

The Impact of Mobile Device Preference on the Quality of Experience

Abubkr Elmnsi¹, Niemah Osman¹ and Is-Haka Mkwawa²

¹The College of Computer Science and Information Technology, Sudan University of Science and Technology, Khartoum, Sudan

²The School of Computing, Electronics and Mathematics, Plymouth University, UK
almnsi27@yahoo.com, niema.osman@gmail.com, Is-Haka.Mkwawa@plymouth.ac.uk

Abstract: *Quality of Experience (QoE) is not only related to network impairments and video signal quality. Recent studies have found that video content preference also has an impact on the QoE. To date, no research has reported the impact of device preference on the QoE. In this context, we investigate the impact of mobile devices preference on the QoE for video services. We evaluate the QoE of watching videos using mobile devices of different models, sizes, resolutions and densities. The experimental results based on subjective tests have shown that QoE is highly correlated with user preference on mobile devices.*

Keywords: *Quality of Experience, Quality of Service, Mobile devices, Video, MOS.*

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1. Introduction

Mobile devices such as smart phones and tablets have witnessed exponential growth in number over the last decade. According to the Cisco Visual Networking Index (VNI) Global Mobile Data Traffic Forecast Update, more than half a billion mobile devices and Internet connections were added in 2015 [1]. In addition, video traffic accounted for 55% of the total mobile traffic in 2015 [1]. In this context, it is important to evaluate the Quality of Experience (QoE) with respect to different types of mobile devices in order for service providers and device vendors to increase revenue and avoid churn.

QoE is a measure of a customer's experiences with a given service such as TV, voice and video calling and gaming services to assess the services [2]. QoE is important for end user performance measurement to assess users' satisfaction to service providers. The parameters that affect QoE can be classified into three groups [3], Quality of video/audio content at the source, Quality of Service (QoS) which refers to the delivery of content over the network and human perception, which includes expectations and ambiance. It is very important to measure the QoE to guarantee the execution of the service agreement.

According to the ITU-T P.10/G.100 [4], the definition of QoE is the overall acceptability of a service or an application as perceived subjectively by its users. This

definition should include some other factors such as the end user devices, service infrastructure, network bandwidth, user expectation and the environment where the end user is communicating [5]. The recommendations from the ITU-T for evaluating QoE with subjective tests are described in ITU-T Rec. P.800 [6]. The ITU-T recommends the PESQ model (ITU-T Recommendation, P.862) [7] and the E-model (Recommendation ITUT G.107) [9] to evaluate the quality of Voice over IP (VoIP). There are three classifications for QoE measurement; Machine Learning based techniques [9], [10], [11] liner and non-liner regression techniques [12], [13] and finally artificial intelligence techniques [9], [10], [11].

The impact of video content preference has been investigated in several studies [14], [15], [16], [14], [17], but none have investigated the impact of mobile device preference on the QoE over video service. With respect to mobile device specifications, there are some challenges for managing video traffic and displaying video to ensure an acceptable QoE for end users. This is due to the fact that the perceptual quality of video content depends on the properties of the display device and the viewing conditions [18].

In general, mobile devices impact QoE in terms of their display size, resolution and device make and model. In this study, the impact of mobile device size, resolution and device make and model is

investigated to examine the impact of mobile devices preference on the QoE for video services.

Mobile devices with similar display size and resolution but from different manufacturers were used in the experiment. From subjective tests conducted in Sudan at the National University in Khartoum, it was concluded that mobile device preference had an impact on QoE for video services.

This research is important for service providers such as YouTube and FlexiNet because the results can be used as input to video streaming adaptation schemes in order to provide acceptable video quality under different network conditions.

The rest of this paper is organized as follows; related work is discussed in Section 2. The experimental setup is discussed in Section 3. Section 4 presents the results and discussion. Conclusions and future work are outlined in Section 5.

2. Related work

Authors in [19] aimed to assess the QoE in video streaming when the user is employing tablet devices that vary in terms of display size, resolution, hardware configuration and operating system. Authors conducted subjective video quality assessment on 216 video streams at two different bitrates (200kbps and 400kbps) with H.264/AVC. The videos were reproduced on Apple iPad 2 and the Samsung Galaxy Tab GTP1000. The values of the coefficients were very similar for both devices; and playout delay error was greater in the iPad 2 with respect to the Galaxy Tab. They also found that there is a strong correlation between the proposed quality index and the MOS for the iPad 2 and the Galaxy Tab.

