Quality that Matters: QoE Monitoring in Education Service Provider (ESP) Networks

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***Abstract*—Education Service Providers (ESPs) play a crucial role in the digitization of education as they equip students and teachers with reliable devices and provide high quality Internet access at schools. This paper investigates four months worth of continuous measurements conducted by an ESP using a large-scale, passive, in-device Quality of Experience (QoE) monitoring system deployed into a nationwide network of education-purpose devices. These measurements cover more than 800 education centers and about 4000 devices, used both in schools and at home. Using this rich dataset, we present an exhaustive characterization of the browsing behavior, and a quantification of the web and video QoE in this educational context. Web QoE results showed a better performance for school Wi-Fi networks compared to home connections, suggesting that several issues may arise for ESPs due to the increasing relevance of home-schooling caused by the COVID-19 pandemic.**

***Index Terms*—QoE; Educational Networks; Distributed Network Monitoring; Web Browsing; Network Measurements**

I. Introduction

Nowadays, the Internet-supported educational paradigm has become a reality, with students and teachers remotely accessing to digital contents and online platforms, which transform the overall learning experience. In this context, the role of Education Service Providers (ESPs) is indispensable, working with the national education systems to help them implement comprehensive reforms towards digitization. While ESPs are not the same all over the world, they typically take care of at least two essential services: deliver devices for students and teachers (either laptops or tablets) and provide Wi-Fi Internet access at schools. Thus, like Internet Service Providers (ISPs), ESPs need Quality of Experience (QoE) monitoring to analyze their services performance, as any degradation would impact on the quality of education. An advantage of the ESPs over ISPs, to face the lack-of-visibility problems that network monitoring has, is that they have access to the users devices to deploy application-layer QoE monitoring systems, providing an augmented degree of visibility into the activity, behavior, and performance of different applications.

In collaboration with Plan Ceibal [1], a major ESP which leads a nationwide one-to-one computing program in Uruguay, we implemented and deployed a passive web QoE monitoring system directly within the end-devices. We collected measurements from more than 800 education centers and about 4000 devices from teachers and students, who may use them both in schools and at home. At schools, the QoE would depend on two factors managed by the ESPs, the device and the Wi-Fi Internet access. On the other hand, when the users are at home, they may still use the devices provided by the ESP, but in that case they rely on their own Internet connection. While the present study was prior to the COVID-19 outbreak, the results of the analysis for the latter case are very important for the current situation, due to the increased relevance of home-schooling during the pandemic.

A first study focusing on passive QoE monitoring in ESP networks has been presented by us in [2], which was to the best of our knowledge the first ESP study of its kind in general. This work extends our previous work by elaborating in more detail on the characteristics of web sessions in school and home networks. Further, the monitored web and video QoE influence factors enable a network-wise QoE comparison. Web QoE was higher in schools than at homes, which can be explained by the high-end Wi-Fi infrastructure at schools, compared to the poorer quality of unplanned home networks. This fact raises an alert for the ESP and the education system in the new educational context given by the COVID-19 pandemic.

This work is therefore structured as follows. Section II describes related works on QoE and QoE monitoring. Section III presents the implemented monitoring system and describes the dataset. The characteristics of the monitored web sessions are analyzed in Section IV, before the characteristics of QoE influence factors are investigated in Section V. Finally, Section VI concludes and outlines future works.

II. Related Work

Quality of Experience (QoE) of a multimedia system is influenced by context, user, system, and content level factors [3]. With respect to system factors of web browsing, response times were identified as the most important QoE factor [4]. Thus, the first web QoE models were based on page load time (PLT), e.g., [5]. Subsequently, refined approaches were proposed which are based on the time until the visible portion of a web page has been fully loaded [6].

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For video QoE, most works on (adaptive) video streaming agree that initial delay, stalling, and quality adaptation are the most dominant QoE factors [7]. Stalling, i.e., playback interruptions due to buffer depletion, is considered the worst QoE degradation [8], and should be avoided. Furthermore, video streams should be played out with high visual quality [9]. In contrast, initial delay impacts the QoE only slightly [5].

The monitoring of QoE-relevant KPIs has been widely addressed in the literature, normally focused on fixed networks and considering in-network or network side measurements. In [10], authors provide an overview on QoE-based network monitoring approaches and their associated challenges.

