A Quantitative Study on the Effects of Learning with Mobile Devices in MOOCs

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***Abstract*—Massive Open Online Course (MOOC) platforms were initially designed for a desktop learning experience delivered via the Internet. With the increasing acceptance of mobile devices, learners started accessing the MOOC platforms through the browser application on their smartphones and tablets. However, native mobile applications offer better system integration and enhance the learning experience. As the concept of mobile-assisted seamless learning emphasizes the ubiquitous access to learning material, the relevance of mobile devices in the learning process will increase further. This paper investigates the different learning behaviors when using mobile devices on the HPI MOOC platform. For this, influencing aspects, that can not always be controlled by the learner, are examined for native applications and mobile websites – such as the size of the screen and the current network state of the mobile device. The results of a quantitative study show highly significant differences between the usage of native applications, mobile websites, and the overall average of the HPI MOOC platform. It was proven that the size of the screen has a large practical effect when using native applications. Furthermore, course items and videos are more often consumed when the device is connected to a WiFi network. This study creates the basis for future research to improve the support of mobile-assisted seamless learning methods for MOOCs.**

***Index Terms*—Mobile Learning, MOOCs, Mobile-Assisted Seamless Learning, Technology-Enhanced Learning**

I. Introduction

Initially designed for bringing university-like courses to the masses via the Internet, Massive Open Online Courses (MOOCs) have been proven to work also in other application areas like further training and guidance for new employees in an enterprise context [1] as well as in supporting front-line responders in health emergencies [2]. Although the core concepts of MOOCs remain the same, learners require adapted features to fit the needs of these application fields [1], [2]. This is also reflected in their learning behavior and patterns, which are influenced by various factors like the topic of the course, learning objectives, and available devices like smartphones and tablets.

The first instances of MOOC platforms were designed for a learning experience that takes place in a stationary environment. Through websites, access to the learning material was provided for everybody who has access to the Internet. With the increasing acceptance of mobile devices like smartphones and tablets, MOOC platform providers started to support responsive layouts for their websites to enable an adequate learning experience on these devices [3]. The next evolutionary step was achieved through dedicated native mobile applications. They offer a more streamlined interface for the interactions of the learners by adopting navigation patterns and appearances which fit right into the user interface of the mobile device. At the same time, native applications can provide better system integration and allow advanced features like offline capabilities and notifications to enhance the learning experience.

This work aims to broaden the understanding of the different learning activities and arising challenges of mobile learning in the context of MOOCs. Therefore, we investigate the learner behavior on mobile devices in the HPI MOOC platform. To define the scope of this paper, we defined the following research questions:

RQ1 Do learning activities on mobile devices differ from learning activities performed on websites?

RQ2 What are the possible aspects that have an impact on the learning behaviors on mobile devices?

To provide a background to these questions, we outline the pedagogical rationale in Section II. Following this, Section III discusses related work. In Section IV, we explain the researched aspects of mobile learning in detail. Afterward, we present the results of our quantitative studies in Section V. This paper concludes with Section VI.

II. Pedagogical Rationale

In this section, we outline the pedagogical rationale associated with mobile learning techniques in the context of MOOCs. This forms the theoretical background of this paper.

A. Mobile-Assisted Seamless Learning

Wong and Looi coined the term *Mobile-Assisted Seamless Learning* [4]. They investigated the situations where context switches can occur when learning in a mobile and ubiquitous environment. Out of the ten resulting levels of mobile-assisted seamless learning, the following are of particular interest for this work.

1) Ubiquitous Access to Learning Material: Mobile devices are exposed to a variety of aspects, which are often hard to control. The most prominent factor is the unreliability of the network connection. As MOOC platforms operate as online

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services, all relevant user data and learning material are stored online. A major challenge for mobile devices lies in providing an equivalent learning experience regardless if a connection to the Internet exists or not. Additionally, the learning material should adapt to environments with low bandwidth to avoid excluding rural areas.

