Analysis of Learner Interest, QoE and EEG-based Affective States in Multimedia Mobile Learning

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***Abstract*—Multimedia clips, such as lecture recordings and screencasts, are increasingly used in both formal and informal learning contexts, such as flipped classroom, blended learning, MOOCs and mobile learning. In order to create effective educational multimedia applications, it is increasingly important to understand the factors contributing to the learning performance and learner experience. This paper presents research findings from a subjective study with 60 participants, conducted to investigate the effects of learner's interest, QoE, and EEG-based affective states on learning performance in a multimedia-based mobile learning scenario. The results show that with careful design, similar learning performance and experience can be achieved on both small and large screen mobile devices, such as smartphone and tablet. Moreover, learner's interest and QoE were shown to have a strong effect on learning. While males and females achieved similar learning performance, they presented significant differences in terms of interest, QoE and EEG-based affective states. Moreover, the results show promising potential of using EEG data to automatically detect learner's interest.**

***Index Terms*—Mobile learning, multimedia, learner interest, quality of experience, affective states, electroencephalography.**

I. Introduction

E-learning is gradually shifting towards mobile learning, as mobile devices such as smartphones and tablets are becoming more powerful, affordable and accessible to global learners. According to recent market reports, the global market for mobile learning services is estimated to grow from $7.98 billion in 2015 to $37.6bn by 2020 [1]. Mobile learning comes with many benefits, in particular that it enables pervasive learning, anytime, anywhere and across many formal, informal and social contexts [2]. Mobile learning content also evolved to include high quality multimedia clips, educational games, and more recently virtual and augmented reality. In particular, multimedia content emerged as the dominant educational medium for online training platforms such as PluralSight and Lynda, as well as for massive open online course (MOOC) platforms, such as Coursera, edX and Udacity [3].

Various research studies have investigated the benefits of using educational clips for both in-class and online learning. For example, using YouTube videos in an undergraduate nurse teaching course, was shown to improve student engagement, critical awareness and facilitate deep learning [4]. The flipped classroom approach, where students receive educational videos to be watched before class, was shown to improve learning performance across different subjects, such as computer science [5], mathematics [6], or classical Chinese learning [7].

Multimedia-based learning also poses a multitude of challenges, both technical and pedagogical. Over the past decades, much research work focused on investigating the factors contributing to learner's performance, as well as on modelling, personalisation and adaptation solutions for e/m-learning. However, there are contradicting findings and limited common understanding regarding which factors are most important and how to best use multimedia for teaching and learning. Flipped classroom and MOOCs would typically require self-motivation and active-learning from the student, which in turn can explain the improved performance [8]. Moreover, previous research also indicated that students tend to be overconfident on their learning from videos, and recommended to interpolate short tests or quizzes to help boost their learning performance [9].

This paper presents research findings from a subjective study with 60 participants, conducted to investigate the effects of learner's interest, QoE and affective states on learning performance in multimedia-based mobile learning. The study followed a mixed methods approach where learning performance was assessed using pre and post-test knowledge assessment questionnaires, while interest and QoE were self-reported by participants. Interest is an indicator of motivation and has a positive impact on learning [10]. QoE and in particular video quality was considered as it is a main factor contributing to user's engagement with multimedia services [11].

Rather than using questionnaires, the Emotiv EPOC [12] neuroheadset was used to capture EEG-based affective states (i.e., engagement, frustration, meditation and excitement). Previous research studies have validated the Emotiv EPOC affective data against questionnaires, and showed its potential to measure factors such as: engagement with mental tasks [13], motivation in game-based e-learning [14], or emotions resulting from feedback appraisal in intelligent tutoring systems [15]. Other automatic approaches that were also explored include detection of user interest using eye-tracking [16], and emotion recognition from student face images [17].

The rest of paper is structured as follows. Sections II and III present the subjective study design and the results analysis. Section IV discusses the findings and concludes the paper.

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II. Subjective Study Design

A. Mobile Devices

A smartphone and a tablet device were used for the subjective study, in order to investigate the impact of device type on learning. The smartphone was a Samsung Galaxy with 4.3 inch touchscreen and 800×480 resolution. The tablet was a Google Nexus, with 7 inch screen and 1280×800 resolution. Both devices have a 1.2 GHz multi-core CPU and 1 GB of RAM memory, being capable to play full-HD 1080p videos without any issues. Both devices run on Google Android OS, which was preferred as it is more open and facilitated building and testing the mobile app used in the study, as well as routine tasks such as backup of the log files after each participant.

