A Survey of Emerging Concepts and Challenges for QoE Management of Multimedia Services

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Quality of Experience (QoE) has received much attention over the past years and has become a prominent issue for delivering services and applications. A significant amount of research has been devoted to understanding, measuring, and modelling QoE for a variety of media services. The next logical step is to actively exploit that accumulated knowledge to improve and manage the quality of multimedia services, while at the same time ensuring efficient and cost-effective network operations. Moreover, with many different players involved in the end-to-end service delivery chain, identifying the root causes of QoE impairments and finding effective solutions for meeting the end users' requirements and expectations in terms of service quality is a challenging and complex problem. In this paper we survey state-of-the-art findings and present emerging concepts and challenges related to managing QoE for networked multimedia services. Going beyond a number of previously published survey papers addressing the topic of QoE management, we address QoE management in the context of ongoing developments, such as the move to softwarized networks, the exploitation of big data analytics and machine learning, and the steady rise of new and immersive services (e.g., augmented and virtual reality). We address the implications of such paradigm shifts in terms of new approaches in QoE modeling, and the need for novel QoE monitoring and management infrastructures.

CCS Concepts: • **Networks** → **Network monitoring**; **Network management**; • **Computing methodologies** → **Machine learning**; • **Human-centered computing** → *Human computer interaction (HCI)*;

Additional Key Words and Phrases: QoE modeling, crowdsourcing, QoE monitoring, QoE management, data analytics, SDN, NFV, monitoring probes, encrypted traffic

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1 INTRODUCTION

Recent developments in the telecommunications and networking communities, centred around cloud-based infrastructures as well as the gradual migration towards softwarized networks and 5G architectures, are paving the way towards new service delivery opportunities. A number of novel and emerging multimedia service use cases are envisaged, characterized by requirements such as

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high bandwidth, ultra-low latency, high reliability, and high user mobility. While video transmission is expected to prevail as a dominant application in the near future, new service trends exploiting immersive technologies, such as virtual/augmented reality [117] or multi-sensorial media [49, 84], impose QoE-related requirements at both the network and application layers which require further research and standardization efforts. In this paper, we focus on emerging trends that have key implications on future QoE management mechanisms.

1.1 Emerging trends

Meeting multimedia service requirements calls for effective and flexible QoE management mechanisms integrated into the service delivery process. Novel network architectures and protocol designs are needed to overcome technical bottlenecks and challenges associated with delivering advanced multimedia services in the future Internet. In the telco domain, the ongoing paradigm shifts towards Network Function Virtualization (NFV) and virtualized networks, as well as Software Defined Networking (SDN), have strong implications on the QoE management domain. While NFV serves as a technology for decoupling hardware resources from software and functionality, SDN separates the control and forwarding planes and enables programmability of the NFV networking infrastructure. As such, these technologies enable new QoE management-related mechanisms such as programmable and flexible resource allocation to meet heterogeneous service requirements, and dynamic service orchestration. While such mechanisms offer clear opportunities, challenges arise, such as performance monitoring, and latency resulting from virtualization. Going beyond centralized data centers, virtualization and cloud technologies are being pushed towards the network edge, with the Mobile Edge Computing (MEC) paradigm playing a key role in minimizing latency and meeting application QoE requirements [100].

To-date, QoE management has been addressed from multiple, often complementary perspectives, with different control points spread along the delivery path [115]. *QoE-driven application management* has primarily addressed control and adaptation on the end-user and application host/cloud level, often studied from an application provider perspective in the context of optimizing the quality of Over-The-Top (OTT) applications and services. As an example, applications such as HTTP-based adaptive video streaming dynamically adapt to varying network conditions so as to maintain a high level of QoE. Such mechanism represent an application control loop which is often independent of network management mechanisms. On the other hand, network providers generally rely on performance and traffic monitoring solutions deployed within their access/core network to obtain insight into impairments perceived by end users. *QoE-driven network management* mechanisms have thus focused on the network provider point of view and considered control mechanisms such as optimized network resource allocation and efficiency (in particular in wireless systems [75, 86]), admission control, QoE-driven routing, etc. Such control thus aims to facilitate efficient network operations and maintain high QoE, without directly managing the applications. Recently, network-based QoE monitoring mechanisms have been greatly impacted by the widespread use of traffic encryption in OTT traffic, leaving ISPs to search for novel approaches such as those based on machine-learning methods for estimating QoE (or QoE indicators) from encrypted traffic [2, 97]. The increased exploitation of data analytics and big data techniques is foreseen in the context of monitoring users' QoE, through new metrics combining both network and behavioral data [131, 140].

Given the inherent benefits when performing application-aware network management and network-aware application management [118, 151], studies have shown that further potential lies in integrated and cross-layer QoE management approaches [16, 69, 75], stemming from various forms of cooperative agreements and information exchange between involved stakeholders [4, 65]. With services being delivered via a chain of different providers, challenges lie in specifying the underlying business models and Service Level Agreements crucial to meeting user quality requirements. To this end, financial incentives, economic aspects, and regulatory aspects all play key roles in realizing cooperative approaches.

1.2 Contribution beyond previous surveys

A number of survey papers have been published in the past 2–4 years giving various overviews of QoE management-related studies. An in-depth overview and comparison of previous studies is given by Barakovic and Skorin-Kapov [13], who focus in particular on QoE modeling, monitoring, and control in wireless networks. Schatz *et al.* distinguish between QoE-driven *application management* (observing both pro-active and re-active approaches) and QoE-driven *network management* approaches [115]. A further systematic comparison of mechanisms for QoE-centric *coordinated* application-network interaction is proposed by Schwarzmann *et al.* [118], based on the exchange of monitoring and control information between involved entities.

Among the most recent surveys, Robitza et al. [110] provide an in-depth overview of quality monitoring models and probing technologies, and provide insights into major challenges faced by ISPs. More specifically, Zhao *et al.* give a comprehensive overview of studies on the QoE management of video transmission over various types of networks [149]. The authors especially highlight research efforts addressing the role of context and human factors in the video QoE management process, which have until recently been for the most part neglected. Duan *et al.* [34] further summarize recent results that focus on understanding and exploiting the human factor in designing mobile networks, resulting in enhanced system efficiency and QoE.

The overview presented in this paper (summarized in Figure 1) is intended to be complementary to previously published surveys, and for the most part discusses work published in the last 2–3 years. Our focus is on discussing key developments and emerging concepts in the networking and service delivery domains that have strong implications on both the theoretical and practical realization of QoE management techniques. The paper structure is portrayed in Figure 2 and is organized as follows. Sec. 2 surveys emerging approaches in QoE modeling, focusing on different methods for subjective data collection and new modeling approaches. Key concepts related to monitoring QoE and related metrics are discussed in Sec. 3, considering trends in the deployment of monitoring infrastructures, and the challenges imposed with the widespread adoption of encrypted traffic. Sec. 4 focuses on QoE management mechanisms in softwarized networks. Finally, perspectives for QoE management are discussed in Sec. 5, addressing economic and business aspects, and challenges with respect to new multimedia domains characterized by immersive applications. Concluding remarks are given in Sec. 6. The Online Appendix to this paper discusses different QoE optimization objectives, and metrics beyond MOS to be considered for QoE management purposes.

2 QOE MODELING

QoE models are the foundation for QoE monitoring and management approaches, since they identify the relevant QoE parameters, and to which extent they influence the QoE. The models may focus on the different impacts of provisioning and delivery problems due to insufficient resources on QoE. The provisioning-delivery hysteresis [61] postulates the necessity to control quality (e.g., HTTP adaptive streaming), instead of suffering from uncontrollable impacts like packet loss caused by congestion. Thus, the provisioning-delivery hysteresis demands for proper QoE management based on appropriate QoE models.

In general, we distinguish between full-reference, reduced reference, and no-reference models. In the context of QoE management and monitoring, we typically have reduced reference or even

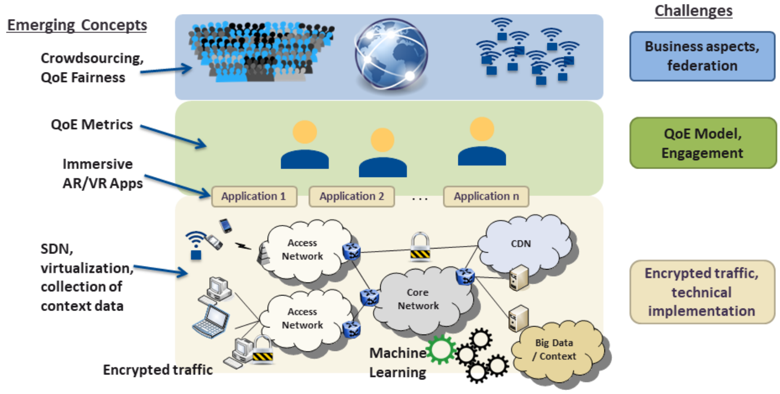

Fig. 1. Key developments and emerging concepts with implications for QoE management.

QoE Modeling (Sec. 2)
Survey on QoE models (Sec. 2.1)
Subjective data collection
- Active learning (Sec. 2.2.1)
- Crowdsourcing (Sec. 2.2.2)
- Psychophysiological assessment (Sec. 2.2.3)

Modeling approaches
- Data-driven, machine learning (Sec. 2.2.4)

QoE Monitoring (Sec. 3)
Monitoring infrastructures
- Client-side monitoring (Sec. 3.1)
- In-network and distributed monitoring (Sec. 3.2)
- User behavior and engagement monitoring (Sec. 3.3)

Big data analytics and data-driven approaches (Sec. 3.4)
Traffic encryption
- Applicability of machine learning techniques to estimate QoE (Sec. 3.5)

QoE Management (Sec. 4)
QoE management in softwarized networks
- Exploitation of SDN (Sec. 4.1)
- NFV and service orchestration (Sec. 4.2)
- Exploitation of MEC (Sec. 4.3)

Perspectives (Sec. 5)
Novel infrastructures (Sec. 5.1)
Economic and business aspects (Sec. 5.2)
New service domains (Sec. 5.3)
- Immersive AR/VR, Multisensory

Fig. 2. Paper structure (note: the Appendix to this paper is available online).

no-reference models, as the full-reference requires the original content for comparison with the transmitted, degraded content. Thus, QoE management typically requires models which are fed with some objectively measurable QoS parameters, such as packet loss or video bitrate.

2.1 Survey on QoE Models

The literature provides several classification schemes for QoE models as portrayed below.

Some classification criteria for QoE modeling approaches

- type of application or service [116, 135], e.g., image [36], voice, video [26], web service,
- availability of reference information [41]: full reference, reduced reference, no reference, e.g., [26, 36] for image and video models,
- type of input data as in ITU standardization activities [6, 26]: media-layer (or signal based) models, parametric packet-layer models, parametric planning models, bitstream layer models, hybrid models,
- blackbox vs. whitebox models [6]: machine learning methods applied to QoE [7], fundamental relationships between QoS and QoE [6, 116].

Schatz *et al.* [116] surveyed available QoE models for voice communication services, audio-visual services, and also web-based services including web browsing. Chikkerur *et al.* [26] focus on media-layer video quality models which include speech or video signal in the QoE model. Such signal-based models are often used for codec comparison and optimization. In contrast, parametric packet-layer models only rely on packet-header information without processing the media signals, which is appropriate for QoE management and network quality monitoring. Bitstream-layer models extract additional information from the bitstream, i.e., from partly decoded media. The focus of such packet-layer and bitstream models is low computational effort and easily measurable input parameters. The classification according to ITU standardization activities represents the purpose of the models. Network planning models allow to predict QoE of new networks and services by considering quality planning parameter settings. Of course, combinations of the modeling approaches exist, i.e., using information extracted from packet headers, bitstreams or media signals. For Internet-based video delivery, HTTP adaptive streaming (HAS) is the dominant technology. Currently, there is no widely accepted QoE model for HAS, but ITU-T provides a parametric bitstream-based quality assessment model in ITU-T P.1203 (formerly referred to as P.NATS) [68], while the key influences factors of HAS are surveyed in [45, 121].

For generic cloud services, there are some studies on their QoE influence factors. A QoE-based classification scheme for cloud services proposed by Hoßfeld *et al.* [65] distinguishes the level of interactivity, service complexity, usage domain and multimedia intensity. Subjective QoE results reported by Casas *et al.* [20] relate QoS parameters like network round-trip time or network bandwidth with QoE for cloud services with different requirements, such as those requiring low latency and interactivity (e.g., Cloud storage systems), multimedia On-Demand services (e.g., YouTube video streaming), communication and telepresence (e.g., Lync Online videoconferencing), and highly interactive services (e.g., Virtual Cloud Desktop). Nevertheless, no concrete models are provided. The current focus in most QoE modeling research is on video streaming, voice services, and to some extent web browsing applications. We emphasize that QoE models are fundamental for the implementation of QoE-driven cross-layer and application-layer management mechanisms. For many applications, including cloud services, no concrete QoE models exist and there are limited QoE management efforts, but there are preliminary QoE-related works for, e.g., social TV [132], 3D QoE [59], haptic internet [5], telemedicine [22] and immersive AR/VR applications (Sec. 5.3).

