Stay at Home and Learn: Did the COVID-19 Pandemic Influence Mobile Learning in MOOCs?

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***Abstract*—The outbreak of the COVID-19 pandemic also affected learning activities on MOOC platforms. The field of application for mobile learning in MOOCs has been weakened through the changes in daily lives. To quantify this impact, user interaction data of the past two years was evaluated in an observational study for two MOOC platforms.**

Since the start of the pandemic, a drop in mobile learning activities and active mobile learners has been noticed on one of the platforms while activities on the other platform remained stationary. No changes have been detected in the usage behavior of active users of mobile applications or with the utilization of different network connections. The adoption of mobile learning in MOOCs appears to be driven by the offered course topics and breaks in the course schedule, rather than by external factors that restrict the mobility of learners. Dedicated applications for mobile devices for MOOCs are mostly used in a familiar environment with a WiFi connection. This behavior became more pronounced with the start of the pandemic.

***Index Terms*—MOOCs, Mobile Learning, COVID-19**

I. Introduction

With the outbreak of the COVID-19 pandemic in 2020, industries were required to adapt to the new circumstances, people were forced to stay at home, and daily routines were disrupted [1]. These changes also affected the learning industry and learning activities on MOOC platforms [2]–[4]. On one hand, people had to deal with more important tasks than education. On the other hand, there was the opportunity to use the newly available time for investments into personal growth or further employee training in a safe environment. ClassCentral announced the *Second Year of the MOOC* [5], as they noticed a significant increase in newly registered users and drastically more server load after March 2020. Next to this renewed popularity of MOOCs, the daily schedule of people changed. Instead of commuting to the office every day, employees from entire industry sectors were asked to work from home instead [6]. With that, time slots for learning, as well as the motivation to learn, were likely to be impacted [1], [7]. To provide learners the opportunity to integrate learning routines into their daily schedules, MOOC platform providers offer designated applications for mobile devices [8]. These applications often provide a reduced but accompanying feature set compared to the primary web platform. One of the more prominent features is the ability to enable learning activities in a non-stationary context. Building on that, learning items are also accessible via cellular data connection or may be downloaded to the mobile device for truly network-independent learning activities. These key features of mobile learning activities have been weakened through the changes in daily lives caused by the COVID-19 pandemic. Yet, there are also reports of increased usage of mobile learning [9]. To quantify this effect in the context of MOOCs, we choose to evaluate the user interactions tracked over the past two years. We formulated the following research questions to guide the analysis:

RQ1 How did the usage rate of mobile applications for MOOCs (active users and visits to the content) change over the last two years?

RQ2 Did users of the mobiles applications change their behavior in visiting content in the last two years?

RQ3 Did learners change the network connection types used to access course content with mobile applications over the last two years — suggesting a change in mobility?

II. Methodology

For this observational study, we evaluated the user interactions tracked in the period from October 1, 2019, until March 1, 2022. We considered two MOOC platforms that focus on different topic areas. First, openHPI[1] offered 46 courses on computer science and digital transformation. In the studied period, openHPI has tracked over 25 million visits to learning items. Second, 109 courses ran on openSAP[2], which targeted a business audience and provided training for employees and customers about SAP's IT solutions. There were over 70 million visits to the provided learning material in the timeframe of this study. Both MOOC platforms provide the same feature set as they build on the same software foundation. The accompanying mobile applications for each platform are available for iOS and Android.

This study only focuses on visits to learning material. A respective event is triggered each time a user opens the page of a learning item. As it is common in MOOCs, these learning items can be of different types: videos, text items, quizzes, etc. In this study, all item visits have been considered equally. The events are then stored in a separate database alongside the

[1]https://open.hpi.de
[2]https://open.sap.com

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TABLE I: Ratio of Visit Events by Country (Top 5)

	DE	AT	CH	US	IN	GB	ES	others
openHPI	81%	4%	3%	2%	1%	1%	<1%	10%
openSAP	16%	1%	1%	13%	22%	3%	3%	43%

Values in parentheses are not part of the Top 5 countries.

context they were triggered in. Among other data, this context contains a timestamp, information regarding the used device, and the utilized network connection. In cases of a missing network connection, these events are stored locally on the mobile device before being transferred to the server.

