Christoph Meinel, Thomas Staubitz, Stefanie Schweiger, Christian Friedl, Janine Kiers, Martin Ebner, Anja Lorenz, George Ubachs, Catherine Mongenet, José A. Ruipérez-Valiente, Manoel Cortes Mendez (Eds.)

EMOOCs 2021

2021 – xii, 295 p.
ISBN 978-3-86956-512-5
DOI https://doi.org/10.25932/publishup-51030

Behavioral Patterns in Enterprise MOOCs at openSAP

Muhittin Şahin[1], Marc Egloffstein[2], Max Bothe[3], Tobias Rohloff[3], Nathanael Schenk[4], Florian Schwerer[4], and Dirk Ifenthaler[5]

[1] Ege University and University of Mannheim
musahin@mail.uni-mannheim.de
[2] University of Mannheim
egloffstein@uni-mannheim.de
[3] Hasso Plattner Institute, Potsdam
max.bothe,tobias.rohloff@hpi.de
[4] SAP SE, Walldorf
nathanael.schenk,florian.schwerer@sap.com
[5] University of Mannheim and Curtin University
ifenthaler@uni-mannheim.de

While Enterprise MOOCs have been established alongside academic MOOCs in recent years, there is still only limited evidence on learner behavior in MOOCs with a clear focus on job-related training and professional development. This short paper addresses this gap by analyzing learner behavior in openSAP Enterprise MOOCs. By means of lag sequential analysis, data from 13 MOOCs from the topic areas business, design, and technology with a total number of N = 72,668 learners have been analyzed. Consistent high-level behavioral patterns over all three topic areas could be identified. Implications for future research and development are being discussed.

1 Introduction

Massive Open Online Courses (MOOCs) have been a growing element in higher education for more than ten years. Especially the advantage of reaching large numbers of learners worldwide seems to be attractive for universities and educational organizations [5, 10]. Over the recent years, MOOCs have also become a viable alternative for corporate training and professional development [6]). One of the most advanced implementations is openSAP, an open learning platform related to the Tech/IT-sector. While many companies do not seize the full potential of MOOCs for training and development [4] or even lack adequate support [8], openSAP implements so-called Enterprise MOOCs [18] to successfully convey knowledge about new technologies and business topics within the organization as well as to external stakeholders throughout the enterprise ecosystem [15]. Against the background of the common criticism of MOOCs in terms of instructional quality [7] or completion rates [13], openSAP seeks to constantly optimize its offering and thus to improve the learning experience. Therefore, the existing R&D partnership with the Hasso Plattner Institute (technical expertise) has been extended with the University of Mannheim, Chair of Learning, Design and Technology (instructional design and learning analytics expertise). As part of the partnership, several research activities seek implications for learning design of MOOCs to further advance the openSAP offering, and its learning experience [9]. This paper reports an initial case study of this R&D partnership focusing on the behavior of learners in openSAP Enterprise MOOCs. More specifically, the research project seeks to (1) identify typical behavioral patterns in openSAP Enterprise MOOCs and (2) find out if such patterns differ between courses from different topic areas. The remainder of this paper introduces the openSAP University and describes how the R&D partnership addressed the research questions using a Lag Sequential Analysis (LSA) approach. Then, the context and findings are presented. The paper closes with a discussion of implications and an outlook for future research.

2 The openSAP University

As part of SAP's digital education strategy, the openSAP learning platform (available at open.sap.com) was established in 2013 to meet the increasing demands of partners, customers and suppliers for knowledge on corporate strategy, business innovations and product releases in a timely manner [16]. openSAP delivers knowledge via scalable online courses, thus suitable for larger audiences. The courses are open to everyone and free of charge, providing videos, quizzes, and interaction in a digital classroom over a fixed period of time. The main topic areas are technology and software, business, or design; while some additional courses provide insights on corporate social responsibility-related topics. The technical infrastructure is based on the HPI MOOC platform developed at the Hasso Plattner Institute in Potsdam, Germany. In early 2021, the platform counts more than 1.1 million unique registrants from over 200 countries with more than five million enrollments in around 250 different courses.

With respect to instructional design (ID), openSAP courses follow an elaborate xMOOC model, providing a structured and well-organized offering [2]. Course completion can be achieved upon two kinds of certificates. Learners receive a so-called Confirmation of Participation (CoP) by accessing at least 50% of the overall course content. In addition, the participants will obtain a Record of Achievement (RoA) when achieving at least 50% of the points available in the weekly assignments and the final exam.