Regarding in-network measurements, several works have been investigating video QoE, such as [11], [12], which are based on deep packet inspection (DPI). However, the wide adoption of end-to-end encryption has turned previous DPI-based approaches unreliable or even unfeasible, which motivated a surge of papers focusing on the analysis of in-network measurements through machine learning (ML) models. For example, in [13]–[16], authors apply different machine learning approaches to estimate the QoE or QoE-relevant metrics by extracting features from the network. Some of these works exclusively focus on video streaming, where they train ML models on simple features from the stream of encrypted packets, such as packet times, packet sizes, or throughput. Also for ML-based QoE monitoring of web browsing, first approaches have been proposed, such as [17].

The complementary approach is in-device application measurements, which was investigated in several works. For example, [18] followed this approach for YouTube QoE monitoring, relying on in-browser tools to directly collect KPIs such as playback delay, stalling events, or video resolution. YoMoApp [19], [20] passively measures QoE-relevant features of YouTube in smartphones.

The advantage of application-side monitoring is that it provides accurate measurements for QoE assessment, as these can be directly observed, without the need of additional estimation or mapping approaches. However, only rarely devices and applications can be accessed for such kind of monitoring. This is why the presented QoE monitoring of a nationwide educational service provider brings valuable insights into web browsing and its QoE.

III. Methodology

The passive QoE monitoring system is based on a Chrome browser plugin, as this is the most popular browser worldwide - and in particular in Uruguay, with a share of more than 80% according to [21]. The plugin generates an anonymized user ID and collects for every web page accesed the browsing timestamp, the URL, and page load timing information. If a video element is embedded, the plugin will periodically record the video streaming progress every 250ms (e.g., current playtime, buffer, player state, video resolution, video id, screen resolution, advertisement clips) in a YoMoApp-style log [19], [20], [22]. Finally, the plugin process the video logs to compact the streaming information and extracts the QoE metrics for each video (e.g., initial delay, stalling events, resolution changes). The QoE measurements for both web browsing and video are sent to a centralized server, which stores them in a database.

TABLE I: Distribution of the web browsing and video QoE measurements when devices are used at schools.

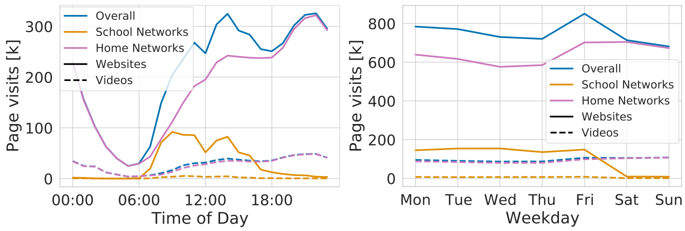
	Web QoE		**Video QoE**	
	Schools	Records	Schools	Records
Elementary and Primary Schools	497 (61%)	429,576 (52%)	444 (65%)	95,496 (62%)
Secondary Schools	208 (26%)	284,347 (34%)	163 (24%)	42,441 (27.6%)
Technical Schools	86 (11%)	109,993 (13%)	61 (9%)	14,991 (10%)
Teacher Training Centers	18 (2%)	6,156 (1%)	12 (2%)	596 (0.4%)

The QoE monitoring system was deployed in a real-world educational scenario, installing the described plugin in the laptops handed over to teachers and students by Plan Ceibal [1], who used them both in schools and at homes. The users gave their consent to collect the anonymized data from their devices, which was handled according to the Uruguayan and European privacy protection legislation. The measurements were collected during the last four months of 2019, which corresponds to the end of the school year in Uruguay, and also the time of greatest network usage at schools [23], [24]. The web browsing QoE dataset has 5,641,034 records corresponding to 3,887 unique devices, while the dataset for video QoE has 678,549 records from 3,258 unique devices. As expected, most of the users with web navigation data also have video data (90%), given the current popularity of such content.

The data was collected from 84,772 different IP addresses, of which only 818 (1%) correspond to schools, but they account for almost 15% of the records in the dataset (the distribution is shown in Table I). All schools have high-end Wi-Fi Internet access and the backbone is an ISP broadband optical fiber connection. With respect to the geographic distribution, the dataset includes information from the 19 different provinces of Uruguay. Most of them are concentrated in the two largest ones (Montevideo and Canelones) which together have 43% of the schools and 42% of the QoE records.

