The Impact of Mobile Learning on Students' Self-Test Behavior in MOOCs

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ABSTRACT
Students can use personal mobile devices to access Massive Open Online Courses (MOOCs) in addition to desktop computers. However, user interfaces are often only scaled to smaller screen sizes and interaction patterns of a desktop learning experience do not always fit well with the characteristics of mobile devices. Adequate solutions for answering self-test questions on mobile devices often do not exist. In this paper, we explore the currently shown interaction patterns of MOOC learners when answering self-tests to make an informed decision about the requirements for the appropriate solution on mobile devices. The students' context was categorized into Desktop Web, Mobile Web, and Mobile Application. In an observational case study, the interaction events of two courses were analyzed regarding these device groups. Desktop Web is the most used environment. No practical differences between device groups were identified for subsequent attempts. Learners stick to a single device group and often only participate once in a self-test. Also, learners using mobile applications spend more time submitting self-tests.

Author Keywords
MOOCs; Mobile Learning; Spaced Repetition Learning

CCS Concepts
•**Applied computing** → **E-learning;** *Interactive learning environments;*

INTRODUCTION
Massive Open Online Courses (MOOCs) offer university-like courses to a greater audience. The learning material provided in MOOCs consists of knowledge-providing items – like videos and reading material – as well as knowledge-assessing items – like self-tests and graded assignments [12]. Students may move freely and at their own pace in the provided learning material [4]. They have full access to a MOOC's learning material through a web application running in a browser on stationary desktop computers or portable laptops. With the rise of Internet-capable handheld devices – like smartphones and tablets – learners were able to access the same material via mobile browsers on smaller screens [11] and in a non-stationary context [17]. While learning activities on mobile devices were first bound the mobile browsers, the next evolutionary step was the introduction of designated mobile applications for MOOC platforms to improve the learning experience [14].

In the MOOC context, self-test questions support learners to validate new knowledge – often in the form of multiple-choice and multiple-answer questions. Later they can be used to increase retention rates by spaced repetitions [2]. As of now, our mobile applications have not received first-class support for self-tests. Interaction patterns of desktop computers are reused – resulting to a non-optimized learning experience on mobile devices. Adequate solutions for answering self-test questions on mobile devices often do not exist [10]. Although self-tests are well suited for short follow-up sessions that can be triggered in a mobile context. With this work, we explore the currently shown interaction patterns of MOOC learners with different device groups when participating in self-tests. In this way, we want to determine the requirements for an ideal solution for mobile applications. For this, we defined the research question as follows: What differences in learning behavior do students show when utilizing different device groups for answering self-test questions in MOOC courses?

FOUNDATIONS
With the variety of devices that students can use to access the MOOC material, new usage patterns [6, 15] and challenges arise [3]. However, learning activities with those device groups have only been subject to few research studies [14].

Mobile Learning
While Mobile Learning has been subject to research before, the rising popularity and technological advancement of handheld mobile devices created a variety of research opportunities [5, 7]. Although mobile devices have a relatively small screen, they are considered highly personal devices and hold the potential to create unique engagement levels [9].

Spaced Repetition Learning
Spaced Repetition Learning is the process of re-evaluating and refreshing previously acquired knowledge with a temporal distance to the acquisition [13]. It has been promoted as an effective technique to increase the knowledge retention rate [8]. Already short review sessions have been proven to be beneficial [1]. Therefore, typical interaction patterns with mobile devices are an appropriate match for recap activities.

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RESEARCH METHODOLOGY

For this observational case study, two courses of openHPI – an instance of the HPI MOOC Platform – have been evaluated. Both courses – internet-working2019[1] and data-engineering2020[2] – featured a similar course design over six weeks. Further details are included in Table 1.

Study Design

Next to its web application, which is accessible via desktop and mobile browsers, dedicated mobile applications for iOS and Android are offered for the HPI MOOC Platform. Thus, learners can access the course material via three device groups.

Desktop Web (DW)

The *Desktop Web* device group covers all learning activities performed via browsers on desktop computers and laptops. The learning material is displayed on medium to large screens and is almost exclusively used for stationary learning activities. This device group represents the original access method for MOOCs and therefore holds the majority of the performed learning activities.

Mobile Web (MW)

When accessing the HPI MOOC Platform via a browser on mobile devices, learners have access to the same set of features as the *Desktop Web* device group. The user interface of the platform is adapted to the smaller screen sizes without comprising the feature completeness. Navigating the MOOC platform with those devices can feel a bit lavish to some students. In contrast to desktop computers, those mobile devices include network capabilities to access the Internet via a cellular network or with a WiFi connection. Therefore, learning activities with the *Mobile Web* group can be performed in a stationary or mobile setting.

