Stationary vs. Non-stationary Mobile Learning in MOOCs

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ABSTRACT

Mobile devices enable users to access information ubiquitously, including in the online learning scenario. This though requires users to multitask and divide their attention between several tasks at once whilst "on-the-go" (e.g. watching a video, walking down the street and keeping track of the traffic at the same time). In order to accommodate learners in this situation, most of today's Massive Open Online Course (MOOC) platforms provide mobile access to their content. Prior works have conducted lab studies to investigate the impact the learning condition (in particular stationary vs. on-the-go) has on mobile MOOC learners. User studies beyond the lab setting though are scarce. We here describe a study in a more realistic setup where 36 participants each participated in two mini-MOOCs while in a stationary and real-life mobile learning situation. We find participants' learning gains slightly lowered in the on-the-go condition (−7%). We also find that on average participants spend 10% more time on video-watching and 23% less time on question-answering in the learning on-the-go compared to the stationary condition.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI**; **Empirical studies in ubiquitous and mobile computing**; • **Applied computing** → *E-learning*;

KEYWORDS

Mobile Learning; MOOCs; Divided Attention; User Study

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1 INTRODUCTION

Rapid development of mobile technology and its wide availability have made mobile devices a piece of technology most of us carry around every day—in developed countries 98% of inhabitants, and in developing countries 50% of inhabitants were found to have mobile-broadband subscriptions in 2017 [17]. The popularity of mobile devices has also affected the way new knowledge is acquired—a significant number of people use mobile devices for learning. A survey on lifelong learning [22] from 2012 found 56% of learners to use smartphones on a daily basis, whilst a study on mobile language learning [6] in 2017 reported 38% of learning sessions to take place while in transit. Thus, mobile learning, defined in [13] as *"any sort of learning that happens when the learner is not at a fixed, predetermined location, or learning that happens when the learner takes advantage of the learning opportunities offered by mobile technologies"*, has become an inevitable part of the learning process.

Today's learners have many course options to choose from. Many universities offer MOOCs on a wide range of subjects, delivering their content on MOOC platforms such as edX, Coursera or Udacity. While early versions of MOOC platforms lacked support for mobile devices [16], today's responsive web apps and native mobile apps (for Android and iOS) [11] allow learners to gain new knowledge in variable learning situations, including learning whilst on-the-go. Prior works have found the learning situation—a set of environmental and intentional constraints [2]—in which learning occurs to be a critical component of mobile learning [15, 18–20].

A typical learning situation for MOOCs is *stationary* learning, where a learner usually uses a desktop or laptop computer to access course content. These devices have large screens compared to mobile devices, and tend to be used while sitting in a comfortable environment which contributes to enhanced focus on the learning task at hand. In contrast, mobile devices have small screens and are used in diverse and varying non-stationary learning situations (e.g., whilst walking, waiting in a traffic jam), placing the learner in a constantly changing environment with distractions that require her attention. These distractions, imposed by the environment, force learners into numerous context switches and multi-tasking [18], leading to increased cognitive load [3, 6, 22], and even frustration [5]. In the context of this paper, we refer to learning in a non-stationary situation with a mobile device as *learning on-the-go*.

The majority of studies on mobile learning in MOOCs *simulate* non-stationary learning on mobile devices in lab conditions [5, 14] and few consider the impact of multitasking and external distraction on learners in different learning situations [23]. As little is known about how various *real-life conditions* affect MOOC learners and learning on-the-go on mobile devices, we conducted a user study to this effect and investigated the following research questions:

RQ1: To what extent does learning on-the-go on mobile devices affect MOOC learners' learning gains?

RQ2: To what extent does learning on-the-go on mobile devices affect MOOC learners' consumption of learning materials?

Our results show slight decreases in learning gains (-7%) in the on-the-go learning situation compared to the stationary one; we also observe learners to behave quite differently depending on the learning condition: on-the-go learners prefer to spend more time (+10%) on video materials and less time on quizzes (-23%) than their stationary counterparts.

2 BACKGROUND

When discussing learning on-the-go, two research areas have to be considered: (i) multitasking and attention fragmentation imposed by the surrounding environment as well as (ii) mobile learning.

