Article

Quality of Experience Management in Mobile Networks: Techniques, Constraints, and Emerging Trends for Value-Added Services

Kinge Mbeke Theophane Osee[1*], Valery Nkemeni[1], Michael Ekonde Sone[2]

[1] Faculty of Engineering and Technology, Department of Electrical and Electronic Engineering, University of Buea, P.O. Box 63 Buea, Cameroon
[2] College of Technology, Department of Electrical and Electronic Engineering, University of Buea, P.O. Box 63 Buea, Cameroon
Email: kinge.mbeke@yahoo.com

Received: 17 March 2025; **Revised:** 6 May 2025; **Accepted:** 17 June 2025

Abstract: The integration of Quality of Experience Management (QoEM) into mobile networks has significantly transformed the telecommunications industry by aligning service delivery more closely with user expectations. This paradigm shift is particularly crucial as user perception of service quality (i.e., perceived QoE) has become a key differentiator in competitive telecom markets, directly impacting overall user satisfaction and retention. This paper presents a comprehensive review of current QoEM techniques, with a particular emphasis on Machine Learning (ML) approaches for predicting user experience and ensuring high-quality service delivery. Additionally, the integration of Software-Defined Networking (SDN) and Network Functions Virtualization (NFV) is highlighted as a key trend in the development of user centric management systems, enabling dynamic network adjustments based on real-time QoE feedback. However, despite these advancements, the transition from traditional Quality of Service (QoS) metrics to QoE-aware frameworks presents significant challenges. These include the complexity of balancing resource allocation across diverse services to maintain optimal user experiences, as well as technical constraints in real-time QoE monitoring. Furthermore, as demand for high-definition streaming and low-latency applications continues to grow, advanced traffic management solutions are becoming increasingly essential. This review also explores emerging trends in Value-Added Service(s) (VAS), particularly within the context of 5G and 6G networks. We conclude this paper by indicating that the effective advancement of QoEM in mobile networks requires interdisciplinary collaboration between academia and industry. Key areas of focus include network architecture, user behaviour analytics, and content delivery mechanisms. A multidisciplinary approach is essential for addressing the complexities of existing QoEM models and ensuring superior user experiences in next-generation networks.

Keywords: Quality of Experience (QoE), Quality of Experience Management, User satisfaction, Value-Added Service, Mobile Networks, Machine Learning, User-centric QoE

DOI: https://doi.org/10.37256/cnc.3120256766

1. Introduction

The continuous advancement in mobile network technologies is enabling a plethora of new multimedia streaming services [1]. To remain competitive in the race for user acquisition and retention, telecom operators are going beyond simply providing services to individual subscribers. As the mobile service market becomes increasingly sophisticated and competitive, telecom providers must prioritize customer-oriented services and performance indicators. To be competitive in the 5G era and beyond, operators must examine user experiences through metrics such as Quality of Experience (QoE). The telecom industry is rapidly evolving with a proliferation of Value-Added Services (VAS), and effective Quality of Experience Management (QoEM) is vital for delivering high-quality VAS. The significance of QoEM cannot be overstated as users demand more immersive and interactive applications, such as augmented reality (AR), virtual reality (VR), cloud gaming, and telemedicine. These services require both a solid network performance and a deep understanding of perceived QoE, a subjective evaluation together with other traditional Quality of Service (QoS) metrics that influence user satisfaction [2] [3].

QoE refers to the overall satisfaction users derive from a service, combining both technical performance metrics and personal perceptions [4] [5]. Since QoE is multidimensional, it requires advanced management techniques that can adapt to the dynamic conditions of mobile networks. Recent advancements in Machine Learning (ML) and Artificial Intelligence (AI) have brought about the development of more sophisticated QoEM strategies that utilize real-time data analytics to enhance user experiences [6]. Additionally, the imminence of 5G and future 6G technologies is set to transform QoEM by offering ultra-low latency and extensive connectivity, thus ushering in a new wave of applications that will require exceptional levels of service quality [7].

Despite these technological advancements, significant challenges remain in the field of QoEM. Issues such as scalability in high-density environments, real-time adaptation to changing user behaviours, and the complexities of guaranteeing security and data privacy in personalized QoE solutions continue to pose hurdles for effective implementation [8] [9]. More so, the interplay between QoE and QoS metrics requires further exploration to ensure that technical performance aligns with user satisfaction, exposing the need for a more integrated approach to QoEM [10] [11].

Therefore, this review aims to provide a comprehensive overview of existing QoEM techniques, their limitations, and emerging solutions tailored for the next generation of VAS. By synthesizing insights from emerging technologies, network engineering, ML, user behaviour analytics, this review addresses both current challenges and future opportunities, illuminating the path forward in QoEM. The interdisciplinary nature of this work stresses on the importance of collaboration between academia and industry to develop holistic QoE solutions that enhance user satisfaction and drive the evolution of mobile networks in this increasingly digital world [12] [13].

1.1 Contextualizing QoE in Mobile Networks

Advancements in telecom network technologies and services present significant challenges for network operators and service providers. Key challenges include the increasing diversity and complexity of infrastructures, devices, services, and technologies, increasing user mobility, new quality-performance demands from mobile multimedia applications, and the need to ensure complete service connectivity and availability [14]. Due to their limited scalability and flexibility, traditional network management systems struggle to deal with these issues. The demands and evolving structure of communication networks, combined with substantial capacity growth, led to the birth of new paradigms such as 5G and the evolution of mobile broadband.

5G marks the transition to a fully developed SDN and NFV ecosystem. Alongside this shift towards virtualization and softwarization, these technologies simplify network infrastructures by separating the control plane from the data plane and facilitate multi-tenancy. These changes are envisaged to bring several advantages to network vendors and Service Providers (SPs); of services like Cloud Gaming, Voice over Internet Protocol(VoIP), Development and Operations (DevOps), by drastically reducing network deployment and management costs, enhancing QoE, and driving the realization of new high-value services and applications such as IoT [1].

5G supports an abundance of new applications and services, including Ultra-High-Definition (UHD) and 3D video streaming, wearable devices, connected vehicles, the Tactile Internet, and the Industrial Internet. These applications are dynamic and flexible, with adaptability to changing QoE requirements and necessitating adjustments to network configurations. [15]. The wide range of potential 5G use cases foresees the existence of many customized services on the same physical infrastructure. There is a consensus within the research community on the huge potential that autonomic and cognitive systems can have in emerging 5G multi-Radio Access Technology (multi-RAT) networks. These networks include 5G-NR (New Radio) to provide high-speed and low-latency, 4G Long Term Evolution for coverage fallback, Wi-Fi 6/7 used for high-density indoor Internet of Things (IoT), Non-Terrestrial Networks (NTNs), for example, Starlink to serve remote/global coverage [16] [17].

Cognitive systems aim to bring intelligence to networks by allowing networks to detect the presence of a variety of conditions and adapt to them. Autonomic systems on the other hand, are even more ambitious and aim at making networks self-organizing and self-repairing entities. The explicit goal of autonomic networks is to create systems that manage themselves by supporting functions like self-configuration, self-optimization, self-healing, and self-protection, all with minimal external intervention even in the presence of adversarial conditions.

Despite the tremendous progress made in the last few years, there are still several critical issues and challenges that must be addressed to deploy effective and flexible autonomic 5G networks. These challenges have made QoEM a critical aspect of modern mobile networks, particularly as the demand for more sophisticated VAS like AR, VR, IoT applications, cloud gaming, and video streaming continues to rise. These services require both a substantial bandwidth and also impose stringent demands on latency and reliability to ensure a satisfactory user experience. For instance, AR and VR applications necessitate real-time responsiveness and high-quality visuals, which are heavily influenced by the underlying network performance [18] [19]. Similarly, cloud gaming services need consistently low latency to provide an immersive gaming experience while video streaming services, in order to maintain quality, must adapt to varying network conditions [20].

So, mastering the interplay between QoE, network performance, and user satisfaction is pivotal to mobile networks. QoE presents the inherently subjective view of reflecting the user's perception of service quality. This perception can be influenced by various factors, including network performance metrics (e.g., latency, jitter, packet loss) and individual user expectations [21] [22]. Hence, for QoEM to be effective, it must consider both technical performance and user-centric metrics to ensure that users feel satisfied with the services they receive.

1.2 Purpose of the Review

The rapid advances in wireless networks and mobile devices have brought forth a broad assortment of pervasive applications and services deployed to bring a multitude of comforts to users. Albeit with varied stringent concerns towards the QoE of these services. QoE is a multifaceted, user-centric, and transcendent measure that is applied to characterize the performance of mobile services from the user acceptance viewpoint. It is founded on a convoluted interplay of multiple entities, including network, system, application, service, and user. Therefore, an understanding of this interplay, the QoEM trajectory in mobile networks, the investigative attempts, the methodologies, the current obstacles being faced, and the lucrative endeavours in QoEM is conventionally needed.

The objective of this review is to provide a comprehensive overview of the existing QoEM techniques, their setbacks, and the emerging solutions tailored for the next generation of VAS. By synthesizing current research and practices, this review aims to highlight the critical aspects of QoEM in mobile networks, especially given the evolving context of user demands and technological advancements.

The review begins by illustrating the theoretical background and purpose, followed by an in-depth analysis of the manifold aspects of QoEM. After a large body of provision on operative QoEM and applicable methodologies in mobile networks, conclusions are drawn, and many pertinent research prospects are presented.

1.3 Contributions of this Paper

Although a significant amount of effort has been spent over the years on QoS management, there is still little focus on QoE in the existing literature. The intense competition of services in this context of dynamic mobility will push users to subscribe to overlay networks. The IP-based nature of emerging networks grabs the mobility feature of these new users, and mobile operators have an interest in offering desirable services in terms of QoE since they are the core competence edge in the new generation of networks. However, providing good QoE in mobile environments remains an open issue. One of the first major reasons is to find and formalize the principal technologies needed to achieve the QoE of a service and what their inter-relationships are [15]. Another issue is to put in place a future-proofing platform, capable of monitoring the QoE of services in an interface network/internetwork; the outputs from such monitoring solutions could be very profitable for operators to propose future services with assured QoE agreement. Also, it is hard to provide desirable QoE when a service is delivered over an overlay architecture, because a portion of the network providers do not control the end-to-end transmission, leading to bandwidth restrictions and intensive competition for the delivery of the service.

To contribute to the exploration of QoEM in mobile networks, this review provides the following contributions:

- Presents the limitations of current QoEM techniques for VAS. This is to understand the challenges faced by existing QoEM systems in order to identify areas that require improvement and innovation.

- Elaborates on the impact of emerging technologies (e.g., AI, edge computing, 6G) in optimising QoEM. In a bid to investigate the potential of new technologies towards enhancing QoEM, to provide insights into future directions for research and development.
- Identification of user-centric models needed for personalized QoE. To develop models that account for individual user preferences and behaviours, creating tailored QoE experiences that meet the diverse needs of users.

This review presents a novel contribution by advocating for an interdisciplinary approach to QoEM that combines insights from network engineering, ML, user behaviour analytics, and emerging technologies. By integrating these diverse fields, the review aims to propose innovative solutions for enhancing QoEM in mobile networks, such as leveraging ML algorithms to provide predictive insights into user behaviour, which can be used to optimize dynamic resource allocation [23] [24]. In addition, incorporating User Behaviour Analytics (UBA) can help tailor services to individual preferences, thereby enhancing overall user satisfaction [5].

1.4. Organization of the Paper

The rest of the paper is structured as follows: Section 2 highlights the methodology used for this review. Section 3 presents the theoretical background and conceptualization of QoEM This is followed by a discussion of the user-centric factors influencing QoE in Section 4. Section 5 discusses the evolution of mobile networks and their impact on QoE. Section 6 highlights the techniques employed for QoEM in mobile networks using some practical case studies. Section 7 discusses the limitations in QoEM, paving the way for the discussions of emerging trends and future directions in QoEM in Section 8. The paper ends with a synthesis of key findings, highlighting novel insights and a call to action in QoEM in Section 9.

2. Review Methodology

This section presents the research methodology; as shown in Figure 1 below, employed to investigate the research questions and scope of this review. It presents a description of the research design, data collection, sampling, data analysis procedures, and the total number of papers used at the different stages to achieve the study's objectives. This methodology, inspired by the approaches used in [25] [2] [19] [26], is structured to ensure that the research process is objective, reliable, and valid, offering a clear roadmap for addressing the research questions. By aligning the chosen approach with the nature of the research problem and the scope of the study, this section ensures that the findings contribute meaningfully to the field of QoEM in telecom networks in relation to VAS. The chosen methods are justified on the basis of their suitability for addressing the research objectives, guaranteeing a robust and credible study.

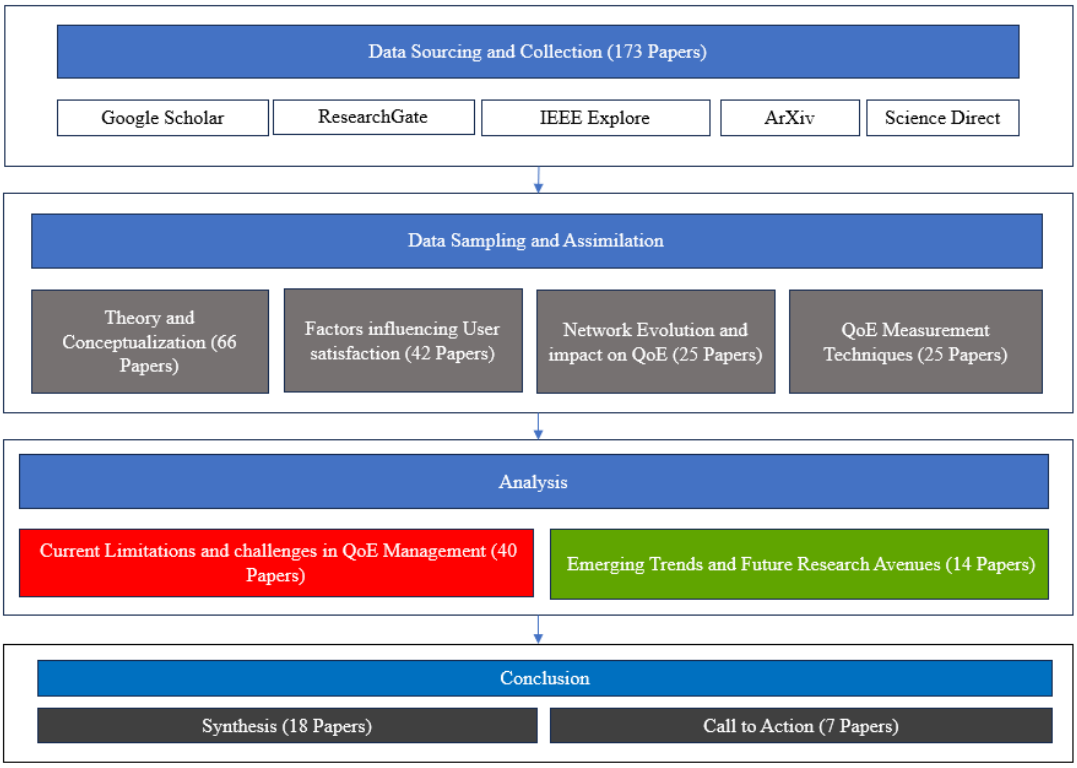

Figure 1: Research methodology

Keywords such as Quality of Experience, QoE, Mobile Networks evolution, User Satisfaction and VAS were used in isolation to perform preliminary searches. After obtaining a set of documents, we adjusted our search format by using different AND /or OR combinations of a string of those keywords for more comprehensive results. A tunnelling approach was used to expand our search by sourcing from the reference list of the top 10 search results or articles whose titles largely matched our theme for further reading. A total of 642 open-access articles written in English with at least one citation were obtained.

Further analysis was done on the titles, abstracts, keywords, introductions, and conclusions of those articles for coherence with our research questions. After this, a thorough reading of the articles of interest was done. Studies published within the last 10 years were prioritized before expanding our search to outside of this 10-year window. Studies whose main theme did not explicitly align with our research purpose were discarded, and a total of 172 studies were used to constitute our work. As described above, Figure 2 below visualizes the frequency distribution of the studies used per year of the 172 papers used to constitute our work.

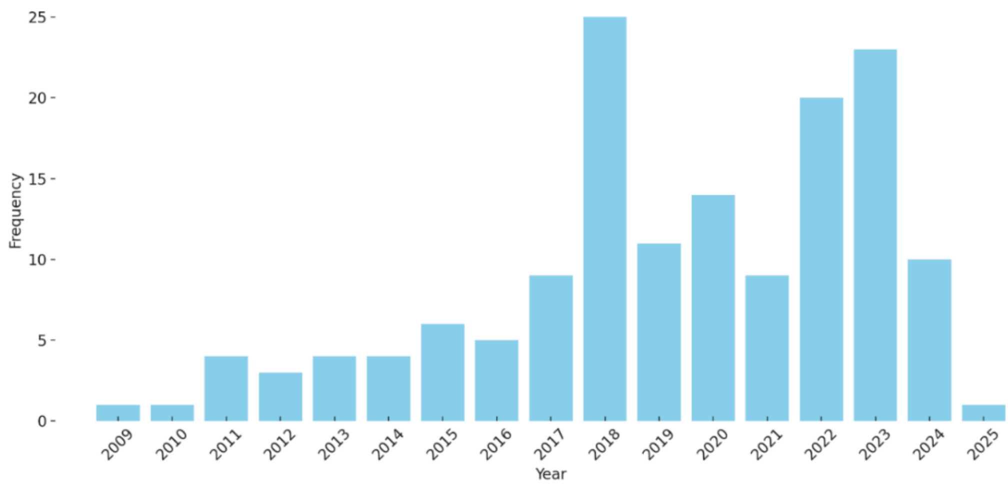

Figure 2: Studies frequency by year of publication

All comparative analyses, including tables and visual summaries presented in subsequent sections of this paper, are based on the authors' original synthesis of the reviewed literature unless otherwise stated.

3. Theoretical Background and QoE Conceptualization

The research on QoE in mobile networks has garnered great interest and evolved significantly over the years, reflecting the growing need to understand user satisfaction beyond traditional QoS metrics. The initial framework laid down by Allayiotis [27] introduced the MWQoE model. This model integrated various QoS predictors, such as latency, with non-intrusive data collected from mobile devices, user context, and web metrics. This marked a pivotal shift by demonstrating that a more comprehensive feature selection algorithm could yield more accurate predictions of user-reported QoE for mobile web services. However, it also revealed that many existing studies were limited by their network-centric focus, neglecting user context and subjective experience.

Finley et al [28] furthered this discourse by analysing the disparity between perceived and delivered QoS in mobile Internet communications. Their findings revealed a complex, non-linear relationship between network performance and user satisfaction, emphasizing that a user's acceptance of services hinges on the balance between perceived and delivered QoS. This insight underscored the necessity for operators to understand user perceptions to enhance service acceptance.

Building on these foundations, Alreshoodi and Woods [29], by surveying the correlation models between QoS and QoE for multimedia services, articulated the challenge of predicting QoE from objective QoS metrics. Noting that while many existing models offer partial solutions, a holistic approach to understanding user experience remains vital. This perspective was echoed in the work of Ickin et al [30], who argued that effective QoEM for mobile applications demands an integrated approach that extends beyond traditional QoS frameworks. This underscored the need to consider not only network performance but also application design, device capabilities, and user context to meet the diverse expectations of mobile users.

Mitra et al. [31] added a coat to this discussion by emphasizing the importance of user perceptions in QoE. They illuminated the multifaceted nature of QoE, which encompasses human-computer interaction, cognitive science, and economics. Their review reinforced the idea that QoE cannot be solely defined by technical metrics, as they shone light on the need for a more nuanced understanding of how context impacts user experience.

Al-Shehri et al. [32] to further contextualize this evolution, addressed the transition from a QoS-centric to a QoE-oriented evaluation in the era of 5G networks. They posited that as networks evolve, so too must the metrics used to assess quality, as they advocate for a dual focus on both QoS and QoE to enhance user satisfaction.

Li et al. [33] added a critical layer towards practical applications by proposing a crowdsensing-based analytical framework to understand user perceptions of Over-The-Top (OTT) web browsing. Their approach highlighted the limitations of traditional network evaluation methods, advocating for a more user-centric perspective in QoE assessment. This shift was crucial in driving improvements in service perception and network optimization.

Bouraqia et al. [1] contributed to this dialogue by assessing the challenges of measuring QoE in streaming services. They posited that traditional QoS metrics often fail to capture the nuances of user experience, which necessitated a re-evaluation of how QoE is defined and measured across different service types.

The tutorial and survey by Barakabitze et al. [15] further emphasized the importance of advanced network management paradigms, such as SDN and NFV, in ensuring QoE in future networks, underscoring the necessity for automated systems that can adapt to user requirements, thereby enhancing overall service delivery.

