

Observations on Emerging Aspects in QoE Modeling and Their Impact on QoE Management

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Abstract—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 modeling QoE for a variety of media services. In this position paper we provide an overview of state-of-the-art findings and discuss emerging concepts and the challenges they raise with respect to managing QoE for networked media services. We address the implications of this evolution in our understanding of QoE in terms of new approaches in QoE modeling that are necessary for achieving a more comprehensive QoE management paradigm.

Index Terms—QoE modeling, QoE management, context factors, user level factors, user behavior

I. INTRODUCTION

All Quality of Experience (QoE) monitoring and management approaches in the literature are fundamentally based upon QoE models, since they identify the relevant parameters, and to which extent they influence the QoE. These models often focus on the various impacts of a service’s provisioning and delivery problems on QoE. The provisioning-delivery hysteresis [1] postulates the necessity to actively control quality (e.g., HTTP adaptive streaming), instead of passively suffering the uncontrollable impact of impairments such as packet loss caused by congestion. Thus, there is a need for proper QoE management based on appropriate QoE models.

In the context of QoE management and monitoring, we typically have no-reference (often parametric) or reduced-reference models, as full-reference ones require the original content for comparison with the transmitted, degraded content. This implies a need for objectively measurable QoS parameters, such as packet loss or video bit rate. In this direction, the literature provides several works which identify the key QoE influence factors for several multimedia and cloud applications which are typically derived by subjective experiments¹. In [2], we provide some pointers to existing surveys on QoE modeling and discuss emerging approaches such as active learning methods for large parameter spaces, and data-aware QoE modeling. In this paper, we focus on the emerging aspects in QoE modeling, such as pricing,

user expectations, and energy consumption, and how they affect (and should mold) QoE monitoring and management techniques. We highlight complementary approaches to QoE (e.g., engagement) in order to emphasize their potential to overcome current problems in QoE management, such as end-to-end encryption, which render some established monitoring methods (e.g., DPI) obsolete.

The main contribution of this position paper is to summarize what we identify as key directions and emerging aspects in QoE modeling (cf. Figure 1) and their impact on QoE management. We first discuss new trends and influence factors that have recently received more attention. Secondly, we look at emerging approaches and models that complement QoE models and have a different perspective on user-centric models. The latter include user behavior models; in particular engagement and user churn models. A comprehensive framework for QoE and user behavior modeling is provided in [3] which allows joining a multitude of existing modeling approaches under the perspective of service provider benefit, user well-being and technical system performance.

We categorize quality influencing factors into context, user, system and content level² [4], [5]. For QoE management, the system level factors are of major interest, since the QoE models used usually map changes in the technical parameters at the system level into the user-perceived quality of the service. The system level abstracts the transmission network and factors like bandwidth, devices and screens (e.g., size and resolution), but also the implementation of the application e.g., video buffering strategies. The investigation of the influence of those parameters on QoE is prevailing in literature.

Nevertheless, other context-, user- or content-level factors are bound to play a key role in more comprehensive QoE models. The current view on these factors in the literature seems is to ignore them for simplicity. However, it seems clear that a) this is technically incorrect and b) some of these factors can be actually better understood, and hence should be included into the QoE modeling process. Figure 1 provides an overview on the structure of the paper and the discussed emerging aspects in QoE modeling.

¹Conferences such as QoMEX are key events for subjective user studies on QoE, e.g. for identifying key influence factors and to derive proper QoE models for multimedia applications.

²Please note that the content level is seen as part of system influence factors in [4], as well as in the Qualinet Whitepaper on Definitions of QoE.