3 Sequential Analysis of Online Learning Behavior

Sequential analysis is a well-established method of inferential statistics [19], which can be employed for investigating behavior of learners in online learning systems [17]. It is regarded as a suitable approach when investigating behavior within an ongoing interaction [1] and thus has been applied to various MOOC settings (e.g. [3]. Sequential relationships of observations and events with each other are also considered in sequential analysis [1]. Log-linear models, lag sequential methods, z-scores and sequential pattern mining can be used to carry out sequential analysis and determine sequential patterns. In order to identify typical learning behaviors of learners, transition probabilities are used to identify significant patterns [1]. The stochastic models provide the mathematical basis for precisely computing learning-dependent changes in learning environments such as MOOCs [12]. The analytics process of LSA for this project consists of six distinctive steps: (1) develop event sequence, (2) map out transitional frequency matrix, (3) derive transitional probability matrix, (4) calculate z-scores and carry out test of significance, (5) draw state transition diagram.

4 Learner Behavior in Enterprise Moocs

4.1 Sample, Data Collection, and Procedure

User events from 13 openSAP courses from the topic areas Business, Design and Technology have been analyzed with regard to patterns in learner behavior. The courses in the sample show variations in terms of length, effort, and design parameters like assessment configuration or additional ID elements (e.g. reflection prompts or coding exercises). Table 1 provides on overview of the courses in the sample.

The data used to conduct LSA consists of learners' interactions with the digital learning environment on the basis of traceable system states and events. In a preliminary step of data preparation, the event data generated by interactions with the platform was coded into delineable sessions. A session is based on a sequence of events whose interval does not exceed 60 minutes, i.e. sessions expire after an hour of inactivity.

Learners' interactions with digital learning environments can be classified into three categories: learner-content, learner-discussion (learner-learner), and learner-instructor [14]. Following the HPI MOOC platform's overall structure, the learner events in a course can be assigned into four main categories: L – Learning (e.g. video playbacks, self-test submissions, visits to learning items), D – Discussion (e.g.

Table 1: Descriptive information on the courses in the sample

Topic area	Course	Course length (weeks)	Max effort (hours)	Assessment config.[a]	Add. ID elements	Enrollments[b]	Number of active learners[b]	Number of interactions
Business	xm1	1	3	w	0	4609	2597	125147
	leo2	2	8	w+f	1	10542	5626	534548
	pa1-tl	3	12	w+f	1	6904	4070	415258
	s4h15	4	16	w+f	0	18265	12277	2023627
	sbw1	6	24	w	1	11664	6270	731436
Design	build1	4	16	w+f	2	7749	4350	355387
	cwr1-1	3	12	w+p	2	1810	1005	82072
	dafie1	5	20	w+p	2	5283	2678	204060
	sps3	5	20	w+p	1	6629	3143	380989
Technology	ieux1	1	4	w	0	13431	6784	205950
	java1	5	30	w+e+f	3	21693	11757	3866382
	mobile3	5	25	w+f	1	10374	5928	807607
	sps2	3	12	w+f	1	10940	5783	721967

Note. [a] w: weekly assignment; f: final exam; e: graded exercise; p: peer assessment; [b] at course end.

post comments), P – Progress (e.g. visits of the progress page) and A – Announcement (e.g. visits of the announcement page).

In the first step of LSA, event sequences were created session by session for each learner based on the interactions with the learning platform. An example of a simple event sequence would be: LLLLDDLLLPDAALLLL. In the second step, transitional frequency matrices were created. Then, the transitional probability matrix was mapped out. Transitional probability is a conditional probability; events occur in different times and "lag" is used to express these time differences [1]. In order to test the statistical significance of the transitions, z-scores were calculated, together with a Bonferroni adjustment to determine the z-score threshold. In the last step, a state transition diagram was generated for displaying the results.

4.2 Results

4.2.1 Behavioral Patterns in openSAP Courses

Over all 13 courses in the sample, significant transitions between the four main categories could be traced. Table 2 shows the respective z-scores.