Finally, the comprehensive review carried out by Panahi et al. [34] not only focused on QoS metrics and user satisfaction models but also critically examines existing customer experience management frameworks. Thereby, encapsulating the ongoing research efforts aimed at refining methods for measuring and managing QoE in mobile networks, by illuminating the role of real-time data and automation in enhancing user experiences. This synthesis of existing literature presents a clear trajectory towards a more integrated and user-centric approach in understanding and managing QoE in mobile networks.

Users of the mobile network often have some expectations about the services provided to them by various solutions. Other factors aside, such as the user's cognitive and behavioural state, the cost of a service and the quality of the network services contribute to the determination of the QoE the user will have by using a particular network service. If users do not get their desired QoE from the network service they are using, they may decide to switch to another provider or may even stop using that service or application altogether. Thus, the measurement and prediction of QoE can avail users and let them enjoy personalized VAS from the various service providers.

3.1 Defining QoE and QoS in the Context of Mobile Networks

QoE and QoS are two important concepts in mobile networks, each serving distinct yet interrelated roles in the assessment of user satisfaction and service quality. QoS is basically a technical measure that quantifies the performance of a network in terms of metrics such as bandwidth, latency, packet loss, and jitter. It is objective in nature and can be measured using various tools and methodologies [35] [36] [37].

In contrast, QoE is a subjective measure that reflects an end user's overall acceptability of a service. It encompasses not only the technical performance of a service, but also the user's expectations, context, and personal experiences, making it inherently subjective [38] [39].

The distinction between QoE and QoS is vital because QoS can be optimized without necessarily improving QoE. For instance, a network may exhibit high QoS metrics, such as low latency and high throughput, and still, users may report low satisfaction due to factors like poor customer service or unmet expectations [28]. This highlights the criticality of understanding user perceptions and the contextual factors that influence their experiences, which are the crux of QoE [40] [41]. Figure 3 below depicts a QoE framework that illustrates the different factors to be considered in the evaluation of QoE.

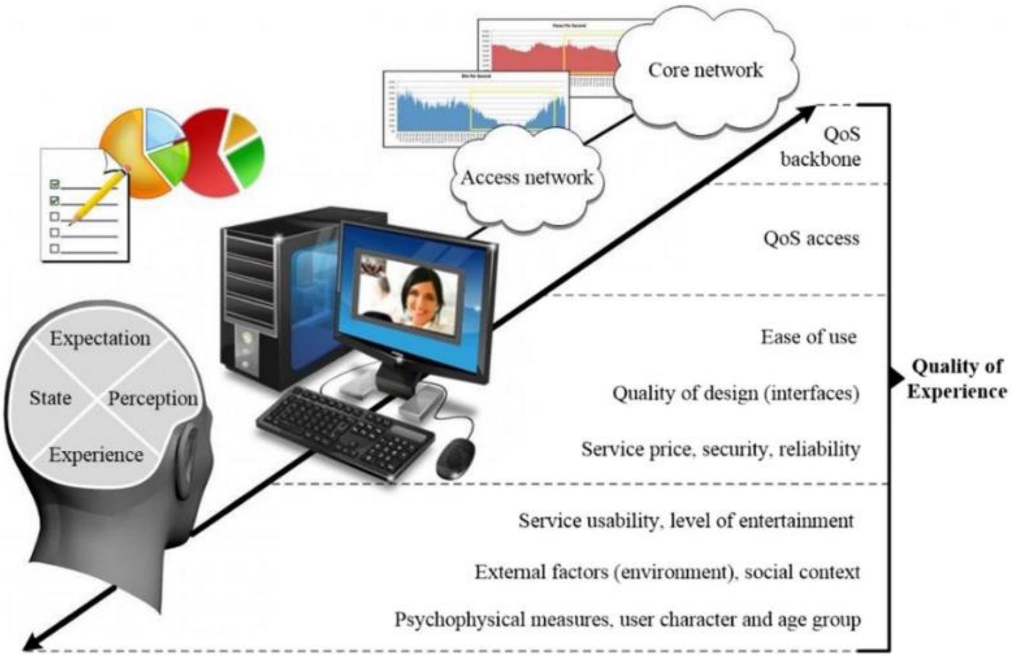

Figure 3: QoE framework [42]

So, in order to model the relationship between QoE, network metrics, and user satisfaction, a conceptual framework can be employed. This framework posits that QoE is influenced by both QoS metrics and user-specific factors, such as expectations and previous experiences. For example, a study carried out by Sackl et al [38] emphasizes that user expectations significantly shape their subjective quality perception. This indicated that QoE is not solely determined by technical performance but also by how well the service meets user expectations. Furthermore, the framework can incorporate various dimensions of service quality, such as reliability, responsiveness, and tangibles, which have been shown to affect customer satisfaction in mobile networks [43] [44].

In this conceptual framework, QoS metrics will serve as the foundational layer, providing the technical parameters necessary for service delivery. These metrics should be monitored and optimized by network operators to ensure a baseline level of service quality. Above this layer, user expectations and contextual factors interact with the QoS metrics to shape the QoE. This interaction can be modelled using ML and statistical techniques to predict user satisfaction based on both QoS data and user feedback [45]. Ultimately, this framework will underscore the necessity for mobile network providers to not only focus on technical improvements but also to understand and manage user perceptions to enhance overall QoE [36] [46].

3.2 QoE and User-Centric Models

User-centric QoE models are emerging as essential frameworks in understanding how users perceive and interact with digital services, especially in the sphere of streaming, gaming, and other multimedia applications. It is evident that traditional metrics such as bandwidth and latency, while important, do not fully encapsulate the user experience. User-centric models use perceived QoE as input to predict and optimize overall user satisfaction through intelligent design. These QoE models encompass a wider range of factors, including user behaviour, expectations, and contextual elements that tremendously influence how users evaluate their experiences. To address this range of factors, operators need to adopt the idea of a QoE-focused, user-centric network paradigm, in which both infrastructure and service are designed to meet the user's QoE demands, as demonstrated in Figure 4.

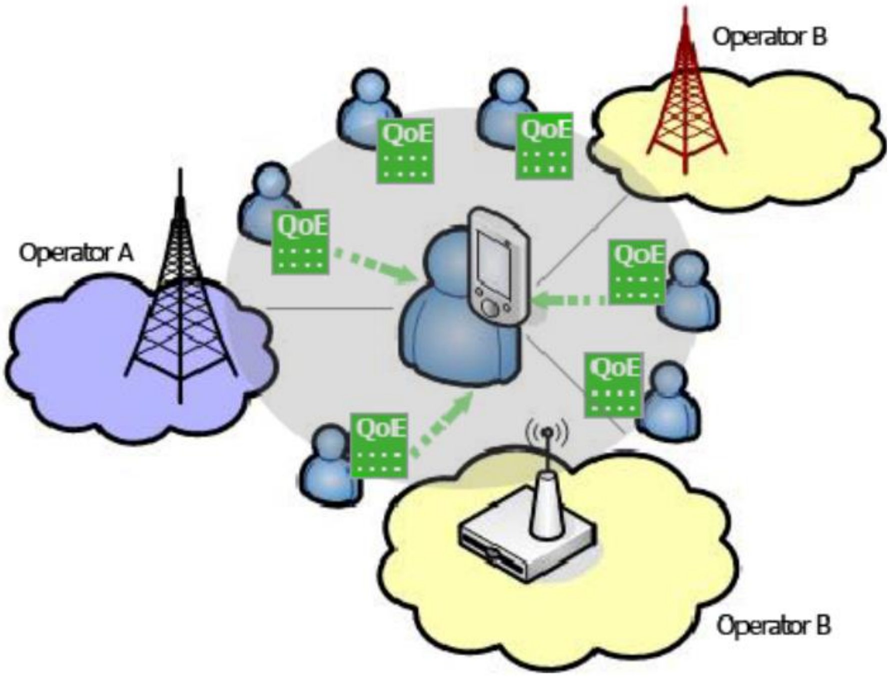

Figure 4: User-centric QoE-focused network paradigm [47]

We see that the comprehensive taxonomy of QoE factors can be categorized into two primary domains: network-related factors and user-related factors. On one hand, network-related factors include metrics such as latency, jitter, and throughput, which traditionally are critical in determining the technical performance of a service. For example, latency impacts the responsiveness of applications, while jitter impacts the consistency of data packet delivery. If not managed effectively, both can degrade the user's experience [1] [48]. However, these metrics alone do not provide a complete picture of user satisfaction.

On the other hand, user-related factors embody aspects like perception, expectations, and emotional responses [49]. These factors are vital since they reflect the subjective experience of the user. For instance, a user's emotional state can greatly influence their perception of service quality. Research has indicated that users with higher emotional reactivity tend to focus more on negative experiences, which adversely affect their overall satisfaction with a service [50] [51]. Furthermore, user expectations play a pivotal role because if a service fails to meet the anticipated quality, it can lead to user dissatisfaction, regardless of the actual technical performance [52].

Recent studies have highlighted the integration of emotional intelligence and user engagement as a vital component of QoE [53] [54] [55]. It has been shown that emotional intelligence allows users to navigate their experiences more effectively, influencing their satisfaction levels and their overall quality perception thereof [56]. In addition, the context in which a service is used; for example, the user's environment, the time of day, and concurrent activities, can also shape their QoE [57]. For instance, the same user watching a video in two different settings, say, a noisy environment and a quiet place, may report two different experiences, even if the technical quality of the stream doesn't change.

Therefore, user-centric QoE models present a shift from traditional metrics to a more holistic understanding of user experiences. By grouping QoE factors into network-related and user-related domains, researchers and practitioners can better face the complexities of user satisfaction in digital services. This approach both enhances the design and delivery of services and fosters a deeper understanding of the interplay that exists between technology and human emotion.

3.3 VAS and QoE

A VAS refers to a supplementary service that enhances a user's experience and provides additional value to the user beyond the basic telecom services. In mobile networks, VAS for example Mobile Payments, Over-The-Top (OTT) services, video calling/conferencing have become increasingly significant as they cater to the evolving needs of users who demand more interactive, immersive, and personalized experiences. With the coming of 5G and 6G, the role of VAS has substantially grown in shaping QoE, as these services require advanced network capabilities to deliver the desired high-quality performance. VAS such as AR, VR, cloud gaming, and telemedicine, exemplify the increasing demand for enhanced QoE. These applications not only rely on high bandwidth and low latency for service delivery but also require robust QoEM strategies to ensure user satisfaction. For instance, cloud gaming requires consistent performance to prevent latency and maintain user engagement, while XR applications necessitate real-time data processing and minimal latency to create immersive user experiences [58] [59].

3.4 Emerging VAS and their Unique QoEM Approaches

In this era of ever-changing and fast-growing mobile networks, VAS has gained a spark of interest increasing the imposition to adopt and use them. On the basis of this interest, VAS plays an important role in enhancing service providers' revenue and users' QoE in mobile networks.

Due to the ongoing metamorphosis induced by 5G technologies, multimedia streaming services have become the primary, if not, the exclusive traffic model of future networks. Ushering in an era that will see streaming content cover a large streaming rate and a high number of users with different streaming qualities will use different applications.

A. Cloud Gaming: These services allow users to play video games streamed from remote servers, eliminating the need for high-end hardware. Cloud gaming relies on stable network performance since minor fluctuations in latency or bandwidth can impact the gaming experience. To address this, adaptive bitrate streaming and lag compensation techniques have been proposed for QoEM[60] [59]. Predictive algorithms that adjust video quality based on real-time network conditions can enhance user satisfaction by minimizing interruptions. Building on the foundations of the underlying principle of user experience optimisation, by adapting to available resources and conditions, like a network's capabilities to improve QoS and QoE. To this effect, Yang et al [61] employed computation offloading strategies such as OPPOrtunistic Computation Offloading (OPPOCO) and ad-hoc cloudlet assistance to enhance mobile users' QoS and QoE.

B. AR/VR: AR/VR applications require ultra-low latency and high bandwidth. QoEM for these services must ensure stable frame rates and minimal motion-to-photon latency to prevent user discomfort. Techniques like edge computing can be employed to process data closer to the user, reducing latency and thereby improving overall QoE [62] [63]. Additionally, a deeper understanding of user behaviour and preferences can lead to personalized experiences that enhance engagement and satisfaction [64].

C. Telemedicine: These services have gained prominence, especially as an aftermath of the COVID-19 pandemic. These services demand reliable video and audio quality to facilitate remote consultations and effective communication, factors with a direct influence on user experience. To ensure effective communication between healthcare providers and patients, QoEM in telemedicine must address factors such as video resolution, audio clarity, and latency. The implementation of QoE assessment frameworks that monitor user feedback and network performance can help to optimize service delivery in real-time [65]. Moreover, guaranteeing data privacy and security is paramount in telemedicine. This necessitates robust QoEM strategies that comply with regulatory standards [66].

Hence, the growing role of VAS in mobile networks illuminates the need for effective QoEM strategies tailored to the unique requirements of each service. As mobile networks keep evolving, particularly with 5G rollout and beyond, integrating advanced technologies such as AI, edge computing, and ML will be essential for

QoE optimisation and the enhancement of user satisfaction across various VAS. Table 1 below provides a structured summary of the primary QoEM approaches discussed in section 3, highlighting the associated authors, adopted metrics, key focus areas, validation methods, strengths, limitations, and typical application domains

Table 1: Comparative analysis of QoEM approaches. (Arranged from most recent year downwards)

Reference	Year	Approach	Focus Area	Key Metrics Used	Strengths	Limitations
[34]	2024	Comparative analysis of existing literature, frameworks, tools, and ML approaches	QoE measurement frameworks and ML-based QoE prediction	MOS, stalling events, throughput, handover success, user device and network parameters	Comprehensive overview of frameworks and tools; includes both open- and closed-source; highlights integration of ML for QoE prediction	Lack of standard benchmarking datasets; black-box nature of ML models; challenges in interpretability and generalizability
[55]	2024	Comparative experiments on MELD dataset with five DL models (Transformer, CNN-LSTM, BERT-LSTM, MM-Transformer, proposed weighted Transformer)	Emotion recognition in intelligent user interfaces	AUC, F1 score	Superior feature extraction and multimodal fusion; dynamic User Interface adaptation; tested on public MELD dataset with robust generalization	Relies on MELD dataset limits; potential performance under unseen real-world conditions not evaluated; details on computational cost missing
[62]	2024	Simulation of Adaptive traffic engineering and QoS/QoE support for SOSDN in Containernet (Mininet extension); comparison with OSPF and PQ methods.	Service-oriented SDN QoS/QoE provisioning across networking and computing domains	Packet loss, delay, jitter, bandwidth, QoE scores, multi-criteria QoS integral metrics	Integrates networking and computing resource management; adaptive multi-criteria routing; considers individual user QoE; simulation-based validation	Complexity in setting weighting coefficients; scalability and real-world deployment challenges not deeply covered
[43]	2023	Pearson correlation and linear regression analysis	Service quality impact on customer satisfaction in Nepalese cellular mobile industry	Tangibles, Assurance, Reliability, Responsiveness, Empathy, Convenience, Complaint Handling, Network Quality	Uses both correlation and regression analysis; covers multiple service quality factors; relevant sample size (400 users)	Data collected only in Kathmandu Valley; limited to Nepal Telecom and Ncell users; primary data limitations
[45]	2023	GBDT-based ML Model with SMOTE and Factor Analysis using Confusion matrix, robustness test, comparative model evaluation (Decision Tree, GBDT, XGBoost, CatBoost)	User satisfaction prediction in mobile social networks	Accuracy, Recall, F1-Score, AUC (~0.99)	High generalization ability (GBDT F1 >90%), robust performance with parameter optimization, and addresses unbalanced data	Relies on data from one provider (China Mobile Beijing), potential overfitting risk without broader validation
[57]	2023	Systematic Literature Review with critical analysis of recent studies	Improving QoE in fog computing	Latency, packet loss, throughput, and user satisfaction	Comprehensive SLR highlighting open challenges and future research gaps	No original experimental data, mostly secondary analysis
[42]	2022	Experimental analysis with statistical comparison of spline approximation versus noisy signals	Cellular networks QoE/QoS monitoring and enhancement	Key Performance Indicators (KPI), Key Quality Indicators (KQI), Mean Opinion Score (MOS), Root-mean-square error	Real-time computation, improved accuracy with confidence intervals, simple calculations with CHS splines	No external datasets used/generated; lacks broader experimental validation beyond simulations
[50]	2022	Paired t-tests, Pearson correlations, AMOS structural equation modelling using APIM, bootstrap mediation analysis	Effect of emotional reactivity on marital quality and mediating role of perceived partner responsiveness in Chinese middle-aged couples	Emotion Reactivity Scale (ERS), Perceived Partner Responsiveness Scale (PPRS), Quality of Marriage Index (QMI)	Large sample size of 550 couples from diverse regions in China; use of validated scales; consideration of partner and actor effects	Focus limited to emotional reactivity, perceived responsiveness, and marital quality, without personality, socioeconomic, or attachment style considerations
[51]	2022	Multilevel modelling of Ecological Momentary Assessment (EMA) data over 7 days	Sleep quality and emotion regulation in young adults (18–24 years)	Self-reported sleep quality and duration; positive and negative emotion intensity and duration; positive and negative emotion regulation strategies assessed multiple times daily	Naturalistic moment-to-moment data collection; focus on both positive and negative emotions; multi-level modelling	Self-report sleep measures without actigraphy; relatively small sample (N=101); limited range of sleep duration; no contextual data on emotional episodes
[59]	2022	Systematic literature review of 33 recent (≤5 years) scholarly articles from multiple databases	Networking issues and solutions related to cloud gaming	Latency, Bandwidth, Delay, Packet Loss, QoE, Graphics Quality, Cost, Complexity	Comprehensive summary of key network challenges and various solutions including edge computing and ML	Limited literature scope, possible exclusion of newer sources; needs extension with more databases and tools

[63]	2022	Simulation-based experiments with haptic datasets and congestion models, metrics evaluation via QoS and QoE measurements	QoS/QoE provisioning for delay-sensitive tactile internet and teleoperation applications	SNR, PSNR, SSIM, HSSIM, MSE, MOS	Dynamic haptic codec selection reducing congestion, balancing stability and transparency, real-time network congestion estimation using ECN and LSTM	Uses TCP protocol which could add extra overhead; currently mostly simulation-based, future plans for real device integration
[65]	2022	Comprehensive survey and review	QoE-driven IoT architecture, including system design, resource management, ML-based prediction	QoE Cause Factors: user, application, service, network, physical/system metrics (e.g., transmission rate, delay, jitter, energy consumption)	Provides holistic and extensive classification of QoE factors, detailed mapping of metrics and ML approaches in IoT; discusses resource management solutions	No original experimental evaluation; relies on comprehensive literature analysis without proposing new models
[49]	2021	Subjective testing with dataset collection from users in different areas and groups; statistical analysis with Pearson correlation, Cohen's Kappa, MAPE; ANN training and validation	QoE modelling under different operating situations: area diversity and user diversity in cellular networks	QoE, QoS parameters (device, radio, data parameters), Cohen's Kappa for Inter-Rater Reliability, Mean Absolute Percentage Error (MAPE)	Addresses the impact of area density and user groups on QoE; uses IRR to verify dataset reliability; applicable to LTE and 5G technologies; links QoS to business RoI	Limited to datasets from two areas and two user groups; subjective testing in real environments lacks full control of network factors; only four multimedia applications were tested
[15]	2020	Tutorial and Survey	QoEM of multimedia streaming in future softwarized networks	QoE metrics (subjective/objective), QoS, QoBiz, network and user parameters	Comprehensive overview of QoEM integrating SDN/NFV, emerging architectures, and new application domains (AR/VR, gaming)	Limited experimental validation, mainly survey-based; practical implementations sparsely covered
[1]	2020	Synthesizes prior studies, standards, ITU recommendations, and databases	QoE measurement, modelling, control, challenges in streaming	QoE influencing factors, subjective MOS, objective QoS parameters, hybrid metrics	Comprehensive overview of QoE measurement techniques and challenges; covers subjective, objective, hybrid approaches	Mainly a survey, does not propose new models; ML and ethical challenges only briefly discussed
[64]	2019	Qualitative synthesis of past research with some quantitative summarization of QoS/QoE metrics	Review of QoE in cloud gaming models, frameworks and QoS impact on gaming experience	QoE (MOS), delay, jitter, packet loss, frame rate, bitrate	Comprehensive literature survey covering both subjective/objective QoE; identifies key QoS parameters, highlights gaps and open issues	Lacks new experimental data; depends on existing studies; some models reviewed lack integrated QoE reporting
[56]	2018	Quantitative study examining mediation effects using survey data	Impact of abandonment schema on marital quality via trait emotional intelligence	Abandonment Schema Scale, Trait Emotional Intelligence (trait EI) measure, Marital Quality scales (conflict resolution, communication, marital satisfaction ENRICH subscales)	Controlled for socioeconomic variables; used validated scales (ENRICH); first study linking abandonment schema and trait EI	Cross-sectional data limits causal inference; data only from Iranian married women; did not control for other psychological mediators (e.g., attachment styles)
[31]	2018	Survey and comparative analysis of state-of-the-art QoE modelling, measurement and prediction methods	Comprehensive review	Multiple QoE and QoS parameters, context parameters, user ratings (MOS etc.)	Thorough compilation and critique of current approaches; highlights importance of multi-parameter and time-based QoE modelling; identifies challenges related to context and unified single-scale QoE measurement	Does not provide new experimental or empirical evaluation; does not address regulatory and ethical concerns regarding user data
[33]	2018	Analytical framework using mobile crowdsensing with ML potential on an LTE network	OTT web browsing service perception degradation analysis	Key Quality Indicators (KQIs): first packet delay, page delay, service intensity, KPI correlations	Uses real user data from smartphones; comprehensive factor analysis; proposes a framework and algorithms	No cooperation with network operators for real-time verification; predictive model integration is future work
[46]	2018	Literature review, case studies on mobile Web browsing QoE, conceptual models and summary of prior work	QoEM for future networks focusing on multimedia and web services	Perceived Web site loading time, aesthetics, usability, quality of information, number of taps, network QoS parameters	Comprehensive multidimensional QoE analysis integrating multiple influence factors (IFs) and features, consideration of mobile vs desktop contexts, holistic overview of QoEM challenges and frameworks	Limited concrete implementation details, mostly conceptual and survey nature; lack of a unified framework fully addressing all influencing factors simultaneously
[60]	2018	Network emulation and preliminary subjective tests of Real-time lag compensation in cloud gaming.	Lag compensation for FPS cloud gaming	Network latency, QoE scores	Real-time lag equalization, open-source platform use	Limited scale, early-stage VM deployment
[61]	2018	Opportunistic Computation Offloading (OPPOCO) simulation using OPNET based on real mobility data from Haggle Project	Mobile edge computing, opportunistic offloading via ad-hoc cloudlet-assisted modes	Number of serviced nodes, computation capacity, QoS, QoE	Novel OCS mode balancing remote cloud and ad-hoc cloudlet offloading; energy-efficient and practical	Simulation limitations: absence of AP positions, inability to simulate certain offloading modes