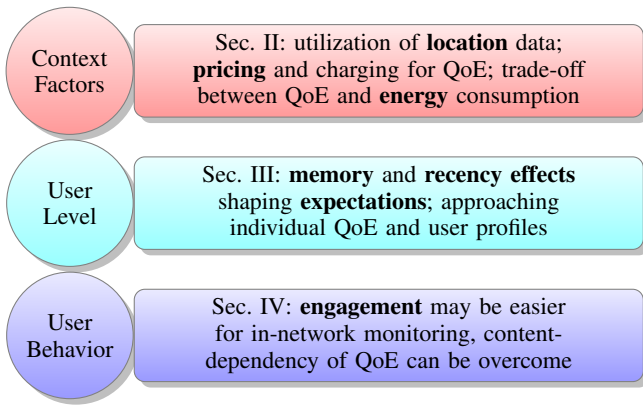


Fig. 1. Emerging factors in QoE modeling and complementary approaches.

II. CONTEXT FACTORS: SPATIAL LOCATION, PRICE, ENERGY

The context level takes into account for example the environment where the user is consuming the service, but also the service’s price, and its energy consumption (particularly for mobile services). The spatial and temporal location of the user may be interesting in QoE modeling, as historical data and models of e.g., network QoS at a certain location and time of the day/week may be utilized to improve performance predictions. [6] considers mobile consumption of videos. More precisely, mobility with periodical loss of radio coverage, which can for example occur in a tunnel or during hand-over events, is approached using context monitoring. The context information (e.g., when the tunnel occurs or about the radio coverage in general) can be collected through crowd-sensing via other users and collaboratively processed in a cloud, and it enhances the video quality-adapting decisions to avoid or minimize stalling. Similarly, [7] relies on collected knowledge from the crowd and includes location and speed in the decision on which quality representation to request the next chunk in a HAS³ context. These are clear examples of the interest of performing context monitoring for QoE management.

Other contextual factors such as price or energy represent aspects complementary to QoE and result often in a trade-off situation for the end user, e.g., higher price may lead to better service and improved QoE. Thereby, the context factors can be distinguished [3] between QoE context factors (*type I*, in [3]), influencing mainly the perceptual process in QoE, and behavioral context factors (*type II*), affecting mainly user behavior like engagement or churn.

The basic observation is that “the price to be charged for a certain service is not only a consequence of the service quality provided (QoE based on QoS), but at the same time has itself a certain impact on quality perception, and thus serves also as a (*type I*) context factor influencing the user state based on his or her willingness-to-pay” [3]. This mutual influence of price and QoE is modeled with a fixed-point model [8] shown to be convergent.

For mobile users, there exists another important trade-off between QoE and a very valuable resource in mobile devices, namely battery life [9]–[11]. User surveys have shown that the energy consumption is seen as a major QoE factor by end users [11], and users react on that by, e.g., changing between WLAN and 4G which leads to different battery duration, as well as different QoS profiles. Energy consumption is seen as a context *type I* factor [3]. Thus, QoE management needs to account for energy consumption for mobile users. On the one hand, optimized QoE and energy consumption may be achieved at the same time. For example, reduced download times allow to switch off the radio components and transition to an energy-efficient idle state. On the other hand, for some applications QoE and energy savings move in opposite directions. For instance, in video streaming, higher resolutions are preferred by end users [12], which requires however more processing power and larger data volumes to be transmitted. Other types of service, such as SnapChat, with its focus on ephemeral, highly processed video clips, and much younger demographics, might very well show different demands in terms of video quality (e.g., higher tolerance to delay, lower dependence of QoE on perceptual video quality).

Video providers can also influence the power consumption at the end user device by adjusting the video delivery to the end user. While a download of the video contents with full network throughput requires the least time, both the content provider and the user’s data quota may suffer from wasted traffic when the user aborts the video earlier. Therefore, server-side streaming mechanisms of video providers allow to adjust this trade-off [13].