The courses on both studied MOOC platforms were free of charge and were initially published in teacher-guided form with a start and end date. After the guided course period ended, the courses remained available as self-paced courses without further guidance. Although the majority of the user interactions usually occur within the course period, this study considers all tracked visit events — during the course period and thereafter. Table I lists the five countries of each platform with the most recorded visit events. The country was determined via the IP address of the learner. For openHPI, most learning activities were recorded from German-speaking countries. Whereas openSAP additionally attracts more international learners, mainly from the United States and India. These numbers are in line with the usage of mobile applications in a global enterprise context [10].

A. Data Processing

To enable the analysis of the collected user interactions, the data needed to be processed first. For this, the events triggered by mobile applications needed to be identified. Further, the data was always put relatively to the overall reference group (e.g.: visits on mobile applications vs. all captured visits to learning items). This process removes the trend in the overall data (*De-trending*) . By doing so, we are able (1) to analyze the usage rate of mobile applications independent of increasing or decreasing activities on the entire MOOC platform, as well as (2) to compare the usage rates between MOOC platforms.

As new content on both MOOC platforms is usually published every week, the learners tend to develop a weekly learning schedule. That imposed the risk of miscounting active users if they are only active on specific days of the week. To compensate for this repeating pattern, the moving average over seven days was calculated for the tracked data (*Differencing*).

B. Used Methods

In this paper, the gathered data was evaluated in two ways. For the quantitative analysis, different times series have been calculated to help answer the formulated research questions. The exact calculation of the time series data will be described alongside its evaluation. Each descriptive time series was tested for stationarity by using the *Augmented Dickey-Fuller* test, with a confidence level of 95%. Besides that, the time series data was discussed in a qualitative way to highlight distinctive changes and to allow to reason about external factors like offered courses or yearly breaks in the curriculum.

III. Results & Discussion

In this section, the collected data is evaluated and discussed from different perspectives to answer the formulated research questions. Our general hypothesis is that the usage of mobile applications decreased when the pandemic hit and social distancing measure were put into place[3], as those restricted the mobility and change daily routines of learners. Being more stationary lowers the number of use cases for mobile applications to be used, e.g., on the daily commute. Desktop computers on the other side offer more comfort (e.g., bigger screens). However, there is the possibility that learners stick to their learning routines regardless of changed circumstances.

A. Usage Rates of Mobile Applications

For both studied MOOC platforms, Figure 1 shows the ratio of learners making use of the mobile applications, as well as the ratio of visits to learning items originating from mobile applications. For openHPI, up to 20% of all active learners utilized one of the available mobile applications. These learners accounted for about 14% of the recorded visit events. In March 2020, we could notice a significant drop in both the ratio of mobile application users and the ratio of visits from mobile applications. The ratio of users of the mobile applications decrease to 9%, while the ratio of visits drops to 4% shortly after. Since then, only 12% of the users utilize mobile applications (approx. 7% of the visits). The actual calculated time series data shows some deviations over time. We explain these deviations being caused by various courses of different topic areas attracting different user groups. Since November 2021, both the ratio of users and visits decrease slightly, with the ratio of visits decreasing more noticeably.

For openSAP, we could record a different behavior over time. First, the adoption rate of mobile applications is lower compared to openHPI: 8% of the learners use the mobile applications which account for 6% of all visits. This is likely to be caused by the business context of openSAP. Here, learners use the MOOC platform for employee training, which is more likely to happen in a stationary work setting with desktop computers. Second, openSAP did not see a decrease in activities with the mobile applications in March 2020. In comparison to openHPI, we again link this to the business context of openSAP. This would indicate that learning with mobile devices and therefore also mobile applications is more likely to be used in a learners' spare time. The learners on openSAP, who continued using the mobile applications throughout the pandemic, apparently saw the mobile application as an integral part of their learning process. Another factor influencing the observed learner behavior is the more international community on openSAP. While European countries enforced more strict countermeasures from the beginning of the pandemic, other

[3]This study refers to March 15, 2020 as the international starting date of the first social distancing measures. The actual date for each country discussed was between March 13 and March 25.

(a) openHPI

(b) openSAP

Fig. 1: Ratio of Active Mobile Users and Their Visits to Learning Items With Mobile Applications (Rolling 7-Day Average)

countries took different approaches [11]. Similar to openHPI, there is a decline in activities on openSAP since October 2021. We can not reason about this behavior, yet.