[66]	2018	Simulation-based performance analysis comparing QoE, profits, and fairness	Collaboration between OTT providers and ISPs for joint QoEM in multimedia services	QoE delivered, provider profit, QoE fairness index, customer churn	Proposes a general reference architecture for collaboration; integrates economic and technical views; compares approaches with simulations	Practical obstacles like network neutrality and privacy concerns, dependence on user consent for data sharing, lack of real-world deployment
[32]	2017	Systematic literature review, classification of metrics, comparison of subjective and objective QoE metrics, discussion of future directions	Comprehensive taxonomy and analysis of telecom metrics; evolution from QoS to QoE; metric use in emerging systems (5G)	QoS metrics (e.g., delay, throughput, packet losses), QoE subjective (MOS, DSCQS), QoE objective, UX metrics, ARPU, customer churn	Thorough overview of major metric categories; highlights complexity in metric bundling and stakeholder views; emphasizes dual QoS-QoE evaluation paradigm, especially in 5G; discusses challenges in real-time and subjective metric use	No novel metric proposals; limited experimental validation; complexity of integrating multi-stakeholder views remains an open challenge
[27]	2017	Lab experiments with MOS comparison of the User-centered MWQoE model	Mobile Web	QoS, context metrics, Bayesian MWQoE metric, MOS	Non-intrusive, context-aware, validated with user feedback	Limited real-world scale, needs more data
[28]	2017	Field study combining user surveys and device-based network measurements	Mobile user satisfaction related to network speed and availability	TCP download throughput (min, median, last), upload throughput, latency (RTT), measurement burstiness, number of measured locations, device type, Likert-scale user satisfaction scores	Large real-world dataset, integration of subjective and objective data, considers temporal and spatial factors	Basic model fits, some predictors like upload throughput not significant, no direct signal strength metric
[38]	2017	Empirical user studies and modelling	User expectations in QoE for networked multimedia services	Subjective quality ratings (MOS), expectation questionnaires, quality prediction error reduction	Integrates expectations explicitly into QoE models; proposes direct assessment of expectations; controlled experimental setups for triggering expectations; improves prediction accuracy	Lab-based studies with limited real-world validity; some influence of test paradigms on expectations ("Schrödinger's cat problem"); complexity of questionnaires
[58]	2017	Experimental controlled indoor network setup with network emulator; subjective testing (MOS) with 40 subjects; objective video quality assessment; psychometric curve fitting	Mapping network QoS to user-perceived QoE in 2D and 3D video streaming under network impairments	Packet loss, jitter, delay, throughput, QoE (MOS), VQM, SSIM, psychometric functions	Comprehensive analysis using multiple video sets, including 2D and stereoscopic 3D, controlled network emulator setup, psychometric curve modelling	Focus on RTP video streaming; may not generalize to all streaming protocols like HTTP/TCP; limited to video content types tested
[39]	2016	Experimental usability testing of 30 subjects with four variants of virtual personal assistants (audio-only to immersive 3D)	QoEM evaluation for multimodal virtual personal assistants with varying levels of immersion	Presence, Involvement, Attention, Reliability, Dependency, Easiness, Satisfaction, Expectations (8 dependent variables)	Developed a scale for QoE based on unique variables per variant; demonstrated highest QoE with immersive 3D system; used Exploratory Factor Analysis to focus on significant variables	Small sample size (30 subjects), diversity in subject background; limited range of assistant tasks; subjective perceptions influenced by novelty of virtual assistant variants; need for more comprehensive task testing
[40]	2016	End-user perspective survey	QoS of mobile networks in Afghanistan	Call quality, network coverage, user satisfaction	Large sample size (1,515 users), detailed statistical analysis, and proposed practical technical solutions	Focused primarily on end-user perception, limited network-side measurement
[41]	2016	Layered QoEM framework	QoE evaluation and management in Multimedia IoT applications	Mean Opinion Score (MOS), 95% Confidence Interval, Video bitrate, Data accuracy, Network delay, Data presentation type	Comprehensive layered approach considering multiple influence factors across IoT architecture layers; Practical validation with vehicular MIoT application; Generalizable framework with a second smart surveillance use case	Limited user population (24 subjects), limited to specific test conditions (vehicular MIoT); Evaluation focused on subjective testing without extensive real-world deployment
[36]	2015	Conceptual Framework and Simulation-based Study	End-to-end QoEM in mobile cellular networks (LTE case study)	QoE level (e.g. MOS), VoIP flows, QoE reporting period, resource allocation metrics	Proposes a detailed QoEM framework with three building blocks (QoE-controller, QoE-monitor, QoE-manager); addresses signalling overhead and accuracy; incorporates load balancing between macro and small cells	Simulation-based results; complexity of real-time QoE acquisition and integration; potential privacy issues with some QoE models; focus on VoIP flows mainly
[48]	2015	Analysis and integration of numerous subjective studies, technical evaluations, and existing literature	QoEM in HTTP Adaptive Streaming (HAS)	Stalling, initial delay, adaptation amplitude and frequency, bandwidth utilization,	Thorough review of subjective and objective HAS QoE studies; multidimensional adaptation analysis; stakeholder	Mostly relies on synthesizing prior work; lacks novel empirical data; some conflicting results in referenced studies

				image quality, frame rate, resolution	perspective; identification of open issues and future challenges	
[37]	2014	Surveys and analysis of existing literature; large-scale subjective tests, objective evaluation, data mining techniques	Evolution of video quality assessment from QoS to QoE	MOS, DMOS, QoS parameters, Quality Metrics, User behaviours	Comprehensive overview covering subjective, objective, and data-driven methods,	No new experimental data, mostly review; some methods limited by lab environment applicability and cost,
[29]	2013	Survey on QoS/QoE Models	Multimedia Services	Delay, Throughput, Packet Loss	Broad taxonomy of QoS-QoE relations.	No experimental verification.
[44]	2013	Empirical study with structural equation modelling (SEM)	Mobile service quality and its impact on customer satisfaction	Availability, perceived risk, ease of use, compatibility of devices, and entertainment services), Customer satisfaction, Perceived risk	Developed a scale specifically including mobile device compatibility, analysed relationships between dimensions and satisfaction; used validated measurement model.	Focused only on mobile phones as devices; sample details not fully described; may not generalize to all mobile services or geographic regions
[30]	2012	4-week user study with Experience Sampling Method (ESM), Day Reconstruction Method (DRM), Android sensor logs	Mobile application users in natural daily environments	User-perceived QoE (MOS), QoS metrics (SRT, RTT, throughput), context data (network, device, usage)	Combined unobtrusive automatic sensing with real-time user feedback; included both contextual and network factors; multi-faceted QoE analysis	Limited capture of extreme network conditions; challenges in capturing the full variety of QoS metrics due to device and privacy constraints; relatively short study duration
[35]	2011	SLA-based bandwidth reservation scheme with Bandwidth Broker. Simulation over 20 mobile WiMAX networks with varying IPTV/non-IPTV traffic loads	Ensuring QoS for mobile IPTV over mobile WiMAX networks by dynamic bandwidth reservation through SLA negotiation	IPTV user satisfaction level, bandwidth utilization	Increases IPTV user satisfaction without significantly reducing total bandwidth utilization; Dynamic and scalable bandwidth allocation	Limited to simulation results, real-world deployment issues not addressed
[47]	2011	Conceptual framework and experimental approach for user-centric QoE-based network selection	User-centric mobile internet network selection, QoE modelling, middleware design, decentralized QoE knowledge base	MOS, cost, security, energy saving	Clear presentation of the user-driven decentralized QoE concept and integration with middleware; thorough explanation of testing methodology (Agile, TDD, Living Labs)	Limited implementation details of the distributed knowledge base; lack of large-scale real-world test results in the paper; conceptual focus
[52]	2011	Inter-disciplinary user-centric QoE evaluation	Multimedia VoIP service quality from the user perspective	User perception, conjoint analysis utilities, UTAUT factor, speech codec quality levels	Combines laboratory speech quality tests with user behaviour and intention models; holistic analysis of acceptance and usage intention	Limited to VoIP speech services; results from controlled user clinic, limited long-term adoption context
Note: All comparisons and categorizations reflect the authors' synthesis of referenced literature and do not represent results of new experiments unless indicated						

The comparative analysis of QoEM approaches presented in Table 1 highlights the diversity of existing approaches for QoEM for VAS services, each presenting specific advantages and inherent challenges. Thus, emphasizing the necessity for hybrid or adaptive strategies that combine the strengths of multiple paradigms to address the complex and dynamic requirements of next-generation mobile services. In the subsequent sections, we explore the factors influencing QoE before looking at the technical methods employed for QoEM and evolving trends that aim to bridge these gaps.

4. Factors Influencing User Satisfaction and QoE

To efficiently design and improve products and services in contemporary digital landscapes, it is essential to understand how QoE impacts user satisfaction. Research posits that numerous factors contribute to users' perceptions and overall satisfaction, including product quality, usability, customer support, pricing, and personalization. In this chapter, we present a synthesis of these factors.

4.1 User-Specific Factors

Product Quality: Product quality is a fundamental determinant of user satisfaction. Research has shown that a superior product quality positively correlates with higher satisfaction levels among users. Especially when users have considerable product experience.

Borsci et al. [67] confirm that users with more experience report greater satisfaction. This suggested that high-quality products are more likely to foster positive user experiences. Quality incorporates various dimensions, including performance, reliability, and durability, which as a collective whole influence a user's willingness to recommend a product and return for future purchases.

Usability and User Experience: Significantly affects a user's perceived QoE and overall satisfaction. Ke and Su in [68] emphasize that usability dimensions closely align with user experience and mediate the relationship between a system's success factors and its net benefits.

To achieve increased satisfaction, effective usability necessitates that users can perform tasks without unnecessary difficulties. [69] [70] further assessed usability in specific contexts, reinforcing that positive usability experiences, especially in technology use among older adults, directly influence users' attitudes toward technology. More so, the Usability Metric for User Experience (UMUX) framework detailed by Kamil [71] stressed that evaluating usability via properly selected metrics can yield insights about user satisfaction, making it an important consideration for product design.

Customer Support: Another critical aspect influencing user satisfaction is customer support. Promptness and effectiveness in delivering customer support can alleviate user frustrations and foster trust. [72] highlights that supportive and effective assistance contributes to a user's perceived value and experience when engaging with a product or service. High-quality support that addresses user concerns can mitigate negative experiences, thereby significantly enhancing overall satisfaction.

Price and Value: The study carried out by [73] postulates that e-commerce platforms that effectively utilize personalized marketing approaches; to enhance user experiences and optimize customer interactions, improve perceptions of value. Also, price sensitivity varies among users, making perceived value a significant influencer of satisfaction. Therefore, users are more likely to feel satisfied when the perceived benefits of a product outweigh its cost, indicating that optimal pricing strategies are essential for maintaining user satisfaction.

Personalization and Customization: *Is* seen as a vital factor in enhancing user satisfaction, tailoring experiences to individual preferences can significantly boost engagement. In [74] the authors describe how web personalization; delivering relevant content to users based on their preferences and behaviours, augments user interaction and satisfaction. Similarly, Zheng et al [75] highlighted that user experience in mass customization hinges on the personalization capabilities that cater to user needs. Providing social and emotional interactions designed to enhance satisfaction. In addition, incorporating personal values into service design, as discussed in [76], can lead to more meaningful and satisfying user experiences, particularly in the gaming industry where co-creative experiences are pivotal.

Contextual Factors: These factors, while important, are highly variable across user populations and scenarios. They include Device Capabilities (Screen size, processing power, and battery life impact the ability to render high-quality multimedia content), User Expectations and Context (that vary by user demographics, context of use, for example, commuting vs. home use, and prior experience with similar services) and Content Type and Sensitivity (Different services, for example, video streaming, gaming, video conferencing, having varying QoE sensitivities based on their interactivity, latency tolerance, and resolution demands) [1] [31].

Table 2 consolidates the user-specific factors discussed thus far that influence user satisfaction in mobile network services, highlighting their impacts, affected service categories, and supporting references.

Table 2: Summary of user-specific factors influencing QoE in mobile networks

User-Specific Factor	Impact on QoE	Services Highly Impacted	Criticality Level	Reference
Product Quality	Overall service stability, functionality richness, and absence of bugs.	Streaming services, Online Gaming	High	[67] [77] [27] [78]
Usability and User Experience	Intuitive navigation, ease of service use, and low cognitive load.	All Services	Medium - High	[68] [69] [70] [71]
Customer Support	Responsiveness and effectiveness of customer care teams impact satisfaction.	Telco Services, Cloud Services	Medium - High	[72] [13] [36] [40]
Price and Value	User satisfaction is influenced by the perceived cost-benefit ratio of the service.	Subscription-based Services, VoIP	Medium -High	[31] [64] [1] [72]
Personalization and Customization	Tailored recommendations and adaptive content improve perceived relevance and enjoyment.	Wearable devices, Streaming Services	Medium - High	[74] [15] [75] [76]
User Expectations	Quality degradation perception based on context, Tolerance for delays,	All Multimedia Services	High	[34] [6] [9] [11]

Environmental Context	Movement (commuting), surroundings influence signal quality and perception.	VoIP, Video streaming	Medium - High	[1] [19] [40] [79]
Device Capability	Limits rendering quality, affects battery consumption, and responsiveness.	Mobile Streaming, Video Conferencing	Medium -High	[15] [7] [31] [9]
Content Type and Sensitivity	Higher demands for bandwidth and resolution for sensitive content types.	4K Streaming, Cloud Gaming, AR/VR	Medium - High	[2] [22] [79] [58]
Note: All comparisons and categorizations reflect the authors' synthesis of referenced literature and do not represent results of new experiments unless indicated				

4.2 Network Factors

Research has already established the relationship between network QoS parameters and QoE outcomes [1] [15] [31] [34] . Thus, in this subsection, we proceed directly to a focused analysis of the most critical technical factors. The aim is to synthesize and highlight the specific technical metrics that exert the greatest global influence on user-perceived satisfaction in mobile environments. Table 3 presents the key technical parameters affecting user-perceived QoE, derived from the selected studies, and their typical impacts on mobile network services.

Table 3: Summary of network factors impacting QoE in mobile networks

Technical Metric	QoE Impact	Services Highly Impacted	Criticality Level	Reference(s)
Latency	Reduces responsiveness, critical for real-time applications.	Online Gaming, Video Conferencing, AR/VR Services	High	[59] [7] [11] [19]
Packet Loss	Causes media freezes, distortions, and loss of voice quality.	Video Streaming, VoIP, Live Broadcasting	High	[7] [11] [13] [19]
Jitter	Introduces instability in packet delivery, degrades live communications.	VoIP, Online Gaming, Remote Control Apps	Medium - High	[13] [15] [20] [57]
Throughput/Bandwidth	Affects media quality, buffering, and download/upload speeds.	Streaming Services, Cloud Gaming, IoT Apps	High	[59] [9] [38] [57]
Bitrate Adaptation Events	Perceived as quality degradation when frequent or abrupt.	Adaptive Streaming (DASH, HLS), Cloud Gaming	Medium	[15] [20] [38]
Note: All comparisons and categorizations reflect the authors' synthesis of referenced literature and do not represent results of new experiments unless indicated				

4.3 Factors Criticality and Service Sensitivity Analysis

After identifying both the user-specific and technical factors influencing QoE, this subsection presents a factor criticality and service sensitivity analysis. First, a combined criticality heatmap highlights the overall importance of each factor based on its potential impact on user satisfaction across mobile services. Secondly, a service sensitivity network diagram depicts the relationships between individual QoE factors and the specific service categories they most affect, providing insights into service-specific vulnerabilities. Together, these analyses offer a comprehensive understanding of both the global significance and the targeted influence of QoE determinants in mobile network environments.

Figure 5 presents the combined criticality heatmap of the key factors influencing QoE in mobile networks, incorporating both network and non-network factors. Each factor is mapped based on its criticality level (Medium, Medium-High, or High) derived from literature and analysis, with these levels represented by green, orange and red colours respectively on the plot. This visualization aims to provide a rapid identification of the most critical factors, such as latency, packet loss, and user expectations, which demand prioritized attention for QoE optimization efforts across diverse mobile services.

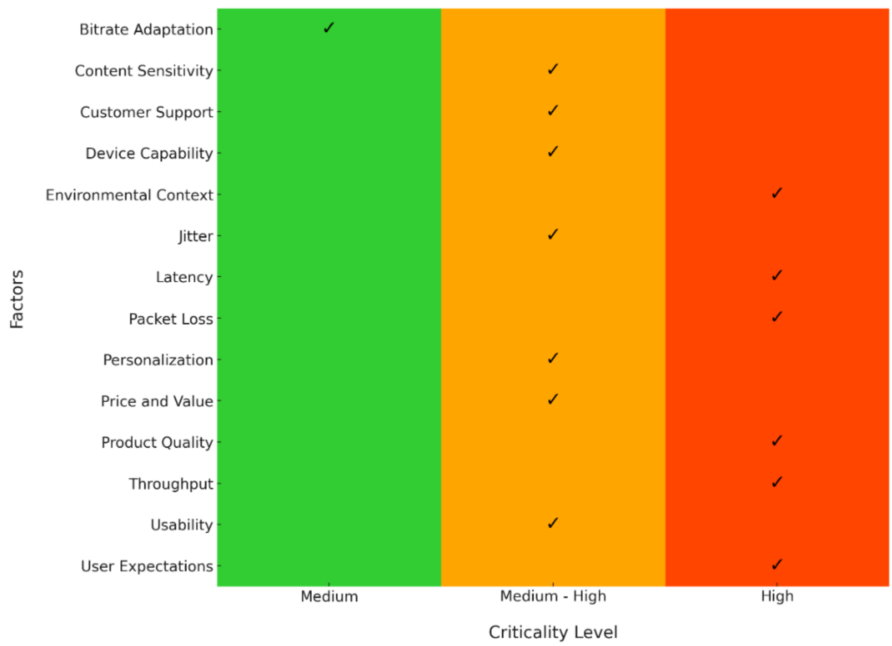

Figure 5: Key factors Influencing QoE and their Criticality Levels

Figure 6 illustrates the service sensitivity network derived from Tables 2 and 3, mapping the relationship between key QoE factors (both network and non-network) and the mobile services they most critically impact. The diagram provides a visual overview of how specific factors (in blue) such as latency, price, usability, or packet loss influence various service categories (in green). This supports a clearer understanding of service-specific vulnerabilities and QoE optimization priorities.

