Towards a Better Understanding of Mobile Learning in MOOCs

Tobias Rohloff
Hasso Plattner Institute
Potsdam, Germany
tobias.rohloff@hpi.de

Max Bothe
Hasso Plattner Institute
Potsdam, Germany
max.bothe@hpi.de

Jan Renz
Hasso Plattner Institute
Potsdam, Germany
jan.renz@hpi.de

Christoph Meinel
Hasso Plattner Institute
Potsdam, Germany
christoph.meinel@hpi.de

***Abstract*—The pervasive presence of mobile devices and growing trends like ubiquitous learning make new demands on Massive Open Online Courses (MOOCs). Users learn increasingly on the go and with multiple devices, instead of being tied to a fixed workstation. However, there is a lack of research how the usage of mobile devices influences the learning behavior and outcome in MOOCs. Thus, this paper presents a first quantitative study to examine this question. To enable a statistical analysis, a proof-of-concept implementation outline is presented, which enhances the Learning Analytics capabilities of the openHPI MOOC platform with contextual data to process various learning behavior metrics. Based on an analysis of four courses, it was found that users who additionally learnt with mobile applications showed a higher engagement with the learning material and completed the course more often. Nevertheless, the reasoning must be addressed with qualitative analyses in future, to better support their learning process and success on mobile and stationary devices.**

***Keywords*—Mobile Learning, Learning Analytics, MOOCs**

I. Introduction

Portable computing devices like notebooks, smartphones, tablets and wearables have become an integral part of our daily lives. They are getting cheaper, smaller, and most of them are connected to the Internet. The pervasive presence of these devices has made computing become ubiquitous [1]. Studies show that by 2020 about 70% of the worldwide population will use smartphones and up to 90% will be covered by mobile broadband networks [2]. This also affects the still growing trend of Massive Open Online Courses (MOOCs). Initially, MOOCs were only accessed online with web-based platforms, but the large availability of mobile devices and upcoming trends like ubiquitous learning caused new requirements on MOOCs. To provide proper access on mobile screens, the platforms were optimized with responsive layouts first. Additionally, most of the major MOOC providers published mobile applications in the recent years, to support learning at any time and any place, online and offline [3].

Also openHPI, the MOOC platform from Hasso Plattner Institute, faced these new circumstances and brought its platform to mobile devices. A survey conducted in 2016 with 840 participants showed that 84% of openHPI's users already own a smartphone and 60% have a tablet. Next to these changed technical requirements, mobile and ubiquitous learning also changes the way students use and interact with MOOC platforms. Instead of being tied to a fixed workstation, students can learn on the go now. At openHPI, 97% of users learn at home, 26% learn at work and 9% learn at the public transport according to the survey. Additionally, some users reported that they used openHPI at a hotel, a library or while they were waiting at the doctor. That indicates a fundamental change in how students learn on MOOC platforms if they use mobile devices next to the web platform.

Related research about MOOCs and mobile learning focuses on the conceptual compatibility and synergistic characteristics between both formats [4], as well as how mobile technologies can enrich the MOOC concept [5]. But not much work is available regarding the usage of regular MOOC content on mobile devices and how the learning behavior differs from the usage of stationary devices, like notebooks and desktop computers. Therefore, this paper examines the following research question: How does the usage of mobile devices influences the learning behavior and outcome in MOOCs?

In order to comprehend the users' learning behavior, their platform interactions must be captured. Thus, advanced Ubiquitous Learning Analytics (ULA) capabilities are necessary on all client applications, which additionally track contextual properties. A proof-of-concept implementation is outlined in Section II. Then, Section III describes how the captured data is processed and provides an inferential statistical analysis and discussion of the learning behavior of users with and without the usage of mobile devices. At last, Section IV concludes with a summary of this paper's contributions and findings, and discusses approaches to further examine the research question.

II. Ubiquitous Learning Analytics

This section provides an overview of the Learning Analytics (LA) capabilities of the openHPI MOOC platform and describes how the event tracking was enriched with contextual data and introduced for mobile, to provide a proof-of-concept implementation outline.