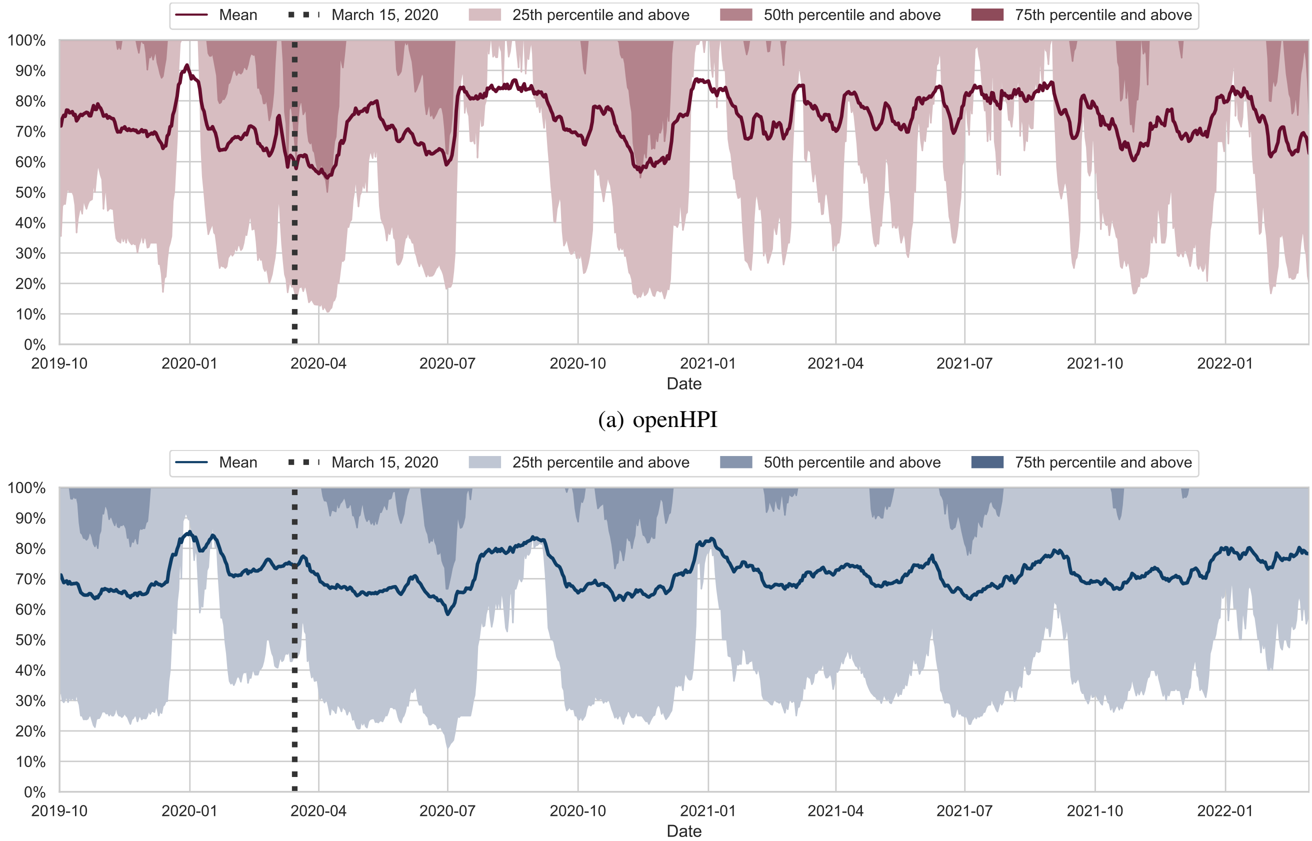
As for the statistical test for stationary of the time series data, only the ratio of visits from the mobile applications about all recorded visits yielded a statistically significant result ($p = 0.039$) on openSAP. This is in line with the previously observed characteristics of the time series data. In addition to testing the whole time series data for stationary, we also examined the plateau visible in the data between April 2020 and October 2021. Here we were able to confirm a stationary learner behavior with a statistically significant magnitude for both discussed metrics for openHPI (active users: $p = 0.044$; visits: $p = 0.009$) and openSAP (active users: $p = 0.006$; visits: $p = 0.007$). This can be explained by the social distancing measures the were still enforced during this period and a need for learners to change their behavior did not exist.