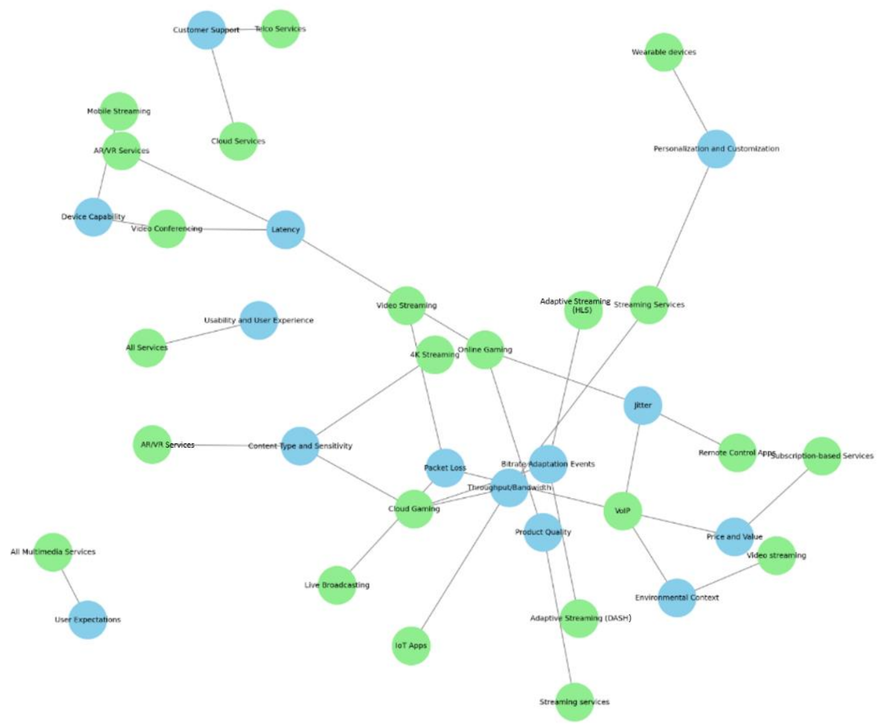

Figure 6: Network Diagram mapping QoE Factors to the most impacted Services

Hence, from the above factors, user satisfaction and QoE can be seen as multifaceted constructs influenced by various factors, such as product quality, usability, customer support, price, and personalization. Understanding these factors from a well-rounded academic perspective allows product developers and service providers to make informed decisions aimed at enhancing user experiences and satisfaction levels. Continuous research in these areas is essential to further refine approaches for optimizing user satisfaction and subsequently driving product success.

5. Mobile Network Evolution and its Impact on QoE

The evolution of mobile networks has tremendously transformed the way we communicate with one another, access information, and experience digital services. Each generation of mobile networks has brought about advancements in speed, latency, capacity, and reliability. These advancements directly impact the QoE for users, especially in how they interact with mobile devices and digital services. This section presents an overview of the evolution of mobile networks and its impact on QoE.

5.1 4G and QoEM

The advent of 4G LTE (Long Term Evolution) technology has significantly transformed the mobile communications ecosystem, setting a strong foundation for high-bandwidth and low-latency services. This transformation directly influenced user expectations across various applications, particularly in video streaming, social media, and mobile gaming. 4G LTE made it possible for users to experience substantial improvements in data rates, enabling seamless streaming of high-definition content and real-time interactions on social media platforms.

The technology's capability to support data rates of up to 300 Mbps and 75 Mbps for downloads and uploads, respectively, has fundamentally altered user expectations, as consumers now anticipate instant access to content without buffering or delays [80].

Furthermore, the low latency characteristic of 4G LTE, often around 30-50 milliseconds, enhanced the user experience in multimedia streaming and interactive applications [81]. This reduced latency necessitates real-time feedback and interactions, which are critical for maintaining user engagement in a fast-paced gaming environment. This has resulted in users not only expecting high-quality content but also responsiveness and reliability in their mobile applications. Also, LTE by integrating advanced technologies such as Multiple Input Multiple Output (MIMO) and carrier aggregation further optimized network performance, adhering to the growing demands for bandwidth-intensive applications [80] [15].

Despite these, the management of QoE in 4G LTE is fraught with challenges. One of the primary issues is network congestion, which occurs when the volume of data traffic exceeds the network's capacity. This congestion may and can lead to service interruptions, increased latency, and a decline in overall user satisfaction [82] [6]. So, as mobile operators strive to accommodate the exponential growth in user traffic, they also face the dual challenge of optimizing infrastructure utilization at the same time, ensuring a satisfactory QoE for end-users [83].

Also, Djuikom et al [84] emphasized that service disruptions can occur during handover, especially when users move between different base stations (BSs). This can interrupt ongoing sessions and degrade the QoE. The complexities in managing QoE is further compounded by the need to strike a balance between subjective user perceptions and objective network performance metrics, requiring a comprehensive understanding of the factors that affect QoE, including device capabilities, network conditions, and user expectations [6] [15].

5.2 5G and QoEM for VAS

The introduction of 5G technologies revolutionized the management of QoE for various mission-critical applications, including autonomous vehicles, remote surgery, and immersive AR and VR services. Key features of 5G; network slicing, edge computing, and massive MIMO (Multiple Input Multiple Output), play pivotal roles in advancing QoEM by providing tailored resources and low-latency connections essential for these applications.

5.2.1 Impact of 5G Technologies on QoEM

A. Network Slicing: Being one of the most significant advancements in 5G, allows the physical network to be divided into multiple virtual networks; each optimized for specific applications or services, minimizing interference and maximizing performance [85]. This capability is crucial for mission-critical applications with diverse and stringent requirements. For example, to ensure timely data exchange for safe navigation, autonomous vehicles require ultra-reliable low-latency communication (URLLC). While remote surgery demands high bandwidth and low latency for real-time video feeds and control signals [86] [87].

B. Edge Computing: The integration of edge computing with 5G networks advances QoE by reducing latency and improving data processing speeds. In a bid to minimize the time it takes for data to be transmitted to and from centralized cloud servers, edge computing processes data closer to the end user. This is advantageous, particularly for applications like immersive AR/VR, where even slight delays can significantly degrade the user experience [88] [89]. For example, it is critical in VR applications, to maintain a latency below 20 ms for a seamless experience. Edge computing facilitates this by handling data processing at the network's edge, as Alencar et al [90] demonstrated using Fog computing.

C. Massive MIMO: This technology enhances the capacity and efficiency of wireless communication by employing a large number of antennas at the base station. This allows for simultaneous transmission to multiple users, improving overall network throughput and reducing latency. In high-density user scenarios such as public events or urban areas, Massive MIMO ensures users experience consistent, high-quality services, essential for applications such as mobile gaming and live streaming. [91] [92].

5.2.2 Benefits of Network Slicing for VAS

The benefits of network slicing for VAS include the following:

A. Dedicated Resources: The allocation of dedicated resources to specific slices, allows operators to ensure that mission-critical applications receive the bandwidth and latency guarantees they require. This is important for applications that do not tolerate delays or interruptions, such as remote surgery, where a momentary lapse in connectivity could have direct consequences [87] [93].

B. Personalized QoE: Network slicing allows for the customization of service parameters based on user needs and application requirements. For example, a network slice dedicated to AR applications can be configured to prioritize low latency and high bandwidth. While another slice dedicated for IoT devices may focus on energy efficiency and reliability. This level of customization improves the user experience by ensuring that each application performs optimally under varying conditions [86] [94].

C. Scalability and Flexibility: Due to its dynamic nature, network slicing allows operators to scale resources up or down based on real-time demand. This flexibility is crucial in managing fluctuating loads, especially during peak usage times or in emergency conditions where additional resources may be instantly required [86] [94].

In summation, the highlighted 5G technologies, significantly enhance QoEM for mission-critical applications. The provision of dedicated resources and performance optimisation based on specific application requirements, ensure that users experience the high-quality service as expected in today's digital landscape.

5.3 6G and Future QoEM

6G (sixth-generation) networks are poised to fundamentally transform different aspects of connectivity and user interaction. 6G networks are envisaged to support emerging technologies like the tactile internet, holographic communication, and multi-modal extended reality (XR) experiences. These technologies will require ultra-low latency, high reliability, and extremely high data throughput [95] [96] [97].

A. Tactile internet: Characterized by its ability to facilitate real-time remote interactions emulating physical touch or presence, is one of the most anticipated 6G applications. By leveraging advanced communication technologies, 6G will enable a seamless integration of digital and physical environments, creating new opportunities for applications in areas like telemedicine, remote surgeries, and immersive gaming experiences with real-time responsiveness demands [95] [96].

As noted in current literature, the aim of 6G extends beyond simply enhancing performance metrics; it has the ambition to offer "everyone-centric customized" services that adapt to the dynamic needs of individual users [98] [99] [100]. So, to address the challenging requirements of 6G applications, it is crucial to emphasize on user-centric designs.

B. AI and intelligent automation: Such customization will be vital for optimizing QoE, ensuring that the user experiences provided are both high in quality and also tailored to varying contexts and requirements. This will necessitate revolutionary End-to-End (E2E) system formulations and adaptive service provisioning algorithms, capable of operating across diverse scenarios and network conditions [98] [99] [100].

C. Adaptive QoEM: Integral to achieving an adaptive QoE framework in 6G networks, is the integration of AI and intelligent automation processes. These systems will facilitate self-optimizing QoEM leveraging ML algorithms for real-time data analysis and decision-making. 6G networks can dynamically adjust resources to meet user expectations and service demands efficiently through continuous monitoring of user-specific QoE indicators which encompass aspects like latency, bandwidth utilization, and content delivery metrics [6].

D. QoE-aware dynamic resource management: Applying AI-driven optimization techniques will enable cross-layer management of network resources, allowing for quicker response times in adjusting to changes in network load or user behaviour. Ultimately enhancing user satisfaction with multimedia streaming and other services [6] [101]

Also, developing QoE-aware dynamic resource management approaches will be pivotal. As these methods will draw on multi-source data gathered from sources like client devices, network states, and application performances in creating comprehensive QoE models [99] [100] [15].

Furthermore, optimizing traffic management based on real-time QoE assessments will ensure efficient resource allocation and fair service delivery across different applications in 6G networks, contributing to the overall network efficiency and improved user experiences [99] [15].

E. Digital twins: This concept is emerging as a sophisticated tool in simulating and optimizing urban environments and service delivery at scale, facilitating responsive network operations in smart city infrastructures and beyond [102] [97].

To summarize, the evolution of mobile networks, especially from 5G and beyond, signals a transformative shift towards a highly interactive digital experience for users. This evolution in technology seeks to seamlessly integrate advanced communication technologies into everyday life through innovative solutions like AR, VR, Telemedicine, Tactile internet, and enhanced holographic communications. These solutions themselves have the potential to cause disastrous impact on users, even with the slightest deviations in service delivery, making QoEM a critical factor. Technologies such as network slicing introduced by 5G and 6G technologies like intelligent automation, adaptive QoEM, and user-centric design principles are all promising efforts to enhance QoEM systems.

6. Techniques for QoEM in Mobile Networks

As networks evolve, user expectations grow [103] [104]. As of February 2025, the number of internet users worldwide stands at 5.56 billion, which is 67.9% of the global population, and with 63.9% of the world's population using social media [105]. Thus, efficient QoEM in mobile networks is now more critical in ensuring that users receive satisfactory service performance. Effective QoEM encompasses monitoring, analysing, and optimizing network performance to respond to user demands. In this section, we present key techniques geared toward QoEM in mobile networks.

6.1 Real-Time QoE Measurement and Prediction

Real-time QoE prediction techniques are increasingly crucial in mobile networks, particularly as user demands and network conditions fluctuate. This has seen ML (ML), deep learning (DL), and reinforcement learning (RL) models emerge as effective tools for dynamic adaptation to these changes.

A. ML and Deep Learning Models: ML algorithms can analyse historical data, such as performance metrics like latency, jitter, and bandwidth, to predict user satisfaction based on identified patterns. For example, deep learning models can process large datasets from multiple different sources, including user interactions and network performance metrics, to accurately provide QoE predictions in real-time [6]. These models adapt to changing conditions, making proactive adjustments to service delivery possible.

B. Reinforcement Learning: RL techniques are more suited for environments where decisions are to be made sequentially over time. In QoEM context, RL can optimize resource allocation by learning from feedback loops on the basis of user satisfaction and network performance. For example, immersive VR video streaming can employ a deep reinforcement learning approach to manage resource allocation to dynamically adjust parameters in order to maintain high QoE even in fluctuating network conditions [89].

Despite these merits, challenges still exist in real-time data collection and feedback loops. Collecting accurate and timely data from diverse sources can be complex, especially in mobile environments where user behaviour varies highly. In addition, establishing effective feedback loops to quickly translate user experiences into actionable insights for network adjustments remains a significant hurdle [106].

6.2 AI and ML for QoE Optimization

AI and ML algorithms play a crucial role in personalizing QoE as they leverage user data to predict satisfaction levels and optimize service delivery. To tailor experiences that enhance user satisfaction, these algorithms can analyse user preferences, historical interactions, and real-time network conditions.

Personalization of QoE: By exploiting user data, AI-driven systems can design personalized service profiles that adapt to individual preferences and behaviours. For example, adjusting graphics settings based on a user's device capabilities and network conditions in a Cloud gaming service, to ensure an optimal gaming experience [81] [6].

6.2.1 Case Studies

A. Cloud Gaming: For a cloud gaming framework as depicted in Figure 7, AI-driven QoE prediction models can dynamically optimize video quality based on real-time network and user data, to reduce latency and buffering, enhancing user satisfaction [107].

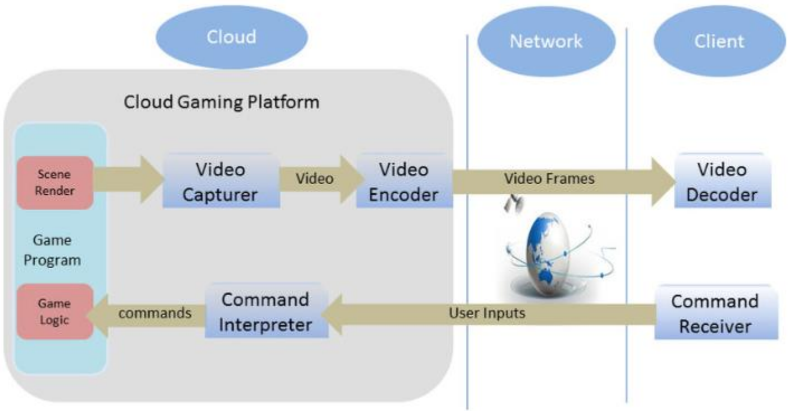

Figure 7: Cloud gaming framework[64]

B. Video Streaming: Studies on video streaming services demonstrated the effectiveness of ML techniques in predicting QoE, based on various information extracted from network monitoring data. Research highlights that using ML for QoE estimation could lead to improved resource allocation and user experience [106] [107]. Thereby, minimising the possibility of unhappy livestream consumers. In Figure 8 below, [106] presents a simplified block diagram of how a predictive monitoring tool can be deployed in the video streaming set-up. The video streaming server and the client are connected for real-time assessment by the network and a feedback loop. The ML Video Monitoring tool classifies the incoming information based on system history, the video content types available, and the output is used to improve the prediction model in the client and control the management loop.

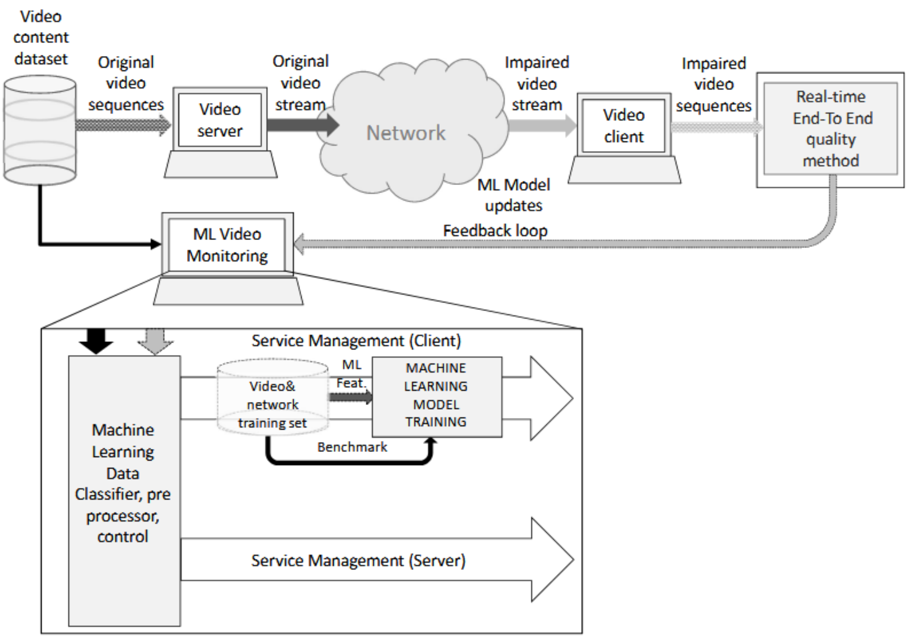

Figure 8: ML application for QoEM in video streaming[106]

6.3 Edge Computing and Caching for Low Latency

Edge computing, as illustrated in Figure 9 below, is pivotal in delivering low-latency, high-quality services by processing data at the network's edge closer to the user. This architecture reduces the distance data must travel, thus minimizing latency and enhancing the overall user experience.

Deploying computing resources at the edge of the network allows service providers to ensure that data processing occurs near the user. A setup that allows for faster response times and improved service reliability. This is critical for applications requiring real-time feedback, such as gaming and AR [108].

Intelligent Caching Techniques can significantly reduce data fetch times for popular VAS like Video-On-Demand (VOD) and live streaming. Networks can decrease latency and improve QoE for users by caching frequently accessed content at the edge. For example, when popular video content is cached closer to users the load times become faster and buffering is reduced, enhancing the viewing experience [81] [15].

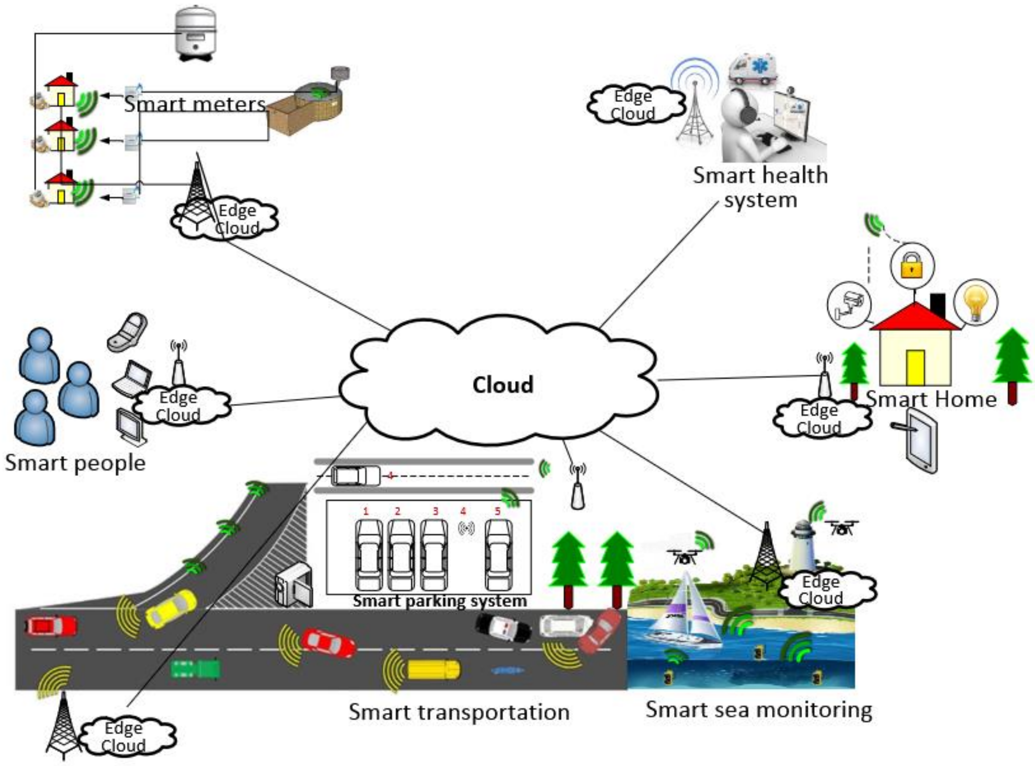

Figure 9: Application of Edge Computing[109]

6.4 Cross-Layer Optimization and Network Management

Cross-layer optimization is critical for improving QoE by coordinating different network layers (application, transport, and network layers) to deliver a seamless user experience.

A. Improving QoE through Cross-Layer Optimization: By integrating information across layers, network operators can make more informed decisions that enhance QoE. For instance, [15] [86] showed that adjusting application-layer parameters based on transport-layer performance can lead to better resource utilization and improved service delivery.

B. Intelligent Network Management: The concept involves dynamic resource allocation based on real-time QoE feedback. [81] [108] [15] demonstrated that by continuously monitoring user experiences and network conditions, operators can adjust resources proactively to maintain optimal service levels. An approach that not only improves user satisfaction but also enhances overall network efficiency.

6.5 ANN-Based QoE Synthesis and Observer Bias Correction

Synthesizing QoE from QoS measurements using Artificial Neural Networks (ANNs) is a technique that bridges the gap between objective network performance metrics and subjective user experiences. The concept involves training ANNs on large-scale QoS measurement datasets to predict user-perceived QoE [110] [111].

While Observer Bias correction from subjective testing is a ZREC (Z-Score Robust Estimation of Confidence) method that corrects biases and inconsistencies in subjective QoE evaluations. Enhancing the reliability of Mean Opinion Score (MOS) datasets and improving the accuracy of supervised learning models trained on subjective data [112].

