

From MOOCs to Micro Learning Activities

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

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

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

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

Abstract—Mobile devices are omnipresent in our daily lives. They are utilized for a variety of tasks and used multiple times for short periods throughout the day. MOOC providers optimized their platforms for these devices in order to support ubiquitous learning. While a combination of desktop and mobile learning yields improved course performances, standalone learning on mobile devices does not perform in the same manner. One indicator for this is the mismatch between the average usage pattern of mobile devices and the time to consume one content item in a MOOC. Micro learning builds on bite-sized learning material and focusses on short-term learning sessions. This work examines the potential of micro learning activities in the context of MOOCs. Therefore, a framework for video-based micro learning is presented, which features a personalized curriculum. Videos are suggested to the user in a non-linear order that is determined by content dependencies, users' preferences and watched videos, as well as explicit and implicit user feedback. A mobile application was implemented to test the approach with restructured MOOC content resulting in 58 connected short videos about engineering education – e.g. web technologies and programming languages. The usage data indicates initial curiosity by the users. To improve retention rates, more user motivation will be required for future studies. A survey gathered additional qualitative feedback. While the content suggestions were seen as a vital feature for such an approach, the results showed good interest and acceptance rates to create a better learning experience for MOOCs on mobile devices.

Index Terms—Micro Learning, MOOCs, Mobile Learning, E-Learning

I. INTRODUCTION

Mobile devices have evolved by getting smaller, easier to use and more affordable. Nowadays, they are omnipresent in our daily lives and are utilized for a variety of tasks. The time spent using mobile devices is still increasing [1]. At the same time, more and more people can access the Internet. In 2017, 98% of the population in developed countries, as well as 50% of the population in developing countries, already own mobile-broadband subscriptions [2]. For 2020, it's predicted that 70% of the world population is supposed to own a smartphone while 90% will have access to mobile-broadband networks [3]. These circumstances have and will further change the way we consume information. Mobile devices can be used to quickly retrieve needed data. Hence, they are used multiple times for short periods throughout the day [4].

When Massive Open Online Courses (MOOCs) [5] began to offer new learning opportunities to everybody in 2011, the learner experience was focused on desktop learning with

traditional websites. However, by 2015 most of the major MOOC platforms provided an additional mobile learning experience [6]. This was achieved by optimizing the website for mobile devices [7] or by creating native mobile apps for iOS and Android. By doing so, they enabled further possibilities for ubiquitous learning [8]. Based on a study among life-long learner, Tabuenca, Ternier, and Specht discovered that already 56% of the participants used their mobile phone on a daily basis in 2012 [9]. Nowadays, MOOCs are being implemented for a variety of different use cases: For example, they provide new ways for enterprise training [10] and offer health education, while the traditional usage for educational purposes still exists [11].

Besides all the advantages and possibilities of mobile learning [12], [13], it is not the best solution for all learner types and learnings activities. Beasley, McMain, Millard, *et al.* discovered in a study that mobile phones distract most learners during their learning activities [14]. When the learning activities take place on a mobile device, the learner is likely to be distracted by today's common notification settings unless the learner explicitly disabled these notifications. However, modern operating systems provide similar notification mechanisms. Nevertheless, some learners prefer to use the traditional desktop application over mobile alternatives because they provide a larger screen and external input devices [15]. Additionally, most MOOC material is produced to be consumed on such larger screens while being stationary - due to the historical development and since this yields better results and learner experiences on average when compared to learning while moving [16]. Still, Rohloff, Bothe, Renz, *et al.* have discovered that users who combine desktop and mobile learning activities achieved better overall course results than users who only use the desktop experience [17]. This opens the question if traditional MOOC content and structure is suitable for mobile-only learner experiences.

When comparing the short usage pattern on mobile devices with the content and structure offered on a MOOC platform, mismatches show up. On average, activities on mobile devices last only for one minute during the day [4], whereas the average duration of all videos on a MOOC platform converges around twelve minutes [18]. This significantly exceeds the session duration on mobile devices and results in the hypothesis that unchanged traditional MOOC content is not suitable for mobile learning. Furthermore, mobile devices are used multiple times throughout the day [4] making it harder for

the learner to stick to the linear MOOCs content navigation.

This forms an opportunity for micro learning to fill the gap. By building on bite-sized learning material and focussing on short-term learning sessions [19], the learner will go through an increased number of feedback cycles. Thus, this enables a better adaptation to the user's learning intents and allow the micro learning system to be used in transient situations. We want to investigate this with an experimental mobile micro learning service, which evaluates a non-linear content navigation through short videos – the most used media type in MOOCs – creating a more personalized curriculum for the learner. Therefore we defined the following research questions:

RQ1 What are the usage patterns and acceptance rates of a video-based micro learning platform?

RQ2 How do non-linear content suggestions compare to conventional linear MOOC navigation?

To further examine such micro learning approach on mobile devices in the context of MOOCs, this paper discusses related work in Section II. In Section III, a structure for reorganizing MOOC learning material is proposed. The testing setup will be explained and the implemented prototype will be evaluated in Section IV. In Section V, possible future work to further enhance the presented approach is laid out. Section VI concludes this works.

II. RELATED WORK

Micro learning aims to support “the growing need of lifelong learning and learning on demand” [20]. It builds on micro content which are content chunks that can be consumed quickly due to the bite-sized content length and only covers a single subject [19], [20]. Such an approach works better with the average session duration of mobile applications described by Böhmer, Hecht, Schöning, *et al.* [4] compared to traditional MOOC content. Hence, micro learning is highly suitable for mobile learning and can be optimized for mobile devices.