A. Learning Analytics with Contextual Data

The openHPI MOOC platform is implemented based on a Service Oriented Architecture (SOA) [6]. Given the architecture proposed in Figure 1, every service can be queried by a HTTP interface to access its stored data. A separate Learning Analytics service was introduced [7]. It is responsible for collecting, processing and storing xAPI-alike events from other services, distributed by a message queue. Currently tracked events on the platform include – but are not limited to – video player events, download events, page visits, forum activities, quiz submissions, course enrollments and completions.

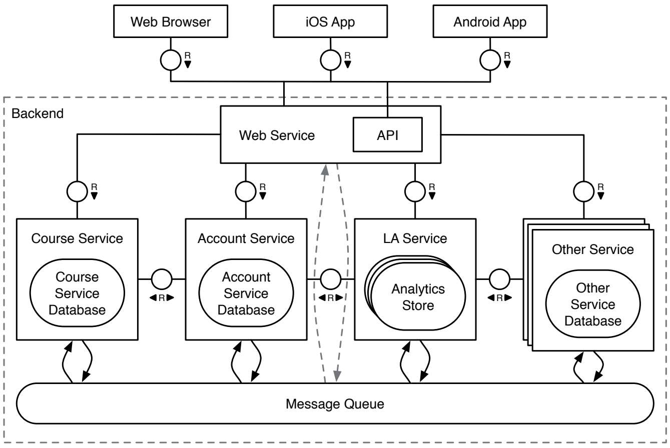

Fig. 1. The Platform's Service Oriented Architecture

Based on the following proposed context model, it is possible to determine the required data that has to be captured. A wide variety of definitions for the terms context and context-awareness are available [8]. For openHPI's domain of e-learning and MOOCs, the entity is specified as the learner and its context is defined as related information about its used device and application, as well as its physical state. The research question of this paper only investigates the learner's used devices, but its local time and place are also part of the context model for future research, to have a full data set of contextual data available.

To gain these insights, every tracked user interaction event is enriched with additional contextual data. A basic information about the device is for example the installed operating system. This is tracked as the *platform*, on which the application *runs on*. To distinguish if the web client or a native mobile client is used on the platform, the *runtime* is captured, in which the application *runs in*. This could be either a certain browser for the web client or the operating system itself for a native application. To determine the type and size of the device, a device name and data about the screen resolution are captured. Additionally, all events capture the users' time and location. This is a strong indicator about the learners' situation, where and when they use the platform. Additionally, information about the network connection are useful to determine the situation because a Wi-Fi network is mostly available on stationary and familiar places, like at home or work. A mobile network connection indicates that the learner is on the go or at a foreign place.

B. Mobile Learning Analytics

The usage of mobile devices causes specific demands on the implementation of Learning Analytics, whereby a differentiation as Mobile Learning Analytics (MLA) is common [9]. Unlike regular computers, mobile devices are frequently exposed to network connection changes and interruptions, particularly while they are still in use. Hence, a MLA implementation has to be aware of network changes and should avoid data losses. This becomes even more important by the circumstance that the mobile applications of openHPI can be partially used offline. Because of that, the MLA implementation has to keep the data until a network connection is available again, even when the application was closed in the meantime. An appropriate data persistence layer was used to fulfill this requirement for openHPI's Android and iOS applications.

Due to the fact that most network providers limit the bandwidth after a certain amount of used data, the MLA implementation should avoid to strain the data usage during mobile network connections extensively. Instead, the use of Wi-Fi networks should be preferred. To address this issue, every event type keeps the information if it should be transferred only via Wi-Fi.

III. Mobile Learning Behavior and Outcome

This section presents a first evaluation how the usage of mobile devices influences the learning behavior and outcome in MOOCs. To process and extract the event data, this paper partially utilizes the previously implemented capabilities of the openHPI platform. The Learning Analytics service provides metrics to gain insights about the user's behavior from interaction events, which was initially introduced by [10] and extended by [11]. The provided metrics are grouped into multiple categories, whereby this paper utilizes metrics about the user's session, activity, discovery and performance. Additionally, a new client usage metric was introduced to evaluate the contextual properties of the used devices and applications.