The authors in [20] studied the user's preference or a video content and how it can affect the video quality. The authors conducted subjective tests and proposed a video quality assessment method by taking the user preference for video content and from their experiment. They found that the values of QoE are highly correlated with the user's preference for video content type.

In [21], authors investigated the impact of image resolution, screen size, and screen resolution on user's perceived image quality. In the experiment, nine mobile phones and a quality monitor were used as test devices and allocated to evaluate the impact on perceived image quality (c.f., Table 1). 1360 data points were attained on the mobile phones. The authors also proposed an integrated assessment parameter to investigate the impact of mutual interaction between the device dependent image quality and image resolution. The assessment model was suggested to

estimate the perceived image quality on different mobile devices. ANOVA was performed to check the significance of influence of the screen size on the perceived image quality. The authors found that the improvement of screen resolution from 1080P to Quad HD did not have any impact, for the 1440P, 1080P, and 720P the variation of perceived image quality for these images were similar to that for the 4K images.

To the best of our knowledge, no prior study has considered the impact of device preferences on the Quality of Experience. In this paper, we go beyond these and investigate the impact of device preferences on the Quality of Experience by using subjective tests.

Table 1. Parameters of display devices

Display device	Screen size (inch)	Resolution	Screen type
P1	4"	1136×640	IPS LCD
P2	4.3"	1280×720	IPS LCD
P3	4.9"	1920×1080	IPS LCD
P4	5.1"	1280×720	IPS LCD
P5	5.1"	1920×1080	AMOLED
P6	5.1"	2560×1440	AMOLED
P7	5.5"	1920×1080	TFT-LCD
P8	5.5"	2560×1440	SLCD
P9	5.7"	1920×1080	AMOLED
M1	30"	4096×2160	OLED

3. Experimental setup

3.1 Participants

This study has been done on two groups of 20 participants. Each participant in each group had to watch 7 short videos (arranged in random order according to ITU-T standard [6]) of less than a minute each on each mobile device. The age of the participants varied from 18 to 23 years old, with average age of 22 years old. All participants were students in computer sciences at the National University in Khartoum, Sudan. Participants had no knowledge of video signaling and processing. They were 55% men and 45% women; all had normal vision and clear understanding of the test.

3.2 Video sequences

Two videos Big Buck Bunny and Elephant Dreams were selected. These videos are standard and are available with highest resolution. FFMPEG was used to encode YUV videos to MPEG-4 ACV/H.264 with the same frame rate (25 fps) and seven different bite rates 2000 Kbs, 2750 Kbs, 3000 Kbs, 3500 Kbs, 3750

Kbs, 4500 Kbs and 6000 Kbs. All videos were one minute long with 25 fps and 720p resolution.

The participants in each group had to randomly watch video sequences, one group watched Big Buck Bunny and another group watched Elephant Dreams on three different mobile phones.

3.3 Mobile devices

Participants were invited to watch video clips (seventeen parts) and evaluate the quality of the video on three mobile devices. This experiment included three mobile devices, Sony Xperia Z, HTC One Max and Samsung Galaxy A3. Screen specifications for these devices are given in Table 2. Each mobile device was formatted and was installed with Android 5.0 (Lollipop) and Android Media Player to ensure that cache and memory were clear before playing the videos. The same media player was used in all tests and mobiles were set up on flight mode to avoid any interruptions during the experiment.

The brightness was adjusted on the same level on all mobile devices, the sleep and portrait mode were disabled. Participants were asked to fill in the Mean Opinion Score (MOS) based on a discrete level as stated in ITU-R quality ratings (from bad (1) to excellent (5)). The experiment used Non-Reference (NR) method because it is practical in multimedia communication.