When bringing micro learning to the MOOC experience, existing content should be reused. For this, the traditional MOOC content has to be segmented in order to reduce the cognitive load [21]. Zhang, Li, Li, *et al.* proposed a scalable partition approach by automatically detecting visual transitions [22]. They point out that such a segmentation creates the foundation for supporting a non-linear content navigation. Che, Yang, and Meinel also examined this topic by analyzing transitions and page layout changes in a separate slide stream [23]. Their adaptive approach reached an accuracy of 85% in detecting content changes. Beside the technical perspective, the micro content items should always preserve the semantic context within an item to ensure a pedagogical sound element.

In order to formalize the content creation, Kovachev, Cao, Klamma, *et al.* [24] defined a process to acquire and organize the micro learning content. It consists of phases for receiving the content material, managing the content and annotating the content with tags. These tags allow the content to be enhanced in terms of context, preference and semantics, as well as connections to other content elements.

Tortorella and Graf [25] defines required components for a system for micro content, which includes a context modeling component and an adaptive engine inside a mobile device. Furthermore, they list potential content types for micro learning, such as video, audio, text and graphical presentations. This adaptive system was transferred to a MOOC platform by Sun, Cui, Guo, *et al.* [26]. They implemented a version of the proposed approach and explored the possibility to provide micro learning via a Software as a Service solution. As a result, a refined personalized learner model was presented, which considers several internal factors, like prior knowledge and preferences, as well as external factors, like learning locations and device types. They categorized the video content according to the duration. Resources with a duration of 15 minutes or shorter remained unchanged, while longer segments were cut programmatically into smaller segments. We plan to use even smaller content items to better match mobile usage patterns. Furthermore, we want to derive the user's curriculum from previous micro learning activities along with explicit and implicit feedback of the learner, leading to a variant of the *Open Learner Model* [27]. Building on that, Verpoorten, Glahn, Kravcik, *et al.* discussed the personalization methods in online learning environments [28]. Among others, they suggest using tracked data of the users as an input for the adaptive systems. This approach provides the advantage that the usage data can also be utilized for quantitative analyses in addition to supporting the system functionality.

Bruck, Motiwalla, and Foerster [29] tested a micro learning approach for desktop computers and mobile phones. They discovered that avoiding an information overload, but still providing a continuous information flow, is crucial for supporting knowledge retention and ensuring user satisfaction. In a mobile micro learning study by Dingler, Weber, Pielot, *et al.*, 38% of the learners used the mobile app prototype in transit [30]. They pointed out the engagement of the participants for quick learning sessions when in transit – underlining the importance of mobile-optimized approaches. However, successful micro learning does not have to be restricted to mobile learning. Gassler, Hug, and Glahn [31] achieved a 75% acceptance rate for a stationary micro learning study.

With this work, we do not plan to replace the existing MOOC concept on mobile devices. All learnings materials should be available all the time across all platforms. Moreover, micro learning can close a gap in mobile learning. This can enhance the MOOC experience through learning material with a reduced content length and a more personalized curriculum based on content suggestions. Therefore we reshaped MOOC learning material and organized the content following the process described by [24]. By defining dependencies between content items, we create a semantical order. For creating personal learner paths, we focused on incorporating previous activities as well as learner feedback. We investigated the technical aspects of connecting this micro content via dependencies to create a content repository, which allows personalized learning paths based on usage data [28]. When designing the user-facing component, we considered the findings of [29] and kept

it simple and non-distracting.

III. A CONTENT REPOSITORY STRUCTURE FOR MICRO LEARNING

When investigating the learning material structure of a traditional MOOC, the content shows a linear structure by being organized into weeks or sections. In order to enable a higher degree of personalization, this linear structure has to be broken up into smaller segments in order to be reused for micro learning. Therefore, this section focuses on how MOOC learning material can be transformed and organized for a personalized micro learning approach.

A. Requirements

In order to provide the required degree of personalization, a content repository structure is needed which is able to compute a curriculum of each user, based on the user's preferences. As the user's preferences can change over time, the next suggested content item has to always be derived from the most recent state. Furthermore, the feedback the users gave on the content should be included. This information especially helps to rate the content for a particular user. Such feedback can be given explicitly or implicitly. By rating suggested items, the users provide explicit feedback. When users discard a suggestion, they provide implicit feedback. Following this concept, the set of videos watched by the users, as well as usage times, session durations and other interactions aid further optimizations for the personalized content suggestion. Taking all these factors into account, it concludes that it would be insufficient to pre-calculate a personalized curriculum. A better approach is to determine the next fitting content on demand when the user requests a new suggestion. Nevertheless, this calculation has to be deterministic in order to be testable and non-confusing to the users.

B. Transforming MOOC Content for Micro Learning

When reusing MOOC content for micro learning, long videos have to be adapted and cut in order to fit into the suggested timeframe of four to six minutes [26]. Depending on the speaker and the structure of the course, this time period covers one to three presentation slides and, thus, creates a good opportunity to split the learning material. This results in a video with a duration within the suggested timeframe. When producing new MOOC content, it becomes useful to make sure that the video always matches the audio, in order to allow a clean cut. Otherwise, new visual information will appear while the audio is still about the previous topic. Such reshaped MOOC content allows moving from a linear curriculum to a more personalized approach as parts can be skipped or reordered to fit the user's preferences. A similar approach was shown in [32] for an e-librarian service.

