate levels	360p-1080p
Client buffer size	20-40 s
Evaluation metrics	Latency, throughput, QoE

Results and Discussion

Network Performance Analysis

Network-level efficiency of the suggested adaptive streaming architecture that takes into account communication is analysed in regards to end-to-end latency, throughput, good put, the ratio of the number of packets delivered, and jitter with different network parameters. With more concurrent learners, traditional streaming schemes have the observable increment in the latency time as a result of competition and overloading of the resources in the access network of wireless. On the other hand, the proposed method has much lower latency and decisions on streaming are adjusted depending on real-time network responses. The behaviour is shown in Figure 3, that is, the end-to-end latency versus the number of learners simultaneously. The findings indicate that the suggested approach can scale better as compared to baseline schemes, and the growth in latency is moderate even when the user density increases. The value of communication-aware adaptation is also manifested through the throughput and good put performance. Whereas throughput explains the rate of raw transmission, good put indicates the real rate of delivery of useful application information. The scheme proposed has a greater good put since it reduces the number of packets lost, retro transmissions, especially

Table 3: Network Performance Comparison

Scheme	Latency (ms)	Throughput (Mbps)	Packet Delivery Ratio (%)	Jitter (ms)
Fixed-bitrate streaming	135	8.2	91.3	22.4
Buffer-based ABR	112	10.5	94.6	17.8
Throughput-based ABR	118	11.1	93.9	19.2
Federated RL ABR	96	12.8	96.4	14.6
Proposed method	**82**	**14.2**	**98.1**	**10.3**

in congestional situations. There is also better ratio of packet delivery and lower jitter which means that the arrival of the packets will be more stable and that network reliability will also increase. These metrics of network performance across the various schemes in the streaming are quantitatively compared and a summary of the results was given in Table 3, which establishes that the proposed scheme notably delivers efficiency in terms of latency and robust delivery as compared to traditional schemes used in the study.

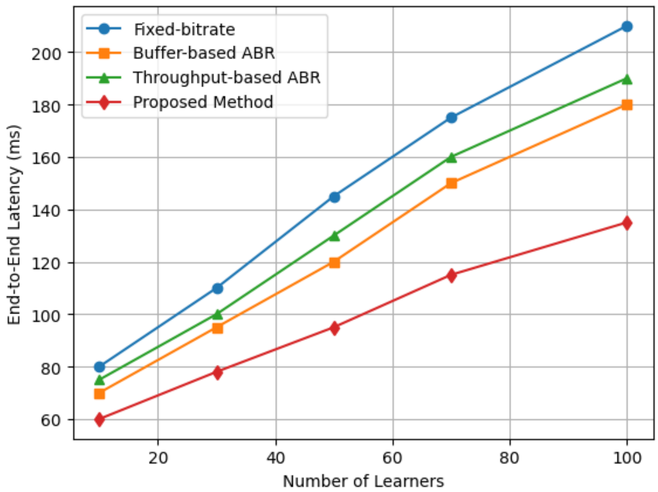

Fig. 3: End-to-End Latency versus Number of Concurrent Learners for Different Adaptive Streaming Schemes.

QoE Performance Evaluation

In terms of learner-centric, start-up delay, rebuffering ratio, average delivered bitrate and bitrate switching stability are used as a measure of quality of experience. The start-up delay is an important parameter in mobile learning because more than a specific delay might put off learners. This proposed adaptive streaming algorithm has a reduced start up delay since the initial bitrates are chosen on a conservative basis depending on the latency and buffer state hence achieving a faster initiation of playback as compared to throughput-based algorithms as well as fixed-bitrate algorithm. The proposed solution greatly minimises rebuffering ratio because it considers the buffer- and delay-aware adaptation logic. The algorithm is able to reduce playback disruption by actively reducing bitrate when buffer depletion risks are detected to occur when the bandwidth is variable. Simultaneously, both the mean transferred bitrate is large, which proves that its changes are positive even though no content quality is compromised. In addition, integration of bitrate smoothing limits leads to better bitrate stability, minimising frequent instances of quality fluctuation which is often seen with aggressive ABR schemes. These advantages of QoE are mathematically measured in Table 3 reporting an enhanced performance of the suggested approach and all measured QoE measures.