2) Using Multiple Devices: As mobile learning is still used as an additive feature when learning with MOOCs [5], the learners will continue to use web platforms in their learning process. This results in at least two utilized devices. However, the learner should not be restricted in the choice of the learning device. He or she should rather have the option to choose the device which fits the best to the learner's needs and tasks.

3) Usage across Multiple Locations: One of the biggest selling points of mobile devices is gained independence from specific locations [6]. Learners do not have to stay at home or at the workplace to consume the learning material. They gain the freedom to choose their learning location and time individually.

B. One-to-one Learning

The concept of one-to-one learning refers to the availability of at least one device per learner [7]. This device does not have to be shared with others during learning activities. In this way, the learners gain more independence in defining their learning process. Also, this creates possibilities for personalizing the learning experience for each learner individually [8], [9]. With the increasing acceptance of smartphones and other mobile devices, the majority of the world population owns a personal mobile learning device that is omnipresent in their lives [10].

C. Self-Regulated Learning

The definitions of Self-Regulated Learning by Pintrich [11] and Zimmerman [12] focus on the concept of setting individual goals for the learners. Furthermore, they emphasize the importance of learners taking control over their learning process. This includes a certain degree of freedom to learn at an own pace and choosing preferred learning devices like mobile devices.

III. Related Work

Bothe and Meinel already identified the level of support for mobile-assisted seamless learning methods in major MOOC platforms [13]. The authors discovered that mobile clients are still mainly considered as secondary learning interfaces and often do not offer the same feature set as web applications. One of the studied MOOC platforms does not even offer a dedicated native mobile application and relies only on their web application for mobile learning. While such circumstances simplify the development process, they also limit the freedom of the learners in defining their learning process.

Rohloff, Bothe, Renz, *et al.* investigated the mobile learning behavior with a quantitative study in the HPI MOOC platform [5]. They categorized the learner by those who use used the native mobile applications in the learning process and by those who did not. The researchers discovered that "users who additionally learned with the mobile apps visited more items, performed better in quizzes, and watched and downloaded more videos, which resulted in a relevant increase on average course completions" [5].

Related research about the acceptance of mobile devices for learning, mostly utilizes the Technology Acceptance Model [14] to determine aspects influencing mobile learners. Park, Nam, and Cha [15] concluded that the learners' attitude had the most impact on the adoption of mobile learning methods. Later on, Chung, Chen, and Kuo [16] reported the system compatibility as the best indicator for the learners' behavioral intention to utilize mobile devices in the learning process. Liaw, Hatala, and Huang [17] took an activity theory approach to this subject. They stated that – among other factors – learner satisfaction, learner independence, and a rich set of system functionality had a positive impact on the acceptance of mobile learning.

Nevertheless, research studies about the learning activities performed on mobile devices when used in conjunction with MOOC platforms or web applications, in general, do not exist. Moreover, user behavior on mobile devices differs from desktop computers [18], [19]. deWaard, Koutropoulos, Keskin, *et al.* have shown that MOOCs and mobile learning are compatible and can provide synergies [20]. In this paper, we take a closer look at the mobile learners of the HPI MOOC platform. Instead of focusing on the proven acceptance of mobile devices in a MOOC context, we investigate the learning activities performed on these devices. For this, we are considering aspects and limitations which are characteristic in a mobile context and might not always controllable by the learner.

IV. Aspects of Learning with Mobile Devices

In this section, we discuss aspects that shape the learners' behavior in a mobile environment. While this list is not indented to be exhaustive, it covers the most distinctive characteristics of mobile devices in comparison to desktop computers.

A. Mobile Websites and Native Applications

With the inclining of the number of personal mobile devices, providers of web platforms optimized their websites for the smaller screen sizes by changing layout, design, and navigation accordingly [3], [6]. Although such an approach changes the usability, it allows a feature alignment conveniently as the same functionality becomes available across multiple different clients. However, usage patterns on mobile devices differ from regular desktop usage. Adjusted responsive websites do not exploit the full potential of mobile devices as they only utilizing the browser application on the mobile device.