The rest of the IP addresses correspond to residential services, and were analyzed via reverse lookups. The majority of the IPs (85%) are fixed services from the public ISP (who has the monopoly on wired connections), while 14% are from mobile services of the three major operators in the country, and the remaining 1% correspond to other services. For other networks that do not correspond to schools, we can only know if the backbone is fixed or mobile, but we do not know if the devices connect to the Internet using Ethernet or Wi-Fi, but we assume that most of them use the latter, as it is actually the most common access technology at homes. It is worth to mention that we do not have any data of other devices usage (e.g. smartphones), neither in schools nor at homes.

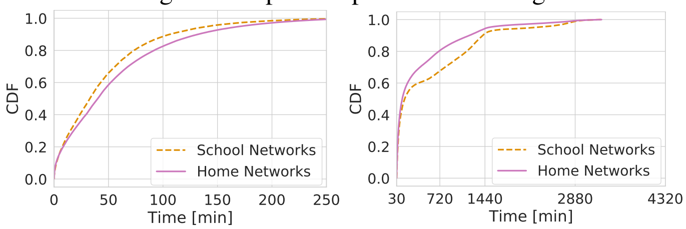
The dataset collected for video playback QoE includes information from 65.531 different IP addresses, of which only 685 (1%) are from schools. The total number of video QoE records corresponding to Plan Ceibal sites is 153,935 (almost



(a) Per hour of day.

(b) Per day of week.

Fig. 1: Temporal aspects of browsing.



(a) Session duration.

(b) Session inter-arrival times.

Fig. 2: Web session characterization.

7% of the total). Repeating the same analysis done for the web browsing dataset, we find similar results for the distribution of data among schools, which is also presented in Table I. Concerning the geographic distribution, in this case Montevideo and Canelones account for 292 schools with 63,477 records (41%), while the rest of the country totals 393 schools with 90,458 records (59%). We shall recall that in all cases, for both web browsing and video, the devices that collected the data were the laptops provided by Plan Ceibal to students and teachers, so all the analysis carried out in our study corresponds to the same type of device.

IV. Characteristics of Web Sessions

The temporal aspects of browsing are depicted in Figure 1. To help the interpretation of the results, it is worth to note that schools in Uruguay typically have a regular part-time schedule (from 8am to 12am or from 1pm to 5pm), while some schools have full-time schedules (from 10am to 5pm). Figure 1a shows the amount of page visits per hour of day overall (blue), as well as split into pages accessed from school networks (orange) and home networks (violet). In this case, two phases can be detected, namely, the time from 7am to 7pm, in which the school networks are utilized, and the time from 7pm to 7am, in which basically no pages are accessed from school networks. In the first phase, the school networks see an increasing amount of page visits during the morning with the peak between 9am and 10am (i.e., about halfway through the morning shift), then a drop during midday, an afternoon peak at 2pm (i.e., at the middle of the afternoon shift), and a gradual decrease of page visits towards the end of the phase. On the other hand, the amount of page visits at homes is strictly increasing from 6am to 2pm, where it saturates until the end of the phase.

In the second phase starting from 7pm, the amount of page visits further increases to a peak at 9pm before it declines during the night hours towards the minimum at 5am. Figure 1a also shows as dashed lines how many of the pages delivered video content, i.e., web pages from which a video was actually streamed and played out in the browser. It can be seen that only few videos were streamed from school networks, which shows that Internet videos are not very widely used for education or entertainment in breaks. In home networks, the amount of page visits for video streaming follows the general trend and accounts for up to one third of the page visits.

Regarding the day of the week, Figure 1b also shows two phases. The first phase is from Monday to Friday, in which page visits from school networks stay on the same level with a low level of video streaming in school networks. In the same time range, page visits from home networks slightly drop from Monday to Wednesday, and then increase towards Friday. The second phase corresponds to the weekend, in which almost no pages are accessed from school networks. However, a high number of page visits and also slightly increased video streaming can be observed from home networks. It has to be noted that these browsing patterns do not generalize to all users and all devices, but it has to be kept in mind that the educational laptops, which monitor the QoE, are mostly used by students and teachers. This is why some general activity patterns of students and teachers, e.g., no school during weekends or decreasing activity in school networks in the afternoon, can be found in Figure 1. Nevertheless, it can be observed that, with respect to browsing, the educational laptops were mostly used outside of schools.

It has to be noted that no significant differences could be observed in terms of user behavior between the laptop usage in home networks with fixed or mobile backbone. Thus, throughout this paper, we just focus on the differences between school and home networks.