6.6 Summary of QoE Techniques

In order for us to consolidate the diverse techniques discussed above, we present in this subsection a structured overview in the form of a taxonomy diagram and a summary table. These elements aim to provide a clear and concise visual synthesis of the main QoEM strategies discussed, highlighting their technical descriptions, strengths, representative case studies, and supporting literature. In Figure 10 below, we present a hierarchical taxonomy of the QoEM techniques synthesized from existing literature, visualizing their categorization.

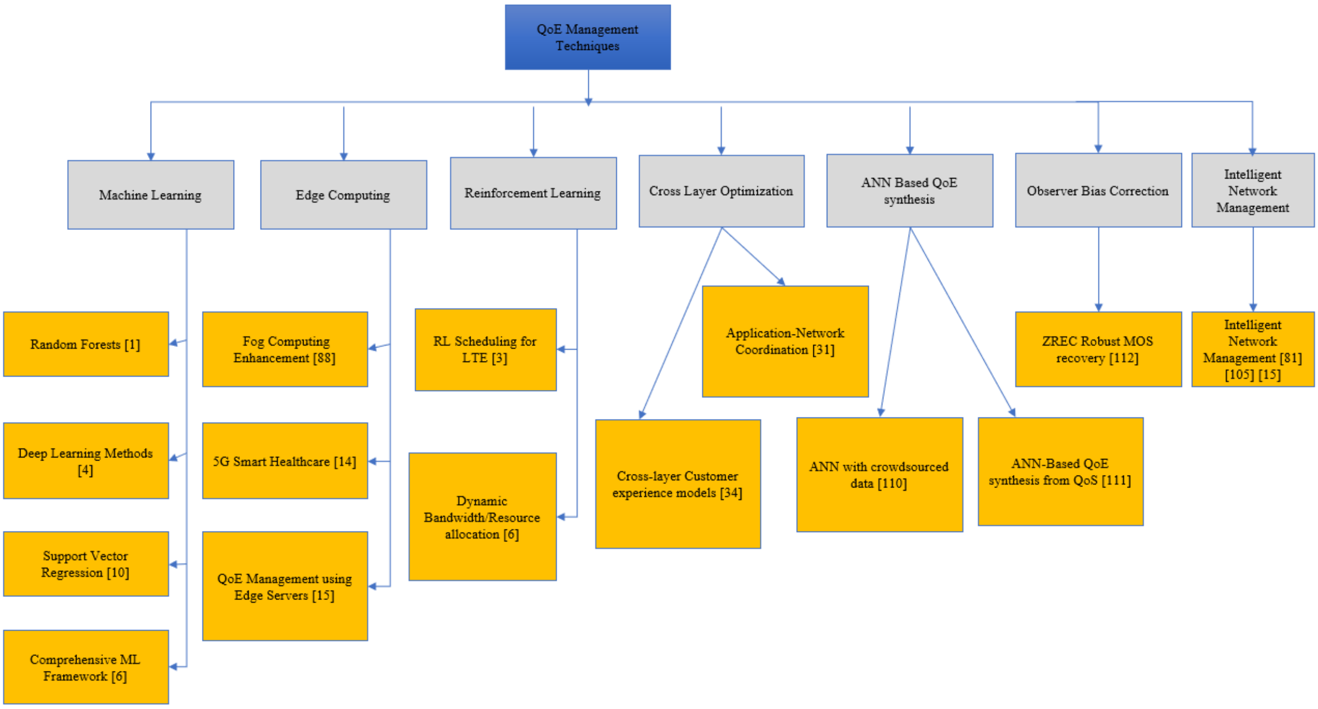

Figure 10: Taxonomy of QoEM techniques

In Table 4 below, we present a comparative summary of the key QoEM techniques, including their technical descriptions, strengths, challenges, their application domains, the maturity of these techniques, case studies and supporting references.

Table 4: Summary of QoEM Techniques

Technique	Technical Description	Strengths	Challenges	Application Domain	Maturity Level(Technology Readiness Level)	Case Study	References
ML for QoE Prediction	ML models like Random Forest, Support Vector Machine, XGBoost, and DL predict user satisfaction based on QoS data.	Predictive, adaptive, proactive QoE control.	Requires large, high-quality labelled datasets; susceptible to model drift.	Video Streaming, social media, Mobile Applications	High (Deployed)	Streaming QoE prediction	[6] [1] [4] [10]
Reinforcement Learning (RL) for Dynamic Allocation	RL dynamically adjusts bandwidth/resources to maximize user QoE.	Real-time self-adaptation in mobile networks.	Long training times, unstable under highly dynamic conditions.	Cloud Gaming, AR/VR Streaming	Medium (Research-Prototype)	LTE RL resource scheduling	[3] [6]

Edge Computing for Latency Reduction	Computation is offloaded to the network edge to minimize latency.	Supports ultra-low latency apps like AR/VR and healthcare.	Requires significant infrastructure investment; limited scalability.	AR/VR Applications, Smart Healthcare, IoT Networks	Medium-High (Emerging Deployments)	Fog computing-enhanced VR services	[15] [14] [90]
Cross-Layer Design for Integrated Optimization	Simultaneous adjustment across network layers to optimize QoE.	Holistic and adaptive performance tuning.	Complex to implement and maintain across heterogeneous networks.	Mobile Broadband Networks, Adaptive Video Streaming	Medium (Research-Industry)	Cross-layer QoE optimization for mobile networks	[31] [34]
Intelligent Network Management	Dynamic resource allocation based on real-time QoE feedback.	Real-time and dynamic adaptation of network resources to improve user experience	Evaluation primarily in simulation/testbed environment, lacking real-world large-scale deployment	Multimedia streaming services	Medium (Research)	Softwarized and Virtualized Networks	[81] [108] [15]
ANN-Based QoE Synthesis	Predicts QoE from QoS data using Artificial Neural Networks (ANNs).	Bridges the gap between technical metrics and user perception.	High computational complexity, overfitting risks.	Crowdsourced Broadband Networks, Smart Home Services	Medium (Research)	Broadband crowdsourced QoE modelling	[110] [111]
Observer Bias Correction in Testing	ZREC method recovers true MOS scores by correcting observer bias.	More accurate supervised learning and benchmarking.	Requires extensive subjective test data; complex statistical modelling.	QoE Benchmarking Studies, Video Streaming Quality Assessment	Medium (Research-Validation)	Robust MOS recovery using ZREC	[112]
Note: All comparisons and categorizations reflect the authors' synthesis of referenced literature and do not represent results of new experiments unless indicated							

In conclusion, integrating real-time QoE measurement, AI-driven optimization, edge computing, and cross-layer management techniques promises a comprehensive strategy for enhancing user experiences in mobile networks. As these technologies evolve, these techniques will play a crucial role in meeting the increasing demands for high-quality, low-latency services.

7. Limitations and Challenges in QoEM

QoE is a significant topic in contemporary telecom networks that aims to evaluate human experience and satisfaction when services are delivered to users over telecom networks [1]. Video streaming is one of, if not, the most popular services that end-users in telecom networks access. In recent years, QoEM has received considerable interest from traditional and emerging networks to further ensure a high level of human experience when they use and promote advancements in future networks. Despite the extensive studies on QoEM in the literature, there still exist several difficulties and challenges that need to be addressed and have a strong demand for future work.

As depicted in Figure 11 below, a typical modern-day network consists of a vast array of service applications delivering a plethora of services through a variety of network domains and infrastructures to end users. These end users, by nature, are mobile and have varying preferences despite being situated in diverse environments

In this section, we illuminate the fundamental difficulties and obstacles in emerging and future targets of QoEM in telecom networks and identify possibilities for encouraging new investigations on QoEM.

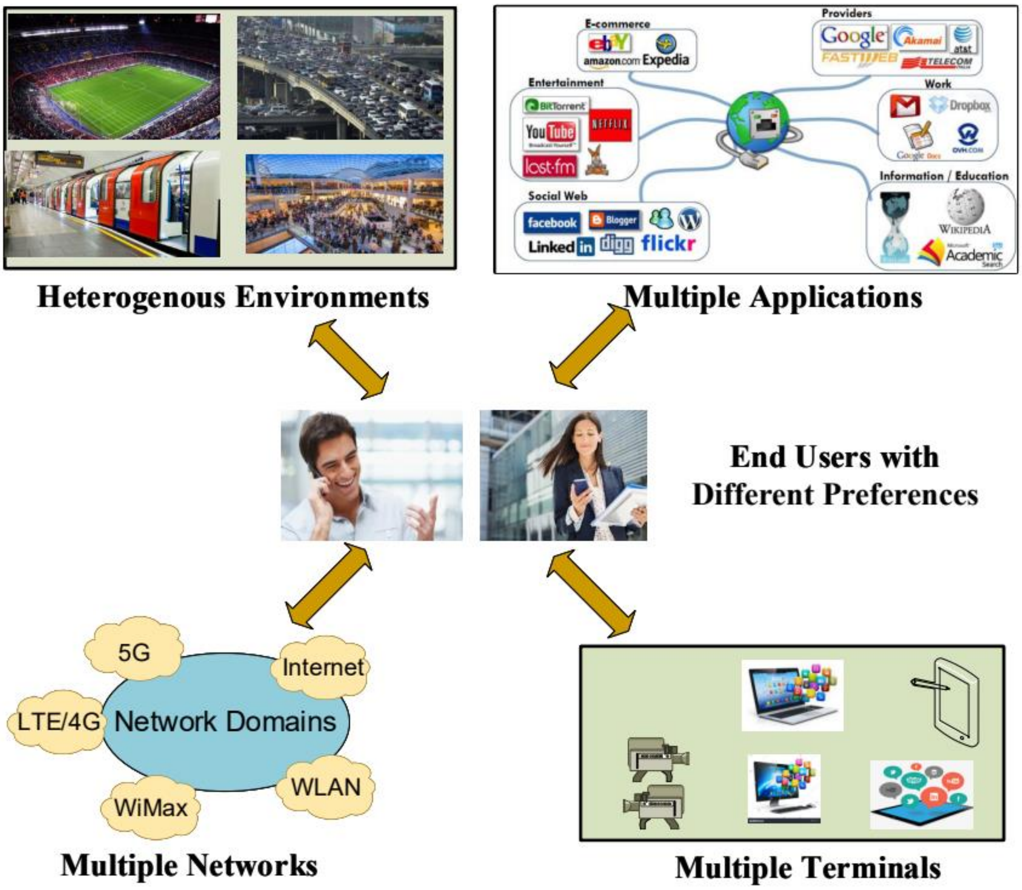

Figure 11: Complex nature of modern networks[15]

7.1 Scalability and Real-Time Adaptation

In large-scale networks that accommodate high-density users and diverse VAS, advancements in QoEM systems face significant challenges.

A. Scalability Challenges: Mobile networks have become the primary platform for most Internet-based services, and the demand for high-quality content continues to increase. The increased demand for video-based services presents a new opportunity for operators to provide VAS and make high revenues. This evolution also brings many challenges for telecom operators in terms of managing the increasing user density and ensuring a seamless user experience. With the development of advanced mobile network technologies, data traffic continues to grow rapidly. Therefore, manually troubleshooting QoE issues in mobile networks is unsustainable.

Although the traditional methods of evaluating users' experience through monitoring infrastructure (see Table 5 below) are not practical for large network operators, the system should not delay awareness of an incident regarding maintenance events. Moreover, VAS performance is affected by different factors, such as packet loss caused by radio channel quality issues, and is no longer easy to tell whether it is the VAS itself that is faulty.

As the number of connected devices and users continues to increase, QoEM becomes increasingly complex. High-density environments, such as urban areas or significant events, can cause network congestion, resulting in degraded service quality [113]. The main challenge lies in the efficient allocation of resources to meet the varying demands of different services while ensuring that all users receive an acceptable level of QoE [114] [15]. Also, traditional QoEM systems may struggle to scale effectively, since they often rely on centralized architectures that can become bottlenecks under heavy load [15].

Table 5: Traditional QoE Assessment Methods and Their Limitations

Techniques	Description	Limitations	References
Deep Packet Inspection (DPI)	Analyses packet headers/payloads using techniques like Matching Algorithm, Cuckoo Filter, ML, and Deep Learning to infer application performance.	Privacy/encryption barriers, high computational cost, and high CPU/memory overhead for large traffic volumes.	[115] [116] [117]

Network Tomography	Indirectly estimates network conditions through statistical inference, like Passive Measurements, Clustering Methods, and Correlation Analysis.	Complex modelling lacks real-time accuracy, computationally expensive for large-scale networks.	[118] [110]
Mean Opinion Score (MOS) Surveys	Subjective user ratings (on a 1–5 scale) collected mostly in controlled lab environments, for example, BT500, P913-12.4, P913-12.6, MLE (Maximum Likelihood Estimation), Z-Scores Normalization,	Lab-only, small samples, prone to bias, impossible to deploy for millions of real-world users.	[112] [119]
QoS-to-QoE Mapping Models	Uses mathematical models or ML, for example, IQX Hypothesis, Non-Linear Equations, Video Quality Metrics (VQM), statistical Analysis of QoE, and Artificial Neural Networks, to predict QoE from QoS metrics.	Over-simplified, ignores device/context variability, static parameters	[111] [37]
Active Probing (Ping/Traceroute)	Applies Ping to check reachability and latency, and Traceroute to map packet paths and identify bottlenecks for diagnosing connectivity issues	Limited insight into application performance, susceptible to ICMP blocking and filtering, challenges with asymmetric routing and load balancing, and not scalable for proactive User Experience monitoring.	[120] [121]
SNMP-Based Monitoring	Employs techniques like Poll-based Data Collection, Net-SNMP, SNMP GET Requests, Management Information Base (MIB) to collect device-level metrics such as availability, CPU/memory, interface stats via SNMP protocols, to infer network health and potential user experience issues	Polling overhead impacts network device performance, limited data granularity and real-time visibility, security vulnerabilities, and lacks an end-to-end user perspective.	[122] [123] [124]
NetFlow/IPFIX Analysis	Tools like nfcapd, ulogd2, and nfpcapd are used to collect flow records from network traffic, capturing details such as source/destination addresses, ports, and packet counts.Analyzes flow-level statistics from routers to monitor traffic patterns and service usage using techniques like Superflows and Filtering Mechanism.	Limited visibility into application behaviour and user experience; high volume data makes real-time analysis difficult.	[125] [126] [127]
Note: All comparisons and categorizations reflect the authors' synthesis of referenced literature and do not represent results of new experiments unless indicated			

B. Real-Time Adaptation: As we have presented earlier, QoE depends on user expectations, context, and device quality. We have also witnessed the development of a plethora of services and devices since the advent of mobile telephony, pushing telecom operators to invest in increasing the overall QoE for these services. Value-added applications such as multimedia streaming have caused an increased per-user bandwidth demand in telecom networks. These services permit the consumption of a range of content over wireless connections using modern, user-friendly services.

Although in the context of video streaming a service flow is considered the unidirectional flow of service packets (from server to client) with specific transport-layer characteristics, for example, bandwidth and latency, crucial in understanding the performance of these applications like YouTube; the overall demand on mobile networks consists both incoming requests (from user devices to servers) and outgoing data (from servers to devices), reflecting the bidirectional nature of modern Internet traffic. Also, user demography is defined as the percentage of active streams at a given time and location. Therefore, as reflected in [128] [15] popular content and user diversity constantly change. Hence, there is a requirement for efficient management of these service flows with an individually defined packet forwarding treatment. This undertaking needs to be done co-operatively between RAN and CN entities in mobile networks [1].

A significant challenge lies in the real-time adaptation of the mobile network to many service-flows with the varying per-user bandwidth requirement imposed by dynamic user behaviour. Especially within the constraints of user plane delays and the impossibility of future information. Also, predictive network QoEM solutions for changes in mobility are limited. On the other hand, the ability to quickly adjust to changes in user behaviour, such as a sudden increase in demand or a shift in user location, is critical for maintaining QoE [129] . Therefore, achieving this level of responsiveness requires sophisticated monitoring and control mechanisms that can process data in real-time. This in itself can be technically challenging and resource-intensive [130].

Barakabitze et al [15], propose several methods for the network QoEM of streaming services, whose QoE is dependent on the delivered bandwidth. QoEM methods were compared, and it was shown that when these methods were implemented with a realistic performance-detrimental policy for capacity re-negotiation, they could not cope with many dynamic service flows. Furthermore, using statistical models, it was shown how the demography of the service flows and the network conditions could restrict the performance of admissible methods. Thus, an upper limit on the network QoEM accuracy was proposed and the challenges for the implementation of network QoEM in future 5G and mobile networks were elucidated.

7.2 Data Privacy and Security

As current network traffic becomes diversified and highly dynamic, monitoring end-user QoE is mandatory so as to prioritize the investments necessary to satisfy end-user expectations and focus on emerging services. Seeing that users are usually willing to pay for better QoE, understanding that it is connected to the cost of providing such services, Telecom operators attempt to gain a competitive advantage over other providers by supplying better QoE to users. Privacy concerns may arise if operators use personalized QoE models to dynamically factor in each user's state in making resource decisions and improve the service experience. Another concern is the security implications of these personalized QoE models as well as the storage of sensitive service data by operators.

Privacy Concerns: Personalized QoE models often require the collection of sensitive user data, including location, usage patterns, and personal preferences. This data can be vulnerable to breaches, leading to unauthorized access and misuse. [131] presents that users may be reluctant to share their data if they perceive a risk to their privacy, which can hinder the effectiveness of QoEM systems. To address these concerns, privacy-preserving techniques such as federated learning and encrypted data analysis are gaining traction. Federated learning is a technique that allows models to be trained on decentralized data without transferring sensitive information to a central server, thereby enhancing user privacy. While encrypted data analysis techniques enable the processing of data while maintaining its confidentiality, ensuring effective QoEM without compromising user security [132] [133]. Other mechanisms to mitigate user privacy concerns include explicitly obtaining user consent, user data anonymization, and secure edge-level processing, incorporated into QoE monitoring systems. These safeguards help ensure compliance with data protection regulations and maintain user trust, especially when dealing with sensitive behavioural and contextual information [36].

7.3 User Behaviour and Perception of QoE

Behavioural factors and user expectations greatly influence perceived QoE. This highlights the limitations of relying solely on objective QoS metrics.

Jie et al [134] articulated that the QoE for multimedia services involved a multi-dimensional analysis where user behaviour patterns and specific context of use could significantly modify perceived service quality. However, this specific reference could not be verified in the current context. This perspective aligned with findings in [135], which underscored that high QoS does not guarantee satisfactory QoE, highlighting the multifactorial nature of user experience in mobile services. Therefore, networks must consider both technical capabilities and also psychological factors that vary across individual users and their interaction with services.

Influence of User Expectations: Understanding user behaviour and expectations is crucial for accurately assessing QoE since user satisfaction is often shaped by expectations that may not align with objective QoS metrics. For instance, Roshan et al [136] reported that a user may perceive a service as unsatisfactory even if the underlying QoS metrics (e.g., bandwidth, latency) are within acceptable ranges. This discrepancy can arise from contextual factors, individual preferences, and prior experiences.

7.4 Aligning QoS Metrics with User Experience

Considering the plethora of QoS management techniques in existence and the inherent objective nature of QoS. Operators relying on existing mechanisms designed on the basis of objective metrics will constantly fall short of accurately managing user satisfaction, since it is subjective in nature. Therefore, it is paramount to create a more accurate assessment of QoE that aligns network QoS metrics with subjective user experiences. This can be done through methods like incorporating user feedback into QoE models, utilizing ML techniques to predict user satisfaction based on QoS parameters, and developing hybrid models that combine both objective and subjective measures [137] [138] [139]. Integrating user perceptions into QoE assessments allows service providers to better understand and meet user expectations, ultimately enhancing overall satisfaction.

7.5 Device Limitations

The varying characteristics of mobile devices, for example, computing power and storage capacity, significantly influence QoE for mobile device users, presenting challenges in effectively managing QoE.

Device Heterogeneity: The diversity in mobile devices, each with varying battery capacities, screen resolutions, and hardware performance, tends to complicate QoEM. This heterogeneity results in inconsistencies in user experiences across different devices [140] [141].

Resource Constraints: Mobile devices usually have limited computing resources, storage capacity, and battery life, which can hinder the performance of computation-intensive tasks like Face recognition and VR. This limitation necessitates offloading tasks to edge servers or the cloud to maintain satisfactory QoE [142] [143].

Energy Consumption: Task offloading from mobile devices to reduce latency and improve QoE can lead to increased energy consumption, which is a critical concern given the limited battery life of mobile devices. Strategies need to be developed to balance energy consumption with QoE, for example, formulating the computation offloading problem as a mixed-integer non-linear programming (MINLP) problem.[144] [145].

7.6 Regulatory and Ethical Challenges

The increasing over reliability of ML-based QoE models on user-centric data necessitates significant regulatory and ethical concerns in dealing with user data. Compliance with frameworks such as the General Data Protection Regulation (GDPR) and the California Consumer Privacy Act (CCPA) is essential to ensure lawful data collection, user consent, transparency, and data minimization [146].