With the launch of the digital market places for iOS and Android, platform providers gained the ability to overcome the limitation of browser applications by developing dedicated applications for their products. These so-called native applications offer much better integration into the mobile operating system. On the one side, this enabled an improved design process for the user interface which in turn increased user satisfaction. On the other side, platform providers had the opportunity to provide unique features that were only possible through these native applications. This includes the download of learning material, as well as learner activation through notifications. On the downside, the feature alignment is no longer guaranteed by the platform providers as it requires additional development resources. Therefore, native applications often provided a subset of the available platform features and occasionally fall back to the websites on the mobile device.

B. Different Screen Sizes

As nowadays most people own a smartphone, the majority of the world population has a device to access the Internet always in reach. Mobile phones are checked regularly, often only for a brief period [21]. Therefore, mobile devices with a small screen diagonal are most commonly used for quick lookups, conversational means, and stopgaps. Learning activities on such devices are rather triggered externally, require the absence of alternatives or demand a need for immediate gratification.

Mobile devices with a larger screen diagonal entered the consumer market at a later point in time due to the necessary technical evolution. These so-called tablets do not experience hard space restrictions as mobile phones do. Therefore, they are perceived as more relaxing on the eyes of the learners [22] and are better suited for longer working sessions [23]. However, the weight for a mobile device increases proportionally with its size. Because of this, tablets are more often used in a stationary setting and are less often directly at the hand of the learner. If a learner owns multiple mobile devices with varying screen sizes, she or he can pick the device which fits the best to the current situation or which is currently at hand. In this way, the learners gain another degree of freedom in defining their learning process.

In a survey we conduct at the end of 2018 among learners of the HPI MOOC platform (N=1028), we asked which mobile devices are available at the learners' hands and if they include these in their learning process. 88% of learners stated that they own a smartphone, while 8% negated this question. 27% use their smartphone to access the learning material and 60% do not use the smartphone. One of the most frequently stated reasons for not using the smartphone was the screen size which was perceived as too small. Tablets are not as commonly available among our learners. 60% states that they own a tablet. 36% do not own a tablet. Nevertheless, tablet owners show a similar willingness to using the tablet in the learning process as smartphone users (Yes: 29%; No: 31%). Again, the participants mentioned the screen size for not adopting the tablet in their learning process. But others were intrigued by the idea.

C. Uncontrollable Network State

One of the characterizing properties of mobile devices is a variety of possible connections to the Internet. As the learner transitions through multiple context switches, a connection to the network can not always be guaranteed.

The most common type of network connection in modern mobile devices is WiFi, which is integrated into all smartphones and tablets. Nowadays WiFi is available in most homes and offices, as well as in public places of big cities. If a mobile device is connected to a WiFi network, one can infer that the user frequently visited this location as the setup process required some manual effort.

In less frequently used places, the users have to rely on cellular mobile data to retrieve content from the Internet. All smartphones and sometimes even tablets support this kind of network connection. While in bigger cities the cellular network coverage is almost everywhere given, rural areas often struggle the provide a stable connection or only can offer a low bandwidth. However, the use of cellular mobile data is essential to enable learning on the go and to guarantee ubiquitous access to the learning material.

Although the coverage of cellular networks increases steadily, there will be always situations where no Internet connection is available or is priced disproportionately expensive – for example in airplanes. In those situations, the learners have to rely on previously downloaded learning material [24]. Depending on the type of content, this might not always be applicable. Interactive content, which needs constant validation on the server-side (e.g. programming exercises), or tasks that require any form of supervision can not be easily performed without a connection to the Internet.

With these network restrictions in mind, learners might adjust their learning behavior depending on the available network state. As cellular mobile data plans can be costly and WiFi is most commonly free or paid as a flat rate model, learners could tend to prefer WiFi over cellular data to save costs. This forces them to either only learn in dedicated places or to plan in advance by downloading learning material beforehand. Regardless of the learner's choice, MOOC platforms should support the learner by adjusting the resolution of the learning material, especially those of videos and images, to her or his learning environment and network state to avoid unnecessary amounts of network traffic.