B. Educational Multimedia Clips

Fig. 1 presents the educational multimedia clips used for the study. These correspond to six categories of educational clips that are common nowadays: animations, demos, documentaries, presentations, screencasts and slideshows [18]. The clips cover a high content variety and were selected by analysing a large pool of educational clips available on multimedia services such as iTunes U and YouTube EDU. The original clips were downloaded at the highest quality available, and had at least 720p resolution.

Two original quality test sequences (A and B) of approximately thirty seconds long were extracted from each educational clip. The sequences presented independent learning concepts. Sequences A were used on the smartphone, while sequences B were used on the tablet. Using a different sequence for smartphone and tablet, ensured that the participants answered each knowledge assessment question a single time.

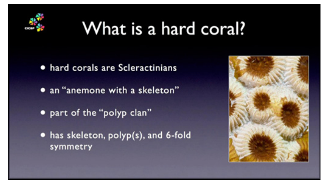
Each test sequence was encoded so to provide a good visual quality level by taking into account the display resolution (i.e., 480p or 720p), educational multimedia profiling recommendations for the wireless streaming scenario [19], and the content spatio-temporal characteristics. Apart of video resolution, framerate and bitrate all other video and audio encoding characteristics were maintained constant.

C. Learning Performance Assessment

A pre and post-test were used in order to assess the participants' knowledge before and after viewing the educational multimedia test sequences. The pre-test consisted of six multi-choice closed questions (one per clip), where participants selected a single answer. A non-response type choice, 'I don't know', was also included in order to minimise the number of correct answer guesses. The post-test questionnaire consisted of 12 multi-choice closed questions (two per clip), that were different from the pre-test questions and did not include a non-response option. These were carefully selected to ensure the answer corresponds to the visual information. The participants answered each question immediately after viewing the corresponding test sequence.

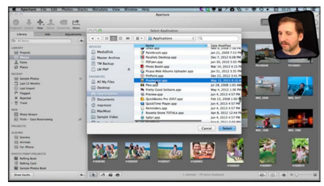
(a) 'ArtOfBook' – documentary

(b) 'AtomSize' – animation

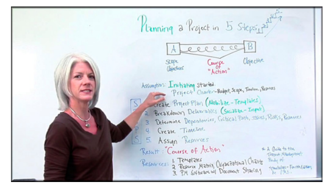


(c) 'CoralsIntro' – slideshow

(d) 'NitrogenIceCream' – demo



(e) 'PhotoEditing' – screencast



(f) 'ProjectPlanning' – presentation

Fig. 1. Educational multimedia clips used in the subjective study.

D. Mobile App

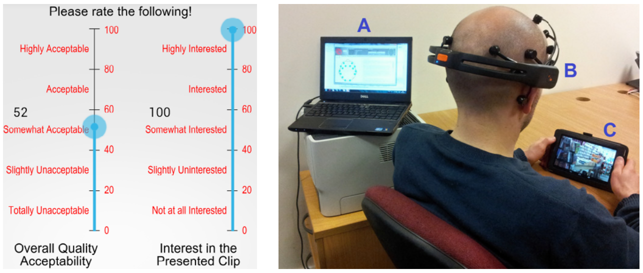
An Android application was developed for displaying the multimedia test sequences and for data collection. After watching each test sequence, the participants answered a post-test question and rated their interest and QoE level. Doing this on the device screen rather than on paper, helped minimise movements and associated noise or loss of EEG signals. In addition to participant's answers, the app also recorded the start and stop timestamps for each test sequence in order to facilitate the data processing and analysis.

1) Learner QoE Assessment: was done based on standard recommendations for subjective multimedia quality assessment [20]. QoE was assessed in terms of quality acceptability as this is a more user-centric measure than traditional MOS [21]. The rating was done using a calibrated slider displayed on the device screen as shown in Fig. 2a. A continuous 0 – 100 scale with discrete levels (i.e., 'totally unacceptable' to 'highly acceptable'), was preferred for its advantages of expanded range and finer distinctions between ratings.

2) Learner Interest Assessment: was performed by using a slider on a continuous 0 – 100 scale with associated discrete levels (i.e., 'not at all interested' to 'highly interested'). This was adapted from the scale used by the Intrinsic Motivation Inventory (IMI) based on the self-determination theory [22].