C. Content Repository Model

This subsection proposes a graph structure to organize the micro learning material in a content repository that is able to fulfill the requirements explained in Subsection III-A. Videos

are enriched with dependencies to other videos and can be organized into groups to allow better dependency management. Furthermore, videos are assigned to one or multiple topic categories based on their conveyed information. The content repository also stores the user preferences and which videos are suggested to and watched by the user. Figure 1 displays the required nodes and corresponding relationships. To improve the readability, the attributes of nodes and relationships were omitted. These attributes are for example timestamps when a video was watched or suggested, as well as weightings of a user's preference for a category or a video's association with a category. Videos without any dependencies are entry points to the content repository by definition. When enriching the content with dependencies, it is highly encouraged to create a dependency tree that is sufficiently flat and forms as many entry points as possible. Additionally, the dependencies of a video can also stretch over multiple levels. To provide an efficient implementation, a graph database should be utilized, which allows a fast graph traversal over all the dependencies of a video [33].

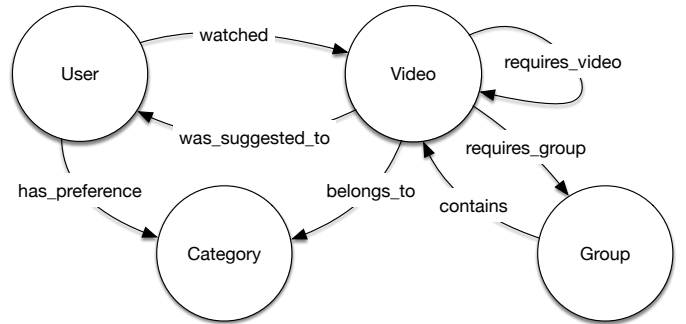


Fig. 1: Content Repository Model

D. Content suggestion

When calculating the next content suggestions, the following parameters and requirements were taken into account:

- A video can only be suggested to a user when all of the dependent videos have already been watched by the user
- Videos that have already been watched will not be suggested again¹
- The user's preferences must be taken into account
- The video's categories must be considered
- The feedback of the user is included (explicit rating of the watched videos, implicit feedback through dismissed video suggestions)

All videos with fulfilled dependencies have to be rated for a given user to determine the next best content suggestion. The implementation of calculating the rating of a video v for a user u is based on the following definitions – considering the node types displayed in Figure 2. The overall rating of a video (Equation 1) is influenced by the user's ratings of the video's categories. In turn, the user's rating of the video's

¹Previously watched videos can be accessed via a separate menu.

category (Equation 2) is determined by combining the user's preferences and the explicit feedback given by rating watched videos (Equation 3).

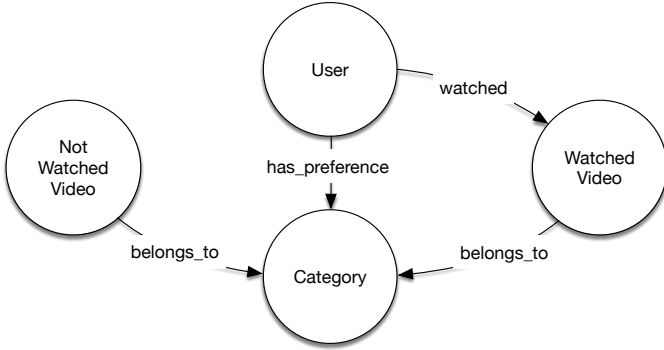


Fig. 2: Determination of Content Suggestion (Graph Schema)

$$r_V(u, v) = \sum_{c \in \mathcal{C}} (w(v, c) * r_C(u, c)) \quad (1)$$

$$r_C(u, c) = f_C(u, c) * p(u, c) \quad (2)$$

$$f_C(u, c) = \frac{\sum_{v \in \mathcal{RV}_u} (w(v, c) * f_V(u, v))}{|\mathcal{RV}_u|} \quad (3)$$

$p(u, c)$: Preference value of user u for category c

$f_V(u, v)$: Explicit feedback of user u for video v

$f_C(u, c)$: Computed feedback of user u for category c

$r_C(u, c)$: Computed rating of category c for user u

$r_V(u, v)$: Computed rating of video v for user u

$w(v, c)$: Weighting of video v in category c

\mathcal{C} : Categories

\mathcal{RV}_u : Videos rated by user u (explicit feedback)

IV. EVALUATION

This section presents the results of testing the micro learning approach with restructured MOOC learning material stored in a content repository. For this, the applied methods and the implemented prototype are described - followed by a quantitative evaluation of the learner behavior and a qualitative evaluation of user feedback.

A. Prototype

The proposed concept was implemented as a prototype for the iOS platform (shown in Figure 3). It featured a simple workflow. First, the users were able to choose multiple categories they are interested in. Next, a single video is suggested to the user. The user can decide to watch or dismiss a video suggestion. When the user completed watching a video, the next video will be suggested by the application. Watched videos will never be suggested to the user again,

while dismissed videos could be suggested the following day. The prototype was tested with the help of the openHPI² community by providing the prototype as a supplementary learning tool to regular MOOC activities. This environment was used to gather insights regarding learner behavior and feedback in an authentic learning context.

We used a mixed method approach for the evaluation of this study. For quantitative insights, we investigated the activity tracking data, which was produced by participants. Partly this data was also used to calculate the content suggestions for the users. To receive qualitative feedback, we asked the users to participate in an optional survey on their device after they watched three videos. If a user decided not to participate immediately, there was always the option to open the survey at a later point via a submenu.

Apple's App Store was used to distribute the application. The test was open to everyone with an iPhone or iPad running at least version 10.0 of iOS but limited to the countries Germany, Austria and Switzerland since the provided content was only available in the German language. The overall evaluation phase was running from March 23 to May 5, 2017. To increase the awareness of the application inside the openHPI learner community, it was promoted in several ways, like social media posts on Twitter and Facebook, global announcements for all platform users, and an email newsletter for the most active iOS users.