Beyond regulatory compliance, ethical challenges arise from risks such as bias amplification, opaque algorithmic decision-making, and unintended profiling. Maintaining transparency, fairness, and accountability in QoE modelling is crucial for sustaining user trust. Existing literature focuses largely on the technical aspects of QoEM and little on compliance and ethical considerations. Future approaches must therefore integrate privacy-preserving techniques such as federated learning, differential privacy, and explainable AI in order to align technological innovation with ethical standards [146].

To conclude, while QoEM systems are essential for delivering high-quality services in mobile networks, they still face significant challenges related to scalability, real-time adaptation, data privacy, and user behaviour. Addressing these challenges requires innovative approaches and technologies that prioritize user experience while also ensuring security and efficiency.

8. Emerging Trends and Future Research Directions

As 6G technologies emerge, they will redefine QoEM for next-gen immersive services like AR, driven by ultra-low latency and unparalleled reliability.

In conjunction with advancements in handsets and next-generation network architectures, mobile streaming services are anticipated to be more critical in the upcoming years. The delight of the immense user prospect could push Mobile Network Operators (MNOs) to invest in enlarged density and design of QoE-focused network infrastructure.

8.1 Autonomous QoEM Systems

The significant potential for autonomous, AI-driven QoE systems is emphasized, as these systems can continuously optimize QoE based on real-time feedback, user behaviour, and network conditions. Possible areas of interest are:

A. AI-Driven Optimization: Autonomous QoEM systems by leveraging on ML algorithms, analyse vast amounts of data from user interactions and network performance metrics. [15] presents that by continuously learning from this data, these systems can make real-time adjustments to service delivery, ensuring that user experiences remain optimal even as conditions change. For example, AI can adjust video streaming quality dynamically based on current network conditions and user preferences, minimizing buffering and enhancing satisfaction.

B. Self-Organizing Networks (SON): The role of self-organizing networks in achieving network optimization without human intervention cannot be over-emphasized. SON solutions make it possible to automate network management tasks like configuration, optimization, and healing, allowing for more efficient resource allocation and improved QoE [147] [148]. By implementing SON technologies, operators without the need for manual adjustments can respond to network changes in real-time, ensuring that users receive the best possible service.

8.2 Blockchain for QoE Transparency and Trust

Blockchain is a technology that offers a promising avenue for enhancing QoEM by fostering transparency and trust. Interesting research avenues include:

A. Immutable Feedback Records: Using blockchain, service providers can create immutable records of user feedback and QoE assessments. This transparency will promote trust among users since they can verify that their evaluations are securely stored and not tampered with [6]. Such a system can also enable more accurate QoE assessments by ensuring that all feedback is accounted for and allowing for detailed analysis over time.

B. Trustworthy Data in User Evaluations: By providing a secured decentralized method for collecting and storing user feedback, blockchain can enhance the credibility of QoE evaluations and support more effective management strategies [149][150]. Thus, guaranteeing that the data used for QoE assessments is trustworthy. This is essential for developing reliable QoE models.

8.3 Hyper-Personalization and User-Centric QoE Models

The creation of hyper-personalized QoE models is an emerging trend that focuses on leveraging historical user data to create unique experiences tailored to the user's individual preferences. Key research directions are:

A. Hyper-Personalization: Using advanced analytics and ML networks can analyse user behaviour and preferences, allowing for hyper-personalized QoE experiences. This approach will enable service providers to adapt content delivery and service parameters to align with the specific needs of each user, thereby enhancing the user's overall satisfaction [3] [6]. For example, by exploiting a user's viewing history and preferences, a video streaming service could adjust its recommendations and streaming quality.

B. Integration of Behavioural Science: Integrating behavioural science with telecoms research can further advance personalized QoE systems [151]. In understanding the psychological factors that influence user satisfaction, researchers will develop models that better predict user responses to different service conditions and contexts, leading to more effective QoEM strategies [151] [152]. This interdisciplinary approach will help create systems that not only respond to technical metrics but also meet user expectations and emotional responses.

8.4 6G and the Future of QoE for VAS

The coming of 6G technology is set to redefine QoEM for VAS, especially in the context of multi-modal, immersive, and interactive services.

A. Redefining VAS QoEM: 6G networks are going to support advanced applications like holographic communication and the tactile internet, which require ultra-low latency and high reliability. This shift will warrant new QoEM strategies that can accommodate the unique demands of these services, to ensure that user experiences are seamless and immersive [153] [10].

B. Role of Network Intelligence and AR: By enabling real-time monitoring and adaptive resource allocation based on user behaviour and network conditions, Network Intelligence is going to play a critical role in shaping future QoE strategies. Additionally, integrating ARinto VAS will require QoEM systems to account for the complex interactions between the digital and physical environments. Thus, ensuring that users receive coherent and engaging experiences [154] [155].

To summarize, the future of QoEM is geared for significant advancements through the capabilities of 6G networks, autonomous systems, blockchain technology, and hyper-personalization. These emerging trends will both enhance user experiences and provide new opportunities for research and innovation in telecoms.

9. Conclusion And Future Directions

9.1 Discussion of Key Findings

This comprehensive review has highlighted significant advancements in QoEM and techniques within mobile networks, particularly given the increasingly demanding VAS like cloud gaming, AR, VR, and telemedicine. Key findings include the following:

A. Advancements in QoEM: There have been notable advancements in the domain of integrating ML and AI into QoEM systems. These technologies facilitate real-time data analytics and predictive modelling. Allowing for dynamic adjustments to service delivery based on user feedback and network conditions [156] [157]. Additionally, the use of edge computing has been recognized as a critical factor in enhancing QoE through the lens of reducing latency and improving resource allocation [15].

B. User-Centric Models: The emphasis on user-centric models has become increasingly important. These models prioritize individual user experiences and preferences, shifting from traditional QoS metrics to a more holistic understanding of user satisfaction [158] [159].

C. Emerging Technologies: The anticipated rollout of 6G technologies presents exciting opportunities for redefining QoEM strategies. With features like ultra-low latency and massive connectivity, 6G promises to support more immersive and interactive applications. This will necessitate innovative approaches to QoE assessment and optimization [160] [161].

Despite these advancements, critical gaps still exist in current QoEM systems. Challenges related to the complexities of ensuring data privacy and security in personalized QoE solutions, scalability in high-density user environments, and the need for standardized metrics that can effectively quantify QoE across diverse applications continue to impede the effectiveness of existing frameworks [162] [163].

9.2 Contributions and Novel Insights

The contributions of this review are multifaceted and provide novel insights into the field of QoEM. They include the following:

A. Interdisciplinary Approach: This review emphasizes the importance of an interdisciplinary approach combining insights from network engineering, ML, user behaviour analytics, and emerging technologies. By combining insights from these diverse fields, the review offers a comprehensive understanding of QoEM, essential for future developments in mobile networks.[6] [15] [164] [165].

B. AI-Driven Optimization: The exploration of AI-driven optimization techniques offers promising avenues for QoEM enhancement. These techniques enable adaptive resource allocation and real-time optimisations driven by user feedback, significantly enhancing user satisfaction [166] [157].

C. Future Outlook on 6G Technologies: This review provides a forward-looking perspective on the impacts of 6G technologies for QoEM, particularly in relation to immersive applications, that demand ultra-low latency and high reliability. This insight underscores the heightened need for innovative QoE frameworks that will accommodate the unique demands of emerging VAS [160] [161].

9.3 Call to Action

To effectively address the existing challenges and leverage the opportunities identified in this review, collaboration between industry and academia is essential. Stakeholders should work together to develop comprehensive and holistic QoE solutions for QoEM that encompass emerging VAS, AI-enabled systems, and autonomous networks. This collaboration should focus on the following:

A. Creating Standardized Frameworks: It is essential to guarantee consistency and reliability in QoEM through the development of standardized frameworks for QoE assessment that can be applied across diverse applications and user contexts[167] [168] [169].

B. Fostering Innovation: Encourage innovative techniques in QoEM, particularly through the integration of AI and ML. This will enhance the ability to adapt to dynamic user needs and network conditions [170] [171].

C. Enhancing User Satisfaction: By prioritizing user satisfaction and leveraging advanced technologies, the telecoms industry will not only enhance service delivery but also maintain a competitive edge in an increasingly digital landscape [14] [172].

9.4 Key Takeaways

We distil the core findings of this review into three practical takeaways that highlight how network providers, service designers, and researchers can leverage QoEM techniques to drive innovation, improve user satisfaction, and prepare for the challenges of future networks. The key takeaways are:

Integrating QoE into Operational Strategies: Mobile network providers should shift from purely QoS-based strategies to user-centric QoEM frameworks that integrate real-time user feedback, contextual data, and ML predictions for dynamic service adaptation.

Service-Specific QoE Customization: As different VAS (e.g., AR/VR, cloud gaming, telemedicine) exhibit unique QoE sensitivities, tailored QoE optimization is essential for delivering value and sustaining user satisfaction. This can be achieved by employing network slicing, edge computing, and predictive ML.

Collaborative and Interdisciplinary Implementation: Effective QoEM requires collaboration between telecom operators, ML/AI engineers, and experts. This synergy is crucial for developing adaptive, context-aware systems capable of meeting the evolving demands of 5G and 6G ecosystems.

In conclusion, by addressing the identified gaps and embracing emerging technologies, telecom industry stakeholders can ensure that user experiences are optimized in the face of rapidly changing technological landscapes.

Funding

No external funding was received for this work.

Conflict of Interest

There is no conflict of interest in this work.

References

[1] K. Bouraqia, E. Sabir, M. Sadik, and L. Ladid, ‘Quality of Experience for Streaming Services: Measurements, Challenges and Insights’, IEEE Access, vol. 8, pp. 13341–13361, 2020. doi: 10.1109/ACCESS.2020.2965099

[2] I. Sousa, M. P. Queluz, and A. Rodrigues, ‘A survey on QoE-oriented wireless resources scheduling’, Journal of Network and Computer Applications, vol. 158, p. 102594, 2020. doi: 10.1016/j.jnca.2020.102594

[3] D. Ciambrone, S. Tennina, D. Tsolkas, and L. Pomante, ‘A QoE Performance Evaluation Framework for LTE Networks’, in IEEE 19th International Symposium on ‘A World of Wireless, Mobile and Multimedia Networks’ (WoWMoM), Chania, Greece: IEEE, Jun. 2018, pp. 14–19. doi: 10.1109/WoWMoM.2018.8449757

[4] M. S. Anwar, J. Wang, W. Khan, A. Ullah, S. Ahmad, and Z. Fei, ‘Subjective QoE of 360-Degree Virtual Reality Videos and ML Predictions’, IEEE Access, vol. 8, pp. 148084–148099, 2020. doi: 10.1109/ACCESS.2020.3015556

[5] R. Elwerghemmi, M. Heni, R. Ksantini, and R. Bouallegue, ‘Online QoE assessment model based on incremental stacked multiclass classifier’, IJCDS, vol. 14, no. 1, pp. 541–550, Aug. 2023. doi: 10.12785/ijcds/140142

[6] G. Kougioumtzidis, V. Poulkov, Z. D. Zaharis, and P. I. Lazaridis, ‘A Survey on Multimedia Services QoE Assessment and ML-Based Prediction’, IEEE Access, vol. 10, pp. 19507–19538, 2022. doi: 10.1109/ACCESS.2022.3149592

[7] A. A. Barakabitze, I.-H. Mkwawa, A. Hines, L. Sun, and E. Ifeachor, ‘QoEMultiSDN: Management of Multimedia Services using MPTCP/SR in Softwarized and Virtualized Networks’, IEEE Access preprint, 2020. doi: 10.1109/ACCESS.2020.3039953

[8] G. Aristomenopoulos, V. Kaldanis, G. Katsaros, and S. Papavassiliou, ‘Experimentally driven quality of experience-aware multimedia content delivery in modern wireless networks’, Int J Communication, vol. 29, no. 14, pp. 2065–2083, Sep. 2016. doi: 10.1002/dac.2936

[9] M. J. Algar et al., ‘A Quality of Experience Management Framework for Mobile Users’, Wireless Communications and Mobile Computing, vol. 2019, pp. 1–11, 2019. doi: 10.1155/2019/2352941

[10] A. Ahmad, A. B. Mansoor, A. A. Barakabitze, A. Hines, L. Atzori, and R. Walshe, ‘Supervised Learning based QoE Prediction of Video Streaming in Future Networks: A Tutorial with Comparative Study’, IEEE Communications Magazine, vol. 59, no. 11, pp. 88-94, 2021. doi: 10.1109/MCOM.001.2100109

[11] T. Spetebroot, S. Afra, N. Aguilera, D. Saucez, and C. Barakat, ‘From network-level measurements to expected quality of experience: The Skype use case’, in IEEE International Workshop on Measurements & Networking (M&N), Coimbra, Portugal:IEEE, Dec. 2015, pp. 1–6. doi: 10.1109/IWMN.2015.7322989

[12] G. Gómez, L. Hortigüela, Q. Pérez, J. Lorca, R. García, and M. C. Aguayo-Torres, ‘YouTube QoE evaluation tool for Android wireless terminals’, J Wireless Com Network, vol. 2014, no. 1, p. 164, 2014. doi: 10.1186/1687-1499-2014-164

[13] A. Colarieti, A. Marotta, M. Mpervarakis, L. Pomante, and V. Tsolkas, ‘QoE provisioning over mobile networks: The CASPER perspective’, in 2017 IEEE 22nd International Workshop on Computer Aided Modelling and Design of Communication Links and Networks (CAMAD), Lund, Sweden: IEEE, Jun. 2017, pp. 1–5. doi: 10.1109/CAMAD.2017.8031639

[14] A. Ahad, M. Tahir, and K.-L. A. Yau, ‘5G-Based Smart Healthcare Network: Architecture, Taxonomy, Challenges and Future Research Directions’, IEEE Access, vol. 7, pp. 100747–100762, 2019. doi: 10.1109/ACCESS.2019.2930628

[15] A. A. Barakabitze et al., ‘QoE Management of Multimedia Streaming Services in Future Networks: A Tutorial and Survey’, IEEE Commun. Surv. Tutorials, vol. 22, no. 1, pp. 526–565, 2020. doi: 10.1109/COMST.2019.2958784

[16] A. Nanjundappa, S. Singh, and G. Jain, ‘Enhanced multi-RAT support for 5G’, in 2018 15th IEEE Annual Consumer Communications & Networking Conference (CCNC), Las Vegas, NV, USA: IEEE, Jan. 2018, pp. 1–2. doi: 10.1109/CCNC.2018.8319293

[17] S. Heine, F. Völk, R. T. Schwarz, and A. Knopp, ‘Concept and evaluation of 5G backhauling via starlink’, IET Conf. Proc., vol. 2022, no. 29, pp. 69–75, 2023. doi: 10.1049/icp.2023.1364
[18] C. Lei, J. Dingde, X. Jiping, L. Fuqiang, and B. Lulu, ‘MIMO Scheduling Effectiveness Analysis for Bursty Data Service from View of QoE’, Chinese Journal of Electronics, vol. Vol 26, no. 5, pp. 1079–1085, 2017. doi: DOI:10.1049/cje.2017.07.018
[19] J. Ruan and D. Xie, ‘A Survey on QoE-Oriented VR Video Streaming: Some Research Issues and Challenges’, Electronics, vol. 10, no. 17, p. 2155, 2021. doi: 10.3390/electronics10172155
[20] P. Juluri, V. Tamarapalli, and D. Medhi, ‘Measurement of Quality of Experience of Video-on-Demand Services: A Survey’, IEEE Commun. Surv. Tutorials, vol. 18, no. 1, pp. 401–418, 2016. doi: 10.1109/COMST.2015.2401424
[21] A. A. Laghari, H. He, M. Shafiq, and A. Khan, ‘Application of Quality of Experience in Networked Services: Review, Trend & Perspectives’, Syst Pract Action Res, vol. 32, no. 5, pp. 501–519, 2019. doi: 10.1007/s11213-018-9471-x
[22] M. Chen, L. Wang, J. Chen, and X. Wei, ‘QoE-Driven D2D Media Services Distribution Scheme in Cellular Networks’, Wireless Communications and Mobile Computing, vol. 2017, pp. 1–10, 2017. doi: 10.1155/2017/8754020
[23] S. Goodarzy, M. Nazari, R. Han, E. Keller, and E. Rozner, ‘Resource Management in Cloud Computing Using ML: A Survey’, in 2020 19th IEEE International Conference on ML and Applications (ICMLA), Miami, FL, USA: IEEE, Dec. 2020, pp. 811–816. doi: 10.1109/ICMLA51294.2020.00132
[24] Z. M. Çınar, A. Abdussalam Nuhu, Q. Zeeshan, O. Korhan, M. Asmael, and B. Safaei, ‘ML in Predictive Maintenance towards Sustainable Smart Manufacturing in Industry 4.0’, Sustainability, vol. 12, no. 19, p. 8211, 2020. doi: 10.3390/su12198211
[25] M. Morshedi and J. Noll, ‘A Survey on Prediction of PQoS Using ML on Wi-Fi Networks’, in 2020 International Conference on Advanced Technologies for Communications (ATC), Nha Trang, Vietnam: IEEE, 2020. pp. 5–11. doi: 10.1109/ATC50776.2020.9255457
[26] A. Collazo Garcia and S. Casas, ‘Quality of Experience in Mobile Applications: A Systematic Mapping of Metrics and Tools’, Int. J. Interact. Mob. Technol., vol. 14, no. 08, p. 126, 2020. doi: 10.3991/ijim.v14i08.12819
[27] E. Allayiotis, ‘Characterization of Mobile Web Quality of Experience using a non-intrusive, context-aware, mobile-to-cloud system approach’, M.S. thesis, Univ. of Central Lancashire, Preston, U.K., 2017. Accessed: Nov. 01, 2024. [Online]. Available: https://clok.uclan.ac.uk/20734/1/20734%20Allayiotis%20Elias%20Final%20e-Thesis%20%28Master%20Copy%29.pdf
[28] B. Finley, E. Boz, K. Kilkki, J. Manner, A. Oulasvirta, and H. Hämmäinen, ‘Does network quality matter? A field study of mobile user satisfaction’, Pervasive and Mobile Computing, vol. 39, pp. 80–99, 2017. doi: 10.1016/j.pmcj.2016.08.014
[29] M. Alreshoodi and J. Woods, ‘Survey on QoE\QoS Correlation Models for Multimedia Services’, IJDPS, vol. 4, no. 3, pp. 53–72, 2013. doi: 10.5121/ijdps.2013.4305
[30] S. Ickin, K. Wac, M. Fiedler, L. Janowski, J.-H. Hong, and A. K. Dey, ‘Factors influencing quality of experience of commonly used mobile applications’, IEEE Commun. Mag., vol. 50, no. 4, pp. 48–56, 2012. doi: 10.1109/MCOM.2012.6178833
[31] K. Mitra, A. Zaslavsky, and C. Åhlund, ‘QoE Modelling, Measurement and Prediction: A Review’, 2018. Accessed: Oct. 14, 2024. [Online]. Available: http://arxiv.org/abs/1410.6952
[32] S. M. Al-Shehri, P. Loskot, and M. Mert, ‘Common Metrics for Analysing, Developing and Managing Telecommunication Networks’, Computer Science-Networking and Internet Architecture, 2017. doi: https://doi.org/10.48550/arXiv.1707.03290
[33] K. Li, H. Wang, X. Xu, Y. Du, Y. Liu, and M. Ahmad, ‘A Crowdsensing Based Analytical Framework for Perceptional Degradation of OTT Web Browsing’, Sensors, vol. 18, no. 5, p. 1566, 2018. doi: 10.3390/s18051566
[34] P. H. S. Panahi, A. H. Jalilvand, and A. Diyanat, ‘Enhancing Quality of Experience in Telecommunication Networks: A Review of Frameworks and ML Algorithms’, 2024. Accessed: Oct. 10, 2024. [Online]. Available: http://arxiv.org/abs/2404.16787
[35] M. Z. Chowdhury, B. M. Trung, Y.-M. Jang, Y.-I. Kim, and W. Ryu, ‘Service Level Agreement for the QoS Guaranteed Mobile IPTV Services over Mobile WiMAX Networks’, The Journal of Korean Institute of Communications and Information Sciences, vol. 36, no. 4A, pp. 380–387, 2011. doi: 10.7840/KICS.2011.36A.4.380
[36] E. Liotou, D. Tsolkas, N. Passas, and L. Merakos, ‘Quality of experience management in mobile cellular networks: key issues and design challenges’, IEEE Commun. Mag., vol. 53, no. 7, pp. 145–153, 2015. doi: 10.1109/MCOM.2015.7158278
[37] Y. Chen, K. Wu, and Q. Zhang, ‘From QoS to QoE: A Tutorial on Video Quality Assessment’, IEEE Commun. Surv. Tutorials, vol. 17, no. 2, pp. 1126–1165, 2014. doi: 10.1109/COMST.2014.2363139