Table 2: z-scores based on the interaction categories

z-score	Announcements	Discussion	Learning	Progress
Announcement	**587.92***	**41.20***	−203.42	**135.13***
Discussion	**30.26***	**2274.35***	−1814.73	**75.90***
Learning	−237.32	−1799.57	**1572.44***	−223.21
Progress	**208.72***	**17.38***	−191.24	**227.52***

Note. z-score threshold: 2.96; * statistically significant transitions

The respective state transition diagram for the high-level interactions is shown in Figure 1.

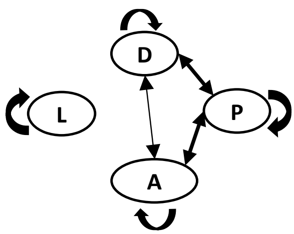

Figure 1: State transition diagram for the overall sample

The state transition diagram shows significant transitions between all the main categories except for the learning category. Looking at high-level interactions, the biggest category in terms of events captured is rather isolated.

4.2.2 Differences in Behavioral Patterns According to Topic Area

In order to tackle the second research question, LSA was carried for each "course bucket" (set of courses from one topic area) separately. The underlying assumption is that learners from the topic areas Business, Design und Technology are using different learning elements in a different frequency through different learning paths, to different dates in time, with a difference in effort and thus show differences in content consumption. Results, again, are illustrated in state transition diagrams (Figure 2 a–c):

As the learning category, again, remains isolated from the others, the data show a consistent pattern on this high level of analysis. Apart from that, behavioral patterns are similar but there are some minor differences. For example, learners interact within the discussion category and then interact with the progress.

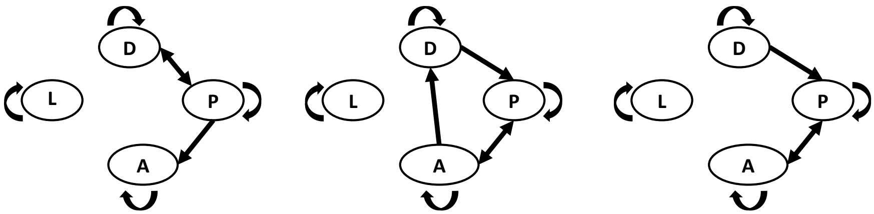

Figure 2: (a) Business courses (b) Design courses (c) Technology courses

5 Discussion and Outlook

This study sought to investigate typical behavioral patterns in openSAP Enterprise MOOCs and if such patterns differ between courses from different topic areas. Findings indicate that (1) there are consistent patterns and that (2) many characteristics of those patterns also apply when a differential perspective is adopted with respect to topic areas. The learning category, for example, which contains the majority of system interactions, remains isolated from the other categories, at least from the high-level perspective employed in this research. This might be due to a clear learner focus on working through the contents and towards the assignments, while the announcement, progress and discussion categories are more likely to be addressed at the beginning or the ending of a learning session. Moreover, announcements are also communicated via additional channels (e.g. e-mail), and the learner progress is evident in the learning area, too. So if there really is a need to better connect learning activities to collaborative (discussion) or meta-cognitive (announcements, progress) activities, cannot yet be decided at this stage.

Thus, there is a need for further analyses, on a more granular level, related to system interactions, as this is also the level on which possible interventions have to be designed to. Likewise, progress and performance data must be combined with the more granular interaction data, in order to discern successful and possibly misleading patterns with regard to learning success. Learner context data collected in accordance with applicable data protection guidelines will add an additional layer of detail here. Eventually, the goal is to develop an analytics-driven behavioral process model that might serve as a baseline for learning design [11]. The high-level behavioral patterns identified mark the necessary initial step to contextualize and interpret user-generated data to identify, understand, and cater different user groups and their learning behavior in an instructional setting, and to ultimately improve the overall learning experience and success.

References

[1] R. Bakeman and J. M. Gottman. *Observing interaction: An introduction to sequential analysis*. Cambridge: University press, 1997.

[2] C. J. Bonk, M. M. Lee, T. C. Reeves, and T. H. Reynolds, editors. *MOOCs and Open Education Around the World*. New York, NY: Routledge, 2015. DOI: 10.4324/9781315751108.

[3] M. S. Boroujeni and P. Dillenbourg. "Discovery and temporal analysis of MOOC study patterns". In: *Journal of Learning Analytics* 6.1 (2019), pages 16–33. DOI: 10.18608/jla.2019.61.2.