A. Evaluated Courses

For the scope of this paper four courses have been examined, which were running in 2017 and 2018. Two from the openHPI platform and two from the openSAP platform, which is based on the same technology as openHPI. All courses had a similar length of 6 weeks and similar examination modalities: every week was structured into multiple short video lectures followed by ungraded self-tests. At the end of every week a graded quiz was conducted and at the end of the courses a final exam was performed. All course contents were completely feasible on mobile, to avoid a bias by non-optimized learning items for mobile like peer assessments or external exercises. The course topics were Internet Security (intsec2018), Big Data (bigdata2017), Machine Learning (ml2) and Cloud Computing (cp5). Therefore, it can be assumed that the target audience had at least an affinity for ICT topics. The courses were certified with a Confirmation of Participation (CoP), if at least 50% of the course material was completed, and a Record of Achievement (RoA), if more than 50% of the maximum number of points for the sum of all graded assignments were earned.

TABLE I
DESCRIPTIVE AND INFERENTIAL STATISTICS FOR LEARNING BEHAVIOR METRICS OF LEARNERS WITH AND WITHOUT MOBILE APP USAGE

		Without Mobile App			With Mobile App			Mann–Whitney U		
Metric	Course	N	Mean	Std.Dev.	N	Mean	Std.Dev.	U	p-value	Cohen's d
Visited Items (Percentage)	intsec2018	4162	0.310	0.374	947	0.402	0.407	1675063.0	<0.001	0.243
	bigdata2017	5805	0.326	0.356	1331	0.397	0.380	3323282.5	<0.001	0.195
	ml2	8567	0.343	0.348	516	0.429	0.354	1825712.0	<0.001	0.247
	cp5	4023	0.260	0.326	336	0.343	0.381	622368.0	0.016	0.253
Avg. Session Duration (Seconds)	intsec2018	4162	977.773	1100.513	947	953.391	875.269	1868585.0	0.013	0.023
	bigdata2017	5795	973.816	948.304	1331	909.371	705.853	3797674.0	0.334	0.071
	ml2	8564	817.083	868.271	516	786.128	578.259	2063573.5	0.011	0.036
	cp5	4023	802.863	831.751	336	771.420	716.840	678590.0	0.902	0.038
Quiz Performance (Percentage)	intsec2018	4162	0.341	0.396	947	0.461	0.404	1662879.0	<0.001	0.301
	bigdata2017	5795	0.368	0.369	1331	0.457	0.357	3395540.0	<0.001	0.243
	ml2	8564	0.479	0.412	516	0.598	0.376	1898503.0	<0.001	0.290
	cp5	4023	0.349	0.385	336	0.403	0.373	632467.0	0.035	0.139
Video Plays (Percentage)	intsec2018	4162	0.185	0.338	947	0.315	0.415	1442882.0	<0.001	0.369
	bigdata2017	5795	0.196	0.296	1331	0.281	0.336	3113444.0	<0.001	0.278
	ml2	8564	0.206	0.278	516	0.300	0.295	1629490.0	<0.001	0.335
	cp5	4023	0.182	0.282	336	0.270	0.342	537533.0	<0.001	0.308
Video Downloads (Percentage)	intsec2018	4162	0.090	0.267	947	0.119	0.300	1833878.5	<0.001	0.106
	bigdata2017	5795	0.114	0.264	1331	0.169	0.295	3315855.0	<0.001	0.204
	ml2	8564	0.046	0.163	516	0.167	0.269	1504152.0	<0.001	0.708
	cp5	4023	0.036	0.156	336	0.075	0.214	610122.5	<0.001	0.237
Slide Downloads (Percentage)	intsec2018	4162	0.092	0.254	947	0.123	0.295	1852733.5	<0.001	0.121
	bigdata2017	5795	0.087	0.207	1331	0.118	0.231	3500232.5	<0.001	0.149
	ml2	8564	0.042	0.143	516	0.115	0.233	1762436.5	<0.001	0.490
	cp5	4023	0.044	0.145	336	0.071	0.193	642374.0	0.054	0.180
Forum Activity (per Day)	intsec2018	4162	0.174	1.138	947	0.256	1.856	1980503.0	0.789	0.063
	bigdata2017	5805	0.306	1.540	1331	0.438	2.286	3814122.5	0.441	0.078
	ml2	8567	0.116	0.758	516	0.126	0.409	2052587.0	0.001	0.014
	cp5	4023	0.074	0.493	336	0.093	0.442	650976.0	0.168	0.039

B. Methodology

The mobile apps are considered as an additional offering next to the web platform to enable users to learn at any time and any place as a seamless learning approach. Therefore, the learners were split into two groups: those who used the mobile apps next to the web platform and those who not. Both MOOC platforms provide an authentic learning environment with real-world users. However, this resulted in unequal group sizes since it is not a controlled experiment environment and users could decide on their own to use the mobile apps or not.