Comparative Analysis

A comparison of the sugges0ted communication-based adaptive streaming system and reference schemes reveals the benefits of optimization of both QoS and QoE goals. Throughput-based ABR schemes are very responsive to changes in bandwidth, however with respect to variable network conditions they are more unstable and rebuffering is more. Buffer-based schemes more stable, but less responsive. Constant-rate streaming works poorly in all conditions because it is not capable of going with network fluctuations. The suggested approach, in comparison, will provide the desirable compromise between the efficiency of networks and the quality perceived by the learners since it will incorporate several network indicators into the adjustment process. The findings reveal that there is an obvious trade-off between the QoS efficiency and QoE enhancement where the activation of the aggressive bitrate selection would enhance the current quality levels without being harmful to the ability to maintain steady playbacks. The proposed framework has successfully overcome this trade-off by the clear consideration of latency, jitter and buffer health, which leads to a reduction in network level overhead and an improvement in the learning experience. On the whole, it can be concluded that adaptation using communication awareness is a concept that should not be overlooked when it comes to scalability and reliability of mobile learning systems using heterogeneous networks.

Discussion on Seamless Learning Experience

The findings made in the above section have shown that communication-sensitive adaptive streaming is an important element in facilitating a smooth learning process in mobile contexts. The proposed framework reduces the number of playback interruptions and ensures the consistency of video quality, which are necessary in order to retain the continuity of learning, by expressly incorporating the feedback provided by the network level in the decision-making process of the streaming. Less time taken to start up and rebuffering allow the learner to follow through on educational content without having to rejoin it often thus facilitating the aspect of sustained attention and better learning. The results of these experiments show that communication-aware adaptation is especially adapted to the applications in the learning domain, where continuity and reliability are more crucial rather than aggressive quality maximisation.

Another important area of seamless mobile learning is robustness in the environment of mobility and dynamism of networks. The differences in bandwidth and delays caused by handover would be very detrimental to the delivery of content as learners transverse various coverage areas in a network. The suggested solution has a resilience to such dynamics that the selection of the bitrates is proactively adjusted according to the latency, jitter, and buffer well-being and not in response to the current changes in throughput. The design minimises the negative impact of the fluctuations that happen during the mobility, and guarantees a smoother playback when passing between wireless access points or cellular cells. As a result, learners have reduced service disruption even in high mobility situations that are also vital in facilitating ubiquitous learning.

Scalability is a key requirement of large-scale mobile learning implementation of increasing the number of simultaneous users. The communication-conscious framework possesses the strong scalability features as its efficient use of the available network resources and the ability to ensure the promised performance in the conditions of increasing the learner density. The system removes the risk of overloading the system and unfair distribution of resources by balancing the QoS effectiveness with the QoE optimization, so that service quality could be consistent among the users. These scalability characteristics have caused the proposed idea to be applicable in the deployment of the tools to an institutional level, e.g. smart campuses and online learning sites, where a consistent and dependable learning experience across the many network configurations is a major challenge.

Limitations and Future Work

Although the shares of the proposed communication-aware adaptive streaming framework are quite promising, a number of limitations need to be recognised. To begin with, the performance measurement is founded on the simulated network models, which are founded on the established assumptions about the variability of channels, the distribution of traffic, and the movement behaviour. Although these models are meant to be realistic to the conditions in the wireless environment, they might not adequately model the complexity and uncertainty of real world mobile networks, including sudden lack of interest, hardware limitations, or diversity in user's behaviour. As a result, the performance improvements witnessed can be different when implementing the framework in the real-life setting.

The other weakness of the current research is the lack of real circumstances of deployment and test. Even though an evaluation can be done through simulation based evaluation and can be controlled and repeatable, when doing the first real deployment, factors to consider are heterogeneity of devices, energy constraints, protocol overheads, and cross-layer interactions, which can affect the system performance. Demonstrating and testing the framework on actual mobile learning platforms or test beds would give more information about its practical feasibility, robustness as well as operational overhead, and would make the research results more generalizable.

The research findings can be used to rectify these limitations in future studies through a number of expansions of the proposed research framework. The idea of edge-assisted streaming optimization can also contribute to further lowering the latency and enhancing the scalability of streaming by utilising more computation and caching resources which are more proximate to learners. By implementing AI-aided prediction of the learner, the proactive adjustment strategies might be applied predicting the engagement plan and network demand and, therefore, increasing continuous learning and QoE further. Furthermore, the combination of the framework with the next-generation wireless technology, such as and later 5G features and 6G radars, would enable the investigation of ultra-reliable low-latency communication opportunities as well as intelligent slicing of the network to consider a large-scale mobile learning network. These extensions can enhance ultimately the reliability, flexibility and the smartness of subsequent mobile learning platforms.