For services with higher tolerance to latency, such as email, instant messaging (including the aforementioned asynchronous video messaging *à la* SnapChat), energy consumption may be reduced by lowering the update frequency, which leads to increased waiting times and “real timeliness” of the service. In [14], the authors quantify the trade-off between QoE and power consumption for web browsing. Shorter page load times and higher QoE can be achieved when the network provider adjusts the inactivity timer, which determines the time a user device is connected to the mobile network. In 3G and LTE, an inactivity timer determines the RRC (radio resource control) state of the user equipment and triggers a change from the Dedicated Transport Channel (DCH) to idle mode or forward access channel (FACH). DCH allows communications with the Radio Access Network (RAN) with a larger bandwidth at the cost of a higher power consumption at the user device. In this context, a multi-stakeholder trade-off emerges: an increased network timer reduces the signaling load in the mobile core network for the RRC state change and thus also the costs for the mobile provider to compensate the signaling load e.g., in the radio network controller (RNC), but it reduces energy efficiency (and hence, battery life) in the user equipment.

³HTTP Adaptive Streaming

III. USER LEVEL FACTORS: EXPECTATIONS AS WELL AS MEMORY AND RECENCY EFFECTS IN QOE MODELING

The user level abstract psychological factors resulting from higher-level cognitive processing like expectations of the user, memory and recency effects which are briefly discussed in the following. The authors in [15] survey literature on expectations in different fields that are psychology, service quality, consumer satisfaction theory, and QoE. As a conclusion of the survey, expectations are a relevant, but vague factor for quality assessment. Instead, expectations are assumed implicitly in the following way. When good or high quality is achieved, at least adequate expectations are met. In contrast, when quality is not optimal, expectations are not met.

As key contribution in [15], an existing conceptual QoE perception model is extended by explicitly including desired and adequate expectations in the quality perception process. The fundamental approach is that quality is a result by comparing desired and perceived features. To quantify the impact of expectations on QoE, the controllability of expectations in subjective QoE studies is addressed. Furthermore, for the assessment and quantification of expectations, a dedicated questionnaire is proposed. Through subjective user studies, it is shown how expectation-related knowledge can be used to increase the accuracy of quality prediction models. As use case web browsing of Google maps was considered. The QoS-QoE model mapped the downlink bandwidth to QoE. In an extended model, an additive term was added which represents the individually quantified desired expectation of a user. Thus, the model takes into account the technical parameter as well as the individual desired expectation which was collected with the proposed questionnaire in which users were asked to rank the importance of network speed. The same modeling approach was used to take into account adequate expectations, but now users were asked to indicate “How long should it take to download a 50 MB file at home?”⁴ Finally, the proposed QoE model is a linear model consisting of the QoS-QoE model (which followed the IQX hypothesis), an (negative) additive term for the adequate expectations and a (positive) additive term for the desired expectations. As a result, the pure QoS-QoE model could be improved. As a conclusion from [15], we postulate that QoE monitoring and management may take into account such expectations. This could be realized with user profiles at the client, the server or the network side. With proper GUIs, it may be possible to inherently get an idea of the individual expectations of a user and to take this into account in QoE management approaches. As a result, the individual QoE may be improved rather than the domain.

Other relevant user-level factors are the memory effect and recency effect which may play a crucial role for QoE modeling considering experience over time. In particular, the memory effect is important for QoE management over an entire session.

⁴It can of course be argued that this type of question is too technical for users to actually relate it to QoE, and better approaches are needed to address this. We could consider separating the more “technical” aspects of QoE (e.g., mappings from QoS to perceptual quality), from the “softer” aspects such as user expectations, demographics, etc.

Instead of focusing only on a single video or a single web page, there is a promising direction to consider session-based QoE management which requires to take into account memory effects. Recency effects are caused by short-term memory and the human ability to memorize certain stimuli. Due to the Internet-based delivery of multimedia contents, temporal fluctuations of media transmission quality emerge and such recency effects are demonstrated for audio [16], [17] and video QoE [18]. Consequently, QoE prediction models take into account such temporal fluctuations, e.g. [19], [20] where peak impairments were used to model exponential decay or rise of QoE as reaction to media quality changes.

