Analyzing User Feedback in Massive Open Online Courses: A Bibliometrics-Based Systematic Review

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ABSTRACT

With the development of technology, MOOCs (Massive Open Online Courses) have gained popularity in the field of e-learning. Considering that MOOCs still have many shortcomings, analyzing users' feedback has become a useful method to improve MOOCs performance. This study used both bibliometric and systematic methods to explore the intellectual structure for MOOCs user feedback literature. The results showed the annual publication figures, the contributing entities, and the relevant publication outlets. Based on co-citation analysis, the study found two clusters of cited references. One deals with the definition, design, and assessment of MOOCs. The other is related to MOOCs discussion forum and students' interactions. Co-word analysis revealed the focus of publications and the future trend. The results showed that current studies have explored different types of user feedback, methods of analyzing user feedback, and the aim of learning user feedback. Future research can extend the use of machine learning techniques, collect user feedback from various sources, and concentrate on different components of user feedback.

CCS CONCEPTS

• **Applied computing**; • **Education**; • **E-learning**;

KEYWORDS

MOOCs, Feedback, Bibliometric analysis, Systematic review

ACM Reference Format:
Xiaomeng Li and Chang Boon Lee. 2022. Analyzing User Feedback in Massive Open Online Courses: A Bibliometrics-Based Systematic Review. In *2022 6th International Conference on Education and E-Learning (ICEEL 2022), November 21–23, 2022, Yamanashi, Japan.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3578837.3578882

1 INTRODUCTION

User feedback, also referred to as comments, opinions, reviews, and word-of-mouth [1], has become an important resource to learn about user's experience. By analyzing feedback, providers can have a better understanding of user's evaluation of product or service quality and make appropriate improvements accordingly. There exist many studies related to reviews and feedback. For example, Jiménez and Mendoza found that review credibility has positive effect on consumers' purchase intention [2]. Calheiros, Moro and Rita analyzed tourist reviews, and their findings unveiled that different review topics generate different sentiments [3].

E-learning is a concept that has evolved since 1983. In the early days, e-learning refers to learning via electronic devices, including computer, television, and videodisk [4]. In the past few decades, researchers have proposed various concepts related to e-learning, and MOOC (Massive Open Online Course) has been a popular trend in this field, especially in the post-pandemic era. With MOOCs, students can participate in courses they are interested in regardless of geographical constraints, enrollment limitations, and entry requirements [5]. In the context of education, users' feedback has been used to evaluate course effectiveness and gain students' opinions, which can help to improve teaching quality and strengthen interactions between students and instructors [6]. In recent years, studies on MOOC user feedback have increased. For example, Hew et al. found that sentiments in learners' reviews have a positive effect on MOOC satisfaction [7]. Ramesh et al. used topic models to analyze contents in MOOC discussion forums to improve student retention [8].

Considering the rising trend of studies related to MOOCs user feedback, it is necessary to have a comprehensive understanding of the literature. Bibliometric methodology enables researchers to apply quantitative techniques to bibliometric data [9], which can build the foundations for scholars to gain an overview of the topic, spot research gaps, and generate innovative ideas. With the advancement of scientific datasets and bibliometric software, bibliometric analysis has gained popularity in various fields, such as management, finance, and hospitality [10] [11] [12]. Bibliometric analysis can be combined with other review methods, for example, systematic review, which relies on qualitative analysis to summarize findings of existing literature in a research field [13]. The aim of this study was to conduct a bibliometrics-based systematic review to answer the following questions:

(1) What is the annual publication trend of existing literature on MOOCs user feedback?
(2) What are the contributions by different research entities, such as countries, institutions, and journals?
(3) What are the fundamental references and research themes?
(4) What are the keywords and emerging research topics on MOOCs user feedback?

The rest of this study is structured as follows: Section 2 is a review of existing MOOC bibliometric studies. Section 3 describes the methodology. Section 4 presents the bibliometric analysis results together with systematic reviews. Section 5 is the conclusion and discussion.