Moreover, we can think of only one plausible explanation for the ratio of mobile application users being higher than the ratio of visits on both MOOC platforms: The mobile applications are a complimentary offer with a reduced feature set and most learners turn towards the web platform at least at some point for specific tasks. This puts the focus of mobile applications on shorter interspersed learning activities. Besides that, the group of learners exclusively relying on mobile applications is relatively small and is opposed to the number of learners who use the mobile application only occasionally.

B. Visit Activities Using Mobile Applications

While the previous analysis considered recorded visit events of all learners, the following analyses examined only changes in usage behavior of learners who actively used the mobile applications. Here, Figure 2 visualizes the use of mobile applications to access the learning material. Next to the mean value across the active learners, Figure 2 also displays the lower bounds for the 25th and the 50th percentile (median) to provide better insight into the structure of the data. In this way, the charts show a simplified box plot for every given date. To give an example, the lower bound of area for the 25th percentile visualize the minimum ratio of learning items being visited with mobile applications by 75% of the mobile learners. Therefore, the larger the area, the more often learners preferred the mobile application over the web platform. If a lower bound is not visualized, it is located at the 100% mark.

For both platforms, the calculated mean value centers around 75% of the items being accessed with a mobile application if the learner incorporates a mobile application in the learning activities. Notably, the mean value is below the lower bound of the 50th percentile (median). This is a result of the data being skewed toward lower usage. This is an indication for many learners not using the mobile applications intensively, but rather using them only for occasional visits to the learning material. As described, Figure 2 only includes the data of learners utilizing a mobile application at least once. Therefore, the tail of learners not using the mobile application was truncated. Additionally, there is an upper bound of 1 that is defined by learners consuming all the learning items



(a) openHPI

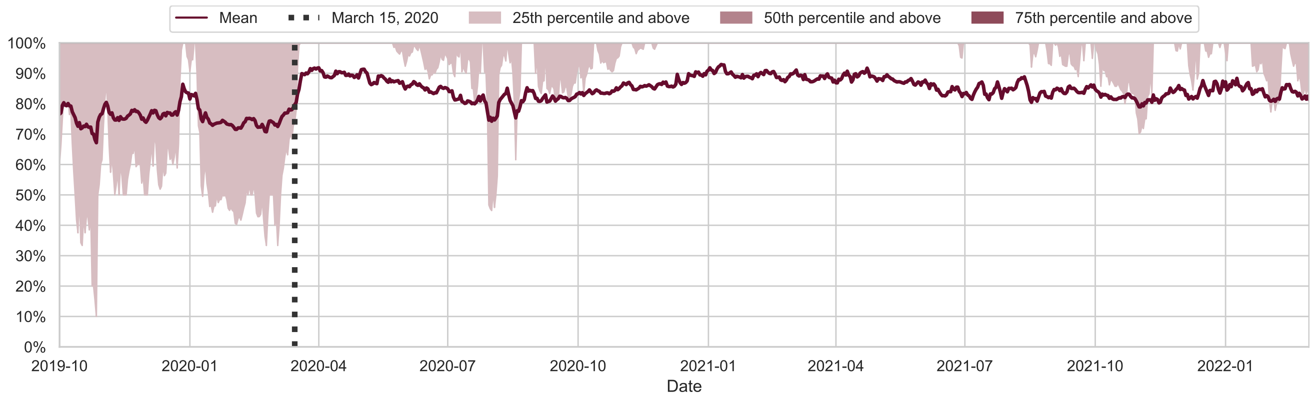
(b) openSAP

Fig. 2: Ratio of Mobile Users' Visits to Learning Items with Mobile Applications (Rolling 7-Day Average)