Another classification criterion is the type of model itself, i.e., *blackbox* or *whitebox* models. Black box models provide an output for any given input, however, the mathematical model and structure is opaque and considered as a black box. This is typically the case for neural networks or other machine learning approaches [7]. In contrast, white box model provide a mathematical model which may often be built on laws from psychophysics, like the Weber-Fechner law or Steven's power law. General relationships between QoE and QoS parameters are derived based on Weber-Fechner's law, e.g., for web browsing (as reported by Reichl *et al.* [107]), leading to a logarithmic form, but also on Steven's power law, e.g., to correlate packet loss and video QoE [7]. The IQX model proposed by Fiedler *et al.* [40] assumes that the QoE sensitivity of a user depends on the actual QoE level yielding an exponential solution. The general relationships and functional forms are discussed in [6, 7, 40, 82, 116]. The ARCU model provides a multi-dimensional view of QoE and helps to systematically identify QoE influence factors as well as their relations [127].

2.2 Emerging Approaches for Deriving QoE Models

Generic relationships between QoE and QoS have been intensively discussed in literature (see Section 2.1), but mainly with a focus on single QoS parameters. However, the generic relationship between them, and how to best model it, are yet not clear. Due to the growth of the parameter space where each parameter adds one dimension of complexity, it is required in practice to come up with proper sampling approaches and parameter selection (Section 2.2.1). Along with an increased parameter space, there is still the desire to conduct subjective studies with reduced turnaround times. Crowdsourcing offers this possiblity and allows to test user-related factors due to the international huge crowd (Section 2.2.2). A better understanding of user-related factors is key to approach also new ways of QoE models targeting individual users. Such personalized or individual QoE models may be utilized to improve the QoE of individual users by adapting, e.g., the video buffer or video adaptation strategies according to user profiles [64]. Recent efforts also consider psychophysiology-based QoE assessment to incorporate psychophysiology signals in QoE (Section 2.2.3). To cope with the large amount of potential parameters derived from packets, bitstreams or signals, data-aware QoE models and machine-learning (ML) based models are arising (Section 2.2.4).

2.2.1 Large Parameter Spaces: Active Learning. Active learning is a subfield of semi-supervised machine learning and has the goal to increase the sampling efficiency for a QoE model. A good survey on this is provided by Settles in [120]. The key idea of active learning is that the learning algorithm selects the data from which it learns most, thus reducing the number of samples while getting the same performance. In the context of QoE studies, active learning determines the next test conditions to be evaluated by subjects. Osting *et al.* [98] used active sampling for paired comparison tests which are used to evaluate the user's preference of a pair of stimuli. In particular, the LIVE video data set[1] was used containing 38,400 paired comparisons. The active sampling strategy then determines the next pairs to be compared by a subject. Ye and Doermann [145] applied adaptive learning for subjective image quality assessment. A method is proposed which actively constructs a set of queries consisting of several test conditions, i.e., test images, based on the expected information gain provided by each test. As a result, the number of required tests can be effectively reduced for achieving a target accuracy.

An active learning approach is developed by Menkovski *et al.* in [88, 89] which is based on Maximum Likelihood Difference Scaling (MLDS). The investigated parameter is the video bitrate for different types of video contents, with the goal being to provide a mapping function between video bitrate and QoE. The idea of MLDS is to scale differences between test stimuli (here: videos with certain bitrates). The combination of active learning and MLDS makes it promising to develop QoE models and to overcome biases from single stimulus ratings, e.g., due to rating scale usage of subjects [46], only. However, MLDS only quantifes the relative difference in quality rather than absolute rating which may be nevertheless sufficient for QoE management. Other approaches for overcoming such rating scale issues are paired comparison tests and mapping the comparison results to absolute quality scores, e.g., based on the Bradley-Terry model or the Thurstone's model [80]. Also training [46] or anchoring [105] may overcome this problem of rating scale usage.

Dynamic test condition selection proposed by Seufert *et al.* [124] provides an approach for conducting QoE studies which are constrained by a fixed budget of user ratings. This can also be extended to continuous QoE studies where a certain parameter range is to be assessed, e.g., QoE for video bitrates between 500 kbps to 3000 kbps. Thereby, the parameter range is split adaptively depending on the test statistic. This approach is especially useful in crowdsourcing environments.

2.2.2 Crowdsourced QoE. For collecting subjective QoE ratings from users, crowdsourcing is another promising direction which has gained huge momentum among researchers [23, 63]. QoE evaluation studies of multimedia applications may be moved from traditional laboratory environments into the Internet and give researchers a powerful tool to access a global pool of subjects. As a result, a diverse population and the heterogeneity of users (as well as their used

[1] http://live.ece.utexas.edu/research/quality/

devices and software configurations) can be taken into account, while at the same time tests can be carried out in real-life environments of the subjects. Due to the large crowd, reduced turnaround times and lower compensation costs for test subjects are appealing for researchers.

Crowdsourcing offers the possibility to extend laboratory studies, e.g., on user-related influence factors or context factors [63]. This is often not possible in a single test carried out in a test lab due to the restricted pool of subjects and limited contexts. Along with the benefits of crowdsourcing, new challenges arise, e.g., conceptual challenges in the test design, unreliability of users and statistical analysis of the results, but also incentives and payment schemes to motivate users [136]. In this context, Redi *et al.*[105] investigated the bias due to the scoring task in crowdsourcing as well as contextual effects, since crowdsourcing-based assessment is usually fragmented into smaller tasks as opposed to laboratory tests. The use of anchor stimuli is beneficial to keep such context effects to a minimum. [46, 63] conclude that training of the subjects and proper reliability questions integrated in the task design improve data quality significantly. Best practices and guidelines are provided by Hoßfeld *et al.* [63]. Existing frameworks for QoE evaluation are surveyed in [62].

2.2.3 Interdisciplinarity: Psychophysics, Psychoyphysiology and Informatics. White box models take into account laws from psychophysics which relate human perception to a physical stimulus. As mentioned, the Weber-Fechner law relates the actual change in a physical stimulus and the perceived change yielding a logarithmic relationship. Steven's power law relates the magnitude of a physical stimulus and the human perception, resulting in a power law formulation. Both laws can be interpreted in the context of QoE modeling by relating QoS parameters to QoE. Emerging from the field of communication networks, the IQX hypothesis [41] relates the perceived change of QoE to the actual QoE level, as users are more sensitive to disturbances in case of high QoE which leads to an exponential model. Those models map measurable QoS parameters to QoE and are typically based on subjective studies where users report the QoE of a stimulus (e.g., an impaired video).

Psychophysiological assessment tries to overcome some problems due to self-reporting, like rating scale issues where users tend to only use part of the rating scale [46]. Too many rating scale items may increase the user's uncertainty how to rate while an insufficient number of items has no discriminatory power [28]. Thereby, psychophysiological measurements are used to explain QoE assessments of subjects and to improve existing QoE models by providing a deeper understanding, especially of user-related factors and their role in QoE modeling. In such experiments [52, 77], psychophysiological signals are measured as response to a physical stimulus. In [35], Engelke *et al.* classify physiological measurements and survey methods that are most accessible and promising for meaningful exploration of multimedia QoE.

Besides giving a deeper understanding of QoE, psychophysiological assessment is not restricted to lab experiments only. Especially in the context of crowdsourcing, it would be interesting to collect such data from a diverse pool of subjects. Thereby, sensors on smartphones or fitness watches may allow to measure or approximate psychophysiological signals. For example, Lebreton *et al.* [79] present a framework for eye tracking on smartphones which may be used in crowdsourcing experiments to collect subjective data. In partiular, the framework helps to provide visual attention as a new kind of information beyond self-reports of the perceived quality. With the advances of devices like smartwatches or other wearables, it will be possible to measure parameters like heart rate, heart rate variability, temperature, blood oxygen, or galvanic skin response [104] to quantify user-related factors in QoE modeling [109].

2.2.4 Data-aware QoE Modeling. To cope with the large factor space found in QoE modeling, the idea of data-aware QoE management emerged. A QoE model is derived by using Principal Component Analysis (PCA) to correlate QoE and QoS based on the features of the data. PCA

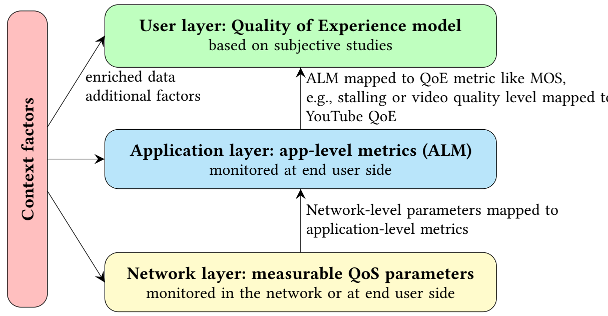

Fig. 3. Problem separation in QoE modeling.

transforms a set of observations of possibly correlated values into a set of linearly uncorrelated variables referred to as principal components. However, the principal components may be difficult to understand and may combine different QoE influence factors and QoS parameters affecting different modalities (e.g., audio and video). Another approach to extract features from a data set is Multidimensional Scaling (MDS) of similarity scores of stimulus pairs as done by Möller *et al.* [92]. The key idea of MDS is to transform the data into distances between points representing perceptual events in the feature space. In [83], Liu *et al.* use PCA to find the impact of QoS parameters on application- and network-level and their influence on QoE for video streaming in wireless networks, whereby the first two principal components explain more than 80% of variability in the data set.

Wang *et al.* [140] propose a data-driven architecture for personalized QoE management in 5G wireless networks and propose machine learning models, since white box models are not existing for all observable parameters or some system parameters may be hidden. As already discussed in Section 2.1, machine learning methods are successfully applied in the QoE domain [7] and various techniques have been utilized, e.g., support vector machines (SVM) for web QoE model [60], recurrent neural network (RNN) model for audio and video transmission [113, 114], decision trees for Internet video QoE [10], Bayesian network for VoIP applications [90].

Although machine learning is a promising direction, we recommend to follow a hybrid approach. Figure 3 illustrates *problem separation in QoE modeling*. QoE models are based on subjective studies. Instead of testing all influencing variables on application- and network-layer in the subjective studies, the relevant measures which may be perceived by the end user are tested only. If possible, the QoE models should be described in a mathematical way with white box models, while machine learning methods may be useful to map parameters to the components of the white box model. Thereby, statistical methods like PCA may be promising to identify the perceptual dimensions.

2.2.5 Summary of Emerging Approaches to Derive QoE Models. Figure 4 summarizes emerging approaches to derive QoE models. We consider the 'user domain', i.e., how subjective data is collected via crowdsourcing and enriched with additional information and psychophysiological signals. In the 'machine domain', data-driven QoE aspects are emerging and consider how to detect main features and utilize machine learning for modeling large-scale parameter spaces. A limitation of many current QoE models is neglecting of context and human factors, which may be attributed to the fact that such data is difficult to collect, or difficult to incorporate into QoE models in an accurate way. Crowdsourcing [63] enables new models taking into account user related factors (e.g., demographics, expectations) in various realistic contexts. Combining emerging approaches from the user and machine domain is a promising path towards multi-factor QoE models.

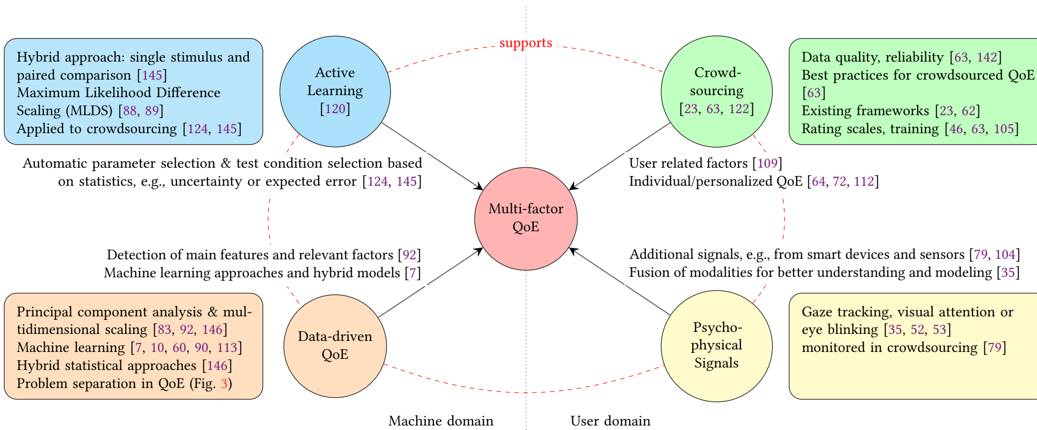

Fig. 4. Summary of emerging approaches to derive QoE models.