V. Evaluation

We conducted a series of quantitative studies to investigate the learning behavior of mobile learners of the HPI MOOC platform. In this way, we want to gain a better understanding of our learners by determining the influencing and limiting aspects of the learning process in a mobile context. Hence, we can answer the defined research questions.

A. Methodology

We conducted our experiments on an instance of the HPI MOOC platform, openSAP, which specializes in enterprise MOOCs and further training of employees and associates. For the scope of this work, we analyzed captured events of learner activities made available by a dedicated architecture for Learning Analytics [25]. We utilized several metrics and context parameters to categorized the learner in respective groups to perform the statistical analysis.

For this study, we are considering all events that were recorded from 2018-01-01 until 2018-07-01 (excluding). During this period, 14 courses were published on this MOOC platform, which ran from 22 up to 50 days. These courses mostly consist of typical MOOC learning material – like videos, text elements, and self-tests.

In the researched period, the MOOC platform was available via the fully responsive web application, as well as native applications for iOS and Android. These native applications are built with an offline-first approach in mind. All retrieved data is stored in a local database on the device. In this way, all previously displayed learning material is thereafter also available without an Internet connection. This does not apply for multimedia content as such data would fill out the available space on the mobile device too quickly. Learners rather have the option to download videos and slides manually. The offline-first approach also includes a mechanism to track events that are performed when no Internet connection is given [5]. These events are temporarily stored in the local database and send to the server when a connection to the Internet becomes available [26].

TABLE I
MOBILE DEVICE DISTRIBUTION

Device Class	All	iOS	Android
Phone Only	10,407	3,683	6,933
Tablet Only	1,671	818	1,000
Both	744	358	257
Total / Either One	12,822	4,859	8,190

In total 209,036 learners used the MOOC platform actively and performed at least one learning activity. Table I shows the distribution of the utilized devices, additionally grouped by the operating systems iOS and Android. The majority of the learners uses a smartphone to access the MOOC platform (10,406 learners) and only a fraction uses a tablet device (1,671 learners). This mirrors the result of the survey about the available learner devices (see Subsection IV-B). Overall, more learners operate Android devices (Android: 8,190 learners; iOS: 4,859 learners), while the iOS operating system shows a wide adoption of tablets (Android: $^{1000+257}/_{8190} \approx 15\%$; iOS: $^{818+358}/_{4859} \approx 24\%$). This study neglects other mobile operating systems due to insignificant usage data. In Subsection V-C1, we explain in detail how we categorize the devices in phones and tablets.

In this study, we focus on the following set of learning activities. The selection is inspired by the research of Rohloff, Bothe, Renz, *et al.* [5] to ensure comparability. We also adjusted the set to only include learning activities that can be performed on all clients equally and are implemented in the native applications.

Visited Item (VI)
: A *Visited Item* event is triggered every time a learner opens any of the available learning items (video, text element, self-test, ...) in a course.

Video Download (VD)
: Every time a learner starts the download of a video stream (regardless of the resolution), a *Video Download* event is captured.

Slides Download (SD)
: Similar to the *Video Download* event, the system tracks each started download of the presentation slides with a *Slides Download* event.

Video Play (VP)
: When the learner starts the playback of a video stream or resumes the playback, an event for *Video Play* is created by the system. This event is also captured for video streams that have been downloaded beforehand.

Video End (VE)
: The *Video End* event indicates that the video playback stopped because the end of the video was reached. This indicates a completely watched video. Such an event will not be triggered if the playback was stopped early.

For the statistical analysis, we compared the share of each of these learning activities under a given condition (treatment) to the overall share of learning activities of all respective learners with a one-sample T-Test. As the research conditions have multiple levels and we can not guarantee a normal distribution of the recorded data, we applied a Wilcoxon test [27] to determine the statistical significance among the different levels. Additionally, we calculated the effect size (Cohen's d) for each statistical test. The results are likely to be affected by Type II errors due to the nature of MOOCs, the large number of participants in MOOC courses and the small adaption rate of mobile devices.