[38] A. Sackl, R. Schatz, and A. Raake, ‘More than I ever wanted or just good enough? User expectations and subjective quality perception in the context of networked multimedia services’, Qual User Exp, vol. 2, no. 1, p. 3, 2017. doi: 10.1007/s41233-016-0004-z
[39] U. Saad, U. Afzal, A. El-Issawi, and M. Eid, ‘A model to measure QoE for virtual personal assistant’, Multimed Tools Appl, vol. 76, no. 10, pp. 12517–12537, 2016. doi: 10.1007/s11042-016-3650-5
[40] M. A. Habibi, M. Ulman, J. Vaněk, and J. Pavlík, ‘Measurement and Analysis of Quality of Service of Mobile Networks in Afghanistan – End User Perspective’, AOL, vol. 8, no. 4, pp. 73–84, 2016. doi: 10.7160/aol.2016.080407
[41] A. Floris and L. Atzori, ‘Managing the Quality of Experience in the Multimedia Internet of Things: A Layered-Based Approach’, Sensors, vol. 16, no. 12, p. 2057, 2016. doi: 10.3390/s16122057
[42] J. S. Al-Azzeh, R. Odarchenko, A. Abakumova, and S. Bondar, ‘Method for QOE monitoring and increasing in cellular networks based on QOE-to-QOS mapping using spline approximation’, J Wireless Com Network, vol. 2022, no. 1, pp. 1–16, 2022. doi: 10.1186/s13638-022-02125-3
[43] J. Goet, ‘Impact of Service Quality on Customer Satisfaction among Nepalese Cellular Mobile Service Providers’, JOM, vol. 6, no. 1, pp. 89–101, 2023. doi: 10.3126/jom.v6i1.58883
[44] A. Özer, M. T. Argan, and M. Argan, ‘The Effect of Mobile Service Quality Dimensions on Customer Satisfaction’, Procedia - Social and Behavioural Sciences, vol. 99, pp. 428–438, 2013. doi: 10.1016/j.sbspro.2013.10.511
[45] S. Zeng, W. Yang, Z. Wang, Q. Zeng, Y. Wang, and X. Liu, ‘Study on User Satisfaction Prediction and Influencing Factors based on GBDT Modelling’, TCSISR, vol. 1, pp. 39–46, 2023. doi: 10.62051/t05r6x47
[46] R. Schatz et al., ‘QoE Management for Future Networks’, in Autonomous Control for a Reliable Internet of Services, vol. 10768, I. Ganchev, R. D. Van Der Mei, and H. Van Den Berg, Eds., in Lecture Notes in Computer Science, vol. 10768. , Cham: Springer International Publishing, 2018, pp. 49–80. doi: 10.1007/978-3-319-90415-3_3
[47] M. Dobler et al., ‘Towards a Decentralized QoE Layer for the Mobile Internet’, in INTERNET 2011 : The Third International Conference on Evolving Internet, Jun. 2011. pp. 14-19. Accessed: Jan. 05, 2025. [Online].Available:https://personales.upv.es/thinkmind/dl/conferences/internet/internet_2011/internet_2011_1_30_30039.pdf
[48] M. Seufert, S. Egger, M. Slanina, T. Zinner, T. Hoßfeld, and P. Tran-Gia, ‘A Survey on Quality of Experience of HTTP Adaptive Streaming’, IEEE Commun. Surv. Tutorials, vol. 17, no. 1, pp. 469–492, 2015. doi: 10.1109/COMST.2014.2360940
[49] P. Anchuen, P. Uthansakul, and M. Uthansakul, ‘QoE Analysis for Improving Multimedia Services Based on Different Operating Situations on Cellular Networks’, IEEE Access, vol. 9, pp. 116215–116230, 2021. doi: 10.1109/ACCESS.2021.3106241
[50] Q. Yuan, Z. Fan, and J. Leng, ‘The Effect of Emotional Reactivity on Marital Quality in Chinese Couples: The Mediating Role of Perceived Partner Responsiveness’, Front. Psychol., vol. 12, p. 787899, 2022. doi: 10.3389/fpsyg.2021.787899
[51] C. E. Parsons, B. Schofield, S. E. Batziou, C. Ward, and K. S. Young, ‘Sleep quality is associated with emotion experience and adaptive regulation of positive emotion: An experience sampling study’, Journal of Sleep Research, vol. 31, no. 4, p. e13533, 2022. doi: 10.1111/jsr.13533
[52] M. R. Quintero and A. Raake, ‘Towards assigning value to multimedia QOE’, in 2011 Third International Workshop on Quality of Multimedia Experience, Mechelen, Belgium: IEEE, Sep. 2011, pp. 1–6. doi: 10.1109/QoMEX.2011.6065704
[53] P. K. Maroju and P. Bhattacharya, ‘Understanding Emotional Intelligence: The Heart of Human-Centered Technology’, in Advances in Computational Intelligence and Robotics, S. Tikadar, H. Liu, P. Bhattacharya, and S. Bhattacharya, Eds., IGI Global, 2024, pp. 1–18. doi: 10.4018/979-8-3693-7011-7.ch001
[54] P. Pulivarthi and A. B. Bhatia, ‘Designing Empathetic Interfaces Enhancing User Experience Through Emotion’, in Advances in Computational Intelligence and Robotics, S. Tikadar, H. Liu, P. Bhattacharya, and S. Bhattacharya, Eds., IGI Global, 2024, pp. 47–64. doi: 10.4018/979-8-3693-7011-7.ch004
[55] S. Duan, Z. Wang, S. Wang, M. Chen, and R. Zhang, ‘Emotion-Aware Interaction Design in Intelligent User Interface Using Multi-Modal Deep Learning’, in 2024 5th International Symposium on Computer Engineering and Intelligent Communications (ISCEIC), Wuhan, China: IEEE, Nov. 2024, pp. 110–114. doi: 10.1109/ISCEIC63613.2024.10810240
[56] P. O’Connor, Z. Izadikhah, S. Abedini, and C. J. Jackson, ‘Can Deficits in Emotional Intelligence Explain the Negative Relationship Between Abandonment Schema and Marital Quality?’, Family Relations, vol. 67, no. 4, pp. 510–522, 2018. doi: 10.1111/fare.12320
[57] W. T. Vambe, ‘Fog Computing Quality of Experience: Review and Open Challenges’, International Journal of Fog Computing, vol. 6, no. 1, pp. 1–16, 2023. doi: 10.4018/IJFC.317110

[58] M. Torres Vega, C. Perra, and A. Liotta, 'Resilience of Video Streaming Services to Network Impairments', IEEE Trans. on Broadcast., vol. 64, no. 2, pp. 220–234, 2017. doi: 10.1109/TBC.2017.2781125
[59] B. Baldovino, 'An Overview of the Networking Issues of Cloud Gaming: A Literature Review', Jinita, vol. 4, no. 2, pp. 120–132, 2022. doi: 10.35970/jinita.v4i2.1581
[60] Z. Li, H. Melvin, R. Bruzgiene, P. Pocta, L. Skorin-Kapov, and A. Zgank, 'Lag Compensation for First-Person Shooter Games in Cloud Gaming', in Autonomous Control for a Reliable Internet of Services, vol. 10768, I. Ganchev, R. D. Van Der Mei, and H. Van Den Berg, Eds., in Lecture Notes in Computer Science, vol. 10768. , Cham: Springer International Publishing, 2018, pp. 104–127. doi: 10.1007/978-3-319-90415-3_5
[61] J. Yang, Y. Miao, C. Han, Y. Tian, X. You, and Y. Jiang, 'OPPOCO: From Ad Hoc Cloudlet-assisted Edge Computation to Opportunistic Computation Offloading', in Proceedings of the 12th EAI International Conference on Testbeds and Research Infrastructures for the Development of Networks & Communities, Dalian, People's Republic of China: EAI, 2018. pp. 1–11. doi: 10.4108/eai.28-9-2017.2273365
[62] M. Beshley, N. Kryvinska, H. Beshley, O. Panchenko, and M. Medvetskyi, 'Traffic engineering and QoS/QoE supporting techniques for emerging service-oriented software-defined network', J. Commun. Netw., vol. 26, no. 1, pp. 99–114, 2024. doi: 10.23919/JCN.2023.000065
[63] M. Zubair Islam, Shahzad, R. Ali, A. Haider, and H. S. Kim, 'Reinforcement Learning-Aided Edge Intelligence Framework for Delay-Sensitive Industrial Applications', Sensors, vol. 22, no. 20, p. 8001, 2022. doi: 10.3390/s22208001
[64] A. A. Laghari, H. He, K. A. Memon, R. A. Laghari, I. A. Halepoto, and A. Khan, 'Quality of experience (QoE) in cloud gaming models: A review', MGS, vol. 15, no. 3, pp. 289–304, 2019. doi: 10.3233/MGS-190313
[65] B. Saovapakhiran, W. Naruephiphat, C. Charnsripinyo, S. Baydere, and S. Ozdemir, 'QoE-Driven IoT Architecture: A Comprehensive Review on System and Resource Management', IEEE Access, vol. 10, pp. 84579–84621, 2022. doi: 10.1109/ACCESS.2022.3197585
[66] A. Floris, A. Ahmad, and L. Atzori, 'QoE-Aware OTT-ISP Collaboration in Service Management: Architecture and Approaches', ACM Trans. Multimedia Comput. Commun. Appl., vol. 14, no. 2s, pp. 1–24, 2018. doi: 10.1145/3183517
[67] S. Borsci, S. Federici, S. Bacci, M. Gnaldi, and F. Bartolucci, 'Assessing User Satisfaction in the Era of User Experience: Comparison of the SUS, UMUX, and UMUX-LITE as a Function of Product Experience', International Journal of Human-Computer Interaction, vol. 31, no. 8, pp. 484–495, 2015. doi: 10.1080/10447318.2015.1064648
[68] P. Ke and F. Su, 'Mediating effects of user experience usability: An empirical study on mobile library application in China', EL, vol. 36, no. 5, pp. 892–909, 2018. doi: 10.1108/EL-04-2017-0086
[69] T. L. Mitzner et al., 'Older adults talk technology: Technology usage and attitudes', Computers in Human Behaviour, vol. 26, no. 6, pp. 1710–1721, 2010. doi: 10.1016/j.chb.2010.06.020
[70] Universiti Teknikal Malaysia Melaka et al., 'A Review on Usability and User Experience of Assistive Social Robots for Older Persons', IJIE, vol. 14, no. 6, 2022. doi: 10.30880/ijie.2022.14.06.010
[71] M. A. F. Kamil, 'User Experience Analysis of LinkedIn Social Media Using Usability Metric for User Experience (UMUX)', JIEET, vol. 7, no. 2, pp. 78–82, 2023. doi: 10.26740/jieet.v7n2.p78-82
[72] 'Enhancing customer loyalty through quality of service: effective strategies to improve customer satisfaction, experience, relationship, and engagement', IRJMETS, vol. 5, no. 5, pp. 427-452, 2023. doi: 10.56726/IRJMETS38104
[73] Z. Duan, 'Data-Driven Personalized Marketing in E-commerce: Practical Applications', AEMPS, vol. 102, no. 1, pp. 79–86, 2024. doi: 10.54254/2754-1169/102/2024ED0103
[74] A. Das and H. Ranganath, 'When web personalization misleads bucket testing', in Proceedings of the 1st workshop on User engagement optimization, San Francisco California USA: ACM, Nov. 2013, pp. 17–20. doi: 10.1145/2512875.2512879
[75] P. Zheng, S. Yu, Y. Wang, R. Y. Zhong, and X. Xu, 'User-experience Based Product Development for Mass Personalization: A Case Study', Procedia CIRP, vol. 63, pp. 2–7, 2017. doi: 10.1016/j.procir.2017.03.122
[76] University of Jyväskylä, J. Elo, J. Lumivalo and T. Tuunanen, 'A Personal Values-Based Approach to Understanding Users' Co-Creative and Co-Destructive Gaming Experiences in Augmented Reality Mobile Games', PAJAIS, vol. 14, pp. 51–81, 2022. doi: 10.17705/1pais.14503
[77] M. E. Dimaro, 'Service Quality for Customers' Satisfaction: A Literature Review', EMSJ, vol. 7, no. 1, pp. 267–276, 2023. doi: 10.59573/emsj.7(1).2023.24
[78] F. Metzger et al., 'An Introduction to Online Video Game QoS and QoE Influencing Factors', IEEE Commun. Surv. Tutorials, vol. 24, no. 3, pp. 1894–1925, 2022. doi: 10.1109/COMST.2022.3177251
[79] T. Hossfeld, M. Seufert, C. Sieber, and T. Zinner, 'Assessing effect sizes of influence factors towards a QoE model for HTTP adaptive streaming', in 2014 Sixth International Workshop on Quality of

Multimedia Experience (QoMEX), Singapore, Singapore: IEEE, Sep. 2014, pp. 111–116. doi: 10.1109/QoMEX.2014.6982305
[80] M. M. Yahaya, Y. Surajo, and A. H. Rawayau, 'An enhanced resource allocation scheme for Long Term Evolution advanced network', FJS, vol. 7, no. 3, pp. 7–12, 2023. doi: 10.33003/fjs-2023-0703-1766
[81] A. A. Barakabitze, I.-H. Mkwawa, A. Hines, and R. Walshe, 'QoE-Aware Dynamic Resource Management in Future Softwarized and Virtualized Networks', IEEE Access, vol. 11, pp. 93310–93330, 2023. doi: 10.1109/ACCESS.2023.3309599
[82] S. Baraković and L. Skorin-Kapov, 'Survey and Challenges of QoE Management Issues in Wireless Networks', Journal of Computer Networks and Communications, vol. 2013, pp. 1–28, 2013. doi: 10.1155/2013/165146
[83] R. I. Tavares Da Costa Filho, F. De Turck, and L. P. Gaspary, 'From 2D to Next Generation VR/AR Videos: Enabling Efficient Streaming via QoE-aware Mobile Networks', in NOMS 2020 - 2020 IEEE/IFIP Network Operations and Management Symposium, Budapest, Hungary: IEEE, Apr. 2020, pp. 1–6. doi: 10.1109/NOMS47738.2020.9110416
[84] G. O. Djuikom Foka, R. Stanica, and D. Naboulsi, 'Handover Forecasting in Cellular Networks: A Spatio-temporal Graph Neural Network Approach', in 2023 14th International Conference on Network of the Future (NoF), Izmir, Turkiye: IEEE, Oct. 2023, pp. 80–88. doi: 10.1109/NoF58724.2023.10302814
[85] X. Chen et al., 'Reinforcement learning–based QoS/QoE-aware service function chaining in software-driven 5G slices', Trans Emerging Tel Tech, vol. 29, no. 11, p. e3477, 2018. doi: 10.1002/ett.3477
[86] A. A. Barakabitze, A. Ahmad, R. Mijumbi, and A. Hines, '5G network slicing using SDN and NFV: A survey of taxonomy, architectures and future challenges', Computer Networks, vol. 167, p. 106984, 2020. doi: 10.1016/j.comnet.2019.106984
[87] M. Liubogoshchev, D. Zudin, A. Krasilov, A. Krotov, and E. Khorov, 'DeSlice: An Architecture for QoE-Aware and Isolated RAN Slicing', Sensors, vol. 23, no. 9, p. 4351, 2023. doi: 10.3390/s23094351
[88] S. Sukhmani, M. Sadeghi, M. Erol-Kantarci, and A. El Saddik, 'Edge Caching and Computing in 5G for Mobile AR/VR and Tactile Internet', IEEE MultiMedia, vol. 26, no. 1, pp. 21–30, 2019. doi: 10.1109/MMUL.2018.2879591
[89] J. Du, F. R. Yu, G. Lu, J. Wang, J. Jiang, and X. Chu, 'MEC-Assisted Immersive VR Video Streaming Over Terahertz Wireless Networks: A Deep Reinforcement Learning Approach', IEEE Internet Things J., vol. 7, no. 10, pp. 9517–9529, 2020. doi: 10.1109/JIOT.2020.3003449
[90] D. Alencar, H. Oliveira, and D. Rosário, 'Dynamic allocation of microservices for virtual reality content delivery to provide quality of experience support in a fog computing architecture', in Anais Estendidos do XLI Simpósio Brasileiro de Redes de Computadores e Sistemas Distribuídos (SBRC Estendido 2023), Brasil: Sociedade Brasileira de Computação - SBC, May 2023, pp. 72–79. doi: 10.5753/sbrc_estendido.2023.709
[91] G. Interdonato, E. Björnson, H. Quoc Ngo, P. Frenger, and E. G. Larsson, 'Ubiquitous cell-free Massive MIMO communications', J Wireless Com Network, vol. 2019, no. 1, p. 197, 2019. doi: 10.1186/s13638-019-1507-0
[92] X. Gao, O. Edfors, F. Rusek, and F. Tufvesson, 'Massive MIMO Performance Evaluation Based on Measured Propagation Data', IEEE Trans. Wireless Commun., vol. 14, no. 7, pp. 3899–3911, 2015. doi: 10.1109/TWC.2015.2414413
[93] Q. He et al., 'Network Slicing to Enable Resilience and High Availability in 5G Mobile Telecommunications', MATEC Web Conf., vol. 246, p. 03028, 2018. doi: 10.1051/matecconf/201824603028
[94] I. P. Chochliouros, A. S. Spiliopoulou, P. Lazaridis, A. Dardamanis, Z. Zaharis, and A. Kostopoulos, 'Dynamic Network Slicing: Challenges and Opportunities', in Artificial Intelligence Applications and Innovations. AIAI 2020 IFIP WG 12.5 International Workshops, vol. 585, I. Maglogiannis, L. Iliadis, and E. Pimenidis, Eds., in IFIP Advances in Information and Communication Technology, vol. 585, Cham: Springer International Publishing, 2020, pp. 47–60. doi: 10.1007/978-3-030-49190-1_5
[95] M. W. Akhtar, S. A. Hassan, R. Ghaffar, H. Jung, S. Garg, and M. S. Hossain, 'The shift to 6G communications: vision and requirements', Hum. Cent. Comput. Inf. Sci., vol. 10, no. 1, p. 53, 2020. doi: 10.1186/s13673-020-00258-2
[96] A. F. Hussein, D. Saha, and H. Elgala, 'Mixed-Carrier Communication for Technology Division Multiplexing', Electronics, vol. 10, no. 18, p. 2248, 2021. doi: 10.3390/electronics10182248
[97] X. You et al., 'Towards 6G wireless communication networks: vision, enabling technologies, and new paradigm shifts', Sci. China Inf. Sci., vol. 64, no. 1, p. 110301, 2021. doi: 10.1007/s11432-020-2955-6
[98] Y. Yang et al., '6G Network AI Architecture for Everyone-Centric Customized Services', IEEE Network, vol. 37, no. 5, pp. 71–80, 2023. doi: 10.1109/MNET.124.2200241
[99] M. M. Nasralla, S. B. A. Khattak, I. Ur Rehman, and M. Iqbal, 'Exploring the Role of 6G Technology in Enhancing Quality of Experience for m-Health Multimedia Applications: A Comprehensive Survey', Sensors, vol. 23, no. 13, p. 5882, 2023. doi: 10.3390/s23135882