3 QOE MONITORING

The exploitation of QoE estimation models requires the collection of necessary input parameters for various types of services. Monitoring architectures commonly collect data using passive or active probes deployed along various parts of the service delivery chain [50, 110]. An important consideration is the specification of monitoring points, determination of what parameters to measure and at what level of granularity, and who such measurements should be exposed to. Data may be collected at different levels (as discussed in Figure 3) [19, 74]. Moreover, data may be considered at different aggregation levels and collected at different time scales to facilitate either monitoring and control in (near) real-time, or subsequent to service usage. A complex task lies in designing a monitoring system able to support identification of possible root causes of QoE impairments, as such causes may occur in different network regions, from the user device, home/access network, core network, CDN, or in supporting services such as DNS [18].

3.1 Client-side monitoring

Applications running on client devices potentially have access to device capabilities, context information (e.g., location), user usage behavior, and application-level metrics. Such information may be used to monitor end user QoE at the application layer, on a per-service, per-user, and per-content level. On the other hand, it is crucial for network operators to also monitor service quality and ensure customer satisfaction. One option is for OTT providers to collect QoE monitoring data, and expose it to network providers via APIs [17]. Used in conjunction with in-network monitoring, this would enable solutions to determine potential root causes of problems, or tune networks. A similar approach is proposed by Ahmed *et al.* in [3]. They propose a solution called *Qualia* for passive QoE monitoring relying on user terminal probes. Factors are monitored across different layers: the user, context, resource, application, and network layers. Their solution assumes different stakeholder roles, namely an end user installing the probe on their device, an OTT provider provisioning an API with access to app-layer data, and an ISP responsible for collecting monitored information from the client, analyzing it in the cloud, and using it for QoE management.

Considering end-device monitoring, Chen *et al.* proposed a tool called *QoE Doctor* for objectively measuring app QoE at both the network and application layers using active measurements [24]. Rather than relying on actual user interactions and feedback, the tool uses UI automation techniques to replay typical user behaviour (e.g., posting a message on facebook, playing a YouTube video), and then objectively measures latency through UI changes on the screen. Given that no access is required to the application logic, the tool is applicable across various mobile app scenarios.

Casas *et al.* [21] combine passive end-device network measurements, application-level measurements, and QoE user feedback in operational mobile networks to study the QoE of popular smartphone apps (YouTube, Facebook, Gmaps, Web Browsing and WhatsApp). As an example, QoE-relevant KPIs (such as stalling, video resolution) of YouTube adaptive streaming are monitored using the YoMoApp tool developed by Wamser *et al.* [123, 139]. YoMoApp[2] allows users to check how well their network performs for YouTube streaming, and see how it compares in terms of performance to other networks in a certain geographical area. It supports collecting subjective QoE feedback from users, as well as network usage statistics and device characteristics. A similar approach was proposed by Nam *et al.* [95], who developed a system called YouSlow[3], designed to monitor YouTube stalling events on clients, collect reported data on Google maps, and calculate ISP statistics in terms of stalling duration and location.

In general, it is clear that the use of crowdsourcing to collect end-device measurements is a promising approach in performing QoE-based network and service performance analysis at a large scale [21]. As an example, applications such as Skype already collect subjective user feedback after every call, thus providing important input for service quality enhancement [51]. As pointed out in [21], a key issue for ISPs wishing to utilize similar tools is addressing customer incentives to install measurement tools on their end device.

3.2 In-network and distributed monitoring infrastructures

While client- and server-side logs provides access to application-level metrics, for the most part ISPs to-date do not have access to probes on the client device, and thus rely on measurements collected using in-network probes. Probes are typically distributed along various parts of the service delivery chain and gather information about the performance of network paths and links. This information then needs to be fed to application-specific QoS-to-QoE models to obtain insights into estimated QoE. An important step in monitoring traffic is classifying the traffic so as to determine the corresponding application type and QoE model to apply.

Towards a standardized monitoring architecture. Despite the trends in migrating towards softwarized networks, there is to-date no standardized QoE monitoring architecture available in the scope of related SDN and NFV standards. One proposal of a generic QoE monitoring architecture for multimedia services was standardized by ETSI [39], resulting as an outcome of the Celtic-PLUS QuEEN project[4]. The architecture assumes an operational layered QoE model, whereby QoE influence factors are categorized into layers (going from a resource layer up to a user layer). The output of a given layer L represents the input to layer $L + 1$, and is specified as a set of indicators representing the "quality" of the system's behavior up to layer L. The actual QoE monitoring architecture consists of distributed probes which provide required parameters across layers to a QoE-agent running the QoE estimation process (Figure 5). Different pluggable QoS-to-QoE mapping models are used for different layers and services, allowing to re-use a QoS model in several QoE agents for different services. QoE-agents may further be distributed along different points in the service delivery path, and the QoE-agent itself can be distributed, allowing for flexible deployment at different layers in the network/application stack, as needed. In the context of NFV, the agent and

[2]YoMoApp is available via Google Play Store
[3]https://dyswis.cs.columbia.edu/youslow/
[4]https://www.celticplus.eu/project-queen/

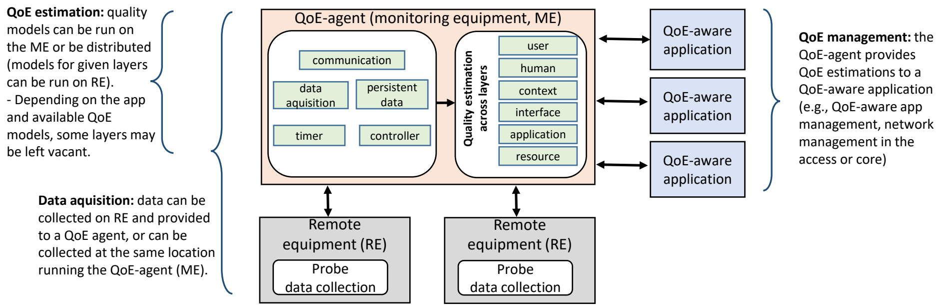

Fig. 5. Architecture of a generic QoE-agent as specified by ETSI TS 103 294 in [39]

probes may be implemented as virtual functions. The QoE-Agent further provides QoE estimations to QoE-aware applications via predefined APIs.

In addition to the QuEEN project, other efforts in developing large-scale distributed QoE monitoring architectures were conducted in the scope of the EU FP7 LEONE project[5], and FP7 mPlane project[6]. Related standardization activities are ongoing within IETF working groups LMAP (Large-Scale Measurement of Broadband Performance) and IPMM (IP Performance Measurements).

Trends in softwarization. In terms of technical implementations, network operators are increasingly turning to SDN-based solutions facilitating centralized control of a dynamically programmable forwarding network. By shifting intelligence to a centralized unit, QoE-driven control decisions can be made based on a global view of the underlying network state. Service chains of virtualized functions can be controlled by an SDN controller and dynamically orchestrated in real-time. Monitoring data needs to be fed to a control plane that is capable of driving QoE control. Furthermore, with standardized northbound APIs, mechanisms are provided for applications to provide requirements to the controller (driven by QoS-to-QoE mapping models), which can in turn invoke traffic management mechanisms to meet differentiated service requirements [71].

Jarschal *et al.* [71] examine how monitoring and exchange of per-flow parameters, application signatures, or application quality parameters can support application-aware QoE-driven network management in an SDN-enabled network. Further investigations into a joint application and network control plane leveraging SDN are reported by Schwarzmann *et al.* [118, 119].

Going beyond programmability of the control plane using SDN, a novel direction to be explored is the potential of exploiting more fine-grained QoS information to estimate QoE, using in-band network telemetry (e.g., using the P4 language) [18, 76]. Such an approach offers the potential for monitoring individual flows and tracking application performance in-band (especially if deployed at Internet exchange points, IXP), with network routers and switches annotating packets with information about per-hop latency and packet loss. The potential of exploiting this technology in the context of QoE monitoring and management remains an open research question.

Considering virtualization trends, operators are beginning to re-design their network functions (e.g., packet gateways, policy servers, IP Multimedia Subsystem) towards virtualized network functions (VNFs) running on commodity hardware. Going from purpose-built, dedicated hardware to running VNFs imposes challenges in meeting performance and low latency requirements. In particular, significant challenges remain regarding the monitoring, enforcement, and management

[5] http://www.cordis.europa.eu/project/rcn/105990_en.html
[6] http://www.ict-mplane.eu/

of real-time services based on NFV [7], such as conversational audio/video, or other emerging 5G service scenarios (e.g., tactile Internet, AR/VR, gaming, mission critical services, etc.). Performance monitoring information related to VNF instances and service chains needs to be considered together with latency requirements when orchestrating service chains and selecting deployment locations for service components [87]. As highlighted in [56], the NFV infrastructure should be able to gather performance information at different levels (e.g., hypervisor, virtual switch, network adapter).

Further challenges are related to the deployment location of actual QoE monitoring probes [56]. Some initial work by Dinh-Xuan *et al.* [31] proposed a VNF for monitoring QoE of video streaming in the network and evaluated its accuracy depending on different placements (network edge vs. near the streaming server). Tselios et al. [134] further discuss the deployment of virtualized QoE-monitoring probes in Mobile Edge Computing (MEC) platforms, with access to network, user, and application-related data. Robitza *et al.* [110] give a detailed overview of QoE monitoring architectures, and discuss the need to deploy virtualized probes, which can communicate with both virtual and physical network elements. A trade-off is to be considered between accuracy (e.g., ensuring precise timestamps of collected data), and cost-effectiveness.

In a recent survey [57] among over 90 mobile operators, key plans were identified in terms of QoE monitoring in the transition to virtualized networks. However, despite these trends, very limited studies have to-date reported on the challenges of QoE monitoring in virtualized networks in real-world deployments. In particular, challenges still remain in assessing the performance of passive monitoring probes deployed as VNFs.

From a measurement infrastructure to an aggregation infrastructure. As highlighted by Bustamante *et al.* [18], many challenges still remain in building a common infrastructure to measure QoE. A key requirement is the gathering, aggregation, and correlation of different measurements, so as to assess overall QoE and perform fault diagnosis. The challenge thus remains how to go from a "measurement infrastructure" to an "aggregation infrastructure", a topic that is further complicated by the multiple stakeholders involved and their willingness and incentives to share measurement data. Clearly, for ISPs to achieve QoE-aware service delivery, access is needed to monitored application-layer KPIs [3]. Ganjam *et al.* [44] envisage a federated QoE optimization architecture whereby application providers and network providers collaborate to improve QoE, leveraging ubiquitous client-side QoE measurements, "big data" platforms for real-time analytics, and new control plane capabilities for ISPs (e.g., SDN, IXPs, NFV).

3.3 User behaviour and engagement monitoring

Given the general aim to maximize service usage and consequently revenue generation, it is of clear interest to operators and service providers to monitor QoE and determine the impact that quality degradation has on user behavior [11]. Going beyond quality metrics (e.g., stalling duration, video bitrate), studies have also considered engagement-centric measures of QoE, such as video viewing time, fraction of video viewed, and number of page visits [10]. A conceptual model that relates the quality formation process to human behavior in multimedia consumption is proposed by Robitza *et al.* [111]. They address how to predict user engagement and study how QoE results in short-term user behavioral (inter)action. A large-scale study was reported by Dobrian *et al.* [32] that investigated and found a strong impact of video quality on user engagement.

While engagement may in many cases be linked to quality metrics and QoE, it has on the other hand been argued that user engagement should not necessarily be considered as a proxy for QoE, given that many variables cannot be accounted for, such as why a user left a service. While this may be due to poor QoE, it may also be due to for example lack of interest. One proposal

[7] See the IRTF Network Function Virtualization Research Group https://trac.ietf.org/trac/irtf/wiki/nfvrg

mentioned in [129] in the context of video monitoring is to use the fraction of watched video as an engagement metric, whereby "early-quitters" could then be removed from consideration. In their studies, Balachandran *et al.* [10] highlight that quality metrics are interdependent, may have counter-intuitive relationships to engagement measures (i.e., the relationship is non-monotonic), and that there are many external factors that potentially confound the relationship between quality and engagement (e.g., type of video, user connectivity). They thus employ a data-driven approach and propose a predictive model of user engagement based on monitored quality metrics. Going from client-side measurements of application-layer video quality metrics to relying only on network-based measurements (as is often the case for network operators), Zubair *et al.* [126] report on a large scale study to characterize the impact of network performance on mobile video user engagement. Their proposed model of the relationship between (core and radio) network factors and video abandonment may be utilized by operators looking to monitor user engagement in real-time. Their findings also show that certain quality-related metrics (such as throughput) do not necessarily indicate lower abandonment. Taking more of a QoE management perspective, Duan *et al.* [34] give a detailed overview of how the monitoring and analysis of human factors (in particular user behavior patterns) can be exploited to guide system/network management and improve QoE.

3.4 Applicability of big data analytics and data-driven techniques

Big data analytics. With the proliferation of IoT technologies and sensor data, richer applications, as well as a massive increase in user-generated content (e.g., social network posts), a wide range of context- and user-related data is becoming available [141]. Challenges thus lie in extracting meaningful and useful information from the collected data, that can further be converted to actionable knowledge and utilized in managing QoE. Big data refers to large scale data collection, manipulation, and storage, and is generally targeted towards outputting patterns or correlations [141]. Machine learning techniques, on the other hand, focus on building learning models to make predictions based on input data. Both concepts are increasingly being applied in the QoE management domain. Zheng *et al.* [150] propose a generic framework for integrating big data analytics with 5G mobile network optimization methods to improve both QoE and network operation efficiency.