Conclusion

The current paper has outlined a mobile learning systems communication-supported design that will cover the issue on the seamless content delivery in dynamic wireless networks. Through the incorporation of live network feedback into a QoS/QoE-conscious adaptive streaming system, the framework in question can efficiently balance the constraints of network performance on the one hand against quality needs, which, in turn, lie in the domain of the learners. Vast simulation evidence indicated that the scheme has major results on end-to-end latency, startup time, and rebuffering instances and has enhanced throughput, revolution of packet delivers and bitrate stability relative to traditional adaptive streaming plans. The effectiveness of the joint optimization of QoS and QoE metrics is supported by these improvements, which ensures learning continuity in different conditions of network load and mobility. Generally, the offered design offers a scalable solution to the next-generation mobile learning platforms that will work in the heterogeneous wireless environments, and also offer significant experience in the realisation of the intelligent and communication-aware educational system.

References

[1] Emara, S., Liu, D., Wang, F., & Li, B. (2024, May). Cascade: Enhancing Reinforcement Learning with Curriculum Federated Learning and Interference Avoidance—A Case Study in Adaptive Bitrate Selection. In *IEEE INFOCOM 2024-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)* (pp. 01-06). IEEE.

[2] Huang, T., Zhou, C., Zhang, R. X., Wu, C., & Sun, L. (2022). Learning tailored adaptive bitrate algorithms to heterogeneous network conditions: A domain-specific priors and meta-reinforcement learning approach. *IEEE Journal on Selected Areas in Communications*, *40*(8), 2485-2503.

[3] Huang, T., Zhou, C., Zhang, R. X., Wu, C., & Sun, L. (2023, May). Buffer awareness neural adaptive video streaming for avoiding extra buffer consumption. In *IEEE INFOCOM 2023-IEEE Conference on Computer Communications* (pp. 1-10). IEEE.

[4] Li, Q., Chen, Y., Zhang, A., Jiang, Y., Zou, L., Xu, Z., & Muntean, G. M. (2022). A super-resolution flexible video coding solution for improving live streaming quality. *IEEE Transactions on Multimedia*, *25*, 6341-6355.

[5] Ma, X., Li, Q., Zou, L., Peng, J., Zhou, J., Chai, J., & Muntean, G. M. (2022). QAVA: QoE-aware adaptive video bitrate aggregation for HTTP live streaming based on smart edge computing. *IEEE Transactions on Broadcasting*, *68*(3), 661-676.

[6] Mandan, N., Saxena, P., & Gupta, M. (2025). DRL Empowered On-policy and Off-policy ABR for 5G Mobile Ultra-HD Video Delivery. *Mobile Networks and Applications*, *30*(1), 72-85.

[7] Naresh, M., Saxena, P., & Gupta, M. (2023, June). Ppo-abr: Proximal policy optimization based deep reinforcement learning for adaptive bitrate streaming. In *2023 International Wireless Communications and Mobile Computing (IWCMC)* (pp. 199-204). IEEE.

[8] Vo, P. L., Nguyen, N. T., Luu, L., Dinh, C. T., Tran, N. H., & Le, T. A. (2023, July). Federated deep reinforcement learning-based bitrate adaptation for dynamic adaptive streaming over http. In *Asian Conference on Intelligent Information and Database Systems* (pp. 279-290). Cham: Springer Nature Switzerland.

[9] Wang, Z., Cui, Y., Hu, X., Wang, X., Ooi, W. T., Cao, Z., & Li, Y. (2021). Multilive: Adaptive bitrate control for low-delay multi-party interactive live streaming. *IEEE/ACM Transactions on Networking*, *30*(2), 923-938.

[10] Xu, Y., Li, X., Yang, Y., Lin, Z., Wang, L., & Li, W. (2023, June). Fedabr: A personalized federated reinforcement learning approach for adaptive video streaming. In *2023 IFIP Networking Conference (IFIP Networking)* (pp. 1-9). IEEE.

[11] Yu, E., Zhou, J., Li, Z., Tyson, G., Li, W., Zhang, X., & Xie, G. (2024). Mustang: Improving QoE for Real-Time Video in Cellular Networks by Masking Jitter. *ACM Transactions on Multimedia Computing, Communications and Applications*, *20*(9), 1-23.

[12] Zhang, J., Zuo, X., Xie, X., Wang, W., & Cui, Y. (2024, June). TransPortal: Keeping Applications Enjoying Tailored Transport Effortlessly. In *2024 IEEE/ACM 32nd International Symposium on Quality of Service (IWQoS)* (pp. 1-6). IEEE.

[13] Zhang, R. X., Yang, C., Wang, X., Huang, T., Wu, C., Liu, J., & Sun, L. (2022, October). Aggcast: Practical cost-effective scheduling for large-scale cloud-edge crowdsourced live streaming. In *Proceedings of the 30th ACM International Conference on Multimedia* (pp. 3026-3034).