E. EEG-based Affective States Assessment

Fig. 2b presents the lab testing environment. The Emotiv EPOC [12] wireless neuroheadset was used to capture EEG data during the subjective testing. The headset enables to record raw EEG signals from 14 sensors at a granularity of 128 samples per second. The data is transmitted over wireless



(a) (b)

Fig. 2. Experimental design: (a) Mobile app QoE and interest assessment sliders; (b) Testing environment (A - laptop PC running EEG calibration and recording software, B - Emotiv EPOC wireless headset, C - mobile device).

connection to a laptop PC, where it is accessed through the Emotiv API and recorded to log files for further analysis.

The Emotiv EPOC SDK incorporates three detection suites: Affectiv Suite, Expressiv Suite and Cognitive Suite. The Affectiv Suite interprets the EEG data using proprietary algorithms, and provides affective measures, namely engagement, frustration, meditation and excitement.

F. Testing Session Description

Each participant was provided with written and verbal instructions and information in the beginning of the testing session. These were related to the purpose of the study, the structure of the testing session, as well as EEG and the Emotiv EPOC headset. Attention was paid to make sure that the testing procedure was clear to each participant. The participants were instructed to ask for clarification if required. Verbal consent of their participation in the study was obtained. The participants were also informed that they can leave the study at any time, however none of them left before completing it.

Next, the participants filled a demographic questionnaire and the pre-test questionnaire. The testing session continued with setting up the Emotiv EPOC headset, while ensuring that all sensors make good contact and provide good quality EEG signals. Before starting the actual testing, the participants were provided with a brief training using different sequences to familiarise them with the tasks. Following the training, the participants viewed six test sequences on the smartphone and six on the tablet. They also answered the post-test question and rated their interest and QoE level after each sequence.

To minimise any effects such as tiredness on the post-test results, the two devices were randomised between participants, while making sure that half of them viewed the clips and answered the questions on the smartphone device first and the other half on the tablet first. Furthermore, the six test sequences were also displayed in a random order across participants on each mobile device.

G. Participants

The study was conducted with 60 participants (37 males, 23 females), whose age was between 20 and 53 years old ($Mean = 28.67, SD = 6.87$). They were attracted through e-mail advertisement, and their participation was voluntary. Most participants were undergraduate or postgraduate students.

TABLE I
PAIRED WELCH t-TEST RESULTS BETWEEN PRE-TEST AND POST-TEST AGGREGATE CORRECT RESPONSE SCORES ($N_1 = N_2 = 60$).

	Pre-Test		**Post-Test**		**Welch t-Test**		
Device	*Mean*	*SD*	*Mean*	*SD*	t	*df*	p
Smartphone	0.717	0.865	4.983	0.854	-26.221	59	.000 ***
Tablet			4.933	0.880	-26.418	59	.000 ***

Signif. codes: $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$, $.p < .1$

III. RESULTS ANALYSES

This section presents the results analysis on learning performance, interest, QoE and EEG-based affective states.

A. Learning Performance Results

The aggregate correct response scores were computed for each participant in three cases: pre-test, post-test on smartphone, and post-test on tablet. The aggregate scores can take values between 0 and 6 if the answers to all six questions are incorrect or correct respectively. Since each participant has three scores at different moments in time, a 'within-subjects' evaluation was done. The Welch t-test for dependent groups was used to assess if there is a statistically significant difference between pre and post-test results.

Table I presents descriptive measures (i.e., mean and standard deviation), and the t-test results. On average across the 60 participants the pre-test aggregate scores are 0.717, while the post-test scores are 4.983 for smartphone and 4.933 for tablet. The t-test results show that the post-test scores are statistically significant higher than the pre-test scores. Moreover, no statistically significant difference was found between the post-test aggregate correct response scores for smartphone and tablet devices ($t(59) = 0.323$, $p = .748$).

B. Impact of Mobile Device Type

The analysis was further expanded to investigate if there is a difference between the two mobile devices in terms of the other metrics: interest, QoE, and EEG-based affective states (i.e., engagement, frustration, meditation and excitement). The analysis was conducted on the 360 data points for each device (i.e., 6 test sequences rated by 60 participants). The analysis was also conducted for the post-test results encoded as 0 and 1 for incorrect and correct answer respectively. The EEG-based affective states were computed as the average signal value over the test sequence duration.