In general, the incorporation of contextual information can aid both network and service providers in making more informed decisions related to the QoE of their customers [21]. In [66], Hoßfeld *et al.* discuss how information collected from simultaneous out-of-band channels (e.g., social network trend analytics), can be used to optimize QoE if interpreted in a timely manner.

Data-driven techniques. Assessing QoE from a user perspective and capturing the subjectivity of users without relying on explicit user feedback is clearly a challenging task. Wang *et al.* [140] propose a data-driven architecture for enhanced personalized QoE in the context of 5G networks. In a first (offline) phase, a monitoring agent is installed on the user device and collects QoS data, context data, and subjective user feedback on a per-user, per-service basis. In a second (online) phase, real-time QoS and context data is collected from users during service usage, and used to predict user preferences based on previously trained models.

In [72], Jiang *et al.* propose measurement collection and decision making as a **joint** process together with real-time QoE measurements. Their framework called *Pytheas* provides interfaces through which application sessions can send QoE measurements to update real-time *global views*, and can receive control decisions made by the system (e.g., CDN and bitrate selection).

3.5 Monitoring QoE in the case of encrypted traffic

Most of the aforementioned approaches advocate the collection of QoE monitoring data from both the end user device and the network. While these are viable approaches, they are based on the assumption that the network operator has access to data collected on the user device, which in the case of application-specific data (especially in the case of OTT apps) is commonly not the case.

Consequently, ISPs to-date rely primarily on passive traffic monitoring solutions deployed within their network to obtain insight into degradations perceived by end users. Shafiq *et al.* [125, 126] focus on monitoring streaming video QoE (in terms of engagement) from a mobile operator perspective. Heuristics are used to model the complex relationships between various network factors and user behavior related to watching mobile videos, thus enabling operators to predict user behavior without any access to client- or server-side logs.

Katsarakis *et al.* [74] studied the statistical relations between QoS and QoE for encrypted and adaptive YouTube video streaming. For every video session, a vector of network and application QoS features was computed, and the Statistically Equivalent Signature (SES) method was used to identify multiple minimal-size sets of QoS features with maximal predictive power for a target QoE value. In a more generic approach, Aggarwal *et al.* [2] proposed the Prometheus system, which relies on ML techniques to relate passive in-network measurements to applications' QoE, without knowledge about specific application services. Results with over 80% accuracy are reported when network traffic features were used to classify QoE into two classes ("good quality" and "bad quality") using data collected in the core network of a large cellular operator. Dimopoulos *et al.* [30] proposed a methodology for detecting video streaming QoE-related KPIs. While Dimopoulos *et al.* differentiate between models that classify video stalling, average video quality, and video quality variations, Orsolic *et al.* [97] rely on QoE models to convert these KPIs to a QoE class and build a single ML model. They proposed a methodology for the classification of end users' QoE when watching YouTube videos, based only on statistical properties of encrypted network traffic.

Summary of QoE monitoring aspects addressed in this Section

- Client-side monitoring:
  - provides access to user- and context-related data required for a holistic view of QoE [78],
  - can be performed using passive [3, 21, 123, 139] or active [24] measurements,
  - is challenging for ISPs, due to incentive issues [21],
  - is addressed within standardization, e.g., the 3GPP QoE reporting framework [1].
- Measurement probes:
  - may be distributed across various locations along the service delivery path [3, 21, 24, 39, 139],
  - may collect data and feed quality estimation models at various layers [39].
- Trends in softwarization:
  - enable new ways of collecting application-level and network-level measurements via standardized APIs [71, 73, 96, 118],
  - enable the deployment of virtualized probes at both the client and network side [57, 110], with challenges related to monitoring accuracy, probe placement [31, 56, 91] and latency [87].
- Big data analytics and data-driven approaches:
  - enable the move to *personalized* QoE [140],
  - require an architectural change to collect and aggregate large amounts of data from customer devices and network elements [150],
  - enable QoE management decisions in the network, such as optimized resource allocation [150] and improved SDN-based traffic engineering [29],

  - advocate closed-loop solutions integrating QoE-related control decisions with real-time QoE measurements [11, 72].
- Encrypted traffic:
  - makes it difficult for network operators to monitor and manage QoE, requiring new approaches to monitoring [110],
  - is susceptible to ML approaches for predicting user engagement [126], application-layer KPIs [30], or overall QoE for OTT applications [30, 97].

4 QOE MANAGEMENT

The literature on QoE-driven cross-layer, and application-layer management mechanisms is plentiful. Just in recent years, there has been an explosion of papers e.g., on HAS and QoE, and on QoE-driven scheduling algorithms for wireless networks. In the interest of avoiding redundancy, we will not expound on these in this paper, but rather provide pointers to relevant surveys for the reader to peruse. In the context of application-layer schemes, and in particular HAS, we refer to [121]. At a high-level, QoE-driven application-layer management schemes focus on adapting the service to underlying network conditions, and do not exert direct control of the network (mostly due to the fact that this is not feasible in most cases). Such adaptation mechanisms are limited in the sense that they perform local optimizations, and do not ensure optimal (nor necessarily fair) QoE among multiple clients sharing network resources. Cross-layer approaches, on the other hand, involve various forms of application-network interaction and exploit information available at different layers to inform the management mechanisms of other layers. As detailed by Schwarzmann *et al.* [118, 119], such a cross-layer exchange of information can further drive optimization and control actions at the application-level, network-level, or both. With regards to cross-layer, QoE-driven approaches, we note [13, 16, 37, 75, 103, 128]. We point the interested reader to a further discussion of different metrics and optimization objectives considered in driving QoE management and optimization decisions, provided in the Online Appendix to this paper.

Recent years have seen the rapid adoption of virtualization technologies for both networks (SDN) and network functions (NFV), both prominent concepts also in the definition of 5G networks. The use of these technologies opens new challenges and opportunities for QoE management. On the one hand, the use of virtualization can make certain tasks (such as e.g., passive network monitoring) harder to perform well (due to e.g., unavailability of specialized capture cards in commodity hardware), but on the other hand, it enables a wide range of means for improving QoE. Whereas in traditional networks everything tends to be inherently distributed, SDNs concentrate the control plane, achieving good visibility of network state in a single point, and simplifying the decision making process in cases such as improving QoE for certain flows/applications across the network. Likewise, NFV enables rapid adaption and scaling of network services, which allows to cope with varying loads and conditions with greater flexibility than in traditional network setups. In the 5G context, these two concepts also enable Mobile Edge Computing (MEC), which brings services closer to the users, enabling load reductions in the network, lower latencies, etc. In the remainder of this Section, we focus further on open research issues and ongoing trends related to QoE management in emerging softwarized networks.

4.1 Exploitation of the SDN paradigm

The advent of SDN has made possible a variety of approaches to consider QoE when doing network management [151]. These tend to be grounded on the SDN controller's centralized view of the network's state, and its ability to enforce faster and more flexible reactions to e.g., congestion situations. Figure 6 portrays example QoE related components in the context of SDN.

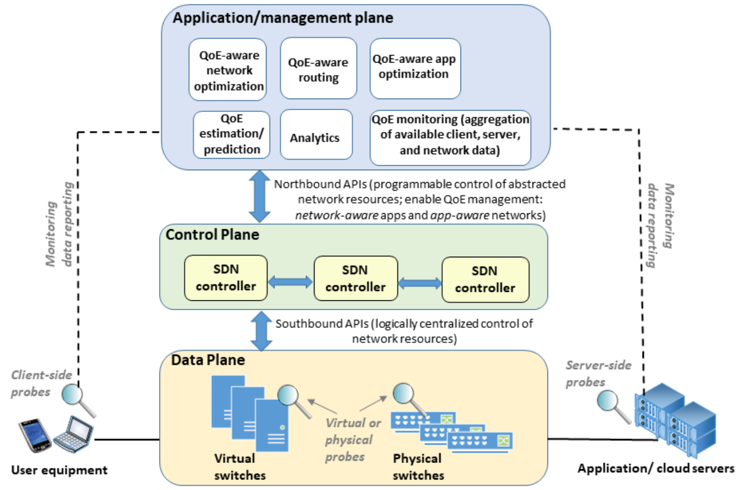

Fig. 6. QoE monitoring and management components mapped to an SDN architecture.

In the context of QoE-driven network management, Kassler *et al.* [73] address the problem of QoE-driven path assignment by proposing a pre-negotiation phase during which a QoS matching and optimization function (QMOF) produces feasible service configurations based on application-specific parameters, providing both an optimal configuration and several sub-optimal ones (resulting in a so-called Media Degradation Path, MDP). At the SDN controller, a Path Assignment Function tries to optimize the configurations for concurrent sessions based on their MDPs, then issuing the relevant OpenFlow[8] directives to the switches in the network. QoE-centric flow routing has further been addressed by Dobrijevic *et al.* [33], who apply metaheuristics to optimize path assignment.

In a more cross-layer approach, the SDN controller's global view of the network can be used to inform e.g., media elements about how to manage quality. For example, Bouten *et al.* [16] and Bentaleb *et al.* [15], propose different approaches to limit the number of HAS representations avaliable to clients, based on information gathered by the SDN controller. This results in overall improvements in the video playback. Awobuluyi *et al.* [9] consider real-time video applications in 5G networks. They exploit SDN and H.265's scalability, by collecting data about the network topology and state from the SDN controller, estimating QoE, and based on that, deciding how to best stream the video content (e.g., path selection, alternative paths for different layers).

A more generic approach to managing OTT services by means of SDN is provided by Liotou *et al.* [81], with a focus on 5G networks. They propose a "QoE-Serv" element (mapped to the SDN management plane), which collects information from user equipment and the network (both access and core), allowing the OTT provider to better understand the QoE for any given user of a service. The QoE-Serv element can, if QoE is estimated to be too low or to be about to drop, request action from the SDN controller (presumably based, e.g., on subscription tiers).

4.2 QoE management in the context of NFV and service orchestration

As with SDN for the actual networks, network functions and services are also on the path to virtualization. Contrary to the SDN field, where OpenFlow became the *de-facto* standard for

[8] OpenFlow is a standardized protocol between SDN controllers and network devices, providing controllers direct access to and manipulation of the forwarding plane of (both physical and virtual) network devices.

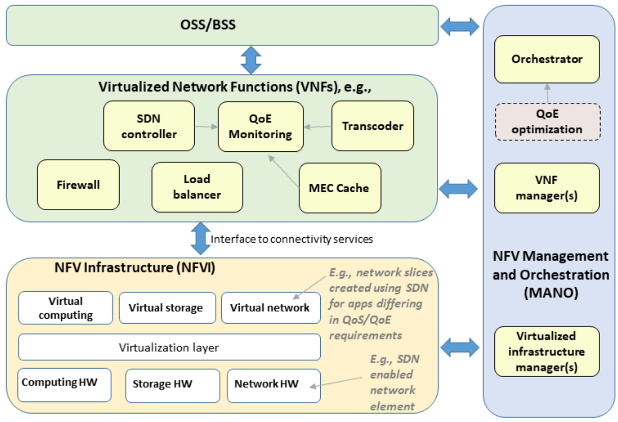

Fig. 7. High-level view of QoE monitoring and management components within an NFV architecture.

controller-switch communications, the NFV field is more fragmented and significantly more architecturally complex. As of this writing, there are two main reference architectures for NFV management and orchestration (MANO), ETSI NFV MANO [38], and ONAP (Open Network Automation Platform, formerly AT&T's ECOMP) [8]. The ETSI NFV MANO architecture has been under intense standardization work since 2013, and is composed of three main elements: the VNF, the NFV Infrastructure (NFVI), and NFV MANO. Several implementations of it exist, including the reference Open Source MANO, OSM[9] (in its second release, as of this writing). ONAP is the result of AT&T's opening of their ECOMP platform, which has been in production for over two years now. Both architectures share similarities (like their complexity), but also have significant differences, and it is not clear at present which one will end up being dominant in the market.

As they stand, neither architecture addresses QoE directly, and even broader aspects such as service assurance (SA) are not so clearly defined (ONAP defines a component for Data Collection, Analytics and Events — DCAE, and there are some proposed extensions to the ETSI NFV MANO with SA components [138], but many details are still missing).

Some literature on using NFV for managing QoE has begun to emerge recently. In [12], Barakabitze *et al.* proposed a so-called "QoE-Softwarized" architecture, which uses NFV and SDN (with the latter bearing most of the work) to implement QoE management mechanisms. It is not clear, however, how such an architecture would integrate into a MANO context.

In general, we could see QoE-oriented VNFs co-existing with service- and network-specific ones, and performing e.g., monitoring or estimation tasks based on data collected from them. That data could be fed to an optimization component within the NFV orchestrator to aid it in its tasks. Network slicing may be seen as a key feature/enabler for flexible and dynamic allocation of network resources to support diverse requirements of 5G applications. Figure 7 depicts how these QoE components could fit in an NFV MANO-like architecture. We once again note that meeting low latency requirements imposes a challenge in the context of managing services based on NFV and those running in cloud environments, as discussed in Sec. 3.2. Such challenges may be tackled by exploiting the MEC paradigm, as discussed in the following section.