For every user different metrics were processed based on the Learning Analytics events with contextual data. The *Client Usage* metric was used to split the learners into the two introduced groups. Additionally, seven metrics about the learning behavior were calculated. The *Visited Items* metric provides the number of unique visited learning items normalized to the total number of items in a course as percentage, which is the main criteria to gain a CoP. The *Average Session Duration* is the total duration of all sessions in relation to the total number of sessions. A single session is calculated by all consecutive events with no wider gap then 30 minutes. The *Quiz Performance* shows the average percentage of correct answers of all quizzes, which is a strong indicator if a RoA was gained. The *Video Plays* metric shows the percentage of unique watched videos in relation to the total number of videos in a course. Similar, the *Video Downloads* and *Slide Downloads* metrics provide the percentage of unique videos and slides downloaded in relation to the total number of videos in a course. At last, the *Forum Activity* shows the sum of all textual forum contributions like questions, comments and answers, as well as forum observations like question subscriptions and question visits, normalized to the number of days between a course start and end date.

For both user groups all learning behavior metrics were examined for statistically significant differences with a Mann-Whitney U test for two independent samples (Table I). Also, the effect sizes were calculated with Cohen's d for groups with different sample sizes. In Table II descriptive statistics about both groups' age, gender and learning outcome are presented.

C. Analysis and Discussion

For the learning behavior metrics in Table I it can be seen that learners who used the mobile apps visited more learning items on average, with a highly significant difference ($p < 0.001$) in three courses and a significant difference in one course ($p = 0.016$). Also, a small effect was measured in three courses ($d > 0.2$). For the average session duration, a significant difference was found in two courses, but no practical effect was proven. The quiz performance shows a higher average for learners who used the mobile apps, with a highly significant difference in three courses ($p < 0.001$) with a small

TABLE II
DESCRIPTIVE STATISTICS FOR DEMOGRAPHICS AND LEARNING OUTCOME OF LEARNERS WITH AND WITHOUT MOBILE APP USAGE

			Demographics		Outcome	
Course	Group	N	Age Mean	Female Quota	CoP Quota	RoA Quota
intsec2018	without app	4162	45.6	0.138	0.281	0.172
	with app	947	39.9	0.154	0.369	0.270
bigdata2017	without app	5805	43.0	0.162	0.279	0.115
	with app	1331	41.2	0.129	0.331	0.184
ml2	without app	8567	39.1	0.090	0.288	0.164
	with app	516	36.5	0.036	0.368	0.225
cp5	without app	4023	39.9	0.114	0.203	0.130
	with app	336	37.3	0.067	0.318	0.250

effect size ($d > 0.2$) and a significant difference in one course ($p = 0.035$) but without a practical effect size. For all courses the video plays and video downloads metric showed higher averages with highly significant differences ($p < 0.001$). A small practical effect ($d > 0.2$) was proven for the video plays metric of all four courses. For the video downloads metric two courses had a small effect size ($d > 0.2$) and one course even had an intermediate effect size ($d = 0.708$). The slide downloads metric shows slightly higher averages for users who used the mobile apps with highly significant differences ($p < 0.001$) in three courses, but only one course with a small practical effect ($d = 0.49$). For the forum activity only one course shows a highly significant difference ($p = 0.001$), but no course had a practical effect.

It can be summarized that users who used the mobile apps visited more items, performed better in quizzes, and watched and downloaded more videos. Highly statistical differences and small statistical effect sizes were proven. From the perspective of the authors – with regards to their experience and domain knowledge of operating MOOC platforms – the results are considered of practical relevance. However, no significant differences and effects were shown for the average session durations, slide downloads and forum activities. Also, large and unequal sample sizes from authentic learning environments like MOOCs lead quickly to highly significant results and affect the probability of Type II errors.