2.1 Multitasking and Fragmented Attention

Multitasking is the act of attempting to engage simultaneously in two or more tasks that have independent goals [8]. Learning on-the-go requires learners to multitask and divide their attention between several tasks efficiently, with one of the tasks being learning.

The cost of multitasking is lowered performance and accuracy for simultaneous tasks [7, 8]. Applied to learning, switching between different activity contexts, induced by distractions from other tasks or the environment, can thus lead to decreased learning gains. The learning on-the-go situation imposes a specific need for situational awareness—a task that has to be executed simultaneously alongside learning. Several studies on this aspect have been carried out. Krasovsky et al. [10] investigated the effect of texting while walking in mixed reality conditions (seeing obstacles ahead through the back camera of smart-phone) and found participants to prioritize texting over gait—thus slowing down. Harvey and Pointon [9] explored fragmented attention in mobile web search tasks with participants either walking on a treadmill, navigating an obstacle course, or performing web searches in a stationary position. The authors found the contextual situation to indeed affect search effectiveness (both objective and perceived) with participants in the walking condition reporting higher difficulty and higher cognitive workloads than those in the stationary condition. Xiao and Wang [23] investigated the impact of fragmented attention on mobile MOOCs in a lab setting by monitoring participants' heart rates; they found fragmented attention to hurt learner performance.

2.2 Mobile Learning

Mobile learning has been around for decades and offers a possibility to learn across time and space [20]. The main distinguishing factor between mobile learning and traditional learning is the variety and unpredictability of the learning situation in which learning can take place [18]. The latter makes different demands on learner attention level, body posture, environment, and social context, compared to conventional learning in a classroom or stationary online learning.

Mobile learning is not only concerned with the use of a mobile device to access course content. Sensor data of mobile devices can also be leveraged to provide context-sensitive learning in MOOCs [19]. Sensor data was used by Dingler et al. [6] to detect learner context and boredom levels during microlearning sessions on-the-go. Although no evidence of a link between boredom and opportune moments of learning were found, the authors highlight that context information retrieved from phone sensors can be helpful for mobile learning. Similarly, mobile device accelerometers were employed by Music et al. [12] to estimate attention levels based on changes in user gait patterns. A study by Tabuenca et al. [22] focused on learning situation patterns of mobile devices; the authors found a link between learning activity (e.g., reading, watching) and the location where it takes place (e.g., the sofa is a favorite place for reading tasks).

Learning is a task with high cognitive demands [4]. Cognitively demanding tasks (such as reading an article and writing an essay) may appear to be incompatible with the use of mobile phones while on-the-move, whereas activities with low cognitive loads (e.g., social networking, texting, taking pictures) are compatible with body movement. Moreover, the use of mobile phones whilst learning has been found to be a distraction for many learners [1] in a traditional study setting. In the MOOC setting, it is also likely that incoming notifications, text messages, news and so on will take MOOC learners' attention away from the learning task. Becking et al. [2] argue that on-the-go learning situations are uncomfortable because of the lack of space for taking notes, and the potential for interruptions.

Mobile devices can also affect how learning is perceived by learners, as shown by Dalipi et al. [5] who compared the learning experience on desktop and mobile platforms for three well-known MOOC environments (edX, Coursera, and Udacity). The authors found learners to be most satisfied with desktop platforms. Mobile devices with their small screens and a lack of external input devices caused negative emotions and frustrations due to the difficulties to perform some of the learning tasks.

In our study, we explore mobile learning in two different settings: (i) on-the-go under real-life conditions, and (ii) in a more conveniently seated condition. To the best of our knowledge, there is no previous research on learning on-the-go from MOOCs under real-life conditions.

3 EXPERIMENTAL DESIGN

3.1 Learning Situations

We empirically compare the following two *mobile* learning scenarios:

Stationary Scenario (`StaSc`): Learners participate in a *mini*-MOOC (a course consisting of a short lecture video and a number of quiz questions) in the office with a mobile device. We use the results of this scenario as the baseline to measure the impact of non-stationary learning situations to MOOC learning.

Moving Scenario (`MovSc`): Learners participate in a mini-MOOC with a mobile device whilst on-the-go. Specifically, we tasked our study participants with learning whilst walking from building to building on campus, which required them to pay attention to the traffic and their surroundings.