Table II results show that statistically significant difference was only found for engagement, with the participants mean engagement being 0.638 for smartphone and 0.624 for tablet. One explanation could be that two different test sequences extracted from the same clip were used for smartphone and tablet respectively. Moreover, since no statistically significant difference was found for the other metrics, one can conclude that the learning performance and experience was similar for the smartphone and tablet devices. Therefore, the device type did not impact on the learning process.

TABLE II
PAIRED WELCH t-TEST RESULTS BETWEEN SMARTPHONE AND TABLET TEST CASES ($N_1 = N_2 = 360$).

	Smartphone		**Tablet**		**Welch t-Test**		
Metric	*Mean*	*SD*	*Mean*	*SD*	t	*df*	p
Post-test [%]	83.06	37.57	82.22	38.29	0.298	359	.766
Interest	62.472	21.703	63.719	23.619	-1.258	359	.209
QoE	78.575	18.253	79.811	16.836	-1.166	359	.244
Engagement	0.638	0.085	0.625	0.076	2.417	358	.016 *
Frustration	0.532	0.176	0.523	0.190	0.770	358	.442
Meditation	0.335	0.031	0.334	0.034	0.402	358	.688
Excitement	0.374	0.201	0.375	0.205	-0.076	358	.939

Signif. codes: $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$, $.p < .1$

TABLE III
UNPAIRED WELCH t-TEST RESULTS BETWEEN MALES ($M = 37$, $N_1 = 444$) AND FEMALES ($F = 23$, $N_2 = 276$).

	Males		**Females**		**Welch t-Test**		
Metric	*Mean*	*SD*	*Mean*	*SD*	t	*df*	p
Post-test [%]	81.98	38.48	83.70	37.01	-0.595	601	.552
Interest	60.804	23.668	66.783	20.486	-3.584	645	.000 ***
QoE	78.074	17.913	80.993	16.847	-2.206	610	.028 *
Engagement	0.636	0.078	0.624	0.085	1.911	546	.057 .
Frustration	0.529	0.184	0.525	0.182	0.262	589	.794
Meditation	0.331	0.030	0.340	0.035	-3.437	524	.001 ***
Excitement	0.388	0.200	0.353	0.207	2.195	567	.029 *

Signif. codes: $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$, $.p < .1$

TABLE IV
UNPAIRED WELCH t-TEST RESULTS BETWEEN CORRECT ($N_1 = 595$) AND INCORRECT ($N_2 = 125$) POST-TEST ANSWER GROUPS.

	Correct		**Incorrect**		**Welch t-Test**		
Metric	*Mean*	*SD*	*Mean*	*SD*	t	*df*	p
Interest	64.516	22.290	56.336	23.351	3.588	175	.000 ***
QoE	80.309	16.512	73.880	21.144	3.201	157	.002 **
Engagement	0.631	0.080	0.634	0.087	-0.417	171	.677
Frustration	0.529	0.181	0.519	0.191	0.582	174	.562
Meditation	0.334	0.031	0.336	0.037	-0.384	163	.702
Excitement	0.369	0.199	0.398	0.220	-1.336	170	.183

Signif. codes: $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$, $.p < .1$

TABLE V
UNPAIRED WELCH t-TEST RESULTS BETWEEN INTERESTED ($N_1 = 427$) AND UNINTERESTED ($N_2 = 142$) GROUPS.

	Interested		**Uninterested**		**Welch t-Test**		
Metric	*Mean*	*SD*	*Mean*	*SD*	t	*df*	p
Post-test [%]	85.25	35.51	73.24	44.43	2.925	204	.004**
Interest	78.895	11.421	28.803	10.093	49.530	270	.000***
QoE	84.009	14.601	70.430	21.028	7.144	188	.000***
Engagement	0.628	0.079	0.644	0.079	-2.078	243	.039*
Frustration	0.542	0.196	0.500	0.149	2.649	317	.008**
Meditation	0.335	0.033	0.332	0.030	1.029	259	.304
Excitement	0.371	0.203	0.358	0.207	0.662	238	.509

Signif. codes: $^{***}p < .001$, $^{**}p < .01$, $^{*}p < .05$, $.p < .1$

C. Impact of Gender

The Welch t-test for independent groups was used to assess if gender has an impact on learning performance and experience. The groups were unbalanced, 62% males and 38% females. Table III results show strong effects for interest, QoE, meditation and excitement, and a weak effect for engagement. The females presented statistically significant higher interest and QoE than males. In terms of EEG-based affective states, females presented higher meditation level than males while viewing the educational clips, while males presented higher excitement and engagement than females. The frustration and learning performance were similar for males and females.