The demographical means in Table II about age and gender of both groups show no practical relevance from the authors' perspective. Nevertheless, the learning outcome based on gained certificates improves on average for learners who also used the mobile apps, which is supported by the findings of the visited items and quiz performance metrics. All in all, the results of this paper show that mobile learners tend to be more engaged with the learning material and be more successful in general. However, the causality needs to be examined further with qualitative studies, e.g. through user interviews. In future it must be analyzed which learning activities a user performs especially on mobile and which on the web platform with regards to their situation, to better address and support their learning routines and improve their satisfaction and success.

IV. CONCLUSION

This paper presented a first quantitative study to examine the research question how the usage of mobile devices influences the learning behavior and outcome in MOOCs. To enable a statistical analysis, a proof-of-concept implementation outline was presented, which enriched the Learning Analytics event tracking capabilities of the openHPI MOOC platform and its mobile applications. Based on the defined and implemented context model, the tracked interaction events of users' learning activities could be processed into different learning behavior metrics, which were examined about their statistically significant differences and effect sizes between users who only used the web platform and users who also used the mobile applications next to it.

Four courses from two real-world MOOC platforms were studied. It was found that users who additionally learnt 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. Nevertheless, the causality and practical impact for the higher engagement and success needs to be studied in future with qualitative evaluations. It is also planned to examine which activities users specifically perform in which situation on which device, to better support their learning process and success.

REFERENCES

[1] B. Cope and M. Kalantzis, "Ubiquitous Learning: An Agenda for Educational Transformation," *Proceedings of the 6th International Conference on Networked Learning*, 2008.

[2] Ericsson, "Ericsson Mobility Report," 2015. [Online]. Available: https://www.ericsson.com/news/1925907

[3] J. Renz, T. Staubitz, and C. Meinel, "MOOC to Go," in *Proceedings of the 10th International Conference on Mobile Learning*, 2014.

[4] I. deWaard, A. Koutropoulos, N. Keskin, S. C. Abajian, R. Hogue, C. O. Rodriguez, and M. S. Gallagher, "Exploring the MOOC format as a pedagogical approach for mLearning," in *Proceedings of 10th World Conference on Mobile and Contextual Learning*, 2011.

[5] M. Sharples, C. D. Kloos, Y. Dimitriadis, S. Garlatti, and M. Specht, "Mobile and accessible learning for MOOCs," *Journal of Interactive Media in Education*, vol. 2015, no. 1, 2015.

[6] M. Totschnig, C. Willems, and C. Meinel, "openHPI: Evolution of a MOOC Platform from LMS to SOA," in *Proceedings of the 5th International Conference on Computer Supported Education*, 2013.

[7] J. Renz, G. Navarro-Suarez, R. Sathi, T. Staubitz, and C. Meinel, "Enabling Schema Agnostic Learning Analytics in a Service-Oriented MOOC Platform," in *Proceedings of ACM Learning at Scale Conference (L@S2016)*. ACM, 2016.

[8] G. D. Abowd, A. K. Dey, P. J. Brown, N. Davies, M. Smith, and P. Steggles, "Towards a Better Understanding of Context and Context-Awareness," in *Proceedings of the 1st International Symposium on Handheld and Ubiquitous Computing*. Springer-Verlag, 1999.

[9] M. A. Chatti, V. Lukarov, H. Thüs, A. Muslim, F. A. M. Yousef, U. Wahid, C. Greven, A. Chakrabarti, and U. Schroeder, "Learning Analytics: Challenges and Future Research Directions," *eleed*, vol. 10, no. 1, 2014. [Online]. Available: http://nbn-resolving.de/urn:nbn:de:0009-5-40350

[10] J. Renz, D. Hoffmann, T. Staubitz, and C. Meinel, "Using A/B Testing in MOOC Environments," in *Proceedings of the 6th International Conference on Learning Analytics and Knowledge (LAK2016)*. SOLAR, 2016.

[11] R. Teusner, K.-A. Rollmann, and J. Renz, "Taking Informed Action on Student Activity in MOOCs," in *Proceedings of the Fourth ACM Conference on Learning at Scale (L@S2017)*. ACM, 2017.