In order to collect comparable results, all study participants use the same mobile device (a Samsung S5 smartphone[1]) and access the mini-MOOCs with a Chrome browser.

3.2 Learning Materials

We developed four mini-MOOCs on different topics:

- radioactive decay,
- quantum bits,
- water quality aspects, and
- sedimentary rocks.

All mini-MOOCs have the same structure: they each consist of a single lecture video and twenty knowledge questions covering the contents of the lecture video. We selected the videos to all have a similar difficulty level; they all are introductory to the topic. We determined the number of quiz questions based on a power analysis[2]. Since these questions are used not only in the mini-MOOCs but also in the pre-study questionnaire which measures learners' prior knowledge levels, all questions are related to knowledge rather than specific details in the video content. All questions are multiple-choice questions with four answer options. Each question can be attempted only once.

We rely on the answers of our participants in the pre-study questionnaire to select the two mini-MOOC topics each participant knows the *least* about. This selection allows us to best observe learning gains. Table 1 shows the pre-study knowledge scores of our 36 participants across the four topics. The maximum obtainable number of points per topic in our pre-study questionnaire is 20 (i.e., all correct answers).

Table 1: Overview of minimum/median/maximum correctly answered questions per topic in the pre-study knowledge test. Twenty questions were asked per topic. Each participant answered 80 questions in total.

		Pre-study scores		
Mini-MOOC	**Video length**	**Min.**	**Median**	**Max.**
Radioactive decay	6m53	0.0	3.0	9.0
Qubit	12m24s	0.0	1.5	16.0
Water quality aspects	10m45s	1.0	7.0	11.0
Sedimentary rocks	5m03s	0.0	4.0	10.0

3.3 Experimental Steps

In our experiments, each participant went through the following experimental steps:

(1) Answering a pre-study questionnaire with demographic questions, mobile device usage, mobile learning experience and MOOC experience questions. The pre-study questionnaire also contains 4×20 questions on the topics of the four mini-MOOCs.
(2) Assignment of the two mini-MOOCs the participant knows the least about. A participant executes one mini-MOOC in the stationary scenario and one mini-MOOC in the moving scenario. The order of the scenarios and the assignment of the selected MOOC to the scenarios is at random to avoid ordering effects.
(3) In each of the two scenarios (executed one after each other), the participant watches a lecture video and answers 20 questions accompanying the video. The participant is allowed to switch between the video and questions according to her preferences. It is also possible to rewind the video, pause it and so on.

[1] 1080*1920 pixels, 5.1" display screen, 2GB RAM, 2,50 GHz CPU, Google Android 6.0.1
[2] We use the power calculation for two proportions (equal n) with binomial distribution, with parameters $h = 0.8$, sig.level 0.1, and power 0.8.

3.4 Metrics

Learning gain. For **RQ1**, we hypothesize that compared to `StaSc`, the divided attention in multitasking and the possible interruptions and distractions in `MovSc` negatively affect a MOOC learner's learning gain. In our study, the *absolute learning gain (ALG)* and *realized potential learning (RPL)* are used to measure learners' learning gain [21]. *ALG* is the difference in the number of correctly answered questions between the post- and pre-test. *RPL* is then the *absolute learning gain* normalized by the maximum possible learning gain. In our study, we normalize *ALG* by the total number of questions of each topic (i.e. 20).

Time consumption. For **RQ2**, we focus on the amount of time our participants spend on consuming course materials. The time participants spend on watching videos (i.e., *video duration* and *normalized video duration*) and answering questions (i.e., *question duration*) are used as the metrics. As shown in Figure 1, *video duration (VD)* refers to the minutes a participant spends watching the video during learning. *Normalized video duration (NVD)* refers to *video duration* normalized by the video length, which measures the proportion of the video consumed. *Question duration (QD)* is used to measure the amount of time participants spend on questions (this includes video segments after the first question has been answered—participants may rewind the video to seek for question content). We hypothesize that learners spend more time consuming course materials in `MovSc` than in `StaSc` due to their divided attention.

Statistical tests. To measure the statistical significance of the difference between different groups of participants, *Mann-Whitney U test* as a non-parametric test is used in our study.