In total, the created knowledge repository features 58 videos and 8 categories (user preferences). These videos with a maximum duration of 4 minutes were created manually by segmenting 6 video lectures from the openHPI platform about introductory IT engineering education – e.g. web technologies, internet security and programming languages – as well as 9 short OER videos about communication networks provided by the SODIS Content Pool³. Afterward, the knowledge repository was created by defining the semantical order of the videos, assigning dependencies to the videos and tagging the video content with suitable categories. For this first iteration, the content repository was created manually in order to bypass potential technical issues and to have a minimal base that can be extended later on.

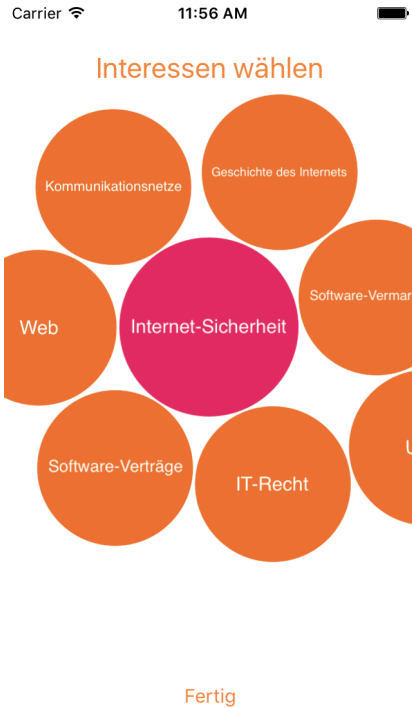
B. Learner Behavior

Overall, 535 users who logged into the system were registered. 5277 video suggestions were presented to these users. 673 video playbacks were started while 2303 suggestions were discarded. The users were categorized into three groups (Table I). Each group holds approximately a third of all users. At end of the study, 181 users were in the watch group who actively used the prototype.

1) *Usage Duration*: Next, we focused on how many days the users interacted with the application. Therefore, the number of days between the first content suggestion and the last content suggestion was calculated. A new content suggestion

²<https://open.hpi.de/>

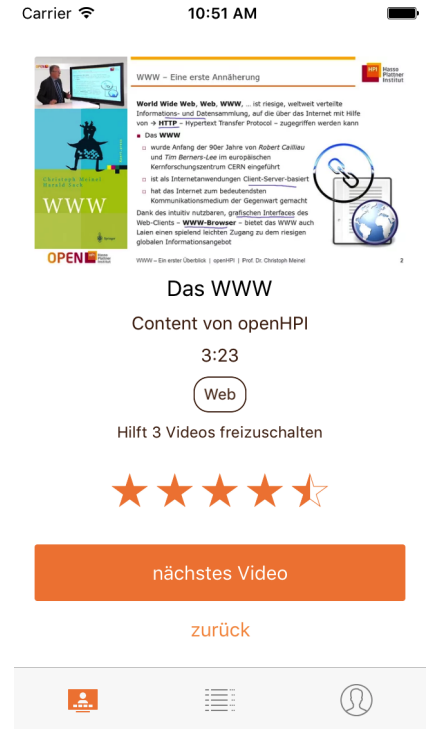
³<https://cp.sodis.de/pool/oer/>



(a) Preference Selection



(b) Video Suggestion



(c) Content Rating

Fig. 3: Prototype Screenshots

TABLE I: User Groups

User Group	Description	Share
No activity	Users who have neither watched nor dismissed a video	33.8%
Dismiss only	Users who have only dismissed but never watched videos	33.5%
Watch	User who have watched and dismissed videos	32.7%

is made every time the user opens the application. Figure 4 displays the number of users for different time periods as a bar chart. The majority of users interacted with the application only for a single day. This number is also influenced by all the users who wanted to try out this concept. The amount of other usage periods is significantly lower. It is notable that the overall usage duration is grouped in an approximately seven-day difference in the second and third week (12-14 days and 18-20 days). This indicates either a weekly usage pattern or a reactivation through the promotional campaigns.

In addition to the overall usage period, we explored the number of days on which the users interact with the application. For that, we counted every day the user got a content suggestion. In Figure 5 the distribution of active days is shown. Trivially, users with an overall usage period of one day can only be active on a single day. Then, the number of usage days decreases exponentially. 116 users were active for two days while 37 users used the application for three days, while

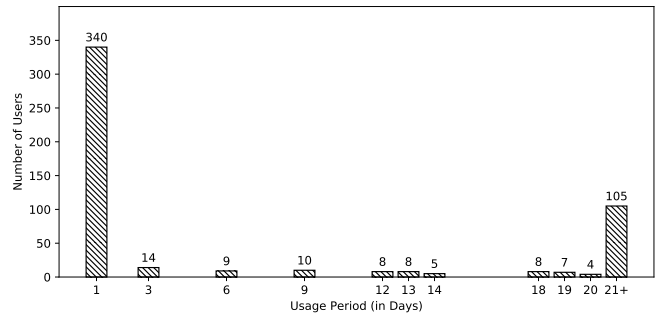


Fig. 4: Usage Period (Bar Chart)

the maximum usage of the application was ten days.