Table 2. Properties of display devices

Device Model	size (inch)	Resolution	Density
Sony Xperia Z	5.0	1080x1920	441
HTC One Max	5.9	1010x1920	373
Samsung A3	4.5	540x960	245

4. Results and discussion

In this study, the variables (mobile screen size, density and resolution) were used to evaluate the quality of experience using MOS. Table 3 and Figure 1 show the MOS scores for seven sequences of Big Buck Bunny video for the first group of participants. The results show that MOS values for Galaxy A3 mobile phone are better than the rest of the devices at low bitrates between 2000kbs and 3740kbs and slightly higher at higher bit rates above 3750kbs. Although the Galaxy A3 mobile phone specifications are inferior compared to other mobile phones in the experiment, but participants gave higher MOS values. This is contrary to the expectations, given the screen densities of each mobile phone, it was expected that MOS values would be in higher for Sony Xperia Z with 441 screen density, followed by HTC One Max and Samsung Galaxy A3 mobile phones.

Table 3. MOS values for Big Buck Bunny

	Sony	HTC	A3
2000kbs	2.55	2.91	3.91
2750kbs	2.94	3.32	4.72
3000kbs	3.08	3.21	4.79
3500kbs	3.58	4.14	4.52
3750kbs	4.01	4.58	4.64
4000kbs	4.00	4.35	4.54
6000kbs	4.10	4.22	4.39

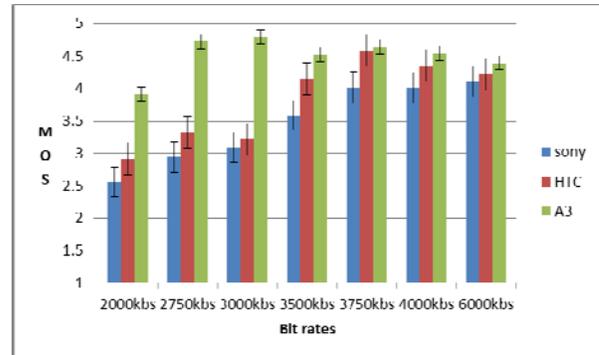


Figure 1. MOS for different mobile phones-Group 1

To eliminate the influence of video content preference on the QoE, participants with no preference to any of the videos in the experiment were chosen. They were asked one question, "Amongst three devices used in the experiment, which device you liked the most?" The response was 74% for Samsung Galaxy A3, 20% for HTC and 6% for Sony Xperia Z (c.f., Figure 2). To support the significance of these results, the P-value from Analysis of Variance (ANOVA) was $0.00056 \leq 0.05$ which denotes that the MOS values show the statistically significant difference with variation in mobile phones in this experiment.

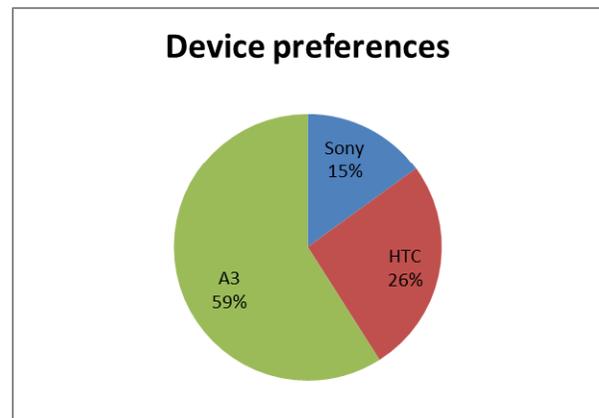
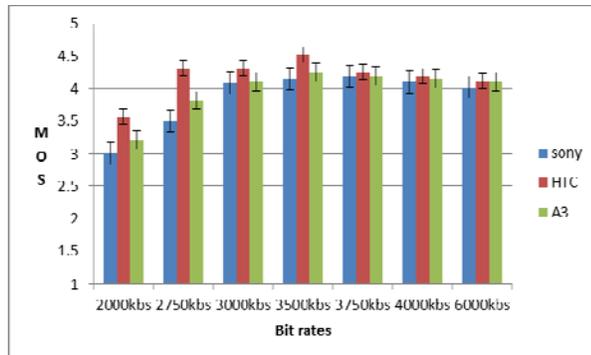


Figure 2. Device preferences distribution-Group 1

Table 4 and Figure 3 illustrate the MOS scores for seven sequences of Elephant Dream video for the second group of participants.