B. Mobile Websites and Native Applications

Before having a closer look at specific aspects that might influence learners on mobile devices, we compare the learning behavior on native applications and mobile websites with the overall learning activities distribution on the MOOC platform. The characteristics of native applications and mobile websites were previously explained in Subsection IV-A.

1) Classification: To distinguish between events triggered in native applications and events triggered in mobile browsers, we introduced two context variables that are decorated to each event: *platform* and *runtime*. The value of the *platform* variable states the operating system of the mobile device – usually iOS or Android. The *runtime* variable stores the current execution context. For native applications, this equals the value of the *platform* variable. While for mobile websites, the identifier name of the mobile browser is used. As a mobile browser type can be available for mobile devices and desktop computers, the *runtime* variable alone is not sufficient to distinguish between native applications, mobile websites, and desktop computers.

TABLE II
SHARES OF LEARNING ACTIVITIES IN NATIVE APPLICATIONS AND MOBILE WEBSITES ($N = 209,036$)

	All		Native				Mobile				Native-Mobile	
Event	Mean	Std.Dev.	Mean	Std.Dev.	1S T-Test	Effect Size	Mean	Std.Dev.	1S T-Test	Effect Size	Wilcoxon	Effect Size
VI	0.1743	0.142	0.0043	0.029	$p < 0.001$	$d = 5.895$	0.0064	0.038	$p < 0.001$	$d = 4.436$	$p < 0.001$	$d = 0.064$
VD	0.0063	0.025	0.0009	0.012	$p < 0.001$	$d = 0.438$	0.0003	0.004	$p < 0.001$	$d = 1.467$	$p < 0.001$	$d = 0.064$
SD	0.0046	0.017	0.0004	0.008	$p < 0.001$	$d = 0.524$	0.0001	0.002	$p < 0.001$	$d = 2.047$	$p < 0.001$	$d = 0.050$
VP	0.0575	0.071	0.0023	0.016	$p < 0.001$	$d = 3.429$	0.0017	0.014	$p < 0.001$	$d = 3.974$	$p < 0.001$	$d = 0.034$
VE	0.0088	0.016	0.0002	0.005	$p < 0.001$	$d = 1.794$	0.0003	0.003	$p < 0.001$	$d = 2.879$	$p < 0.001$	$d = 0.015$

2) Analysis and Discussion: Table II shows the share for each of the five researched learning activities for events triggered by all users. The data is organized by events on the overall platform, as well as filtered for native applications and mobile websites. It can be seen that *Visited Item (VI)* is the most common captured event on the platform, followed by *Video Play (VP)* as the second most common learning activity. This ranking is mirrored for native applications and mobile websites. The share for the learning activities is respectively smaller as many learners only use the web application on a desktop computer in their learning process. When comparing the results for native application and mobile websites with the overall platform data, the one-sample T-Test reports high significant differences for all learning activities ($p < 0.001$). For all but two cases, an extremely high effect size was measured ($d > 1.4$). *Video Download (VD)* and *Slides Download (SD)* show extra small usage rates on mobile websites. This might be since not all mobile operating systems do support file downloads and file management in its entirety. There are also highly significant differences between native applications and mobile websites for all learning activities ($p < 0.001$). Although no practical effect could not be proven.

Based on these results, we can conclude that the learning behavior with mobile devices differs from those performed on websites via desktop computers (RQ1). There appears to be no difference in the practical effect between native applications and mobile websites. Although, this might be influenced by the reduced feature set and the small adoption rate of the native applications. We still believe that these results have some relevance in getting a better understanding of the learning process on mobile devices.

C. Screen Size

With this analysis, we are investigating if and how the device type and respectively the screen size influences the learning behavior on mobile devices. For this, we refer to the groundwork described in Subsection IV-B.