For QoE management over entire sessions, the memory effect may be a key QoE influence factor. The memory effect for web browsing QoE is investigated in [21]. In a subjective study, it was found that in addition to the current web page load time as QoS parameter the user experienced QoE of the last downloaded web page was a significant influence factor. Using support vector machines (SVM), it was shown that the strength of the memory effect even lies in the same order of magnitude as the influence of the QoS level. Hence, the memory effect is a key influence factor for session-based QoE management. The implications of the memory effect on QoE modeling are also discussed in [21] for different modeling approaches that are support vector machines (SVM), iterative exponential regressions and hidden memory Markov models. For the iterative exponential regressions, QoE of a web page i is not only a function of QoS, but also of the previous QoE of web page $i - 1$. This iterative definition accounts for the memory effect with an exponential decay. When using Markov models, the memory effect requires to add one dimension to reflect the previous QoE. Thus, a two-dimensional Markov state representing the previous QoE and the actual QoS level are required to model memory effects. The authors in [22] also observe the memory effect and that “user opinions do not witness the sign of complete recovery after the network problems are rectified.” From those observations we conclude that session-based QoE management is a promising path for future QoE management approaches.

IV. USER BEHAVIOR: USER ENGAGEMENT AND USER CHURN MODEL

Many QoE models require a detailed understanding of the influence factors both at the application layer and the content (semantic) level in order to predict accurately the user perceived quality. However, such parameters require monitoring at the client or server side, while in-network monitoring relies on deep packet inspection or sophisticated statistical monitoring strategies. However, from an operator’s point of view, besides the QoE, the actual user behavior and the *user engagement* can provide complementary information which may be even more useful than just QoE estimates for some purposes. For example, revenue may depend on the user engagement due to successful placement of advertisements. In contrast to QoE monitoring, such engagement measures may be easier to obtain in practice, as it is not required to know a large variety

TABLE I
EMERGING FACTORS IN QoE MODELING AND THEIR IMPLICATIONS FOR QoE MONITORING AND MANAGEMENT.

Emerging aspect	Goal	Implication
Expectations	improve individual QoE rather than domain	user profile required at client, server or network side; may be implemented via GUI
Memory	session-based QoE management: QoE++	extend QoE models for memory effects; QoE monitoring needs to capture previous experiences
Pricing	charge for QoE and monetize QoE management, may serve as service differentiator	experience-level agreements to be established
Energy	prolong battery lifetime of mobile devices	adjust trade-off between QoE and energy consumption
Context	utilize more data for better prediction e.g. network throughput at a certain location and time (e.g. tunnel, train)	context measurement and processing architecture (big data) required
Engagement	understand user activity (instead of QoE), may be more relevant, e.g. for ads companies	content-dependency of QoE can be overcome; engagement may be easier for in-network monitoring
Churn	improve revenue, avoid user churn	QoE management requires churn models; collaborative approaches promising

of application layer and content level influence factors, but network traces (on packet and flow level) may be sufficient to monitor the basic engagement of a user, e.g., the length and throughput of a flow and if it is aborted prematurely. For applications like video streaming, the engagement metrics may be simply the duration of watched video contents (or its ratio compared to the video duration). Nevertheless, this also requires an understanding of basic video information (e.g., video duration) and downloaded video data does not represent necessarily the watched video duration or the engagement of the user. Therefore, engagement models are required which map such network characteristics to a proper engagement metric.

[23], [24] measure user engagement for video services from various service platforms sites and different types of contents including short and long Video On Demand as well as live video. As a result, a high buffering ratio lowers user engagement in terms of video watch time, with the impact being stronger for short videos. Buffering is also a key influence factor for video QoE [5] dominating the other influence factors. Therefore, the relation between QoE and user engagement is of interest. The authors in [25] combine the QoE model in [5] with the measured user engagement data depending on buffering in [23] to draw conclusions how to implement video buffer strategies for VoD.