2) *Watched Videos on Day of Usage*: The next presented metric investigates the number of watched videos on a given day of usage. Therefore, in Figure 6(a) a box plot (whiskers with a maximum of 1.5 times of the interquartile range) of the first 10 days is shown. It builds only on the tracked watch activities and in this way shows always a minimum count of 1 for the number of watched videos. Otherwise, users who have not watched any videos on a specific day would dominate the data. Day one is characterized by users who energetically explore the content (outliers) and users who watched only one video, resulting in a median of 1. The days two to seven show a comparable watch behavior with a median of around 2 watched videos and 50% of the active users of that day

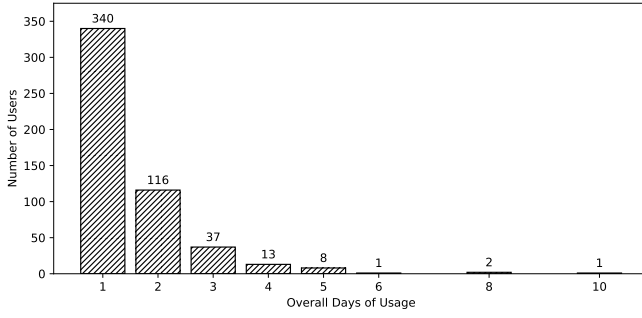


Fig. 5: Overall Days of Usage (Bar Chart)

are watching less than 5 videos. Complementary, Figure 6(b) displays the arithmetic mean of the watched videos across all users on a day of usage. The data show a significant decrease in watch activities per usage day after the first day (with 0.74 to 0.12 watched videos on average). After the fifth day, the value lowers to 0.03 watched videos per usage day. This indicates initial curiosity by the users in such an approach. To improve the retention rate, additional user motivation will be required after the first days of usage.

3) *Watch Order of Videos*: The implementation of a personalized curriculum affects the order in which video content elements are consumed. Every user has their own watch history, which is also influenced by the quality of content suggestions. By rating watched videos, the user can create a higher degree of personalization. This is reflected by a more diverse watch order of videos. Therefore, Table II lists the distribution of the watch order for the five most watched videos. The distribution contains columns for the first five watched videos as well as one column for videos that were watched later. Additionally, the watch count and the number of dependencies are stated for each video. The data shows a clear distribution of the watch order of the videos indicating a custom information flow for different users.

TABLE II: Watch Order (No Dependencies - Top 10)

video id	watch count	dependency count	watch order distribution (in %)					
			1	2	3	4	5	later
38	60	0	26.52	4.72	4.55	6.38	3.12	0.00
1	54	0	18.78	13.21	3.03	0.00	0.00	2.14
26	49	0	11.05	12.26	3.03	4.26	6.25	5.35
46	38	0	11.60	3.77	7.58	2.13	9.38	2.14
47	33	0	6.63	7.55	4.55	6.38	0.00	3.74
57	22	0	4.97	3.77	1.52	4.26	3.12	2.67
56	19	0	2.76	2.83	3.03	0.00	6.25	3.74
55	19	0	2.76	1.89	1.52	4.26	3.12	4.28
49	19	0	2.21	0.94	1.52	4.26	3.12	5.35
54	18	0	1.66	2.83	6.06	0.00	3.12	3.74

Table II includes only videos without dependencies, which are therefore more likely to be suggested and watched earlier. Because of that, Table III shows the ten most-watched videos

with one video dependency. Obviously, the listed videos cannot be played as the first content. Compared to the data in Table II, the values are spread more evenly supporting the claim of a personalized curriculum.

TABLE III: Watch Order (1 Dependency - Top 10)

video id	watch count	dependency count	watch order distribution (in %)					
			1	2	3	4	5	later
42	18	1	0.00	8.49	4.55	4.26	6.25	0.53
44	15	1	0.00	6.60	7.58	0.00	3.12	1.07
27	12	1	0.00	3.77	3.03	2.13	3.12	2.14
2	12	1	0.00	3.77	6.06	2.13	0.00	1.60
39	11	1	0.00	0.94	0.00	6.38	6.25	2.67
43	10	1	0.00	2.83	3.03	6.38	3.12	0.53
41	9	1	0.00	0.00	1.52	6.38	3.12	2.14
30	9	1	0.00	0.94	6.06	0.00	0.00	2.14
33	8	1	0.00	0.94	1.52	2.13	0.00	2.67
40	7	1	0.00	0.00	1.52	2.13	0.00	2.67

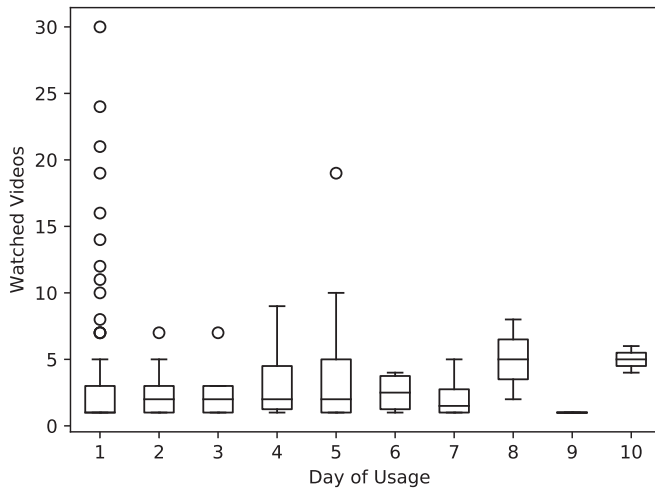
4) *Discussion*: In summary, the collected data supports our assumptions of a mobile learning approach with a personalized curriculum. The users showed different behaviors in usage duration and content choice. But the user's attention was driven by promotions and curiosity. The global announcement activated many openHPI users to try this concept. Therefore, a general interest among openHPI users is given. If such a concept would be integrated into the openHPI platform, it could also provide a method to discover new content and MOOCs matching the user's preferences. The presented metrics provide a foundation for further analyses. Especially, correlations of watched videos and categories were not discussed in the current evaluation. Furthermore, the influence of the personalized curriculum and the explicit feedback on the watch order can be explored.