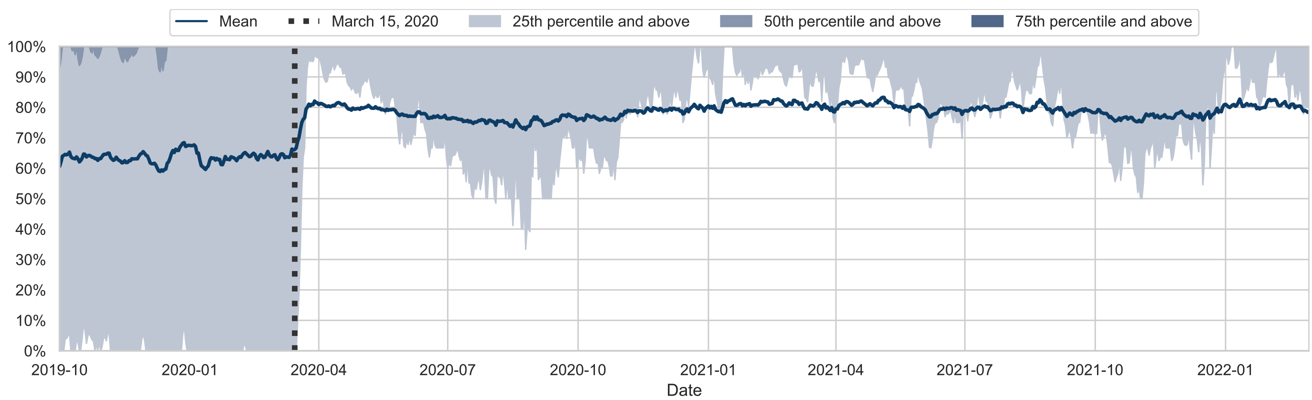
via mobile applications. In contrast to the tail of occasional mobile users, the lower bound of the 75th percentile is not visualized in Figure 2 as those learners already belong to the group of learners visiting all learning material via the mobile applications.

The data tracked for openHPI shows different usage periods. Up to January 2021, longer periods of approx. one month with increased mobile application usage were recorded. These become visible through the visualized area of the 50th percentile and above. From January 2021 until September 2021, the usage changed to shorter, less intensive peaks. Thereafter, the previous pattern appears to be reestablished. By having a closer look at the periods with higher mobile application usage, we discovered a rough correlation with fairly technical courses (programming, technologies, and tools; in 2020), as well as two design thinking courses at the end of the studied period. On openSAP in comparison, the pattern in the recorded data is more homogeneous. Here, courses are with a higher frequency and in parallel. However, the usage of mobile applications does not peak as significantly as on openHPI. Throughout the studied period, there were time ranges with higher mobile application usage. Due to the overlapping course schedule, determining distinctive courses is not trivial. Nevertheless, we were able to find that a series of expert talks, as well as a course about app development, led to an increased usage of mobile applications. On both platforms, yearly events become visible. Fewer learning activities were recorded around the turns of the year. During the summer of 2020, the usage rates also lowered because no courses were scheduled for this period. This effect was mitigated in the summer of 2021 by running a promotion to reactivate older courses free of charge. At first sight, the visualization of the lower bounds of higher percentiles implies that fewer learners utilized only the mobile application to access the learning material — thus creating a broader spectrum of usage. However, since the overall adoption rate of mobile applications did not change significantly during those periods (see Figure 1), this effect was likely caused by the increase in learning activities of some highly motivated learners.

For both platforms, the statistical tests for stationarity return significant results for path of the mean visit ratio (openHPI: $p = <0.001$; openSAP: $p = <0.001$) and the lower bound of the 25th percentile (openHPI: $p = <0.001$; openSAP: $p = <0.001$). This indicates that learners using mobile applications did not change their learning routines in the last two years. Therefore, social distancing measures appear to not affect the learning behavior. This could mean that either (1) learners are not easily willing to change their learning routines, or (2) that the learning routines were not affected because the learners utilize the mobile applications in familiar *safe* locations.



(a) openHPI



(b) openSAP

Fig. 3: Ratio of Mobile Users' Visits to Learning Items with Mobile Applications and WiFi Connection (Rolling 7-Day Average)

C. *WiFi Usage for Visits Using Mobile Applications*

Following up on the last analysis, we wanted to examine if learners moved their learning activities to more familiar places. For this, we tested the mobile learners' behavior for a change in the network connection when utilizing mobile applications. Figure 3 displays the ratio of learning items that were accessed while the mobile device was connected to a WiFi network. Similar to the previous analysis, Figure 3 visualizes the mean value across active learners, as well as the lower bounds for the 25th and the 50th (median) percentiles. The measure of a WiFi connection was chosen as users are likely to have access to the WiFi network of a familiar place. Therefore, we interpret the use of a WiFi connection as learners visiting the place more frequently and spending more time.