Also the derivation of proper engagement metrics is a current and future research topic. For interactive applications like gaming, it is challenging to define engagement, e.g. number of clicks per second, e.g. number of played levels, as simple metrics like play time may not be sufficient. Play time may be crucial for an advertisement company, but the game provider wants to understand the real user's engagement to keep the user investing in the game. [26] suggest that immersion in games can be measured subjectively through questionnaires as well as objectively (task completion time, eye movement). [27] discusses various engagement metrics for online services in general which are classified into (a) popularity based metrics (for a given time frame) like number of distinct users, visits, or clicks, (b) activity based metrics like the average number of page views per visit or the average time per visit, (c) loyalty

based metrics (for a given time frame) like the number of days a user visited the site or the average time a user spent on the site. For the site engagement, [27] proposes different models to capture the engagement from different perspectives including user-based models and time-based models. Another challenge is to measure real user behavior and engagement in laboratory experiments. [28] investigated the experimental biases in user behavior in laboratory tests and found that a significant fraction of users changed their behavior as being involved in a lab test. Here, crowdsourcing experiments or field trials may be an opportunity to overcome the bias. [28] discuss different test designs for user behavior assessment and provide guidelines how to quantify and combat biasing factors.

V. DISCUSSIONS AND CONCLUSIONS

A. QoE++: From QoE Ego-Systems to QoE Eco-Systems

QoE research has advanced significantly in recent years with a focus on the *QoE ego-system* [29]. This means that QoE has been mainly addressed within a single session on a short-time scale for a single user of one concrete application. The QoE models capture the effects of the relevant influence factors on concrete applications. Consequently, QoE monitoring and management mechanisms which aim at improving QoE have a similar focus or are restricted by the underlying QoE models.

To advance in the area of QoE towards *QoE++* [29], new research directions have to be taken by considering the entire *QoE eco-system* (cf. Figure 2) and the stakeholders along the service delivery chain to the end user. In comparison to the traditional QoE ego-system thinking, the QoE eco-system addresses among others the following research topics: in-session vs. global system perspective, short- vs. long-time scales when considering QoE, single vs. multi-user QoE, single vs. concurrent usage of applications and services, user vs. business perspective by addressing all key stakeholder goals.

Current QoE models mainly quantify the influence of various parameters on the perceptual quality. However from a service provider's perspective, it may be more relevant how the user is behaving, as a consequence of the experienced QoE, but also as a consequence of other context factors like

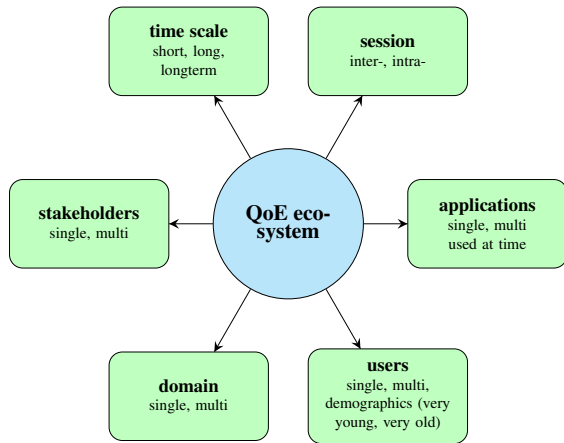


Fig. 2. Illustration of the QoE eco-system.

pricing, privacy, etc. Therefore, user engagement and user churn models are highly important and need to be related to QoE. In particular user engagement models are interesting, as it may be easier in practice to monitor user session duration instead of the video quality, especially in the encrypted Internet in which the majority of traffic is encrypted [30]. From a QoE management perspective, cooperation between stakeholders like content and network providers may be necessary to avoid churn [31], [32] for example by considering the customer lifetime value [33].

Also from the end user’s point of view, there are several trade-offs to consider, such as QoE vs. prices, QoE vs. energy consumption, etc. Therefore, recent efforts consider those context factors in QoE models which lead to different QoE management schemes. Table I summarizes the emerging factors in QoE modeling and complementary approaches and the corresponding implications.