[100] S. Tan, F. Jin, J. Xie, and C. Dun, 'A QoE Driven Cross-Domain Management Architecture for Space-Air-Ground Integrated Network', Wireless Communications and Mobile Computing, vol. 2022, pp. 1–14, 2022. doi: 10.1155/2022/8410133
[101] M. Z. Chowdhury, Md. Shahjalal, S. Ahmed, and Y. M. Jang, '6G Wireless Communication Systems: Applications, Requirements, Technologies, Challenges, and Research Directions', IEEE Open J. Commun. Soc., vol. 1, pp. 957–975, 2020. doi: 10.1109/OJCOMS.2020.3010270
[102] L. Bariah, H. Sari, and M. Debbah, 'Digital Twin-Empowered Smart Cities: A New Frontier of Wireless Networks', Authorea preprint, 2022. doi: https://doi.org/10.36227/techrxiv.20375325.v1
[103] P. Wu, Y. Tu, X. Yuan, A. Jatowt, and Z. Yang, 'Neural Framework for Joint Evolution Modelling of User Feedback and Social Links in Dynamic Social Networks', in Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence, Stockholm, Sweden: International Joint Conferences on Artificial Intelligence Organization, Jul. 2018, pp. 1632–1638. doi: 10.24963/ijcai.2018/226
[104] F. S. F. Pereira, J. Gama, S. De Amo, and G. M. B. Oliveira, 'On analysing user preference dynamics with temporal social networks', Mach Learn, vol. 107, no. 11, pp. 1745–1773, 2018. doi: 10.1007/s10994-018-5740-2
[105] Statista, 'Number of internet and social media users worldwide as of February 2025', Statista. Accessed: Mar. 15, 2025. [Online]. Available: https://www.statista.com/statistics/617136/digital-population-worldwide
[106] M. Torres Vega, C. Perra, F. De Turck, and A. Liotta, 'A Review of Predictive Quality of Experience Management in Video Streaming Services', IEEE Trans. on Broadcast., vol. 64, no. 2, pp. 432–445, 2018. doi: 10.1109/TBC.2018.2822869
[107] S. Schwarzmann, C. Cassales Marquezan, M. Bosk, H. Liu, R. Trivisonno, and T. Zinner, 'Estimating Video Streaming QoE in the 5G Architecture Using ML', in Proceedings of the 4th Internet-QoE Workshop on QoE-based Analysis and Management of Data Communication Networks, Los Cabos Mexico: ACM, Oct. 2019, pp. 7–12. doi: 10.1145/3349611.3355547
[108] J. Calle-Cancho, C. Cruz-Carrasco, D. Cortés-Polo, J. Galeano-Brajones, and J. Carmona-Murillo, 'Enhancing Programmability in Next-Generation Networks: An Innovative Simulation Approach', Electronics, vol. 13, no. 3, p. 532, 2024. doi: 10.3390/electronics13030532
[109] W. Z. Khan, E. Ahmed, S. Hakak, I. Yaqoob, and A. Ahmed, 'Edge computing: A survey', Future Generation Computer Systems, vol. 97, pp. 219–235, 2019. doi: 10.1016/j.future.2019.02.050
[110] J. Lv, Y. Gao, and W. Dong, 'Measurement and QoE Modelling of Broadband Home Networks with Large-Scale Crowdsourcing', in 2018 IEEE 24th International Conference on Parallel and Distributed Systems (ICPADS), Singapore, Singapore: IEEE, Dec. 2018, pp. 954–961. doi: 10.1109/PADSW.2018.8644951
[111] P. Uthansakul, P. Anchuen, M. Uthansakul, and A. Ahmad Khan, 'Estimating and Synthesizing QoE Based on QoS Measurement for Improving Multimedia Services on Cellular Networks Using ANN Method', IEEE Trans. Netw. Serv. Manage., vol. 17, no. 1, pp. 389–402, 2020. doi: 10.1109/TNSM.2019.2946091
[112] J. Zhu, A. Ak, P. L. Callet, S. Sethuraman, and K. Rahul, 'ZREC: Robust recovery of mean and percentile opinion scores', IEEE ICIP 2023. Accessed: Apr. 18. 2025. [Online]. Available: https://www.amazon.science/publications/zrec-robust-recovery-of-mean-and-percentile-opinion-scores
[113] Cisco, 'Cisco Annual Report (2018-2023)', Cisco, White Paper C11-741490–01, 2020. Accessed: Apr. 17. 2025. [Online]. Available: https://www.cisco.com/c/en/us/solutions/collateral/executive-perspectives/annual-internet-report/white-paper-c11-741490.pdf
[114] L. Skorin-Kapov, M. Varela, T. Hoßfeld, and K.-T. Chen, 'A Survey of Emerging Concepts and Challenges for QoE Management of Multimedia Services', ACM Trans. Multimedia Comput. Commun. Appl., vol. 14, no. 2s, pp. 1–29, 2018. doi: 10.1145/3176648
[115] M. Bahaa, A. Aboulmagd, K. Adel, H. Fawzy, and N. Abdelbaki, 'nnDPI: A Novel Deep Packet Inspection Technique Using Word Embedding, Convolutional and Recurrent Neural Networks', in 2020 2nd Novel Intelligent and Leading Emerging Sciences Conference (NILES), Giza, Egypt: IEEE, Oct. 2020, pp. 165–170. doi: 10.1109/NILES50944.2020.9257912
[116] C. Xu, S. Chen, J. Su, S. M. Yiu, and L. C. K. Hui, 'A Survey on Regular Expression Matching for Deep Packet Inspection: Applications, Algorithms, and Hardware Platforms', IEEE Commun. Surv. Tutorials, vol. 18, no. 4, pp. 2991–3029, 2016. doi: 10.1109/COMST.2016.2566669
[117] El-Maghraby et al, 'A Survey on Deep Packet Inspection', in 2017 12th International Conference on Computer Engineering and Systems (ICCES), Cairo, Egypt: IEEE, Dec. 2017, pp. 188–197. doi: 10.1109/ICCES.2017.8275301
[118] L. Plissonneau, 'Network tomography from an operator perspective', Télécom ParisTech, Institut Polytechnique de Paris, 2012. Accessed Apr. 15. 2025. [Online]. Available: https://pastel.hal.science/tel-01078299/file/these_Plissonneau.pdf

[119] S. Pezzulli, M. G. Martini, and N. Barman, ‘Estimation of Quality Scores from Subjective Tests-Beyond Subjects’ MOS’, IEEE Trans. Multimedia, vol. 23, pp. 2505–2519, 2021. doi: 10.1109/TMM.2020.3013349
[120] P. Marchetta, V. Persico, G. Aceto, A. Botta, and A. Pescape, ‘Measuring Networks Using IP Options’, IEEE Network, vol. 31, no. 3, pp. 30–36, 2017. doi: 10.1109/MNET.2017.1600070NM
[121] G. Miranda, D. F. Macedo, and J. M. Marquez-Barja, ‘Estimating Video on Demand QoE from Network QoS Through ICMP Probes’, IEEE Trans. Netw. Serv. Manage., vol. 19, no. 2, pp. 1890–1902, 2022. doi: 10.1109/TNSM.2021.3129610
[122] P. Roquero and J. Aracil, ‘On Performance and Scalability of Cost-Effective SNMP Managers for Large-Scale Polling’, IEEE Access, vol. 9, pp. 7374–7383, 2021. doi: 10.1109/ACCESS.2021.3049310
[123] M. Miyazawa and M. Hayashi, ‘In-network Real-time Performance Monitoring with Distributed Event Processing’, in proc. 2014 IEEE Network Operations and Management Symposium (NOMS), Krakow, Poland. p. 5. doi: doi:10.1109/noms.2014.6838384
[124] R. B. Johnson, ‘Evaluating the use of SNMP as a wireless network monitoring tool for IEEE 802.11 wireless networks.’, M.S. thesis, Dept. of Electrical and Computer Engineering, Clemson University, Clemson, SC, USA, 2009. Accessed: Apr. 29. 2025. [Online]. Available:https://open.clemson.edu/cgi/viewcontent.cgi?article=1579&context=all_theses
[125] P. Jurkiewicz, ‘Flow-models: A framework for analysis and modelling of IP network flows’, SoftwareX, vol. 17, p. 100929, 2022. doi: 10.1016/j.softx.2021.100929
[126] R. Hofstede et al., ‘Flow Monitoring Explained: From Packet Capture to Data Analysis with NetFlow and IPFIX’, IEEE Commun. Surv. Tutorials, vol. 16, no. 4, pp. 2037–2064, 2014. doi: 10.1109/COMST.2014.2321898
[127] F. Ricciato, F. Strohmeier, P. Dorfinger, and A. Coluccia, ‘One-way loss measurements from IPFIX records’, in 2011 IEEE International Workshop on Measurements and Networking Proceedings (M&N), Anacapri, Italy: IEEE, Oct. 2011, pp. 158–163. doi: 10.1109/IWMN.2011.6088499
[128] T. Hoßfeld et al., ‘Quality of Experience Management for YouTube: Clouds, FoG and the AquareYoum’, PIK - Praxis der Informationsverarbeitung und Kommunikation, vol. 35, no. 3, 2012. doi: 10.1515/pik-2012-0024
[129] F. Metzger et al., ‘Context Monitoring for Improved System Performance and QoE’, in Autonomous Control for a Reliable Internet of Services, vol. 10768, I. Ganchev, R. D. Van Der Mei, and H. Van Den Berg, Eds., in Lecture Notes in Computer Science, vol. 10768. , Cham: Springer International Publishing, 2018, pp. 23–48. doi: 10.1007/978-3-319-90415-3_2
[130] H. Beshley, M. Beshley, M. Medvetskyi, and J. Pyrih, ‘QoS-Aware Optimal Radio Resource Allocation Method for Machine-Type Communications in 5G LTE and beyond Cellular Networks’, Wireless Communications and Mobile Computing, vol. 2021, no. 1, p. 9966366, 2021. doi: 10.1155/2021/9966366
[131] K. S. Jagarlamudi, A. Zaslavsky, S. W. Loke, A. Hassani, and A. Medvedev, ‘Requirements, Limitations and Recommendations for Enabling End-to-End Quality of Context-Awareness in IoT Middleware’, Sensors, vol. 22, no. 4, p. 1632, 2022. doi: 10.3390/s22041632
[132] H. Kurniawan and M. Mambo, ‘Homomorphic Encryption-Based Federated Privacy Preservation for Deep Active Learning’, Entropy, vol. 24, no. 11, p. 1545, 2022. doi: 10.3390/e24111545
[133] R. Nasirigerdeh et al., ‘sPLINK: a hybrid federated tool as a robust alternative to meta-analysis in genome-wide association studies’, Genome Biol, vol. 23, no. 1, p. 32, 2022 doi: 10.1186/s13059-021-02562-1
[134] T. Jie, X. Yan, C. Yali, and L. Xuhui, ‘Multi-path QoE Routing Algorithm for wireless mesh network Based on Q-Learning’, J. Phys.: Conf. Ser., vol. 2384, no. 1, p. 012040, 2022. doi: 10.1088/1742-6596/2384/1/012040
[135] S. Y. Yoon et al., ‘Mobile data service QoE analytics and optimization’, in 2015 IEEE International Conference on Communication Workshop (ICCW), London, United Kingdom: IEEE, Jun. 2015, pp. 1699–1704. doi: 10.1109/ICCW.2015.7247425
[136] M. Roshan, J. A. Schormans, and R. Ogilvie, ‘Video-on-demand QoE Evaluation Across Different Age-Groups and Its Significance for Network Capacity’, ICST Transactions on Mobile Communications and Applications, vol. 3, no. 9, p. 153557, 2018. doi: 10.4108/eai.10-1-2018.153557
[137] J. Nightingale, P. Salva-Garcia, J. M. A. Calero, and Q. Wang, ‘5G-QoE: QoE Modelling for Ultra-HD Video Streaming in 5G Networks’, IEEE Trans. on Broadcast., vol. 64, no. 2, pp. 621–634, 2018. doi: 10.1109/TBC.2018.2816786
[138] M. H. H. Omar, K. Justin P., K. Windmi Jonathan M., T. Stanislas David Wendkouni, and S. Oumarou Pr, ‘Using QoE Metric as a Decision Criterion in Multimedia Heterogeneous Network Optimization: Challenges and Research Perspectives’, Journal of Computer Networks and Communications, vol. 2024, pp. 1–18, 2024. doi: 10.1155/2024/7864757
[139] B. Agarwal, M. A. Togou, M. Ruffini, and G.-M. Muntean, ‘A Comprehensive Survey on Radio Resource Management in 5G HetNets: Current Solutions, Future Trends and Open Issues’, IEEE Commun. Surv. Tutorials, vol. 24, no. 4, pp. 2495–2534, 2022. doi: 10.1109/COMST.2022.3207967

[140] L. Zou, R. Trestian, and G.-M. Muntean, 'E3 DOAS: Balancing QoE and Energy-Saving for Multi-Device Adaptation in Future Mobile Wireless Video Delivery', IEEE Trans. on Broadcast., vol. 64, no. 1, pp. 26–40, 2018. doi: 10.1109/TBC.2017.2722221
[141] A. Mehrabi, M. Siekkinen, and A. Yla-Jaaski, 'Energy-Aware QoE and Backhaul Traffic Optimization in Green Edge Adaptive Mobile Video Streaming', IEEE Trans. on Green Commun. Netw., vol. 3, no. 3, pp. 828–839, 2019. doi: 10.1109/TGCN.2019.2918847
[142] A. A. Laghari, H. He, M. Shafiq, and A. Khan, 'Impact of storage of mobile on quality of experience (QoE) at user level accessing cloud', in 2017 IEEE 9th International Conference on Communication Software and Networks (ICCSN), Guangzhou: IEEE, May 2017, pp. 1402–1409. doi: 10.1109/ICCSN.2017.8230340
[143] H. Zhao, W. Du, W. Liu, T. Lei, and Q. Lei, 'QoE Aware and Cell Capacity Enhanced Computation Offloading for Multi-Server Mobile Edge Computing Systems with Energy Harvesting Devices', in 2018 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI), Guangzhou, China: IEEE, Oct. 2018, pp. 671–678. doi: 10.1109/SmartWorld.2018.00133
[144] J. Luo, 'QoE-driven computation offloading for Edge Computing', Journal of Systems Architecture, vol. 97, pp. 34–39, 2019. doi: https://doi.org/10.1016/j.sysarc.2019.01.019
[145] M. Chen, Y. Hao, M. Qiu, J. Song, D. Wu, and I. Humar, 'Mobility-Aware Caching and Computation Offloading in 5G Ultra-Dense Cellular Networks', Sensors, vol. 16, no. 7, p. 974, 2016. doi: 10.3390/s16070974
[146] R. Macmillan, 'Big data, Machine Learning, consumer protection and privacy', in TPRC47: The 47th Research Conference on Communication, Information and Internet Policy 2019, July 2019, p. 68 Accessed: Jan. 05, 2025. [Online]. Available: https://ssrn.com/abstract=3427206
[147] A. Sharama and Dr. Jaswinder Singh, 'Survey of technologies of self-organizing networks (SON)', IJET, vol. 7, no. 4, p. 2581, 2018. doi: 10.14419/ijet.v7i4.16831
[148] R. Amiri, M. A. Almasi, J. G. Andrews, and H. Mehrpouyan, 'Reinforcement Learning for Self Organization and Power Control of Two-Tier Heterogeneous Networks', IEEE Trans. Wireless Commun., vol. 18, no. 8, pp. 3933–3947, 2019. doi: 10.1109/TWC.2019.2919611
[149] M. S. Arbabi, C. Lal, N. R. Veeraragavan, D. Marijan, J. F. Nygård, and R. Vitenberg, 'A Survey on Blockchain for Healthcare: Challenges, Benefits, and Future Directions', IEEE Commun. Surv. Tutorials, vol. 25, no. 1, pp. 386–424, 2023. doi: 10.1109/COMST.2022.3224644
[150] L. Zavolokina, N. Zani, and G. Schwabe, 'Designing for Trust in Blockchain Platforms', IEEE Trans. Eng. Manage., vol. 70, no. 3, pp. 849–863, 2023. doi: 10.1109/TEM.2020.3015359
[151] N. Wehner, A. Seufert, T. Hoßfeld, and M. Seufert, 'Explainable Data-Driven QoE Modelling with XAI', in 2023 15th International Conference on Quality of Multimedia Experience (QoMEX), Ghent, Belgium: IEEE, Jun. 2023, pp. 7–12. doi: 10.1109/QoMEX58391.2023.10178499
[152] M. K. Banjanin, M. Stojčić, D. Danilović, Z. Ćurguz, M. Vasiljević, and G. Puzić, 'Classification and Prediction of Sustainable Quality of Experience of Telecommunication Service Users Using ML Models', Sustainability, vol. 14, no. 24, p. 17053, 2022. doi: 10.3390/su142417053
[153] D. Pal and T. Triyason, 'A Survey of Standardized Approaches towards the Quality of Experience Evaluation for Video Services: An ITU Perspective', International Journal of Digital Multimedia Broadcasting, vol. 2018, pp. 1–25, 2018. doi: 10.1155/2018/1391724
[154] D. Ghadiyaram, J. Pan, and A. C. Bovik, 'Learning a Continuous-Time Streaming Video QoE Model', IEEE Trans. on Image Process., vol. 27, no. 5, pp. 2257–2271, 2018. doi: 10.1109/TIP.2018.2790347
[155] A. Mongi, 'Modelling Video Streaming Quality of Experience using Taguchi and Fuzzy Logic Methods', JICTS, vol. 1, no. 1, pp. 32–43, 2023. doi: 10.56279/jicts.v1i1.22
[156] C. Park and A. Balasubramanian, 'A Look Into the Performance of mmWave 5G, 3G, 4G/LTE using PC Application, iPerf3 and DASH', J Stud Res, vol. 12, no. 1, 2023. doi: 10.47611/jsrhs.v12i1.4109.
[157] A. Angus, C. V. Murudkar, and R. D. Gitlin, 'Machine Learning for QoE Prediction and Anomaly Detection in Self-Organizing Mobile Networking Systems', IJWMN, Vol. 11, No. 2, 2019, doi: 10.2139/ssrn.3383948
[158] I. Vetoshko and V. Noskov, 'Evaluation of voice transmission quality in the lte networks', ITS, no. 2, pp. 22–26, 2021. doi: 10.20535/2411-2976.22021.22-26
[159] G. Bekaroo, A. Santokhee, and J. C. Augusto, '5G Smart and Innovative Healthcare Services: Opportunities, Challenges, and Prospective Solutions', in 5G Multimedia Communication, 1st ed., Z. S. Bojkovic, D. A. Milovanovic, and T. P. Fowdur, Eds., First edition. | Boca Raton, FL : CRC Press, 2020.: CRC Press, 2020, pp. 279–297. doi: 10.1201/9781003096450-15
[160] R. Odarchenko, 'Evaluation and Improvement of QoE and QoS Parameters in Commercial 5G Networks: 5G-Tours Approach', IJC, pp. 462–474, 2023. doi: 10.47839/ijc.22.4.3353
[161] M. Z. Chowdhury, Moh. K. Hasan, Md. Shahjalal, E. B. Shin, and Y. M. Jang, 'Opportunities of Optical Spectrum for Future Wireless Communications', in 2019 International Conference on Artificial

Intelligence in Information and Communication (ICAIIC), Okinawa, Japan: IEEE, Feb. 2019, pp. 004–007. doi: 10.1109/ICAIIC.2019.8668981
[162] Dr. S. Singh, 'The Role of Artificial Intelligence in 5G Network Management: A comprehensive study', Int. J. Res. Publ. Rev., vol. 4, no. 11, pp. 2862–2866, 2023. doi: 10.55248/gengpi.4.1123.113203
[163] K. Lin et al., 'Remote fault management and control system of hydropower station based on 5G inspection robot', in International Conference on Computer, Artificial Intelligence, and Control Engineering (CAICE 2022), Y. Yan, Ed., Zhuhai, China: SPIE, Dec. 2022, p. 78. doi: 10.1117/12.2641056
[164] A. A. El-Saleh, M. A. Al Jahdhami, A. Alhammadi, Z. A. Shamsan, I. Shayea, and W. H. Hassan, 'Measurements and Analyses of 4G/5G Mobile Broadband Networks: An Overview and a Case Study', Wireless Communications and Mobile Computing, vol. 2023, pp. 1–24, 2023. doi: 10.1155/2023/6205689
[165] X. Li, H. Guo, W. Xie, and X. Ding, 'A 5G Coverage Calculation Optimization Algorithm Based on Multifrequency Collaboration', Electronics, vol. 12, no. 19, p. 4044, 2023. doi: 10.3390/electronics12194044
[166] E. Kapassa, M. Touloupou, A. Mavrogiorgou, and D. Kyriazis, '5G & SLAs: Automated proposition and management of agreements towards QoS enforcement', in 2018 21st Conference on Innovation in Clouds, Internet and Networks and Workshops (ICIN), Paris: IEEE, Feb. 2018, pp. 1–5. doi: 10.1109/ICIN.2018.8401587
[167] T. Abar, A. Ben Letaifa, and S. El Asmi, 'User behaviour-ensemble learning based improving QoE fairness in HTTP adaptive streaming over SDN approach', Advances in Computers, Elsevier vol. 123, pp. 245–269, 2021. doi: 10.1016/bs.adcom.2021.01.004
[168] A. Yousafzai, I. Yaqoob, M. Imran, A. Gani, and R. Md Noor, 'Process Migration-Based Computational Offloading Framework for IoT-Supported Mobile Edge/Cloud Computing', IEEE Internet Things J., vol. 7, no. 5, pp. 4171–4182, 2020. doi: 10.1109/JIOT.2019.2943176
[169] A. Hussain et al., 'DLSA: Delay and Link Stability Aware Routing Protocol for Flying Ad-hoc Networks (FANETs)', Wireless Pers Commun, vol. 121, no. 4, pp. 2609–2634, 2021. doi: 10.1007/s11277-021-08839-9
[170] Z. Ezzedine, A. Khalil, B. Zeddini, and H. Ouslimani, 'A Survey on Green Enablers: Challenging Study for AI-based 5G Energy Efficiency Network', Engineering, 2024. doi: 10.20944/preprints202404.0474.v1
[171] W. Brown, O. Johnson, and G. Wilson, 'The Impact of 5G Technology on Retail Marketing and Supply Chain Operations', Business, Economics and Management, 2024. doi: 10.20944/preprints202407.2073.v1
[172] E. Chirivella-Perez, J. Gutiérrez-Aguado, J. M. Alcaraz-Calero, and Q. Wang, 'NFVMon: Enabling Multioperator Flow Monitoring in 5G Mobile Edge Computing', Wireless Communications and Mobile Computing, vol. 2018, no. 1, p. 2860452, 2018. doi: 10.1155/2018/2860452