For the analysis of web sessions, the single page visits have to be mapped to sessions first. As proposed in literature [25]–[27], a 30 minutes threshold as think-time is used. This means that a web session ends if a user does not request a new web page within 30 minutes after the last web page request. This classification approach results in 209,020 different sessions by 3,887 users in total, so every user initiated around 53 sessions on average. Figure 2a analyzes the observed session duration, which is computed as the time between the first webpage request and the unload of the last webpage of a session. The x-axis shows the duration in minutes and the y-axis indicates the value of the CDF. The distribution of the session duration in school networks is depicted as dashed orange line, and ranges from a few seconds up to a few hours. To exclude some extreme outliers, the 95th percentile, which corresponds to 4.5 hours, is investigated. Except for the ca. 10% sessions with very short duration, an almost uniform distribution of the duration can be observed up to the 60th percentile, i.e., up to 45 minutes, which is the typical duration of a school lesson. Afterwards, the CDF shows a slight bend and flattens for larger session durations. When comparing sessions in home networks (solid violet), it can be seen that sessions at schools (dashed orange) show a generally shorter duration, which could be due to time limited

TABLE II: Top domains per network with their total traffic share in percentage.

Network	1st Domain	2nd Domain	3rd Domain	4th Domain	5th Domain
School	Google (19.11%)	PortafolioDocente (12.89%)	Alumnos.Sea (7.33%)	Ceibal.Schoology (5.82%)	YouTube (4.43%)
Home	Google (19.26%)	YouTube (11.85%)	Facebook (4.56%)	Instagram (3.36%)	Ceibal.Edu (2.86%)

usage of the educational laptops during classes.

Figure 2b shows the corresponding CDFs of the inter-arrival time of sessions, i.e., the time between two consecutive session starts. The CDF for the home networks grows very fast up to the median at 119 minutes, after which the CDFs flatten. For sessions in school networks, the median is at 159 minutes and in the following region between 300 and 600 minutes the CDF flattens more strongly than for the home network. The reason is that such breaks between sessions are not very common for students and teachers. Instead, very often long breaks occur between the end of school and the start of school at the next day, which are in the range of 600 and 1380 minutes. This can be seen from the CDF, which shows an almost linear increase in this region. Breaks of shortly below one day (1440 minutes) are more frequent and indicate regularities in the student or teacher's schedule, and larger breaks up to three days (4320 minutes) can also be observed. These are mostly due to weekends, when there are no classes.

With respect to the number of page loads issued by a user, the analysis revealed that slightly more page loads are issued over school networks. This might be a side effect of the low amount of video streaming or it might be due to explorative tasks in class (e.g., information search and reading). However, a similar stay duration on the single pages for both networks could be observed. This finding is not surprising, given the fact that the behavior of the same set of users was monitored in all networks. Thus, our results suggest that the browsing behavior of users is independent of the used access network.

It is worth to note that the educational laptops were not only used for school activities, but could be freely used by students and teachers. Table II lists the top domains per network and their total traffic share. Thus, the most popular websites in schools were the search engine `Google` (19%), `PortafolioDocente` (13%), which is an administrative tool for teachers, and `Alumnos.Sea` (7%), which is a learning assessment system. In the home networks, we also observe that `Google` is the most frequent visited domain. Further, we observe that social networks are more popular showing `YouTube`, `Facebook`, and `Instagram` in the top five domains. Moreover, the appearance of `Ceibal.Edu` (main webpage of Plan Ceibal) shows that students and teachers also access educational resources outside of schools, e.g., to study/work from home, and the appearance of `Hestia.Mides` (0.6%), which is a website of the Uruguayan social development ministry related with support programs for low-income families, in the top 20 domains shows that also parents of the school children use the educational laptops.

Table III presents the parameters a, b, c of simple exponential ($f(x) = a \cdot \exp(-b \cdot x) + c$) or logarithmic ($f(x) = a \cdot \log(b + x) + c$) fittings for the observed characteristics of web sessions. The

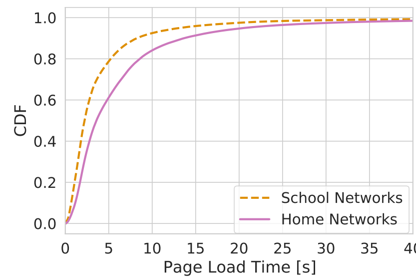


Fig. 3: Page load time distribution.

high coefficient of determination R^2 indicates that the goodness of the fits is very high, i.e., the fittings accurately resemble the observed data. These fittings can be used to simulate or emulate realistic browsing on laptops in future research works. Note again that the fittings for home networks include observed web sessions from home networks with both fixed and mobile backbone, as they only showed very small differences.