B. Emerging Approaches to Deriving QoE Models

A limitation of many current QoE models is their neglecting of context and human factors, which may be attributed to the difficulty (or even unfeasibility) of collecting it, or incorporating into QoE models in an accurate way. The emerging approaches to QoE modeling can enable the inclusion of these factors into more comprehensive QoE models.

Crowdsourcing ...

- provides collection of subjective data, i.e., quality assessment, QoE but also user engagement,
- allows to investigate large-scale parameter spaces and multiple factors also for web-based services (Internet apps, cloud apps),
- enables new QoE models taking into account user related factors (e.g. demographics, expectations), but also to derive individual QoE models,
- requires best practices and guidelines for its correct implementation (e.g. data quality, reliability, rating scales, training).

Personalized QoE may be approached with ...

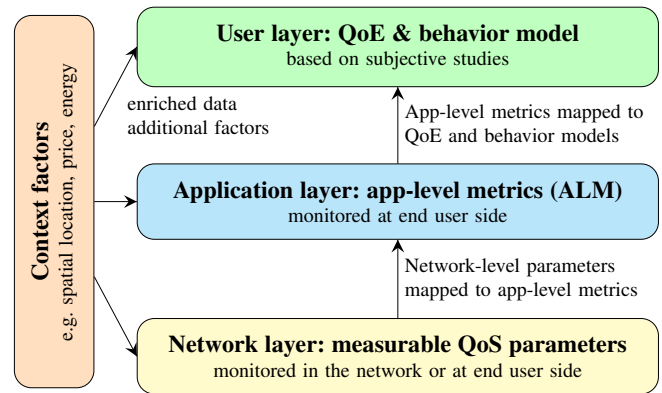


Fig. 3. Problem separation in QoE modeling.

- subjective tests through crowdsourcing and diversity of crowd, but longitudinal laboratory tests may nevertheless be necessary to collect long-term information from individuals,
- psycho-physiological measures to get a better understanding of personalized QoE,
- data-awareness and machine-learning to integrate the relevant factors in a black-box model.

Machine learning and active learning ...

- enable automated subjective tests leading to “optimal” QoE models, e.g., by minimizing uncertainty of models or increasing information gain, constrained by a certain cost budget,
- provide a black box approach for QoE modeling, but may also be combined with white box models by performing proper problem separation in the QoE modeling (Figure 3).

In [2], more details are discussed on these emerging approaches to assessing and modeling QoE.

C. Conclusions and Recommendations

QoE management is fundamentally dependent on its underlying QoE models. Today, beyond the complex business-incentive issues of implementing QoE management in large, multi-stakeholder contexts (which remains an open problem), some performance aspects of QoE management are limited by the models at our disposal. In particular, QoE management should deal not only with the technical components of improving QoE, but also with some of the business aspects of the service (minimizing churn, etc.). These aspects are being addressed by new approaches to understanding QoE and its relation to user behavior, and should therefore be considered as new building blocks for QoE management.

In light of the discussed above, we posit that in order to enable more sophisticated and better-working approaches to QoE management, QoE needs to be understood in a wider context — a QoE eco-system, including its relation to user behavior patterns and the “softer” influence factors that are not so well understood today. In that sense, it may be worth

structuring the creation of QoE models into “technical” sub-models (e.g., QoS to perceptual quality mappings), and other user-focused sub-models covering the “softer” factors, as depicted in Figure 3 (this could be achieved for instance by layering, as in [34]).

Furthermore, it is important to note that as technology advances (e.g., moving to 5G networks, better screens, new technologies such as VR/AR), so will user expectations. This implies that QoE models come, implicitly, with a “best before” date, and should be treated accordingly.

A possible way around this lies in treating QoE models as living, evolving entities. The use of crowdsourcing for updating ground truths, along with suitable machine learning approaches can help in this regard, allowing QoE models to evolve along with the underlying technologies and user expectations and habits.