Mobile Applications (MA)

Mobile applications improve usability and streamline interaction patterns [16]. However, when providing multiple clients for accessing the MOOC platform, implementation efforts will increase. Therefore, the mobile applications of the HPI MOOC Platform only focus on providing the core features of the MOOC platform. Other functionalities are available through embedded web views. At the moment, all self-test items use the described fallback to an embedded web view and are fully functional in this way. Hence, the same implementation is used to display and validate self-tests across all three device groups.

Data Collection and Processing

The tracked interactions of the learners have been analyzed after the course end. Only events from the course period have been considered. Due to the underlying technological architecture, tracking events for self-test submissions and visits to learning items had to be merged to annotate self-test submissions with the respective context of the student's device. The student's context was determined by mapping the last visit to a self-test item to the submit event of the same item. This approach introduces a certain imprecision, as some visit events could have been lost during data collection. If any data fields were missing for the feature calculation, the entire self-test submission was omitted (listed in Table 1). The majority of the excluded submissions resulted from a too short time gap to the previous submission. Furthermore, the results can only include data of learners who submitted at least one self-test. Based on the exported data, two features have been calculated:

Attempt Learners can submit answers to self-test items multiple times. Only submissions that are at least 15 minutes apart have been considered. Only the learner's first three attempts for a self-test item have been evaluated due to few attempts thereafter (see Table 1).

Time Deviation Factor When submitting self-tests, the start and end times are tracked to calculate the time students spend on self-tests. Time effort estimations for self-tests can either be set manually by course instructors or are calculated based on the included questions and answer options. The time spent for submitting a self-test was normalized by the time effort estimation to ensure comparability. Submissions that exceed a ratio of 100 have been excluded.

RESULTS AND DISCUSSION

To provide an overview of the learning behavior shown in the two courses, basic statistics have been gathered to outline the context of the evaluation. In both courses, 90% of the learners used the *Desktop Web* in their learning process. 22%–25% of the learners included mobile applications, while 14%–17% utilized a mobile browser. In both courses, there is a strong tendency towards the *Desktop Web* when it comes to accessing content items and submitting self-tests. Approximately 80%–85% of the learners used the *Desktop Web* environment. 10%–15% interacted with mobile applications, while only 4%–5% of the learners utilized a mobile browser for those tasks. When it comes to mobile devices, learners prefer mobile applications over mobile browsers. Although 14%–17% of the learners used a mobile browser at least once, the *Mobile Web* device group is less popular for accessing learning content and submitting self-tests. More details regarding a general overview are displayed in Table 1. It is worth noting that often only a single self-test submission is created per item (94%).

The device group distribution for the individual attempts is shown in Table 2. It can be seen that there are no practical differences between the device groups. In the *internetworking2019* course, the number of submissions with mobile devices (*MA* & *MW*) slightly increases in subsequent attempts. For the *data-engineering2020* course, the number of mobile submissions (*MA* & *MW*) peaks on the second attempt.

Device Group Transitions

Transitions between the device group have been investigated. For this, the device group for a self-test submission has been compared to the device group of the previous self-test submission of the same learner independent of the self-test item. The accounted number of transitions was normalized by the number of outgoing transitions of each device group. The resulting transition graphs are shown in Figure 1. Each directed edge is labeled with the likelihood for the next device group based on the behavior observed in the courses. In both

[1] `https://open.hpi.de/courses/internetworking2019`
[2] `https://open.hpi.de/courses/data-engineering2020`

						Self-Test Submissions					
	Device	Learners*		Total Item Visits		Total		Share by Attempt†			
Course	Group	N	Share	N	Share	N	Share	1	2	3	(4+)
internetworking2019	DW	3138	90.1%	579538	84.1%	73856	85.5%	95.2%	3.5%	1.3%	2.5%
63 self-test items	MA	765	22.0%	75100	10.9%	8406	9.7%	94.4%	3.9%	1.7%	4.3%
66.4% considered submissions	MW	503	14.4%	34493	5.0%	4161	4.8%	95.8%	2.9%	1.4%	2.7%
data-engineering2020	DW	9453	90.1%	2511680	80.2%	411511	81.4%	97.6%	1.7%	0.7%	0.9%
125 self-test items	MA	2637	25.1%	475071	15.2%	71036	14.1%	97.1%	2.1%	0.8%	1.1%
75.4% considered submissions	MW	1752	16.7%	145595	4.6%	22497	4.5%	97.3%	2.1%	0.6%	0.9%

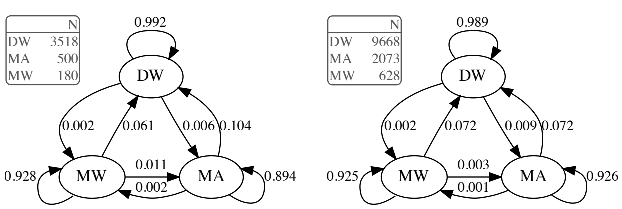
*Learners can use multiple device groups and are counted in all respective groups †Normalized by the total number of submission in the device group