To sum up, web sessions in school networks behave differently because of the different context of browsing and institutional peculiarities, such as time-limited school lessons. We analyzed these characteristics and provided models, which can be used to simulate or emulate realistic web sessions in home and school networks in network management studies.

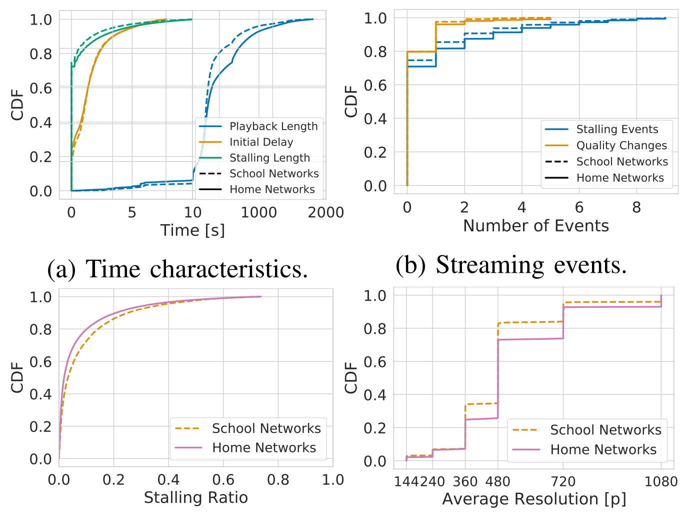
V. Characteristics of QoE Influence Factors

Next, the monitored QoE influence factors are investigated in detail to evaluate the network performance of school networks, and compare it to home access networks. Figure 3 analyzes the observed page load times during the study with respect to the used network. It includes the CDF of the page load times of the school network (dashed orange) as well as the CDF for home networks (solid violet). Note that the CDFs include the page load times of all sub-pages of a domain.

The school CDF shows an almost uniform distribution of the PLTs until around 3.4s, which corresponds to 68% of the page loads. The mean and median PLT of the school networks are 4.6s and 2.2s, respectively. In contrast to the school CDF, the CDF for the home networks exhibit significantly higher PLTs. In particular, the home networks show a significant worse performance than the school networks, with a mean PLT of 6.8s and a median of 3.6s. Note that the mix of browsed pages is rather different between school and home networks since much more videos are watched in home networks. However, the general trend is confirmed when comparing only the same content. For example, the average PLT of `Google`, which is the most popular website in both networks, is 3.03s in school networks, but slightly higher in home networks with an average PLT of 3.45s. A possible reason to explain this difference is that the Wi-Fi access at schools corresponds to a planned network with high-end equipment, while at homes the Wi-Fi is usually

TABLE III: Fittings of the characteristic distributions of web sessions in school networks and in home networks.

Metric	Fitting Function	Param. - School	R^2 - School	Param. - Home	R^2 - Home
Session Duration	EXP	[a=-0.963, b=0.020, c=1.015]	0.998	[a=-0.958, b=0.016, c=1.019]	0.998
Page Load Count	EXP	[a=-1.018, b=0.055, c=0.978]	0.998	[a=-0.936, b=0.071, c=0.946]	0.994
Page Stay Duration	LOG	[a=0.165, b=-0.696, c=0.052]	0.963	[a=0.154, b=-0.674, c=0.066]	0.972



(a) Time characteristics. (b) Streaming events.

(c) Stalling ratio. (d) Average video resolution.

Fig. 4: Video streaming characterization.

of poorer quality and without planning (e.g., consumer-grade WiFi routers, no channel and Tx power management to reduce interference between neighboring APs). Additionally, users might have bandwidth-limited data plans for Internet access. When splitting the residential services into networks with fixed and mobile backbone, it could be observed that networks with mobile backbone gave slightly worse page load times, which was expected due to the technology characteristics. However, these differences were marginal.