C. Survey Feedback

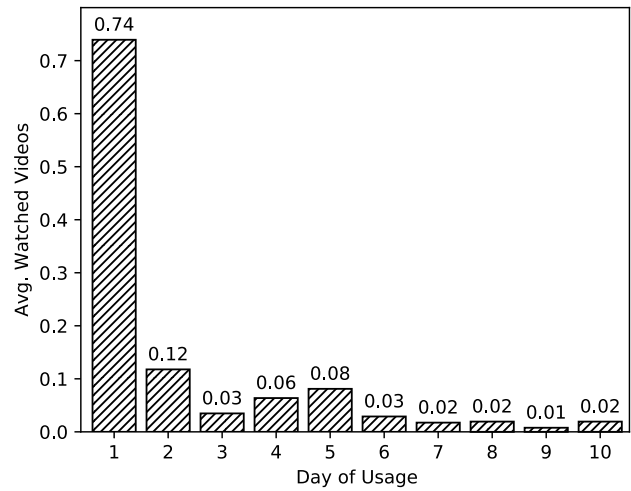
In order to receive quantitative feedback, we asked the users of the application after three watched videos to participate in an optional survey. In total, 28 learners responded to the survey, with an age range from under 20 years to over 70 years. The majority of users were between 30 and 59 years old (64%). 71% of the participants were male and 21% female, while the other participants did not provide an answer. The results show that the majority of the users (89%) operated the application at home while 19% also used the application in transit mode. The conceivable occasions for utilizing the application are manifold for the users. The survey participants emphasized long waiting periods, like in public transport or at the airport, as well as during a daily routine, for instance before going to bed or after waking up.

As for the provided content, the survey participants were asked to rate the length of the content on a Likert scale⁴. 39% of the users found that the length of the content was just right

⁴1: too long, 2: a bit too long, 3: just right, 4: a bit too short, 5: too short



(a) Box Plot



(b) Bar Chart

Fig. 6: Watched Videos on Day of Usage

(3); whereas 46% of the users said that the provided content was a bit too short (4). If the content would be lengthened, the provided content becomes comparable to the video content of successful MOOCs. This indicates that such video material is already suitable for micro learning if the content creation guidelines are respected during production. Furthermore, the quality of the algorithm for content suggestions is reflected in the responses of the users. The users stated on a Likert scale⁵ if their preferences were adequately considered. 36% were unable to decide whether the suggested content fits their preferences (3) and only 11% perceived the content as suitable (5) while 29% tended to accept the suggestions (4). Meanwhile, 75% of the users would like to assess their newly gained knowledge in the form of a quiz or similar. The majority of users confirmed our assumptions about mobile learning. They stated to prefer a personalized curriculum, simple navigation and short videos. However, video content optimized for devices in portrait orientation is not of high interest.

In the survey, the users were also able to give individual feedback. The application's "simple, plain UI" as well as the "easy handling" were highlighted. Furthermore, the concept was described as "ingenious" while the introduction to the application was perceived well. When asked about improvements, users primarily requested more videos and a broader variety of featured topics. They already gave suggestions, which included specific computer science topics. In addition, users proposed that videos of the same topic should be more likely to be suggested after each other.

This micro learning concept and the corresponding implementation received overall positive feedback through the survey. Users already contributed ideas on how to further improve the prototype. The suggested content also has to match better with the users' preferences in order to create

higher user retention. In summary, the feedback indicates that such a concept can be a useful learning method and a valuable addition to existing MOOC platforms.

V. FUTURE WORK

Some aspects could not be realized in full detail in this work. Therefore, this section provides an overview of possible future improvements to further support learning behaviors and optimize user experiences.

A. Automated Content Repository Generation

To provide content for the implemented prototype, a content repository was created manually. While this knowledge repository only consists of 58 videos and eight categories, this task becomes more and more complex with an increasing number of content elements. Therefore, the creation of the content repository should be automated. If the content is derived from MOOC content elements, this includes a feasible approach to cut the video into smaller segments with an appropriated content length. An automated content segmentation can aid this process [22], [23] by providing possible slicing points as new topics normally start with a new presentation slide. Besides that, the topics for each segment have to be determined automatically to enable a categorization mechanism. Most importantly, the dependencies between content elements have to be detected based on information transferred in the videos.

B. Improved Content Suggestions

The qualitative feedback has shown that the current version of the algorithm for suggesting the next content element does not create the best possible personalized video suggestion. To create a better user experience, multiple factors can be considered additionally. This involves, for instance, suppressing topics and excluding videos if the user discards corresponding video suggestions. Since users can easily switch their context when using a mobile device, this context should influence

⁵1: not at all, 2: rather not, 3: mediocre, 4: quite well, 5: definitely yes

the output of the suggestion algorithm. For example, such a context can carry the current location and local time of the user. To improve the content suggestions even more, additional methods for recommendation systems [34] can be utilized. For example, the algorithm can incorporate previous suggestions and feedback from other users.

C. Integration with MOOC Platforms

Due to the reusability of MOOC content for a micro learning framework, an interlinking of both platforms is possible to be established. For example, if a user's preferences and the watch history match available MOOCs, such courses can be promoted to the user when consuming micro learning content. The same procedure can be applied to advertise upcoming courses. Furthermore, micro learning content can also be provided through different media types, which are already provided by some MOOC platforms. This includes presentation slides, advanced reading material, or audio-only content to enable a usage without a screen.

VI. CONCLUSION

This work presented an initial approach in transforming linear MOOC videos into a more personalized non-linear learning experience. It was shown how traditional MOOC videos can be transformed in order to fit the micro learning approach. The reshaped content was enriched with dependencies and suggested to the users one at a time. These content suggestions are influenced and improved by the content dependencies, users' preferences and watched videos, as well as the explicit and implicit feedback given by the users. In this way, every user gets a personalized content flow, which improves during the usage of the application.