[9] https://osm.etsi.org/

4.3 Mobile Edge Computing as an enabler for QoE management

Mobile Edge Computing brings the idea of the "telco cloud" to the edge of the mobile network, providing virtualization infrastructure, e.g., at the eNodeB. The main idea is that of providing low-latency, high-throughput capabilities, and a clear view into the Radio Access Network (RAN) and context information to applications that may benefit from them (e.g., analytics, transcoding, IoT, hyper-localized caching, location-based services) [67]. MEC extends the notions of NFV and SDN to the network's edge, so similar types of QoE management approaches can be expected, but also integration with radio management mechanisms.

Peng *et al.* [100] propose an architecture for QoE-oriented management of edge services. The proposed architecture mirrors, to a degree, the ETSI NFV MANO one, and is extended with RAN aspects. In particular, they study the use of channel state information from the user equipment to deliver personalized performance from services running in mobile edge. In general, insight into real-time radio network conditions and context information (e.g., location) can be used to dynamically optimize the network and service operation in a QoE-aware manner [67].

In [47], Ge *et al.* propose a MEC-assisted DASH scheme, in which information from the RAN is used to help DASH clients obtain better quality. Their approach is based on a two-level cache replacement strategy (by content and representation popoularity, in that order), and by using information about the RAN status to make decisions about which representations to keep cached.

5 PERSPECTIVES WITH RESPECT TO QOE MANAGEMENT

5.1 Towards novel QoE monitoring and management infrastructures

It seems almost certain that virtualization, both in the network (SDN and NFV) and in the service domain (cloud) will be the dominant deployment approach in the years to come. This presents interesting opportunities for QoE management, since QoE components (e.g, QoE optimization, co-located with an orchestrator as in Figure 7) could have a much more comprehensive view of both the application and network layers, and more importantly, the ability to actuate on both of them. The literature so far shows either some SDN or (to a lesser degree) NFV based approaches to QoE management, but a more comprehensive architecture encompassing both of them is still lacking. We depict such an architecture in Figure 8, wherein most of the current (and likely upcoming) QoE management approaches can be inscribed. We identify three main layers: virtualized networks and infrastructure, the virtualized network functions, and a service layer, which relies on a northbound API to deal with the underlying virtualized environments. QoE management is done via a feedback loop (in the Service Assurance block), which gathers monitoring data, and informs the service layer (which in turn can pass the information to e.g., the NFV MANO or the SDN controller, for concrete action). The top layer includes, besides the traditional OSS/BSS[10] functions, the notion of the "telco cloud", whereby service developers could deploy their whole services on top of a telco's own infrastructure. The architecture therefore includes an SDN layer, and NFV layer, the northbound API and Service Innovation layer, and a Service Assurance component, which would take care of the QoE data aggregation, analytics, etc.

5.2 Economic and business aspects

There is, often, an unspoken assumption when considering QoS/QoE management. This assumption is that implementing QoE management makes sense from a business perspective; i.e., the cost of implementing the management scheme will be offset by larger revenues, lower churn rates, etc. It is not clear, however, how this assumption holds in many real-world scenarios. Most notably, in the

[10]Operations Support Systems / Business Support Systems

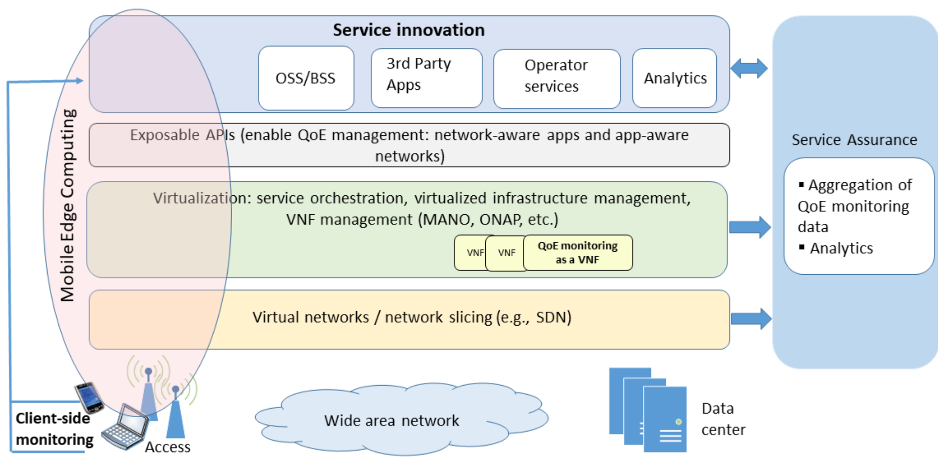

Fig. 8. A high-level architecture for QoE management in future softwarized networks.

case of OTT services, where there are multiple service providers involved, their business interests may be opposed to each other. This exact dilemma has been at the heart of many argumentations on Network Neutrality. While most of the literature on QoE management concerns itself with the technical aspects of actually implementing the management schemes, relatively few works address the business aspects, which are critical for those schemes to become viable in practice.

One issue to consider is that of pricing (i.e., in the face of differing requirements from different users, different pricing strategies may be needed). This has long been a subject of study in the networking community, and has more recently been expanded to consider QoE, most notably by Reichl et al [108]. Reichl's fixed-point model introduces QoE as one of the factors affecting (and affected by) service price, which in turn affects both demand and the resulting QoS (assuming stable network resources), which affects QoE itself. The model has been empirically validated in the context of OTT video [85, 108] in terms of the users' willingness to pay for different quality levels.

Related to the issue of charging users for different QoE levels, there is that of guaranteeing said QoE levels. Some preliminary work has been done by Varela *et al.* [137], by introducing the notion of Experience Level Agreements (ELA) as a QoE-oriented counterpart to traditional Service Level Agreements (SLA). The paper motivates the concept, and points out the outstanding issues standing in the way of its implementation. Beyond the aforementioned incentives for cross-stakeholder cooperation, they point out the difficulty in conveying to users, *a priori*, the difference between QoE levels. That is, how to explain to users the perceptual difference between a "standard" and "premium" quality subscriptions. We note that for some services, such as video, there have been some inroads in this topic, notably by Netflix, which offers HD and UHD subscriptions (with some other minor differences) at different price points. However, while there is a quality-based differentiation (in term of the available content resolutions), there are no guarantees on the delivered service quality, and the provider relies on the users' pre-existing (or at least assumed) knowledge of the visual difference between HD and UHD content.

For a provider, *churn* is especially relevant and "a provider needs to be able to observe and react quickly on quality problems, at best before the customer perceives them and considers churn" [41]. QoE management may therefore by a proper means as distinguishing feature across providers. Further the cost of retaining existing customers is typically lower than to win a new customer. Although churn is a major topic in many business sectors and various models exist [54], there is often not sufficient data available about the customers and their QoE over time [106].

To this end, Floris *et al.* [42] and Ahmad *et al.* [4] provide a theoretical user churn model to investigate collaboration between service and network providers and how to avoid user churn. The user churn model is based on [27] which considers quality and pricing as major causes for customer churn. The fundamental assumption is that user churn is a (sigmoid) function of the perceived QoE. Although the model lacks validity due to missing subjective data, it is a promising approach to investigate the interplay between QoE and user churn. By simulations, [4] shows that collaboration between service and network providers may increase revenue and provider better QoE to users. In [42] the customer lifetime value is utilized to identify the most profitable customers.

In [58], Heegaard *et al* describe incentives for network operators to cooperate along the service chain, by sharing more information than they currently do. They argue that the current way of sharing performance information among providers (by means of SLOs attached to their SLAs) is not sufficient, leading to sub-optimal results (either being too risk-averse, or ending up paying more than necessary in SLA violations). They propose a game-theoretic approach to inter-ISP information sharing that results in a finer-grained information exchange that is mutually beneficial.

5.3 Extending QoE management to new domains: immersive AR/VR and mulsemedia applications

Finally, we discuss the notion of QoE in the context of emerging immersive application scenarios. In the past few years, stereo and 360-degree videos are becoming increasingly popular, because they can better preserve immersive experience, allowing people to better record and share their life and experience. A market report predicts that the global market of 360-degree cameras will grow at an annual rate of 35% between 2016 and 2020[11]. Such an increase is further boosted by the growing attention of consumer-grade Head Mounted Displays (HMDs), which provide wide Field-of-Views (FoVs), and come with integrated sensors for determining view orientation and head position. In fact, another market research indicates that the global market of Virtual Reality (VR) related products will reach 30 billion USD by 2020[12]. Due to the increasing popularity of commodity HMDs and new content generation devices, it is expected that there will be a need to extend the capability of QoE management approaches to still accurately quantify, model, and manage QoE when the user consumed content is beyond traditional audio and video materials. Moving beyond the "traditional" senses (hearing, sight), there has been a transition from *multimedia* to *mulsemedia* (multiple sensorial media), characterized by multimedia content enriched with new media objects (olfactory, haptic, gustation). An overview is given by Sulema [130].

Our survey of previous research indicates that there have been numerous efforts exploring the new dimensions in system, content, and user experiences. Such studies can be roughly divided into two categories: research defining new metrics, models, frameworks, or taxonomies, and research seeking to better understand and manage QoE of systems which deliver more than pure audio and video content. Ongoing standardization activities within MPEG focusing on immersive media are being conducted within the scope of MPEG-I (ISO/IEC 23090 - Coded Representation of Immersive

[11] Global 360-degree Camera Market 2016-2020. https://goo.gl/zJCdnO

[12] Augmented Virtual Reality revenue forecast revised to hit $120 billion by 2020. https://goo.gl/nw9mtP

Media). However, challenges remain in defining subjective and objective quality metrics and QoE assessment methodologies, going from VR/AR/360-degree videos to mulsemedia experiences.

5.3.1 Methodological research. QoE of stereoscopic images is a topic that has received significant attention from the community [25, 144]. Benoit *et al.* [14] reviewed the different issues related to 3D image visualization, and proposed a quality metric for the assessment of stereo image pairs using the fusion of 2D quality metrics and of the depth information. Extending the 3D content by one degree, in [143], Wu *et al.* presented a quantitative and qualitative study of the impact of QoS metrics (e.g., end-to-end delay, visual quality) on distributed gaming QoE in 3D tele-immersive (3DTI) environments. They identified a number of non-technical factors, such as age, social interaction, and physical setup, actually played roles in influencing gamers' experiences.

An essential element in a virtual environment is to increase the presence by introducing sensations other than audio and visual inputs, such as haptics, olfactory, and atmosphere. The addon of haptics in virtual reality applications is especially popular as the stimuli and feedbacks are obvious, easy to quantify, and more fun. In [55], Hamam *et al.* provided a comprehensive literature review for QoE management in haptics-enabled virtual environments and proposed a taxonomy for the evaluation of QoE for such systems. The authors also discussed a number of common metrics for perception measures, psychological measures, and physiological measures respectively, and proposed to use a Fuzzy logic Inference System (FIS) to model the QoE of haptic virtual environments.

QoE in augmented reality (AR) also deserves attention due to the potential use of AR in many fields such as medical surgery and emergency response training. Puig *et al.* [102] discussed the different aspects of QoE in AR applications, such as usability, ergonomics, human factors, ethnography, subject quality assessment, and psychophysics, and how these issues differ depending on scenarios. Pallot *et al.* [99] extended the problem by exploring collective user experience when multiple users watch the same sport game via AR technology. A taxonomy of QoE in augmented sports was proposed and aligned to a close field UX (user experience).

5.3.2 Empirical studies and case reports. We further highlight empirical QoE studies related to a variety of immersive applications and scenarios. Recently, Schatz *et al.* [117] presented a study focusing on the impact of stalling events in a fully immersive setting involving users watching omnidirectional videos using a HMD. Another major line of study is that of QoE of mulsemedia applications. A clear research challenge is identifying how and in what way multisensory effects affect QoE. For example, in [147], Yuan *et al.* conducted a user study which indicates that both haptic and air-flow effects in mulsemedia enhances the sense of reality and user enjoyment levels. Also, their results demonstrated that by making use of mulsemedia, the overall user enjoyment levels increased by up to 77%. In [148], three sensorial effects (i.e., haptic, olfaction, and air-flowing) are investigated. Experiments showed that mulsemedia sequences can partly mask the decreased movie quality and that the most preferable sensorial effect seems to be haptic, followed by air-flowing and olfaction. Recent attempts at modeling QoE for spatio-temporal mulsemedia are reported by Jallal and Murroni [70], focusing on the QoE of audiovisual sequences enriched with additional sensory effects such as light, wind, vibration, and scent. A general challenge for researchers is the lack of common test data and raw content needed to conduct studies and facilitate reproducible research. Attempts to fill this gap have been reported by Murray *et al.* [93], who provide a dataset of videos enriched with olfactory content and annotated with subjective user ratings.