The monitored video streamings are characterized in Figure 4. The distributions for the playback length of the watched videos, the length of the initial delay, and the total stalling length are depicted in Figure 4a as CDFs for both networks. Note that the x-axis denotes the time in seconds. The distribution belonging to the school networks is depicted as a dashed line, while the home network distribution is denoted with a solid line. The video playback length (blue) ranges from a few seconds up to around 30 minutes. Streaming sessions in home networks last on average 1.5 minutes longer than streaming sessions in school networks. Around 91% of the streaming sessions lasted for less than 15 minutes in home networks, while in school networks 95% of the sessions lasted less than 15 minutes. This can be explained by the fact that the majority of videos has been watched on YouTube, i.e., mostly short clips.

The CDFs for the length of the initial delay (orange) show that around 76% of the users experienced an initial delay of less than 2 seconds, which can be considered excellent. In general, the length of the initial delay never exceeded 8 seconds and no difference between the access networks could be observed. Most of the users never experienced waiting times caused by stalling (green) in both networks. In general, the distributions for both networks look very similar, whereby the stalling events in home networks last approx. 0.18s longer than in school networks.

Figure 4b presents the number of stalling events and the number of quality changes (orange) observed within the videos for both networks. With respect to stalling events, it can be observed that video streaming in school networks resulted in less stalling events than in home networks. For home networks, 71% of the video streamings suffered no stalling event, while this applies to approx. 75% of the school network users. This trend is also visible for one or more stalling events. The CDFs for the number of quality changes show a very similar behavior. In around 80% of the videos no quality change was observed and only 3% of users experienced two or more quality changes.

The CDF for the stalling ratio in the video streamings with stalling is shown in Figure 4c. For a majority of views, the stalling ratio is close to 0 for both CDFs, which indicates that stalling disturbed the corresponding users usually only shortly. Interestingly, the stalling ratio is generally lower with home network access due to higher video playback length.

Finally, Figure 4d displays the CDFs for the played out video qualities in school networks and home networks. The x-axis depicts the average resolution of the video in pixels. Most videos were played out in 360p, 480p, or 720p, while only a small share of videos used a resolution of 144p and 240p. Further, full HD videos were played out in approx. 7% of the cases. This applies to both networks. Compared to home networks, the amount of played out 360p videos is much higher in school networks. On the other hand, the share of HD videos is larger in home networks. The obtained video streaming characteristics match the findings of other works analyzing mobile YouTube QoE, e.g., [20], [28]. Compared to mobile YouTube QoE, the number of stalling events and quality changes are similar for fixed YouTube QoE. However, the mean played out resolutions are much higher for fixed networks.

All in all, our analysis of QoE influence factors suggested that the school networks provided a better performance for both web browsing and video streaming.

VI. Conclusion and Outlook

The increasing amount of Internet-supported education requires reliable devices and high quality Internet access for successful learning experiences. Therefore, Education Service Providers (ESPs) play a crucial role and are expected to guarantee a high QoE for teachers and students. A nationwide QoE measurement campaign was conducted in collaboration with a major Uruguayan ESP, in which more than 800 schools and about 4000 devices were monitored. All monitored devices were equipped with a browser plugin which allowed the monitoring of user behavior and key performance indicators (KPIs) of web browsing and video streaming.

The monitored data showed that the Internet usage from school networks is very different compared to the activity at homes. Browsing sessions in schools were slightly shorter, which could be due to the time limitation of lessons, and showed longer and more regular inter-arrival times, which could be influenced by the routine time spent in schools and the class schedule. Also, the number of accessed pages during a session and the mix of browsed pages showed differences. The majority of the monitored videos were watched at home, whereby the type of content differed from school networks. In school networks most videos were watched with YouTube, while at home other service providers like Netflix were used. In addition to the characterization, models were provided, which can be used to simulate or emulate realistic web sessions in home and school networks in network management studies.

The QoE influence factors were investigated and it was found that school networks provided a better performance for web browsing. This did not come as a surprise, since schools Wi-Fi infrastructure corresponds to planned networks with high-end equipment, while at homes the Wi-Fi is usually of poorer quality and without planning. In future work, the relationship between QoE and user behavior will be further investigated. However, different metrics and dedicated studies will be needed to investigate this relationship in full detail. Moreover, as the bring your own device (BYOD) effect has increased a lot during the last years, methods will have to be developed to estimate the QoE of users with their own devices. Additionally, models will be required to estimate the QoE across devices, i.e., when two or more devices are used in parallel, e.g., educational laptop and personal smartphone.

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