The users showed initial curiosity about the presented learning concept and used the application intensively during the first days (RQ1). Afterward, the application usage decreased over time. This indicates room for improvements to create higher user retention by encouraging users on a regular basis to use the application. Users of the openHPI platform generally showed positive feedback for the implemented prototype. Through the smaller content segments, the users were able to learn in transient moments, which is not supported by existing learning methods (RQ2). This creates a more omnipresent learning experience. Still, such an approach cannot replace the structured content and knowledge exchange through interactive elements offered by MOOCs and rather provides a useful addition to existing MOOCs. To enable micro learning on longer MOOC content, the segments have to be produced in a way that allows an easy dissection. This includes a synchronization of the audio and video streams to create possible cut marks. Then, this content needs to be categorized and content dependencies have to be defined. Therefore, MOOC content can be reused for micro learning if the content is produced for shorter segments and is placed in a suitable context.

It can be concluded that micro learning is a valuable addition to learning with MOOCs. If integrated correctly, it has the potential to overcome current shortcomings of mobile

learning with MOOC content. Future research has to show how to strengthen to coupling between MOOCs and micro learning activities to increase retention rates and to shape omnipresent learning experiences.

REFERENCES

- [1] App Annie, "2016 Retrospective," Tech. Rep., Mar. 2017. [Online]. Available: <https://www.appannie.com/en/insights/market-data/2016-retrospective-diving-country-metrics/>.
- [2] I. T. Union, *ICT Facts and Figures 2017*, 2017. [Online]. Available: <http://www.itu.int/en/ITU-D/Statistics/Documents/facts/ICTFactsFigures2017.pdf>.
- [3] Ericsson, *Ericsson mobility report 2015*, Ericsson, Ed., White paper, 2015. [Online]. Available: <https://www.ericsson.com/res/docs/2015/ericsson-mobility-report-june-2015.pdf>.
- [4] M. Böhmer, B. Hecht, J. Schöning, A. Krüger, and G. Bauer, "Falling asleep with angry birds, facebook and kindle: A large scale study on mobile application usage," in *Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services*, ser. MobileHCI '11, Stockholm, Sweden: ACM, 2011, pp. 47–56, ISBN: 978-1-4503-0541-9. DOI: 10.1145/2037373.2037383. [Online]. Available: <http://doi.acm.org/10.1145/2037373.2037383>.
- [5] G. Siemens, "Massive open online courses: Innovation in education," *Open educational resources: Innovation, research and practice*, vol. 5, pp. 5–15, 2013.
- [6] F. A. Marco, V. M. R. Penichet, and J. A. Gallud, "What happens when students go offline in mobile devices?" In *Proceedings of the 17th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct*, ser. MobileHCI '15, Copenhagen, Denmark: ACM, 2015, pp. 1199–1206, ISBN: 978-1-4503-3653-6. DOI: 10.1145/2786567.2801609. [Online]. Available: <http://doi.acm.org/10.1145/2786567.2801609>.
- [7] J. Renz, T. Staubitz, and C. Meinel, "Mooc to go.," *International Association for Development of the Information Society*, 2014.
- [8] S. Yahya, E. A. Ahmad, and K. A. Jalil, "The definition and characteristics of ubiquitous learning: A discussion," *International Journal of Education and Development using Information and Communication Technology*, vol. 6, no. 1, p. 1, 2010.
- [9] B. Tabuenca, S. Ternier, and M. Specht, "Everyday patterns in lifelong learners to build personal learning ecologies," in *Proceedings of the 11th International Conference on Mobile and Contextual Learning, mLearn 2012, Helsinki, Finland, October 16 -18, 2012*, M. Specht, M. Sharples, and J. Multisilta, Eds., ser. CEUR Workshop Proceedings, vol. 955, CEUR-WS.org, 2012, pp. 86–93. [Online]. Available: http://ceur-ws.org/Vol-955/.papers/paper%5C_43.pdf.
- [10] J. Renz, F. Schwerer, and C. Meinel, "openSAP: Evaluating xMOOC Usage and Challenges for Scalable and Open Enterprise Education," in *Proceedings of the 8th International Conference on E-Learning in the Workplace*, 2016, ISBN: 978-0-9827670-6-1.
- [11] C. Meinel and C. Willems, *openHPI: the MOOC offer at Hasso Plattner Institute*. Universitätsverlag Potsdam, 2013, vol. 80.
- [12] M. Sharples, I. Arnedillo-Sánchez, M. Milrad, and G. Vavoula, "Mobile learning," in *Technology-Enhanced Learning: Principles and Products*, N. Balacheff, S. Ludvigsen, T. de Jong, A. Lazonder, and S. Barnes, Eds. Dordrecht: Springer Netherlands, 2009, pp. 233–249, ISBN: 978-1-4020-9827-7. DOI: 10.1007/978-1-4020-9827-7_14. [Online]. Available: https://doi.org/10.1007/978-1-4020-9827-7_14.