[4] J. Condé and M. Cisel. "On the Use of MOOCs in Companies: A Panorama of Current Practices". In: *Digital Education: At the MOOC Crossroads Where the Interests of Academia and Business Converge*. Edited by M. Calise, C. Kloos, J. Reich, J. A. Ruiperez-Valiente, and M. Wirsing. Cham: Springer, 2019, pages 37–46. DOI: 10.1007/978-3-030-19875-6_5.

[5] J. R. Corbeil, B. H. Khan, and M. E. Corbeil. "MOOCs revisited: Still transformative or passing fad?" In: *Asian Journal of University Education* 14.2 (2018), pages 1–12.

[6] M. Egloffstein and D. Ifenthaler. "Employee perspectives on MOOCs for workplace learning". In: *TechTrends* 61.1 (2017), pages 65–70. DOI: 10.1007/s11528-016-0127-3.

[7] M. Egloffstein, K. Koegler, and D. Ifenthaler. "Instructional quality of business MOOCs: Indicators and initial findings". In: *Online Learning* 23.4 (2019), pages 85–105. DOI: 10.24059/olj.v23i4.2091.

[8] M. Hamori. "MOOCs at work: what induces employer support for them?" In: *The International Journal of Human Resource Management* (2019). DOI: 10.1080/09585192.2019.1616593.

[9] D. Ifenthaler. "Learning analytics design". In: *The sciences of learning and instructional design. Constructive articulation between communities*. Edited by L. Lin and J. M. Spector. New York, NY: Routledge, 2017, pages 202–211. DOI: 10.4324/9781315684444.

[10] D. Ifenthaler, N. Bellin-Mularski, and D.-K. Mah. "Internet: Its impact and its potential for learning and instruction". In: *The SAGE encyclopedia of educational technology*. Edited by J. M. Spector. Volume 1. Thousand Oaks, CA: Sage, 2015, pages 416–422. DOI: 10.4135/9781483346397.

[11] D. Ifenthaler, D. C. Gibson, and E. Dobozy. "Informing learning design through analytics: Applying network graph analysis". In: *Australasian Journal of Educational Technology* 34.2 (2018), pages 117–132. DOI: 10.14742/ajet.3767.

[12] D. Ifenthaler and N. M. Seel. "A longitudinal perspective on inductive reasoning tasks. Illuminating the probability of change". In: *Learning and Instruction* 21.4 (2011), pages 538–549. DOI: 10.1016/j.learninstruc.2010.08.004.

[13] N. Li, Ł. Kidziński, P. Jermann, and P. Dillenbourg. "MOOC video interaction patterns: What do they tell us?" In: *Design for teaching and learning in a networked world*. Edited by G. Conole, T. Klobučar, C. Rensing, J. Konert, and É. Lavoué. Volume 9307. Amsterdam: Springer, 2015, pages 197–210. DOI: 10.1007/978-3-319-24258-3_15.

[14] M. G. Moore. "Three types of interaction". In: *American Journal of Distance Education* 3.2 (1989), pages 1–6.

[15] J. Renz, C. Meinel, and C. Link. "openSAP: Why Are Enterprise MOOCs Working?" In: *International Journal of Advanced Corporate Learning* 12.3 (2019), pages 59–69. DOI: 10.3991/ijac.v12i3.11262.

[16] T. Rohloff, F. Schwerer, N. Schenk, and C. Meinel. "openSAP: Learner Behavior and Activity in Self-Paced Enterprise MOOCs". In: *International Journal of Advanced Corporate Learning* 13.2 (2020), pages 30–40. DOI: 10.3991/ijac.v13i2.16531.

[17] M. Şahin, S. Keskin, and H. Yurdugül. "Sequential Analysis of Online Learning Behaviors According to E-Learning Readiness". In: *Online Teaching and Learning in Higher Education*. Edited by P. Isaias, D. G. Sampson, and D. Ifenthaler. Cham: Springer, 2020, pages 117–131. DOI: 10.1007/978-3-030-48190-2_7.

[18] F. Schwerer and M. Egloffstein. "Participation and Achievement in Enterprise MOOCs for Professional Learning". In: *Proceedings of the 13th International Conference on Cognition and Exploratory Learning in the Digital Age (CELDA 2016)*. Edited by D. G. Sampson. 2016, pages 269–276.

[19] A. Wald. *Analysis*. New York, NY: Dover Publications, 1973.