The synchronization between multiple stimulus channels can also be a significant factor influencing the QoE. Timmerer *et al.* [133] conducted an empirical study analyzing the effect of inter-media skew between olfaction and visual media on QoE which shows that, in general, a higher QoE is perceived with olfaction presented after video as opposed to olfaction presented before video.

Interesting, the finding is in contrast to that in [94], which indicates that 1) QoE is hard to measure and quantify, and 2) QoE may be highly sensitive to the context. In addition, [48] analyzed the impact of inter-media skew between olfactory and audiovisual media content as well as the impact of delay on the user-perceived experience.

Finally, research has also addressed QoE-related measurements in the context of AR. For examples, Gandy *et al.* [43] conducted a QoE measurement study using a physiological approach, where a three-lead electrocardiogram (ECG) sensor was placed on the subjects' chest as well as galvanic skin response (GSR) and skin temperature sensors mounted on their non-dominant hand. The results implied that the frame rate seems to have a smaller effect in VR applications; the physiological approach, though promising, did not reflect the subjects' anxiety as they reported in questionnaires, which may partly be due to the low signal-to-noise ratio and difficulties in analyzing such measurement data. Meanwhile, the study [101] showed that end-to-end delay, frame rate, image size and head motion speed seem to be important variables impacting the QoE in AR systems. The authors therefore proposed a rate adaptation scheme that can maximize QoE by adjusting system parameters.

6 CONCLUSIONS

The effective and cost efficient management of applications and networks inherently puts end users into focus and calls for various QoE management mechanisms. The aim of this survey paper has been to convey the major emerging aspects of QoE management, from modeling, through monitoring and management mechanisms, to the business aspects and upcoming research lines. Given the current state of the art, we once again highlight the following among them:

Modeling :
- Move towards ecologically valid longitudinal studies conducted in the wild; enriched subjective data with context and psychophysiological signals.
- Novel QoE metrics and assessment methodologies needed for emerging immersive applications, such as AR/VR and mulsemedia.
- Models meant for QoE management require more sophisticated metrics than MOS (See Online Appendix).
- Combinations of crowdsourcing and data analysis/ML techniques will be key.

Monitoring :
- Passive monitoring in the presence of encryption is a key problem to solve.
- Monitoring in 5G/virtualized contexts brings a host of new challenges to be addressed, such as the accuracy of monitored data, the placement of probes, and meeting latency requirements.
- Big data and ML techniques will also be key in this context.

Management :
- SDN and NFV form the key infrastructure for nearly any upcoming QoE management approaches.
- Standardization issues and the complex architectures involved may limit the applicability of QoE management mechanisms in the wild.

Business aspects :
- Economic incentives for different stakeholders to cooperate remain a key roadblock for comprehensive QoE management approaches.

QoE management is a broad topic with a plethora of relevant published papers. This paper is thus not intended to provide a comprehensive survey, but rather to systematically outline the key concepts and challenges that are likely to set the research agenda in the upcoming period.

REFERENCES

[1] 3GPP. 2017. Study on improved streaming Quality of Experience (QoE) reporting in 3GPP services and networks, 3GPP TR 26.909, Release 14, v14.0.0. . (March 2017).

[2] V. Aggarwal, E. Halepovic, J. Pang, S. Venkataraman, and H. Yan. 2014. Prometheus: Toward Quality of Experience Estimation for Mobile Apps from Passive Network Measurements. In *Proc. of the 15th Workshop on Mobile Computing Systems and Applications*. ACM, 18.

[3] A. Ahmad, L. Atzori, and M. G. Martini. 2017. Qualia: A Multilayer Solution for QoE Passive Monitoring at the User Terminal. In *IEEE ICC*.

[4] A. Ahmad, A. Floris, and L. Atzori. 2016. QoE-centric service delivery: A collaborative approach among OTTs and ISPs. *Computer Networks* 110 (2016), 168–179.

[5] A. Aijaz, M. Dohler, A. H. Aghvami, V. Friderikos, and M. Frodigh. 2017. Realizing the Tactile Internet: Haptic Communications Over Next Generation 5G Cellular Networks. *IEEE Wireless Communications* 24, 2 (2017), 82–89.

[6] M. Alreshoodi and J. Woods. 2013. Survey on QoE\ QoS correlation models for multimedia services. *arXiv preprint arXiv:1306.0221* (2013).

[7] S. Aroussi and A. Mellouk. 2014. Survey on Machine Learning-Based QoE-QoS Correlation Models. In *International Conference on Computing, Management and Telecommunications (ComManTel)*. IEEE, 200–204.

[8] AT&T. 2016. ECOMP (Enhanced Control, Orchestration, Management & Policy) Architecture White Paper. (Dec. 2016).

[9] O. Awobuluyi, J. Nightingale, Q. Wang, and J. M. Alcaraz-Calero. 2015. Video quality in 5G networks: Context-aware QoE management in the SDN control plane. In *2015 Intl Conf. on CIT/IUCC/DASC/PICOM*. IEEE, 1657–1662.

[10] A. Balachandran, V. Sekar, A. Akella, S. Seshan, I. Stoica, and H. Zhang. 2013. Developing a Predictive Model of Quality of Experience for Internet Video. In *ACM SIGCOMM Computer Communication Review*, Vol. 43. ACM, 339–350.

[11] Y. Bao, H. Wu, and X. Liu. 2017. From Prediction to Action: Improving User Experience with Data-Driven Resource Allocation. *IEEE Journal on Selected Areas in Communications* 35, 5 (May 2017), 1062–1075.

[12] A. A. Barakabitze, L. Sun, I.-H. Mkwawa, and E. Ifeachor. 2016. A Novel QoE-Aware SDN-enabled, NFV-based Management Architecture for Future Multimedia Applications on 5G Systems . In *Eighth International Conference on Quality of Multimedia Experience (QoMEX)*. Lisbon, Portugal.

[13] S. Baraković and L. Skorin-Kapov. 2013. Survey and Challenges of QoE Management Issues in Wireless Networks. *Journal of Computer Networks and Communications* 2013 (2013).

[14] A. Benoit, P. Le Callet, P. Campisi, and R. Cousseau. 2009. Quality Assessment of Stereoscopic Images. *EURASIP Journal on Image and Video Processing* 2008, 1 (2009), 659024.

[15] A. Bentaleb, A. C. Begen, and R. Zimmermann. 2016. SDNDASH: Improving QoE of HTTP Adaptive Streaming Using Software Defined Networking. In *Proc. of ACM Multimedia*. ACM, 1296–1305.

[16] N. Bouten, S. Latré, J. Famaey, W. Van Leekwijck, and F. De Turck. 2014. In-Network Quality Optimization for Adaptive Video Streaming Services. *IEEE Trans. on Multimedia* 16, 8 (Dec. 2014), 2281–2293.

[17] A. Breznick. Feb. 2017. How to Deliver Higher Mobile Video QoE, a Heavy Reading white paper produced for Akamai Technologies Inc. (Feb. 2017).

[18] F. E. Bustamante, D. Clark, and N. Feamster. 2017. Workshop on Tracking Quality of Experience in the Internet: Summary and Outcomes. *ACM SIGCOMM Computer Communication Review* 47, 1 (2017), 55–60.

[19] P. Casas, B. Gardlo, R. Schatz, and M. Mellia. 2016. An Educated Guess on QoE in Operational Networks through Large-Scale Measurements. In *Proceedings of the 2016 workshop on QoE-based Analysis and Management of Data Communication Networks*. ACM, 1–6.

[20] P. Casas and R. Schatz. 2014. Quality of Experience in Cloud Services: Survey and Measurements. *Computer Networks* 68 (2014), 149–165.

[21] P. Casas, M. Seufert, F. Wamser, B. Gardlo, A. Sackl, and R. Schatz. 2016. Next to You: Monitoring Quality of Experience in Cellular Networks from the End-devices. *IEEE Trans. on Network and Service Management* 13, 2 (2016), 181–196.

[22] C. Cavaro-Ménard, L. Zhang-Ge, and P. Le Callet. 2013. QoE for Telemedicine: Challenges and Trends. In *SPIE Optical Engineering+ Applications*. International Society for Optics and Photonics, 88561A–88561A.

[23] K.-T. Chen, C.-J. Chang, C.-C. Wu, Y.-C. Chang, and C.-L. Lei. 2010. Quadrant of Euphoria: a Crowdsourcing Platform for QoE Assessment. *IEEE Network* 24, 2 (2010).

[24] Q. A. Chen and others. 2014. QoE doctor: Diagnosing Mobile App QoE with Automated UI Control and Cross-layer Analysis. In *Proceedings of the 2014 Conference on Internet Measurement Conference*. ACM, 151–164.

[25] W. Chen, F. Jérôme, M. Barkowsky, and P. Le Callet. 2012. Exploration of Quality of Experience of Stereoscopic Images: Binocular Depth. In *6th Intl Workshop on Video Processing and Quality Metrics for Consumer Electronics*. 1–6.

[26] S. Chikkerur, V. Sundaram, M. Reisslein, and L. J. Karam. 2011. Objective Video Quality Assessment Methods: A Classification, Review, and Performance Comparison. *IEEE Transactions on Broadcasting* 57, 2 (2011), 165–182.

[27] B.-H. Chu, M.-S. Tsai, and C.-S. Ho. 2007. Toward a Hybrid Data Mining Model for Customer Retention. *Knowledge-Based Systems* 20, 8 (2007), 703–718.
[28] L. A. Clark and D. Watson. 1995. Constructing validity: Basic issues in objective scale development. *Psychological assessment* 7, 3 (1995), 309.
[29] L. Cui, F. R. Yu, and Q. Yan. 2016. When big data meets software-defined networking: SDN for big data and big data for SDN. *IEEE Network* 30, 1 (2016), 58–65.
[30] G. Dimopoulos, I. Leontiadis, P. Barlet-Ros, and K. Papagiannaki. 2016. Measuring Video QoE from Encrypted Traffic. In *Proceedings of the 2016 ACM on Internet Measurement Conference*. ACM, 513–526.
[31] L. Dinh-Xuan, M. Seufert, F. Wamser, and P. Tran-Gia. 2017. Study on the Accuracy of QoE Monitoring for HTTP Adaptive Video Streaming Using VNF. In *1st IFIP/IEEE Int. Workshop on QoE Management*. IEEE, 1–6.
[32] F. Dobrian and others. 2011. Understanding the impact of video quality on user engagement. In *ACM SIGCOMM Computer Communication Review*, Vol. 41. ACM, 362–373.
[33] O. Dobrijevic, M. Santl, and M. Matijasevic. 2015. Ant colony optimization for QoE-centric flow routing in software-defined networks. In *Proc. of 11th CNSM*. IEEE, 274–278.
[34] L. Duan, L. Huang, C. Langbort, A. Pozdnukhov, J. Walrand, and L. Zhang. 2017. Human-in-the-loop Mobile Networks: A Survey of Recent Advancements. *IEEE JSAC* 35, 4 (2017).
[35] U. Engelke, D. P. Darcy, G. H. Mulliken, S. Bosse, M. G. Martini, S. Arndt, J.-N. Antons, K. Y. Chan, N. Ramzan, and K. Brunnström. 2017. Psychophysiology-based QoE assessment: a survey. *IEEE Journal of Selected Topics in Signal Processing* 11, 1 (2017), 6–21.
[36] U. Engelke and H.-J. Zepernick. 2007. Perceptual-based quality metrics for image and video services: A survey. In *Next Generation Internet Networks, 3rd EuroNGI Conference on*. IEEE, 190–197.
[37] J. B. Ernst, S. C. Kremer, and J. J. Rodrigues. 2014. A Survey of QoS/QoE Mechanisms in Heterogeneous Wireless Networks. *Phys. Commun.* 13, PB (Dec. 2014), 61–72.
[38] ETSI. 2014. NFV MANO – Network Functions Virtualisation (NFV); Management and Orchestration, v1.1.1. (2014).
[39] ETSI. 2014. Speech and multimedia Transmission Quality (STQ); Quality of Experience: A Monitoring Architecture, ETSI TS 103 294, V1.1.1. (Dec. 2014).
[40] M. Fiedler and T. Hoßfeld. 2010. Quality of experience-related differential equations and provisioning-delivery hysteresis. In *21st ITC Specialist Seminar on Multimedia Applications-Traffic, Performance and QoE*. IEICE.
[41] M. Fiedler, T. Hoßfeld, and P. Tran-Gia. 2010. A generic quantitative relationship between quality of experience and quality of service. *IEEE Network* 24, 2 (2010).
[42] A. Floris, A. Ahmad, and L. Atzori. 2017. OTT-ISP joint service management: a Customer Lifetime Value based approach. In *First IFIP/IEEE Int. Workshop on QoE-Management*. Lisbon, Portugal.
[43] M. Gandy, R. Catrambone, B. MacIntyre, C. Alvarez, E. Eiriksdottir, M. Hilimire, B. Davidson, and A. C. McLaughlin. 2010. Experiences with an AR evaluation test bed: Presence, performance, and physiological measurement. In *2010 IEEE International Symposium on Mixed and Augmented Reality*. 127–136.
[44] A. Ganjam, V. Sekar, and H. Zhang. 2016. In-Situ Quality of Experience Monitoring: The Case for Prioritizing Coverage Over Fidelity. *White-paper submission, CMU/Conviva* (2016), 2.
[45] M.-N. Garcia, F. De Simone, S. Tavakoli, N. Staelens, S. Egger, K. Brunnström, and A. Raake. 2014. Quality of experience and HTTP adaptive streaming: A review of subjective studies. In *2014 6th International Workshop on Quality of Multimedia Experience (QoMEX)*. IEEE, 141–146.
[46] B. Gardlo, S. Egger, and T. Hoßfeld. 2015. Do Scale-Design and Training Matter for Video QoE Assessments through Crowdsourcing?. In *Proceedings of the Fourth International Workshop on Crowdsourcing for Multimedia*. ACM, 15–20.
[47] C. Ge, N. Wang, S. Skillman, G. Foster, and Y. Cao. 2016. QoE-Driven DASH Video Caching and Adaptation at 5G Mobile Edge. In *Proc. of the 3rd ACM Conf. on Information-Centric Networking*. ACM, 237–242.
[48] G. Ghinea and O. A. Ademoye. 2010. Perceived Synchronization of Olfactory Multimedia. *IEEE Transactions on Systems, Man, and Cybernetics - Part A: Systems and Humans* 40, 4 (July 2010), 657–663.
[49] G. Ghinea, C. Timmerer, W. Lin, and S. R. Gulliver. 2014. Mulsemedia: State of the Art, Perspectives, and Challenges. *ACM TOMM* 11, 1s, Article 17 (Oct. 2014), 23 pages.
[50] U. Goel, M. P. Wittie, K. C. Claffy, and A. Le. 2016. Survey of end-to-end mobile network measurement testbeds, tools, and services. *IEEE Communications Surveys & Tutorials* 18, 1 (2016), 105–123.
[51] J. Gupchup, Y. Hosseinkashi, M. Ellis, S. Johnson, and R. Cutler. 2017. Analysis of Problem Tokens to Rank Factors Impacting Quality in VoIP Applications. In *Proc. of 9th QoMEX*. IEEE, 1–6.
[52] R. Gupta, S. Arndt, J.-N. Antons, R. Schleicher, S. Möller, and T. H. Falk. 2013. Neurophysiological experimental facility for Quality of Experience (QoE) assessment. In *Proc. of IM 2013*. IEEE, 1300–1305.
[53] R. Gupta, H. J. Banville, and T. H. Falk. 2017. Multimodal Physiological Quality-of-Experience Assessment of Text-to-Speech Systems. *IEEE Journal of Selected Topics in Signal Processing* 11, 1 (2017), 22–36.