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REFERENCES

- [1] T. Hoßfeld, M. Fiedler, and T. Zinner, “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, 2011.
- [2] L. Skorin-Kapov, M. Varela, T. Hoßfeld, and K.-T. Chen, “A survey of emerging concepts and challenges for qoe management of multimedia services,” *ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM) (SI on QoE Management)*, vol. 14, no. 2, Apr. 2018.
- [3] P. Reichl, S. Egger, S. Möller, K. Kilkki, M. Fiedler, T. Hoßfeld, C. Tsiaras, and A. Asrese, “Towards a comprehensive framework for qoe and user behavior modelling,” in *2015 Seventh International Workshop on Quality of Multimedia Experience (QoMEX)*. IEEE, 2015.
- [4] U. Reiter, K. Brunnström, K. De Moor, M.-C. Larabi, M. Pereira, A. Pinheiro, J. You, and A. Zgank, “Factors influencing quality of experience,” in *Quality of Experience*. Springer, 2014.
- [5] T. Hoßfeld, R. Schatz, E. Biersack, and L. Plissonneau, “Internet video delivery in youtube: From traffic measurements to quality of experience,” in *Data Traffic Monitoring and Analysis*. Springer, 2013.
- [6] F. Metzger, E. Liotou, C. Moldovan, and T. Hoßfeld, “TCP Video Streaming and Mobile Networks: Not a Love Story, But Better With Context,” *Computer Networks*, vol. 109, 2016.
- [7] R. Dubin, A. Dvir, O. Pele, O. Hadar, I. Katz, and O. Mashiach, “Adaptation Logic for HTTP Dynamic Adaptive Streaming Using Geopredictive Crowdsourcing for Mobile Users,” *Multimedia Systems*, 2016.
- [8] P. Reichl, P. Maillé, P. Zwickl, and A. Sackl, “A fixed-point model for qoe-based charging,” in *ACM SIGCOMM workshop on Future human-centric multimedia networking*, 2013.
- [9] S. Ickin, “Quality of experience on smartphones: Network, application, and energy perspectives,” Ph.D. dissertation, Blekinge Institute of Technology, 2015.
- [10] Q. A. Chen *et al.*, “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, 2014.
- [11] S. Ickin, K. Wac, M. Fiedler, L. Janowski, J.-H. Hong, and A. K. Dey, “Factors Influencing Quality of Experience of Commonly Used Mobile Applications,” *IEEE Communications Magazine*, vol. 50, no. 4, 2012.
- [12] M. Seufert, S. Egger, M. Slanina, T. Zinner, T. Hoßfeld, and P. Tran-Gia, “A survey on quality of experience of http adaptive streaming,” *IEEE Communications Surveys & Tutorials*, vol. 17, no. 1, 2015.
- [13] C. Schwartz, M. Scheib, T. Hoßfeld, P. Tran-Gia, and J. M. Gimenez-Guzman, “Trade-offs for Video-Providers in LTE Networks: Smartphone Energy Consumption vs Wasted Traffic,” in *22nd ITC Specialist Seminar on Energy Efficient and Green Networking (SSEEGN)*. IEEE, 2013.
- [14] C. Schwartz, T. Hoßfeld, F. Lehrieder, and P. Tran-Gia, “Angry Apps: The Impact of Network Timer Selection on Power Consumption, Signalling Load, and Web QoE,” *Journal of Computer Networks and Communications*, vol. 2013, 2013.
- [15] A. Sackl, R. Schatz, and A. Raake, “More than i ever wanted or just good enough? user expectations and subjective quality perception in the context of networked multimedia services,” *Quality and User Experience*, vol. 2, no. 1, 2017.
- [16] L. Gros and N. Chateau, “Instantaneous and overall judgements for time-varying speech quality: assessments and relationships,” *Acta Acustica united with Acustica*, vol. 87, no. 3, 2001.
- [17] S. Voran, “A basic experiment on time-varying speech quality,” in *Proc. Intl. Conf. on Measurement of Speech and Audio Quality in Networks*, vol. 14, 2005.