1) Classification: To categorize a mobile device as *Phone* or *Tablet*, we have to either infer the group via a device identifier or define a threshold for the screen diagonal. Mobile devices running the iOS operating system return a unique device identifier for each device model. This identifier has the following scheme `(iphone|ipad)<generation>.<device>`. Therefore, the device category of iOS devices can in easily inferred by the starting string of the device identifier.

In contrast to this uniform device identifier, Android devices return a variety of different device identifier names. Here, we have to rely on the screen diagonal of the devices instead. We are considering all devices with a screen diagonal of 7 inches or smaller as phones. Devices featuring screens that are bigger than 7 inches are categorized as tablets. As different device models with approximately the same size might include screens with different resolutions, we can not only solely rely on the device's resolution. Each Android device supplies a value for its screen density, specifying the number of pixels per inch of the screen. We can utilize this screen density to calculate the screen diagonal with the following formula:

$$diagonal = \sqrt{(\frac{screen\_width}{screen\_density})^2 + (\frac{screen\_height}{screen\_density})^2}$$

The screen density value is only accessible by native applications and not available in the mobile browser. Hence, we are unable the calculated the screen diagonal for events triggered in mobile browsers on Android devices. Therefore, we excluded all events which could not do categorized from this analysis.

2) Analysis and Discussion: In Table III, the learning behavior when using the native application on phones or tablets is presented. Similar to the overall platform usage, *Visited Item (VI)* and *Video Play (VP)* are the most common learning activities for phones and tablets. When comparing the learning behavior on phones and tablets with the overall usage data, the one-sample T-Test reports highly significant results for all learning activities ($p < 0.001$). For *Visited Item (VI)* and *Video Play (VP)* events triggered on tablets, the effect size is extremely large ($d > 1.0$). The Wilcoxon test indicates highly significant differences between phone and tablet usage ($p < 0.001$). A large practical effect was proven for *Visited Item (VI)* events ($d > 0.8$), while a medium effect can be reported for and *Video Play (VP)* events ($d > 0.5$). A small effect was shown for *Video Download (VD)* activities ($d > 0.3$).

Table IV displays the learning behavior on phones and tablets in combination with the mobile website. Here, *Visited Items (VI)* activities make up the majority of the captured events as the number of *Video Play (VP)* events decreased,

TABLE III

SHARES OF LEARNING ACTIVITIES ON PHONES AND TABLETS IN NATIVE APPLICATIONS ($N = 12,824$)

	All		Phone				Tablet				Phone-Tablet	
Event	Mean	Std.Dev.	Mean	Std.Dev.	1S T-Test	Effect Size	Mean	Std.Dev.	1S T-Test	Effect Size	Wilcoxon	Effect Size
VI	0.251	0.242	0.208	0.242	$p < 0.001$	$d = 0.178$	0.043	0.130	$p < 0.001$	$d = 1.600$	$p < 0.001$	$d = 0.850$
VD	0.040	0.111	0.034	0.104	$p < 0.001$	$d = 0.065$	0.007	0.044	$p < 0.001$	$d = 0.758$	$p < 0.001$	$d = 0.336$
SD	0.022	0.089	0.019	0.086	$p < 0.001$	$d = 0.032$	0.003	0.026	$p < 0.001$	$d = 0.718$	$p < 0.001$	$d = 0.254$
VP	0.134	0.153	0.112	0.152	$p < 0.001$	$d = 0.148$	0.022	0.071	$p < 0.001$	$d = 1.580$	$p < 0.001$	$d = 0.755$
VE	0.009	0.035	0.006	0.029	$p < 0.001$	$d = 0.089$	0.003	0.021	$p < 0.001$	$d = 0.290$	$p < 0.001$	$d = 0.142$

TABLE IV

SHARES OF LEARNING ACTIVITIES ON PHONES AND TABLETS IN MOBILE WEBSITES ($N = 30,578$)