D. Factors Impacting on Learning Performance

Another analysis was conducted to investigate if learner interest, QoE and EEG-based affective states have an impact on learning performance. For this analysis, the data were split into two groups. These correspond to correct and incorrect post-test answers, and contain 83% and 17% of data points respectively. Table IV results show strong effects of interest and QoE on learning performance, with the two measures being statistically significant higher in case of correct post-test cases as compared to incorrect post-test cases. Moreover, the statistical analysis indicates that EEG-based affective states do not have an impact on learning performance.

E. Impact of Interest

A final analysis was conducted to further investigate the impact of interest and if this could be estimated using EEG-based affective measures. The data was split into two groups: interested (i.e., for interest ≥ 60, corresponding to 'interested' and 'highly interested' levels), and uninterested (i.e., for interest ≤ 40, corresponding to 'slightly uninterested' and 'not at all interested' levels). These contain 59% and 20% of data points respectively. The other 21% of data corresponding to 'somewhat interested', was considered to represent undecided participant cases and were excluded from the analysis.

Table V results show that the average interest was 78.9 for interested group and 28.8 for uninterested group. Moreover, the results confirm that interest has a strong impact on both learning performance and QoE. An even more important finding is that average EEG-based engagement and frustration measures present statistically significant differences between the interested and uninterested groups. However, engagement is lower and frustration is higher for the interested than for uninterested group, when the opposite would have been expected.

IV. DISCUSSION AND CONCLUSIONS

As multimedia clips are increasingly used as primary teaching and learning material, this paper set to investigate the impact of learner's interest, QoE and EEG-based affective states on learning performance in a multimedia-based mobile learning. A subjective study with 60 participants and 6 educational clips was conducted, with the results revealing several important research findings.

First, the pre and post-test results showed that the participants had little prior knowledge of the educational clips, and they achieved high learning performance. This was statistically equivalent for the two devices, despite using two different test sequences and questions for each clip, one for smartphone and one for tablet. Moreover, the participants presented statistically equivalent interest, QoE and EEG-based frustration, meditation and excitement (with only slightly higher engagement on smartphone than tablet). Therefore, the learning performance and experience would be similar on both small and large screen devices, if consistent design and implementation is followed. This is an important finding for instructional designers and teachers, as it addresses one concern posed by the multitude of mobile devices with different screen size and resolution.

Second, while the learning performance tends to be similar for males and females, gender has an effect on the multimedia mobile learning experience. Males tend to be more excited and to smaller extent more engaged than females. As opposed, females presented a higher level of meditation, interest and QoE than males. The QoE finding could also be interpreted as females being more acceptable to visual quality, which in turn can be a result of higher interest in the educational content.

Third, interest and QoE presented strong effect on learning performance, with being statistically significant higher when participants answered the post-test questions correctly. Moreover, interested learners tend to present both higher learning performance and QoE than uninterested learners. These results confirm the findings of previous research studies (e.g., [11]), and the need for personalised and adaptive e/m-learning systems, that support learning performance through interesting and high quality educational multimedia content.

Fourth, the results did not indicate any statistically significant effect of EEG-based affective states on learning performance. One possible explanation could be that the educational test sequences were very short and the post-test questions were asked immediately after viewing each sequence. As previous research showed, interpolating the questions would boost the learning performance [9].

Finally, the results showed that EEG-based engagement and frustration measures could be used to automatically detect if a learner is interested or uninterested. As EEG devices are increasingly affordable and less intrusive, one could see future m-learning applications and systems that automatically detect learner's interest without the need for self-reporting. Moreover, EEG measures could be combined with other automatic solutions, such as subjective QoE estimation models (e.g., [23]), in order to create individualised affective learner models that would enable highly-personalised learning experiences.

Future work will aim to expand the analysis by considering additional metrics computed from the continuous EEG-based affective data and the raw EEG signals. Moreover, machine learning algorithms will be applied to more thoroughly investigate the potential usage and benefits of consumer-grade EEG devices for multimedia mobile learning applications.

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