Figure 3 features similar characteristics as Figure 2: The presented data is skewed towards learners only occasionally visiting items on cellular data, while most users utilize a WiFi connection for accessing learning items. For both platforms, an increase in WiFi usage can be identified in the visualized data in March 2020. On openHPI, the use of a WiFi connection centered around 75% before March 2020. Thereafter, 85% of all visits to course items with mobile applications were made with a WiFi connection. Additionally, the distribution of mobile visits to learning items changed. Before March 2020, more learners occasionally used the mobile applications. This can be inferred by the prominent visualization of the area for the 25th percentile. After the start of the pandemic, the lower bound of the 25th percentile is only displayed sporadically. The data recorded for openSAP shows a similar learner behavior. Before March 2020, the use of WiFi connections centered around 65% of all item visits made with mobile applications. In this period, up to 75% of the active mobile learners consumed at least occasionally some learning items via a WiFi connection. With the start of the pandemic, the use of WiFi connections increased to 80%, while learners relied more heavily on WiFi connections. We suspect the observed effects are caused by mobile learners who switched to the web platform. As a result, only learners who only have access to a mobile device, as well as highly motivated mobile learners, continued using the mobile applications. For both platforms, no changes based on yearly events can be identified in the data. Mobile learners are still highly likely to use a WiFi connection for accessing the course material [12].

As done for previous time series data, the usage ratio of WiFi connections was also tested for stationarity. Over the whole studied period, only the lower bound of the 25th percentile on openHPI yielded a statistically significant result ($p = 0.034$). Despite the visualization of the tracked data appearing to be steady after April 2020 on both platforms, we could not detect any statistically significant results in this period. This leads to the conclusion that learners have been preferring to use their mobile devices mostly in places where they have access to a WiFi network. This behavior was strengthened with the start of the COVID-19 pandemic and the implementation of social distancing measures. Learners increasingly made more use of mobile applications on a WiFi connection. Therefore, we conclude that despite their potential for learning activities on the go, mobile devices are mostly used in a stationary, familiar environment.

IV. Limitations

Although this study can build upon over two years of data tracked by two MOOC platforms with an active learner community, some limitations are affecting the presented results. First, both MOOC platforms tend toward a German user base. For openHPI, over 80% of the recorded events originated in Germany. The more international focus of openSAP mitigates this impact. Nevertheless, a large part of active learners also lived in Germany. Second, both MOOCs platforms feature content for the IT sector while having different target user groups. Still, similarities in the course schedule and even shared courses can be found. Third, the chosen data processing of a rolling average is always a tradeoff with regard to the granularity of the data. As argued before, we think that the chosen a seven-day window fit the schedule on the studied MOOC platforms the best. But this may obscure other important learning indicators. Other useful aggregation windows (known from web analytics) could be of size 1 or 30 (more fine-grained vs. more coarse-grained), which in turn might provide other insight. For the scope of this paper, these have been excluded from the analysis.

V. Conclusion

This study examined the adoption and usage rates of mobile applications for MOOC platforms during the COVID-19 pandemic. For this, the learners' visits to the course material have been captured and analyzed from October 2019 until March 2022 on two MOOC platforms. We noticed a drop in the overall ratio of mobile learning activities and active learners on one of the platforms (RQ1). At this time, social distancing measures were put into place. While the other MOOC platform did not experience such an incline, the ratio of visits from mobile applications remained stationary over the whole studied period. During the height of the pandemic (April 2020 – October 2021), the ratio of mobile learning activities and active learners remained the same on both platforms. No changes were detected in the behavior of visiting content by active users of the mobile applications (RQ2). The recorded usage appears to be not driven by external factors that restrict the mobility of learners, but rather by the offered course topics and breaks in the course schedule. The utilization of a WiFi connection has been increased with the start of the pandemic (RQ3). As we associate the presence of a WiFi connection with a familiar and frequently visited place, we conclude that dedicated applications on mobile devices are mostly used in a stationary, familiar environment. As shown, mobile applications for MOOC platforms provide an attractive alternative to the primary web platform of MOOCs and still offer the opportunity for network-independent learning activities. Future research directions may focus on a more detailed analysis based on different item types or individual learner behavior.