	All		Phone				Tablet				Phone-Tablet	
Event	Mean	Std.Dev.	Mean	Std.Dev.	1S T-Test	Effect Size	Mean	Std.Dev.	1S T-Test	Effect Size	Wilcoxon	Effect Size
VI	0.214	0.271	0.072	0.190	$p < 0.001$	$d = 0.749$	0.039	0.138	$p < 0.001$	$d = 1.269$	$p < 0.001$	$d = 0.196$
VD	0.007	0.034	0.001	0.013	$p < 0.001$	$d = 0.432$	0.002	0.017	$p < 0.001$	$d = 0.297$	$p < 0.001$	$d = 0.051$
SD	0.002	0.016	0.000	0.005	$p < 0.001$	$d = 0.329$	0.000	0.007	$p < 0.001$	$d = 0.251$	$p = 0.009$	$d = 0.016$
VP	0.042	0.089	0.013	0.055	$p < 0.001$	$d = 0.529$	0.008	0.040	$p < 0.001$	$d = 0.865$	$p < 0.001$	$d = 0.109$
VE	0.006	0.020	0.002	0.014	$p < 0.001$	$d = 0.281$	0.002	0.010	$p < 0.001$	$d = 0.423$	$p < 0.001$	$d = 0.046$

especially on tablets. All learning activities on phones and tablets show a highly significant difference in comparison to all events triggered on mobile websites ($p < 0.001$). *Visited Item (VI)* and *Video Play (VP)* activities showed a large practical effect on tablets ($d > 0.8$) and a medium effect on phones ($d > 0.5$). A small effect ($d > 0.2$) was proven for *Video Download (VD)* and *Slides Download (SD)* on phone, as well as for *Video End (VE)* on tablets. Between phone and tablet usage, all learning activities but *Slides Download (SD)* showed a highly significant difference ($p < 0.001$). However, no practical effect can be proven.

In regards to RQ2, we are confident to report that there exists a difference in the learning behavior on phones and tablets when using the native applications. However, the screen size of the mobile device appears to be irrelevant on mobile websites. The reason for the rare uses of mobile websites might be the loss in user experience compared to native applications or similar. Further studies have to verify this assumption.

D. Network State

The last analysis covered in this study is about the influence of the network state of the mobile device on the learning behavior. The implications and possible network states of mobile devices were already discussed in Subsection IV-C.

1) Classification: To determine the network state for each event, we have to rely on the system functionality of the mobile operating system. Unfortunately, there is no such functionality available in mobile browsers to reliably retrieve the currently available connection to the Internet. Thus, we are only able to run the analysis for native applications. Here, the required state is provided by the respective SDKs. Each captured event is decorated with one of the possible network states: WiFi, cellular, offline. Since some functionality is restricted when operating the native application without an Internet connection, we exclude this state from this study.

2) Analysis and Discussion: The learning behavior for activities performed when connected to a WiFi network or when using cellular mobile data can be seen in Table V. Similar to the platform average, *Visited Item (VI)* and *Video Play (VP)* are the most popular recorded learning activities. Compared to all activities in the native applications, those performed on WiFi or cellular networks show a highly significant difference ($p < 0.001$). An extremely high effect was proven for *Visited Item (VI)* event with a cellular network ($d > 1.0$). A medium practical effect can be reported for *Video Play (VP)* activities in a WiFi network ($d > 0.5$). When comparing the results for WiFi and cellular conditions, the Wilcoxon test returns a highly significant difference for all learning activities ($p < 0.001$). However, only a medium practical effect was proven for *Visited Item (VI)* activities ($d > 0.5$).

Additionally, Table VI shows the usage distribution by network state for the ten countries with the most active learners using the native applications. Most notably, in India, learners perform on average more learning activities on the native applications (49.7%) compared to western countries (18.1% up to 36.9%). This indicates that the price of cellular mobile data and the required infrastructure, as well as other cultural factors, influence the usage patterns on mobile devices depending on the available Internet connection.