Table 1. Learners, Item Visits, and Self-Test Submissions per Attempt in Evaluated Courses

		Subm.	Device Group Ratio		
Course	Att.	N	DW	MA	MW
internet-working2019	1	82222	85.5%	9.7%	4.8%
	2	3058	85.3%	10.8%	3.9%
	3	1143	82.6%	12.4%	5.0%
data-enginering2020	1	492673	81.5%	14.1%	4.4%
	2	9055	78.5%	16.3%	5.2%
	3	3316	80.0%	16.0%	4.0%

Table 2. Device Group Ratio per Attempt

courses, students mostly stick to a single device group and avoid transitions. In the *internetworking2019* course, learning on mobile applications (*MA*) had a chance for 10% to switch to the *Desktop Web* group. All other transitions show negligible likelihoods. Therefore, no further statistical analyses were conducted. Since this study only focuses on self-test submissions, learning activities between submissions have been omitted.



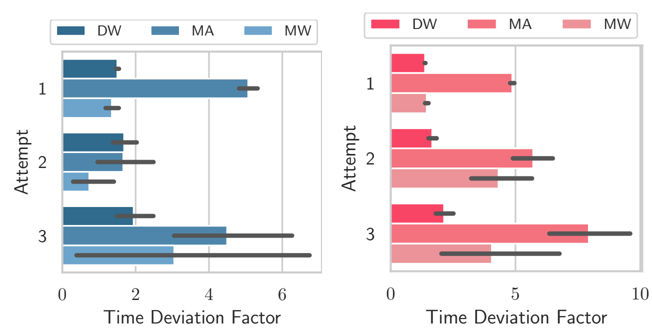
(a) internetworking2019 (b) data-engineering2020

Figure 1. Device Group Transitions

Time Spent Deviation

The time spent on submitting self-tests with the different device groups was examined. For this purpose, the time deviation factor was calculated for all self-test submissions. The results are displayed in Figure 2. When using mobile applications for submitting self-tests, students spent significantly more time on submitting self-tests compared to the other device groups. An exception is the second attempt in the course *internetworking2019*. Here, mobile learners (*MA* & *MW*) used notably less time when compared to other attempts. This might indicate usability issues or unfitting interaction patterns. However, it is hard to reason about based on the available data.

With subsequent attempts, the standard deviation for the submission times increases for all three device groups. In the *data-engineering2020* course, the mean time spent on submission also increases with subsequent attempts. Both observations can be explained by the increased time difference the knowledge acquisition and highlight the importance of spaced repetition learning. A two-way ANOVA revealed significant to highly significant influences of the respective attempt and the device choice in both courses (see Table 3). Post hoc tests by Tukey showed significant differences between all combinations, except for third attempts on *MW* in the *data-engineering2020* course.



(a) internetworking2019 (b) data-engineering2020

Figure 2. Time Deviation Factor per Attempt

Course	Factor	F	PR(>F)
internet-working2019	C(Att.)	3.53	0.029
	C(Device)	946.25	<0.001
	C(Att.):C(Device)	20.41	<0.001
data-enginering2020	C(Att.)	93.31	<0.001
	C(Device)	10008.77	<0.001
	C(Att.):C(Device)	37.56	<0.001

Table 3. Results of Two-Way ANOVA on Influences on Time Deviation

DISCUSSION & CONCLUSION

The *Desktop Web* is the most used environment for answering self-tests – similar to all interactions on a MOOC platform. When using mobile devices, students utilize more often mobile applications instead of relying on the mobile browser. This can be counted as an acceptance of learning with mobile applications in general. To determine the requirements for the adequate solution for self-tests on mobile applications, we explored the currently shown interaction patterns of MOOC learners when submitting self-tests. In an observational case study, the learners' context was categorized into *Desktop Web*, *Mobile Web*, and *Mobile Application*. With regards to the learning behavior, no practical differences between device groups were identified for subsequent attempts. Learners stick to a single device group and often only participate once in a self-test. Further, learners on mobile applications spend significantly more time when submitting self-tests. This could be explained by the use of traditional self-test options — developed for *Desktop Web* — that do not match the usage and interaction patterns on mobile applications. In future studies, alternative self-test formats for mobile devices should be explored to strengthen this device group, e.g., a dedicated tool to recap self-test questions, or triggering shorter spontaneous learning sessions with self-test questions as suggested in [2]. As long as there is no specialized form for self-tests and an adequate notification system, mobile devices can not fulfill their potential to create an omnipresent learning experience.

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