- [18] D. S. Hands and S. Avons, “Recency and duration neglect in subjective assessment of television picture quality,” *Applied cognitive psychology*, vol. 15, no. 6, 2001.
- [19] A. Raake, “Short-and long-term packet loss behavior: towards speech quality prediction for arbitrary loss distributions,” *IEEE Transactions on Audio, Speech, and Language Processing*, vol. 14, no. 6, 2006.
- [20] Z. Chen and H. Nakazato, “Model for time-varying quality of speech services,” in *Global Telecommunications Conference (GLOBECOM’05)*, vol. 1. IEEE, 2005.
- [21] T. Hoßfeld, S. Biedermann, R. Schatz, A. Platzer, S. Egger, and M. Fiedler, “The memory effect and its implications on web qoe modeling,” in *23rd International Teletraffic Congress (ITC)*, 2011.
- [22] J. Shaikh, M. Fiedler, P. Paul, S. Egger, and F. Guyard, “Back to normal? impact of temporally increasing network disturbances on qoe,” in *Globecom Workshops (GC Wkshps)*. IEEE, 2013.
- [23] F. Dobrian *et al.*, “Understanding the impact of video quality on user engagement,” in *ACM SIGCOMM Computer Communication Review*, vol. 41, no. 4. ACM, 2011.
- [24] F. Dobrian, A. Awan, D. Joseph, A. Ganjam, J. Zhan, V. Sekar, I. Stoica, and H. Zhang, “Understanding the impact of video quality on user engagement,” *Communications of the ACM*, vol. 56, no. 3, 2013.
- [25] C. Moldovan and F. Metzger, “Bridging the gap between qoe and user engagement in http video streaming,” in *Teletraffic Congress (ITC 28), 2016 28th International*, vol. 1. IEEE, 2016.
- [26] C. Jennett, A. L. Cox, P. Cairns, S. Dhoparee, A. Epps, T. Tijs, and A. Walton, “Measuring and defining the experience of immersion in games,” *International journal of human-computer studies*, vol. 66, no. 9, 2008.
- [27] J. Lehmann, M. Lalmas, E. Yom-Tov, and G. Dupret, “Models of user engagement,” in *International Conference on User Modeling, Adaptation, and Personalization*. Springer, 2012.
- [28] W. Robitza, P. A. Kara, M. G. Martini, and A. Raake, “On the experimental biases in user behavior and qoe assessment in the lab,” in *Globecom Workshops (GC Wkshps)*. IEEE, 2016.
- [29] T. Hoßfeld, “Qoe++: From ego- to eco-system?” in *Dagstuhl Seminar 15022: Quality of Experience: From Assessment to Application*, ser. Lecture Notes in Computer Science, K. D. Moor, M. Fiedler, P. Reichl, and M. Varela, Eds. Dagstuhl Reports, 2013, pp. 68–69.
- [30] C. Moldovan, V. Burger, F. Metzger, S. Surminski, and T. Hoßfeld, “Viability of wi-fi caches in an era of https prevalence,” in *IEEE ICC Workshop on Advanced Caching in Wireless Networks*, Paris, France, 2017.
- [31] A. Ahmad, A. Floris, and L. Atzori, “Qoe-centric service delivery: A collaborative approach among otts and isps,” *Computer Networks*, vol. 110, 2016.
- [32] —, “Qoe-centric service delivery: A collaborative approach among otts and isps,” *Computer Networks*, vol. 110, 2016.
- [33] —, “Ott-isp joint service management: a customer lifetime value based approach,” in *Integrated Network and Service Management (IM), 2017 IFIP/IEEE Symposium on*. IEEE, 2017.
- [34] M. Varela, L. Skorin-Kapov, F. Guyard, and M. Fiedler, “Meta-modeling qoe,” *Praxis der Informationsverarbeitung und Kommunikation*, vol. 37, no. 4, 2014. [Online]. Available: <http://www.degruyter.com/view/j/piko.2014.37.issue-4/pik-2014-0028/pik-2014-0028.xml>