The results show that the network state of the mobile device has partially an impact on learning behavior (RQ2). Learners are more likely to visit items *(VI)* when connected to a WiFi network compared to a cellular connection. Furthermore, videos will be played *(VP)* more often with a WiFi connection.

TABLE V
SHARES OF LEARNING ACTIVITIES ON WIFI AND CELLULAR IN NATIVE APPLICATIONS ($N = 12,824$)

	All		WiFi				Cellular				WiFi-Cellular	
Event	Mean	Std.Dev.	Mean	Std.Dev.	1S T-Test	Effect Size	Mean	Std.Dev.	1S T-Test	Effect Size	Wilcoxon	Effect Size
VI	0.251	0.242	0.180	0.224	$p < 0.001$	$d = 0.316$	0.066	0.142	$p < 0.001$	$d = 1.304$	$p < 0.001$	$d = 0.606$
VD	0.040	0.111	0.026	0.080	$p < 0.001$	$d = 0.182$	0.015	0.080	$p < 0.001$	$d = 0.321$	$p < 0.001$	$d = 0.139$
SD	0.022	0.089	0.009	0.043	$p < 0.001$	$d = 0.283$	0.012	0.079	$p < 0.001$	$d = 0.119$	$p < 0.001$	$d = 0.044$
VP	0.134	0.153	0.066	0.095	$p < 0.001$	$d = 0.715$	0.064	0.142	$p < 0.001$	$d = 0.491$	$p < 0.001$	$d = 0.013$
VE	0.009	0.035	0.006	0.026	$p < 0.001$	$d = 0.116$	0.002	0.017	$p < 0.001$	$d = 0.377$	$p < 0.001$	$d = 0.155$

TABLE VI
USAGE DISTRIBUTION BY NETWORK STATE FOR THE TEN COUNTRIES WITH THE MOST ACTIVE MOBILE LEARNERS

		WiFi		Cellular	
Country	N	Mean	Std.Dev.	Mean	Std.Dev.
India	4733	0.485	0.431	0.497	0.430
Germany	1564	0.764	0.341	0.204	0.330
USA	1290	0.759	0.358	0.217	0.347
Austria	435	0.607	0.400	0.369	0.397
UK	384	0.723	0.379	0.255	0.370
Brasil	382	0.735	0.364	0.239	0.355
Spain	317	0.671	0.379	0.294	0.374
Netherlands	201	0.744	0.384	0.224	0.374
Canada	277	0.782	0.335	0.181	0.315
Russia	174	0.656	0.380	0.326	0.380

We suspect the increased network traffic as a reason for this behavior. But this can also indicate that learners prefer being stationary when consuming video material. The effects of the network state should be discussed in future research to get a better understanding of the learners' needs and interactions with large-size learning material.

VI. CONCLUSION

This paper investigated the differences in learning behavior on the HPI MOOC platform when using mobile devices. In this way, the next step for a better understanding of the learners' actions and requirements was achieved to increase the support for mobile-assisted seamless learning techniques, especially the ubiquitous access to learning material, as well as the usage of multiple devices and across locations. The study distinguishes between native applications and mobile websites, which both are available on modern mobile devices. The focus was set on influencing aspects that can not always be controlled by the learner. This includes the screen size of devices that are available to the learner, as well as the network state during the learning process.

Therefore, five learning activities were observed for half a year in a quantitative study. The results show significant differences between the usage of native applications, mobile websites, and the overall average of the HPI MOOC platform (RQ1). However, no practical effect was proven between native applications and mobile websites. For native application, the screen size of the mobile device influence the learning activities of visiting items and starting the playback of video with a high significance and a large to medium effect size (RQ2). Such results can not be reported for mobile websites. When connected to a WiFi network, learners explore more items as learners using a cellular connection (RQ2). Furthermore, it can be concluded based on the results that learners prefer watching videos over a WiFi connection (RQ2). This work provides the basis for further enhancements to the HPI MOOC platform and for future research to improve the support and the adoption of mobile-assisted seamless learning methods for MOOCs.

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