[54] J. Hadden, A. Tiwari, R. Roy, and D. Ruta. 2007. Computer Assisted Customer Churn Management: State-of-the-art and Future Trends. *Computers & Operations Research* 34, 10 (2007), 2902–2917.

[55] A. Hamam, A. E. Saddik, and J. Alja'am. 2014. A Quality of Experience Model for Haptic Virtual Environments. *ACM Trans. Multimedia Comput. Commun. Appl.* 10, 3, Article 28 (April 2014), 23 pages.

[56] B. Han, V. Gopalakrishnan, L. Ji, and S. Lee. 2015. Network function virtualization: Challenges and opportunities for innovations. *IEEE Communications Magazine* 53, 2 (2015), 90–97.

[57] Heavy Reading, S. O'Boyle, Scott Sumner. Nov. 2016. Webinar: The Future of QoE Monitoring in Virtualized Networks. (Nov. 2016).

[58] P. E. Heegaard, G. Biczok, and L. Toka. 2016. Sharing is Power: Incentives for Information Exchange in Multi-Operator Service Delivery. In *2016 IEEE Global Communications Conference (GLOBECOM)*. 1–7.

[59] C. T. Hewage and M. G. Martini. 2013. Quality of Experience for 3D Video Streaming. *IEEE Communications Magazine* 51, 5 (2013), 101–107.

[60] T. Hoßfeld, S. Biedermann, R. Schatz, A. Platzer, S. Egger, and M. Fiedler. 2011. The memory effect and its implications on Web QoE modeling. In *23rd Intl Teletraffic Congress (ITC), 2011*. IEEE, 103–110.

[61] T. Hoßfeld, M. Fiedler, and T. Zinner. 2011. The QoE provisioning-delivery-hysteresis and its importance for service provisioning in the future internet. In *7th EURO-NGI Conference on Next Generation Internet (NGI)*. IEEE, 1–8.

[62] T. Hoßfeld, M. Hirth, P. Korshunov, P. Hanhart, B. Gardlo, C. Keimel, and C. Timmerer. 2014. Survey of web-based crowdsourcing frameworks for subjective quality assessment. In *2014 IEEE 16th International Workshop on Multimedia Signal Processing (MMSP)*. 1–6.

[63] T. Hoßfeld, C. Keimel, M. Hirth, B. Gardlo, J. Habigt, K. Diepold, and P. Tran-Gia. 2014. Best practices for QoE crowdtesting: QoE assessment with crowdsourcing. *IEEE Transactions on Multimedia* 16, 2 (2014), 541–558.

[64] T. Hoßfeld, C. Moldovan, and C. Schwartz. 2015. To each according to his needs: Dimensioning video buffer for specific user profiles and behavior. In *2015 IFIP/IEEE Int. Symposium on Integrated Network Management (IM)*.

[65] T. Hoßfeld, R. Schatz, M. Varela, and C. Timmerer. 2012. Challenges of QoE management for cloud applications. *IEEE Communications Magazine* 50, 4 (2012).

[66] T. Hoßfeld, L. Skorin-Kapov, Y. Haddad, P. Pocta, V. A. Siris, A. Zgank, and H. Melvin. 2015. Can context monitoring improve QoE? A case study of video flash crowds in the internet of services. In *2015 IFIP/IEEE International Symposium on Integrated Network Management (IM)*. 1274–1277.

[67] Y. C. Hu, M. Patel, D. Sabella, N. Sprecher, and V. Young. 2015. Mobile edge computing - A key technology towards 5G. *ETSI White Paper* 11, 11 (2015), 1–16.

[68] International Telecommunication Union. 2016. *ITU-T Recommendation P.1203: Parametric bitstream-based quality assessment of progressive download and adaptive audiovisual streaming services over reliable transport.* Technical Report.

[69] K. Ivesic, L. Skorin-Kapov, and M. Matijasevic. 2014. Cross-layer QoE-driven admission control and resource allocation for adaptive multimedia services in LTE. *Journal of Network and Computer Applications* 46 (2014), 336–351.

[70] L. Jalal and M. Murroni. 2017. A nonlinear quality of experience model for high dynamic spatio-temporal mulsemedia. In *2017 Ninth International Conference on Quality of Multimedia Experience (QoMEX)*. IEEE, 1–6.

[71] M. Jarschel, F. Wamser, T. Hohn, T. Zinner, and P. Tran-Gia. 2013. SDN-based application-aware networking on the example of youtube video streaming. In *2013 Second European Workshop on SDN (EWSDN),*. IEEE, 87–92.

[72] J. Jiang, S. Sun, V. Sekar, and H. Zhang. 2017. Pytheas: Enabling Data-Driven Quality of Experience Optimization Using Group-Based Exploration-Exploitation. In *14th USENIX Symposium on Networked Systems Design and Implementation.*

[73] A. Kassler, L. Skorin-Kapov, O. Dobrijevic, M. Matijasevic, and P. Dely. 2012. Towards QoE-driven Multimedia Service Negotiation and Path Optimization with Software Defined Networking. In *SoftCOM 2012, 20th International Conference on Software, Telecommunications and Computer Networks*. IEEE, 1–5.

[74] M. Katsarakis, R. Teixeira, M. Papadopouli, and V. Christophides. 2016. Towards a Causal Analysis of Video QoE from Network and Application QoS. In *Proceedings of ACM SIGCOMM Workshop on QoE-based Analysis and Management of Data Communication Networks, Internet-QoE 2016*. ACM, 1–6.

[75] N. Khan and M. G. Martini. 2016. QoE-driven multi-user scheduling and rate adaptation with reduced cross-layer signaling for scalable video streaming over LTE wireless systems. *EURASIP Journal on Wireless Communications and Networking* 2016, 1 (2016), 93.

[76] C. Kim, A. Sivaraman, N. Katta, A. Bas, A. Dixit, and L. J. Wobker. 2015. In-band network telemetry via programmable dataplanes. In *ACM SIGCOMM*.

[77] E. Kroupi, P. Hanhart, J.-S. Lee, M. Rerabek, and T. Ebrahimi. 2014. EEG correlates during video quality perception. In *2014 Proceedings of the 22nd EUSIPCO*. IEEE, 2135–2139.

[78] P. Le Callet, S. Möller, and A. Perkis. 2013. *Qualinet White Paper on Definitions of Quality of Experience.* Technical Report Version 1.2. European Network on Quality of Experience in Multimedia Systems and Services.

[79] P. R. Lebreton, T. Mäki, E. Skodras, I. Hupont, and M. Hirth. 2015. Bridging the gap between eye tracking and crowdsourcing. In *SPIE/IS&T Electronic Imaging*. International Society for Optics and Photonics, 93940W–93940W.

[80] J.-S. Lee. 2014. On designing paired comparison experiments for subjective multimedia quality assessment. *IEEE Transactions on Multimedia* 16, 2 (2014), 564–571.

[81] E. Liotou, G. Tseliou, K. Samdanis, D. Tsolkas, F. Adelantado, and C. Verikoukis. 2015. An SDN QoE-service for dynamically enhancing the performance of OTT applications. In *2015 Seventh International Workshop on Quality of Multimedia Experience (QoMEX)*. 1–2.

[82] E. Liotou, D. Tsolkas, and N. Passas. 2016. A roadmap on QoE metrics and models. In *2016 23rd International Conference on Telecommunications (ICT)*. IEEE, 1–5.

[83] C. Z. Liu and M. Kavakli. 2016. Data-aware qoe-qos management. In *2016 IEEE 11th Conference on Industrial Electronics and Applications (ICIEA)*. IEEE, 1818–1823.

[84] E. Maggioni, E. Agostinelli, and M. Obrist. 2017. Measuring the Added Value of Haptic Feedback. In *2017 Ninth International Conference on Quality of Multimedia Experience (QoMEX)*. IEEE, 1–6.

[85] T. Mäki, P. Zwickl, and M. Varela. 2016. Network quality differentiation: Regional effects, market entrance, and empirical testability. In *2016 IFIP Networking Conference (IFIP Networking) and Workshops*. 476–484.

[86] M. G. Martini, C. W. Chen, Z. Chen, T. Dagiuklas, L. Sun, and X. Zhu. 2012. Guest editorial QoE-aware wireless multimedia systems. *IEEE Journal on Selected Areas in Communications* 30, 7 (2012), 1153–1156.

[87] A. M. Medhat, T. Taleb, A. Elmangoush, G. A. Carella, S. Covaci, and T. Magedanz. 2017. Service Function Chaining in Next Generation Networks: State of the Art and Research Challenges. *IEEE Comm. Mag.* 55, 2 (2017), 216–223.

[88] V. Menkovski, G. Exarchakos, and A. Liotta. 2011. Tackling the sheer scale of subjective QoE. In *International Conference on Mobile Multimedia Communications*. Springer, 1–15.

[89] V. Menkovski and A. Liotta. 2012. Adaptive psychometric scaling for video quality assessment. *Signal Processing: Image Communication* 27, 8 (2012), 788–799.

[90] K. Mitra, A. Zaslavsky, and C. Åhlund. 2015. Context-aware QoE modelling, measurement, and prediction in mobile computing systems. *IEEE Transactions on Mobile Computing* 14, 5 (2015), 920–936.

[91] H. Moens and F. De Turck. 2014. VNF-P: A model for efficient placement of virtualized network functions. In *2014 10th Intl. Conf. on Network and Service Management (CNSM)*. IEEE, 418–423.

[92] S. Möller, M. Wältermann, and M.-N. Garcia. 2014. Features of quality of experience. In *Quality of Experience*. Springer, 73–84.

[93] N. Murray, O. A. Ademoye, G. Ghinea, Y. Qiao, G.-M. Muntean, and B. Lee. 2017. Olfactory-enhanced multimedia video clips datasets. In *2017 Ninth International Conference on Quality of Multimedia Experience (QoMEX)*. IEEE, 1–5.

[94] N. Murray, Y. Qiao, B. Lee, A. K. Karunakar, and G.-M. Muntean. 2013. Subjective Evaluation of Olfactory and Visual Media Synchronization. In *Proceedings of the 4th ACM Multimedia Systems Conference (MMSys '13)*. ACM, 162–171.

[95] H. Nam, K.-H. Kim, D. Calin, and H. Schulzrinne. 2014. Youslow: a performance analysis tool for adaptive bitrate video streaming. In *ACM SIGCOMM Computer Communication Review*, Vol. 44. ACM, 111–112.