References

[1] M. Gibbs, F. Mengel, and C. Siemroth, "Work from Home & Productivity: Evidence from Personnel & Analytics Data on IT Professionals," *SSRN Electronic Journal*, 2021, ISSN: 1556-5068. DOI: 10.2139/ssrn.3843197.

[2] C. Impey and M. Formanek, "Moocs and 100 days of covid: Enrollment surges in massive open online astronomy classes during the coronavirus pandemic," *Social Sciences & Humanities Open*, vol. 4, no. 1, p. 100 177, 2021, ISSN: 2590-2911. DOI: https://doi.org/10.1016/j.ssaho.2021.100177. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S2590291121000735.

[3] V. Baudo and D. Mezzera, "Insights from a MOOC Platform during COVID-19 Pandemic in Italy," *EDEN Conference Proceedings*, no. 1, pp. 401–409, Sep. 2021, ISSN: 2707-2819. DOI: 10.38069/edenconf-2021-ac0039.

[4] D. Bylieva, Z. Bekirogullari, V. Lobatyuk, and T. Nam, "Analysis of the Consequences of the Transition to Online Learning on the Example of Mooc Philosophy During the COVID-19 Pandemic," *Humanities & Social Sciences Reviews*, vol. 8, pp. 1083–1093, Sep. 2020. DOI: 10.18510/hssr.2020.94103.

[5] D. Shah, *The Second Year of The MOOC: A Review of MOOC Stats and Trends in 2020*, https://www.classcentral.com/report/the-second-year-of-the-mooc/, 2020/12/14.

[6] D. Garrote Sanchez, N. Gomez Parra, C. Ozden, B. Rijkers, M. Viollaz, and H. Winkler, "Who on Earth Can Work from Home?" *The World Bank Research Observer*, vol. 36, no. 1, pp. 67–100, Mar. 2021, ISSN: 0257-3032, 1564-6971. DOI: 10.1093/wbro/lkab002.

[7] A. Roy, M. Yee, M. Perdue, *et al.*, "How COVID-19 Affected Computer Science MOOC Learner Behavior and Achievements: A Demographic Study," in *Proceedings of the Ninth ACM Conference on Learning @ Scale*, New York City NY USA: ACM, Jun. 2022, pp. 345–349, ISBN: 978-1-4503-9158-0. DOI: 10.1145/3491140.3528328.

[8] 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, Madrid: IEEE, Sep. 2018, pp. 1–4, ISBN: 978-1-5386-6533-6. DOI: 10.1109/LWMOOCS.2018.8534685.

[9] S. Saikat, J. S. Dhillon, W. F. Wan Ahmad, and R. A. Jamaluddin, "A Systematic Review of the Benefits and Challenges of Mobile Learning during the COVID-19 Pandemic," *Education Sciences*, vol. 11, no. 9, p. 459, Aug. 2021, ISSN: 2227-7102. DOI: 10.3390/educsci11090459.

[10] M. Bothe, F. Schwerer, and C. Meinel, "Video Consumption with Mobile Applications in a Global Enterprise MOOC Context," in *Innovations in Learning and Technology for the Workplace and Higher Education*, D. Guralnick, M. E. Auer, and A. Poce, Eds., vol. 349, Cham: Springer International Publishing, 2022, pp. 49–60, ISBN: 978-3-030-90676-4 978-3-030-90677-1. DOI: 10.1007/978-3-030-90677-1_5.

[11] T. P. B. Thu, P. N. H. Ngoc, N. M. Hai, and L. A. Tuan, "Effect of the social distancing measures on the spread of COVID-19 in 10 highly infected countries," *Science of The Total Environment*, vol. 742, p. 140 430, Nov. 2020, ISSN: 00489697. DOI: 10.1016/j.scitotenv.2020.140430.

[12] M. Bothe and C. Meinel, "On the Potential of Automated Downloads for MOOC Content on Mobile Devices," in *2020 IEEE Learning With MOOCS (LWMOOCS)*, Antigua Guatemala, Guatemala: IEEE, Sep. 2020, pp. 58–63, ISBN: 978-1-72819-728-9. DOI: 10.1109/LWMOOCS50143.2020.9234338.