- [13] 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.
- [14] R. E. Beasley, J. T. McMain, M. D. Millard, D. A. Pasley, and M. J. Western, "The effects of college student smartphone use on academic distraction and dishonesty," *J. Comput. Sci. Coll.*, vol. 32, no. 1, pp. 17–26, Oct. 2016, ISSN: 1937-4771. [Online]. Available: <http://dl.acm.org/citation.cfm?id=3007225.3007230>.
- [15] F. Dalipi, A. S. Imran, F. Idrizi, and H. Aliu, "An analysis of learner experience with moocs in mobile and desktop learning environment," in *Advances in Human Factors, Business Management, Training and Education*, J. I. Kantola, T. Barath, S. Nazir, and T. Andre, Eds., Cham: Springer International Publishing, 2017, pp. 393–402, ISBN: 978-3-319-42070-7.
- [16] Y. Zhao, T. Robal, C. Lofi, and C. Hauff, "Can i have a mooc2go, please? on the viability of mobile vs. stationary learning," in *Europ. Conf. on Technology Enhanced Learning (EC-TEL)*, Sep. 2018.
- [17] T. Rohloff, M. Bothe, J. Renz, and C. Meinel, "Towards a better understanding of mobile learning in moocs," in *2018 Learning With MOOCS (LWMOOCS)*, IEEE, 2018, pp. 1–4.
- [18] J. Renz, M. Bauer, M. Malchow, T. Staubitz, and C.-t. Meinel, "Optimizing the video experience in moocs," in *Proceedings of the 7th International Conference on Education and New Learning Technologies (EduLearn)*, Barcelona, Spain: IATED, 2015.
- [19] T. Hug, M. Lindner, and P. A. Bruck, "Microlearning: Emerging concepts, practices and technologies after e-learning," *Proceedings of Microlearning*, vol. 5, p. 3, 2005.
- [20] M. A. Job and H. S. Ogalo, "Micro learning as innovative process of knowledge strategy," *International journal of scientific & technology research*, vol. 1, no. 11, pp. 92–96, 2012.
- [21] R. E. Mayer and R. Moreno, "Nine ways to reduce cognitive load in multimedia learning," *Educational psychologist*, vol. 38, no. 1, pp. 43–52, 2003.
- [22] X. Zhang, C. Li, S.-W. Li, and V. Zue, "Automated segmentation of mooc lectures towards customized learning," in *Advanced Learning Technologies (ICALT), 2016 IEEE 16th International Conference on*, IEEE, 2016, pp. 20–22.
- [23] X. Che, H. Yang, and C. Meinel, "Adaptive e-lecture video outline extraction based on slides analysis," in *International Conference on Web-Based Learning*, Springer, 2015, pp. 59–68.
- [24] D. Kovachev, Y. Cao, R. Klamma, and M. Jarke, "Learn-as-you-go: New ways of cloud-based micro-learning for the mobile web," in *Advances in Web-Based Learning - ICWL 2011: 10th International Conference, Hong Kong, China, December 8-10, 2011. Proceedings*, H. Leung, E. Popescu, Y. Cao, R. W. H. Lau, and W. Nejdl, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 51–61, ISBN: 978-3-642-25813-8. DOI: 10.1007/978-3-642-25813-8_6. [Online]. Available: http://dx.doi.org/10.1007/978-3-642-25813-8_6.
- [25] R. A. Tortorella and S. Graf, "Personalized mobile learning via an adaptive engine," in *Advanced Learning Technologies (ICALT), 2012 IEEE 12th International Conference on*, IEEE, 2012, pp. 670–671.
- [26] G. Sun, T. Cui, W. Guo, G. Beydoun, D. Xu, and J. Shen, "Micro Learning Adaptation in MOOC: A Software as a Service and a Personalized Learner Model," in *Advances in Web-Based Learning - ICWL 2015: 14th International Conference, Guangzhou, China, November 5-8, 2015, Proceedings*, F. W. Li, R. Klamma, M. Laanpere, J. Zhang, B. F. Manjón, and R. W. Lau, Eds. Cham: Springer International Publishing, 2015, pp. 174–184, ISBN: 978-3-319-25515-6. DOI: 10.1007/978-3-319-25515-6_16. [Online]. Available: http://dx.doi.org/10.1007/978-3-319-25515-6_16.
- [27] S. Bull and J. Kay, "Student models that invite the learner in: The smili:() open learner modelling framework," *International Journal of Artificial Intelligence in Education*, vol. 17, no. 2, pp. 89–120, 2007.
- [28] D. Verpoorten, C. Glahn, M. Kravcik, S. Ternier, and M. Specht, "Personalisation of learning in virtual learning environments," in *European Conference on Technology Enhanced Learning*, Springer, 2009, pp. 52–66.
- [29] P. A. Bruck, L. Motiwalla, and F. Foerster, "Mobile learning with micro-content: A framework and evaluation," *Bled eConference, 25th Bled eConference eDependability: Reliable and Trustworthy eStructures, eProcesses, eOperations and eServices for the Future*, pp. 17–20, 2012.
- [30] T. Dingler, D. Weber, M. Pielot, J. Cooper, C.-C. Chang, and N. Henze, "Language learning on-the-go: Opportune moments and design of mobile microlearning sessions," in *Proceedings of the 19th International Conference on Human-Computer Interaction with Mobile Devices and Services*, ACM, 2017, p. 28.
- [31] G. Gassler, T. Hug, and C. Glahn, "Integrated micro learning—an outline of the basic method and first results," *Interactive Computer Aided Learning*, vol. 4, pp. 1–7, 2004.
- [32] S. Linckels and C. Meinel, *E-librarian service: user-friendly semantic search in digital libraries*. Springer Science & Business Media, 2011.
- [33] I. Robinson, J. Webber, and E. Eifrem, *Graph databases: new opportunities for connected data*. O'Reilly Media, Inc., 2015.
- [34] P. Resnick and H. R. Varian, "Recommender systems," *Commun. ACM*, vol. 40, no. 3, pp. 56–58, Mar. 1997, ISSN: 0001-0782. DOI: 10.1145/245108.245121. [Online]. Available: <http://doi.acm.org/10.1145/245108.245121>.