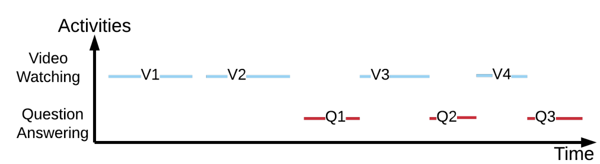

Figure 1: An example of a participant's learning progress. In this example, *video duration (VD)* is $V_1 + V_2 + V_3 + V_4$ and *question duration (QD)* is $Q_1 + V_3 + Q_2 + V_4 + Q_3$.

3.5 Study Participants

In total, 36 subjects participated in our study: 9 women and 27 men. The average age of our participants was 24.4 (std. dev. 2.7; min. age 19; max. age 30). The highest educational degree among our participants were high school diploma (5 participants), Bachelor's degree (21) and Master's degree (10). On average, the participants had used smartphones for 7.33 years (std. dev. 2.0), and all indicated that they use their smartphones daily; 27 participants had used their mobile device to learn in the week prior to the experiment. 26 participants had participated in at least one MOOC, 11 of 26 participants had passed at least one MOOC, and 13 of 26 participants had used mobile devices for MOOC learning before.

One experimental session (recall, that each participant participated in two mini-MOOCs and answered a long pre-study questionnaire) lasted on average two hours. Each participant received 15 Euros as payment. To motivate participants' learning, the participant achieving the highest learning gain in the study received a 5 Euros bonus payment.

4 RESULTS

Let us first consider **RQ1** (learning gains); the ALG and RPL metrics are reported in Table 2. `MovSc` leads to a 7% lower learning gain than `StaSc` (though not statistically significant). For the 20 questions per topic in our study, a ALG value of 0.05 represents one question that was answered correctly in the MOOC learning scenario (after having watched the lecture video) but not the pre-study. Since the RPL metric depends on the score in the pre-study question, a RPL value of 0.05 represents 5% of those questions that were not answered correctly in the pre-study and answered correctly in the MOOC learning scenario.

Table 2: Average (standard deviation) learning gains observed across all participants and the two learning situations.

Learning Situation	ALG	RPL
StaSc	0.504 (±0.130)	0.575 (±0.140)
MovSc	0.474 (±0.145)	0.533 (±0.164)

When considering how much time the participants spend on each course component (**RQ2**) we find a significant difference in the two conditions as reported in Table 3: in the `StaSc` condition participants spent significantly longer on the questions than in the `MovSc` condition. This finding is in line with Harvey and Pointon [9] who observed in their stationary/non-stationary web search experiment participants in the stationary condition to spend more time formulating queries than those in the non-stationary condition.

We also found participants in the `MovSc` condition to spend more time consuming video materials than those in `StaSc`, though this difference was not statistically significant.

Table 3: Overview of average and standard deviation of metrics related to participants' consumption of course materials. ‡ indicates significance at $p < 0.05$ level between `StaSc` and `MovSc`.

Learning Situation	VD (minutes)	NVD	QD (minutes)
StaSc (S)	10.796 (±3.929)	1.304 (±0.572)	16.284 (±6.754)
MovSc (M)	11.883 (±4.125)	1.407 (±0.519)	‡12.581 (±6.323)

5 CONCLUSIONS

In this paper, we considered the question to what extent learning on-the-go affects MOOC learners, focusing on the metrics of learning gain and time spent. We designed a mobile stationary/on-the-go user study with four mini-MOOCs. We recruited 36 participants and collected participants' data through questionnaires, assessment forms, and edX logs.

Our analyses reveal that participants' learning gains slightly lowered in the on-the-go condition (−7%). We also find that on average participants spend 10% more time video-watching and 23% less time question-answering in the learning on-the-go compared to the stationary condition.

Our study has shown that the necessity to multitask and divide attention whilst learning on-the-go contributes to lowered learning gains. Our study has several limitations, which are at the same time avenues for future work: (i) The impact of environmental variables such as light conditions and the crowdedness during learning on-the-go were not considered. These variables may affect participants' learning performance (a busy street requires more multitasking when walking than a quiet street); (ii) To measure the effects of divided attention and learning situations, we simplify learning on-the-go to `MovSc`—learning while walking on campus—in our study. However, as pointed out by Becking et al. [2], the learning situation might be more complicated and unstable in reality. Learners may walk, wait or take a bus or train whilst learning with a mobile device.

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