[96] H. Nam, K.-H. Kim, J. Y. Kim, and H. Schulzrinne. 2014. Towards QoE-aware video streaming using SDN. In *Global Communications Conference (GLOBECOM), 2014 IEEE*. IEEE, 1317–1322.

[97] I. Orsolic, D. Pevec, M. Suznjevic, and L. Skorin-Kapov. 2017. A machine learning approach to classifying YouTube QoE based on encrypted network traffic. *Multimedia Tools and Applications* (2017), 1–35.

[98] B. Osting, J. Xiong, Q. Xu, and Y. Yao. 2016. Analysis of crowdsourced sampling strategies for hodgerank with sparse random graphs. *Applied and Computational Harmonic Analysis* 41, 2 (2016), 540–560.

[99] M. Pallot, R. EYNARD, B. Poussard, O. Christmann, and S. Richir. 2013. Augmented sport : exploring collective user experience. In *VRIC '13 Proceedings of the Virtual Reality International Conference*. Laval, France, 1–10.

[100] S. Peng and others. 2017. QoE-Oriented Mobile Edge Service Management Leveraging SDN and NFV. *Mobile Information Systems* 2017 (2017).

[101] D. Perritaz, C. Salzmann, and D. Gillet. 2009. Quality of experience for adaptation in augmented reality. In *2009 IEEE International Conference on Systems, Man and Cybernetics*. 888–893.

[102] J. Puig, A. Perkis, F. Lindseth, and T. Ebrahimi. 2012. Towards an efficient methodology for evaluation of quality of experience in Augmented Reality. In *2012 Fourth International Workshop on Quality of Multimedia Experience*. 188–193.

[103] Q. M. Qadir, A. A. Kist, and Z. Zhang. 2015. Mechanisms for QoE optimisation of video traffic: a review paper. *Australasian Journal of Information, Communication Technology and Applications* 1 (2015). Issue 1.

[104] R. Rawassizadeh, B. A. Price, and M. Petre. 2015. Wearables: Has the age of smartwatches finally arrived? *Commun. ACM* 58, 1 (2015), 45–47.

[105] J. Redi, E. Siahaan, P. Korshunov, J. Habigt, and T. Hoßfeld. 2015. When the Crowd Challenges the Lab: Lessons Learnt from Subjective Studies on Image Aesthetic Appeal. In *Proceedings of the Fourth International Workshop on Crowdsourcing for Multimedia*. ACM, 33–38.

[106] P. Reichl, S. Egger, S. Möller, K. Kilkki, M. Fiedler, T. Hoßfeld, C. Tsiaras, and A. Asrese. 2015. Towards a comprehensive framework for QoE and user behavior modelling. In *2015 Seventh International Workshop on Quality of Multimedia Experience (QoMEX)*. IEEE, 1–6.

[107] P. Reichl, S. Egger, R. Schatz, and A. D'Alconzo. 2010. The logarithmic nature of QoE and the role of the Weber-Fechner law in QoE assessment. In *2010 IEEE International Conference on Communications (ICC)*. IEEE, 1–5.

[108] P. Reichl, P. Maillé, P. Zwickl, and A. Sackl. 2013. A fixed-point model for QoE-based charging. In *Proceedings of the 2013 ACM SIGCOMM workshop on Future human-centric multimedia networking*. ACM, 33–38.

[109] U. Reiter, K. Brunnström, K. De Moor, M.-C. Larabi, M. Pereira, A. Pinheiro, J. You, and A. Zgank. 2014. Factors influencing quality of experience. In *Quality of Experience*. Springer, 55–72.

[110] W. Robitza, A. Ahmad, P. A. Kara, L. Atzori, M. G. Martini, A. Raake, and L. Sun. 2017. Challenges of future multimedia QoE monitoring for internet service providers. *Multimedia Tools and Applications* (2017), 1–24.

[111] W. Robitza, S. Schönfellner, and A. Raake. 2016. A Theoretical Approach to the Formation of Quality of Experience and User Behavior in Multimedia Services. In *5th ISCA/DEGA Workshop on Perceptual Quality of Systems*. 39–43.

[112] D. Z. Rodríguez, R. L. Rosa, E. A. Costa, J. Abrahão, and G. Bressan. 2014. Video quality assessment in video streaming services considering user preference for video content. *IEEE Transactions on Consumer Electronics* 60, 3 (2014), 436–444.

[113] G. Rubino. 2005. Quantifying the quality of audio and video transmissions over the Internet: the PSQA approach. *Design and operations of communication networks: a review of wired and wireless modeling and management challenges. Imperial College Press, London* (2005).

[114] G. Rubino, P. Tirilly, and M. Varela. 2006. Evaluating users' satisfaction in packet networks using random neural networks. In *International Conference on Artificial Neural Networks*. Springer, 303–312.

[115] R. Schatz, M. Fiedler, and L. Skorin-Kapov. 2014. *QoE-Based Network and Application Management, in Quality of Experience: Advanced Concepts, Applications and Methods.* Springer International Publishing, 411–426.

[116] R. Schatz, T. Hoßfeld, L. Janowski, and S. Egger. 2013. From packets to people: Quality of experience as a new measurement challenge. In *Data traffic monitoring and analysis*. Springer, 219–263.

[117] R. Schatz, A. Sackl, C. Timmerer, and B. Gardlo. 2017. Towards Subjective Quality of Experience Assessment for Omnidirectional Video Streaming. In *2017 9th Intl Conf. on Quality of Multimedia Experience (QoMEX)*. IEEE, 1–6.

[118] S. Schwarzmann, T. Zinner, and O. Dobrijevic. 2016. Towards a Framework for Comparing Application-Network Interaction Mechanisms. In *28th International Teletraffic Congress (ITC 28)*, Vol. 3. IEEE, 13–18.

[119] S. Schwarzmann, T. Zinner, and O. Dobrijevic. 2017. Quantitative comparison of application–network interaction: a case study of adaptive video streaming. *Quality and User Experience* 2, 1 (2017), 7.

[120] B. Settles. 2010. Active learning literature survey. *University of Wisconsin, Madison* 52, 55-66 (2010), 11.

[121] M. Seufert, S. Egger, M. Slanina, T. Zinner, T. Hoßfeld, and P. Tran-Gia. 2015. A survey on quality of experience of HTTP adaptive streaming. *IEEE Communications Surveys & Tutorials* 17, 1 (2015), 469–492.

[122] M. Seufert and T. Hoßfeld. 2016. One Shot Crowdtesting: Approaching the Extremes of Crowdsourced Subjective Quality Testing. In *PQS 2016 5th ISCA/DEGA Workshop on Perceptual Quality of Systems*. 122–126.

[123] M. Seufert, N. Wehner, F. Wamser, P. Casas, A. D'Alconzo, and P. Tran-Gia. 2017. Unsupervised QoE Field Study for Mobile YouTube Video Streaming with YoMoApp. In *Proc. of 9th International QoMEX 2017*.

[124] M. Seufert, O. Zach, T. Hoßfeld, M. Slanina, and P. Tran-Gia. 2016. Impact of test condition selection in adaptive crowdsourcing studies on subjective quality. In *Proc. of 8th International QoMEX 2016*. IEEE.

[125] M. Z. Shafiq. 2015. Tracking Mobile Video QoE in the Encrypted Internet. *White-paper, Univ. of Iowa* (2015).

[126] M. Z. Shafiq, J. Erman, L. Ji, A. X. Liu, J. Pang, and J. Wang. 2014. Understanding the impact of network dynamics on mobile video user engagement. In *ACM SIGMETRICS Performance Evaluation Review*, Vol. 42. ACM, 367–379.

[127] L. Skorin-Kapov and M. Varela. 2012. A multi-dimensional view of QoE: the ARCU model. In *MIPRO, 2012 Proceedings of the 35th International Convention*. IEEE, 662–666.

[128] I. Sousa, M. P. Queluz, and A. Rodrigues. 2017. A Survey on QoE-oriented Wireless Resources Scheduling. *CoRR* abs/1705.07839 (2017).

[129] W. Stallings. 2015. *Foundations of Modern Networking: SDN, NFV, QoE, IoT, and Cloud*. Addison-Wesley Professional.

[130] Y. Sulema. 2016. Mulsemedia vs. Multimedia: State of the art and future trends. In *2016 International Conference on Systems, Signals and Image Processing (IWSSIP)*. IEEE, 1–5.

[131] The 5G Infrastructure Public Private Partnership. Feb. 2015. 5G Vision Brochure. (Feb. 2015).

[132] C. Timmerer and B. Rainer. 2014. The Social Multimedia Experience. *Computer* 47, 3 (2014), 67–69.

[133] C. Timmerer, M. Waltl, B. Rainer, and N. Murray. 2014. *Sensory Experience: Quality of Experience Beyond Audio-Visual.* Springer International Publishing, Cham, 351–365.

[134] C. Tselios and G. Tsolis. 2016. On QoE-awareness through virtualized probes in 5G networks. In *IEEE 21st Int'l Workshop on Computer Aided Modelling and Design of Communication Links and Networks*. IEEE, 159–164.

[135] D. Tsolkas, E. Liotou, N. Passas, and L. Merakos. 2017. A survey on parametric QoE estimation for popular services. *Journal of Network and Computer Applications* 77 (2017), 1–17.

[136] M. Varela, T. Mäki, L. Skorin-Kapov, and T. Hoßfeld. 2013. Increasing Payments in Crowdsourcing: Don't Look a Gift Horse in the Mouth!. In *PQS 2013*. Vienna, Austria.

[137] M. Varela, P. Zwickl, P. Reichl, M. Xie, and H. Schulzrinne. 2015. From Service Level Agreements (SLA) to Experience Level Agreements (ELA): The Challenges of Selling QoE to the User. In *2015 IEEE International Conference on Communication Workshop (ICCW)*. IEEE, 1741–1746.

[138] Verizon, Cisco, Ericsson, HPE, Nokia, Intel, R. Hat, and Samsung. 2016. SDN-NFV Reference Architecture v1.0. (2016).

[139] F. Wamser, M. Seufert, P. Casas, R. Irmer, P. Tran-Gia, and R. Schatz. 2015. YoMoApp: A tool for analyzing QoE of YouTube HTTP adaptive streaming in mobile networks. In *Proc. of EuCNC 2015*. IEEE, 239–243.

[140] Y. Wang, P. Li, L. Jiao, Z. Su, N. Cheng, X. S. Shen, and P. Zhang. 2017. A data-driven architecture for personalized QoE management in 5G wireless networks. *IEEE Wireless Communications* 24, 1 (2017), 102–110.

[141] M. K. Weldon. 2016. *The Future X Network: a Bell Labs Perspective*. Crc Press.

[142] C.-C. Wu, K.-T. Chen, Y.-C. Chang, and C.-L. Lei. 2013. Crowdsourcing multimedia QoE evaluation: A trusted framework. *IEEE Transactions on Multimedia* 15, 5 (2013), 1121–1137.

[143] W. Wu, A. Arefin, Z. Huang, P. Agarwal, S. Shi, R. Rivas, and K. Nahrstedt. 2010. "I'm the Jedi!" - A Case Study of User Experience in 3D Tele-immersive Gaming. In *2010 IEEE International Symposium on Multimedia*. 220–227.

[144] L. Xing, J. You, T. Ebrahimi, and A. Perkis. 2010. Estimating Quality of Experience on Stereoscopic Images. In *2010 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*. IEEE, 1–4.

[145] P. Ye and D. Doermann. 2014. Active sampling for subjective image quality assessment. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*. 4249–4256.

[146] Y. B. Youssef, A. Mellouk, M. Afif, and S. Tabbane. 2016. Video Quality Assessment Based on Statistical Selection Approach for QoE Factors Dependency. In *Global Communications Conference (GLOBECOM), 2016 IEEE*. IEEE, 1–6.

[147] Z. Yuan, S. Chen, G. Ghinea, and G.-M. Muntean. 2014. User Quality of Experience of Mulsemedia Applications. *ACM Trans. Multimedia Comput. Commun. Appl.* 11, 1s, Article 15 (Oct. 2014), 19 pages.

[148] Z. Yuan, G. Ghinea, and G.-M. Muntean. 2014. Quality of experience study for multiple sensorial media delivery. In *2014 International Wireless Communications and Mobile Computing Conference (IWCMC)*. 1142–1146.

[149] T. Zhao, Q. Liu, and C. W. Chen. 2017. QoE in Video Transmission: A User Experience-Driven Strategy. *IEEE Communications Surveys & Tutorials* (2017), 285–302.

[150] K. Zheng, Z. Yang, K. Zhang, P. Chatzimisios, K. Yang, and W. Xiang. 2016. Big data-driven optimization for mobile networks toward 5G. *IEEE Network* 30, 1 (2016), 44–51.

[151] T. Zinner, M. Jarschel, A. Blenk, F. Wamser, and W. Kellerer. 2014. Dynamic application-aware resource management using Software-Defined Networking: Implementation prospects and challenges. In *Proc. of IEEE NOMS 2014*. 1–6.

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