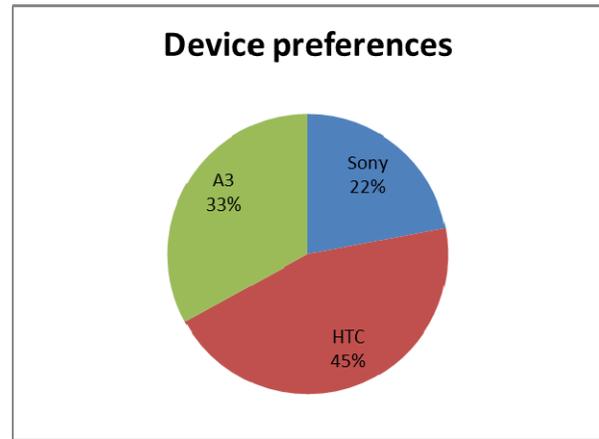
Table 4. MOS values for Elephant Dream

	Sony	HTC	A3
2000kbs	3.01	3.56	3.21
2750kbs	3.5	4.31	3.82
3000kbs	4.09	4.31	4.11
3500kbs	4.15	4.52	4.25
3750kbs	4.19	4.25	4.19
4000kbs	4.1	4.19	4.15
6000kbs	4.02	4.12	4.105

**Figure 3.** MOS for different mobile phones-Group 2

The results show that MOS values for HTC One Max mobile phone are better than Sony Xperia Z and Samsung Galaxy A3 devices at bitrates between 2000Kbs and 3740Kbs and slightly higher at higher bit rates more than 3750Kbs. It was expected that Sony XperiaZ would have better MOS values because it has higher screen density than the rest, but its MOS values were the lowest. Although Samsung Galaxy A3 mobile phone specifications are inferior compared to other mobiles phones in the experiment, its MOS values came second. It was observed that these results are correlated to the participants' preferences to three mobile phones in the experiment as in the first group.

Similarly to Group 1 participants, participants in this second group were also asked one question, "Amongst three devices used in the experiment, which device you liked the most?" The response was 59% for Samsung Galaxy A3, 26% for HTC One Max and 15% for Sony Xperia Z (c.f., Figure 4).

**Figure 4.** Device preferences distribution-Group 2

To illustrate the statistical significance of these results, P-value from Analysis of Variance (ANOVA) was $0.032 \leq 0.05$ which denotes that the MOS values for this second group show the statistically significant difference with variation in the mobile phones.

5. Conclusion and future work

This paper has investigated the impact of device preferences on the Quality of Experience for video services. Results based on subjective tests have shown that there is a correlation between device preferences and QoE. The future work will propose a QoE model that includes device preferences, screen size, resolution and video preferences.

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Abubkr Elmnsi received the BSc. in Computer Science in 2009 from the University of Gezira in Gezira, Sudan and MSc. in Computer science in 2013 from the University of Technology and Science in Khartoum, Sudan. He is currently doing a PhD degree in computer science at the Sudan University of Science and Technology in Khartoum, Sudan. His research interests include Quality of Experience in Multimedia Communication, Computer Networking and Wireless Networks.



Niemah I. Osman received the B.Sc. degree (first-class Hons.) in computer science from Sudan University of Science and Technology, Khartoum, Sudan, in 2002 and the M.Sc. degree (with distinction) in mobile computing from the University of Bradford, U.K., in 2006 and the Ph.D. degree in



Communication Networks from the University of Leeds, U.K in 2015. She is currently an Assistant Professor at the Faculty of Computer Science and Information Technology, Sudan University of Science and Technology, Sudan, and was the Head of Department of Computer Science and member of the university senate in 2007-2008. Her current research interests include performance evaluation of 4G LTE networks and QoE of video services.

Dr. Is-Haka Mkwawa received his PhD in computing from the University of Bradford, UK, in 2004. He is currently with the school of computing, electronics and mathematics at the University of Plymouth. His research interests



include QoE control and management, mobility management in mobile and wireless networks, Software Defined Networking, power saving in IoT, overlay networks, performance analysis and evaluation of IMS mobility management, parallel computing, IMS media plane security for next generation of emergency communication and services and collective communication.