ICEEL 2022, November 21–23, 2022, Yamanashi, Japan

ACM ISBN 978-1-4503-9842-8/22/11.
https://doi.org/10.1145/3578837.3578882

2 LITERATURE REVIEW

Systematic reviews and bibliometric analysis have been applied to review existing MOOCs research. Liyanagunawardena, Adams and Williams conducted a systematic review based on forty-five published MOOC studies during the period 2008 to 2012. They categorized existing literature into eight different areas of interest and explored future research directions [14]. Other related reviews focused on empirical MOOCs studies and summarized the research methods used by these publications [15] [16]. In recent years, researchers have published a number of bibliometric analysis articles related to MOOCs through the use of bibliometric software, which can generate visualization of various networks, such as co-citation, keywords, cited journal, and country collaboration, and these can provide an intuitive description of the research evolution in MOOCs [17] [18].

Prior bibliometric studies about MOOCs mainly held the macro perspective to analyze MOOCs literature, but some specific directions also deserve attention, such as learner engagement, continuance intention and course completion. These three aspects have received great interests in MOOCs research [19] [20] [21]. However, learner feedback is also an important aspect, because researchers and practitioners can find guidance to improve MOOC design and enhance teaching quality by mining information from users' opinions. This study can fill the research gap in existing literature and present a knowledge map in MOOCs research field. In addition, this study combined bibliometric and systematic methods, which provided both quantitative and qualitative analysis results to gain deeper insights and provide future research direction.

3 METHODOLOGY

This study selected Web of Science (WOS) for data collection. WOS has been widely used for bibliometric research [22]. It contains large amount of bibliographic information, and it has useful tools for analyzing research performance. First, the study filtered papers with "MOOC(s)" or "Massive Open Online Course(s)" in the title, abstract, and keywords. Other search terms which have been used to extract the relevant papers included "online review(s)", "comment(s)", "eWOM", and "feedback" [1]. As MOOC discussion forum contains large volume of user posts [8], this study also added the term "discussion forum". The search terms were combined by "AND" in the WOS search engine. There was no timespan limitation for the publications and the publication type was limited to journal articles and proceedings. For data analysis, two bibliometric tools were used: Citespace and Bibliometricx R. The two bibliometric tools have different functions that supplement each other. After duplicates removing, 528 records were remained for further study.

Bibliometric analysis techniques can be divided into two categories, namely performance analysis and science mapping [13]. Performance analysis is used to examine the contributions of different research entities, such as countries, institutions, journals and authors, and the contributions were measured by the number of publications and citations. Science mapping techniques are used to show relationships between different research entities, including co-citation analysis, co-word analysis, co-authorship analysis and so forth, and these techniques present the intellectual structure of the research field [23]. To answer the research questions in Section 1, we applied both performance analysis and science mapping. Systematic literature review was also applied to elaborate on the bibliometric findings.

4 RESULTS

4.1 Performance analysis

The results of performance analysis revealed the following: (1) the annual publication trend, (2) the most contributing countries and institutions, and (3) the most relevant publication sources. Figure 1 shows the publication trend of user feedback in MOOCs between 2013 to 2022. In total, there were 528 related publications during the period. The topic started to capture researchers' attention in 2013, with less than 10 publications a year. From 2013 to 2017, the publications had a rising trend, and they reached 96 in 2017. The increasing number of publications indicated that research in MOOCs user feedback has gained popularity, and this trend is related to the development of social media and eWOM research [24]. From 2017 to 2020, the numbers showed a decreasing trend, but the average publication was at least 40 per year. There was a reversal of the decreasing trend in 2020, however. Note that data for 2022 is for the first five months by the time of data collection, and therefore it will not show the actual trend until the year has passed.

The illustration of the top 10 contributing countries and institutions is shown in Table 1. Authors from USA contributed 242 articles, followed by China (180), UK (94), and Spain (56). For institutions, researchers from Central China Normal University have published 21 articles, followed by Pennsylvania State University (18), Purdue University (13), and University of Southampton (13).

Table 2 shows the sources of publications. The most prolific journal is The International Review of Research in Open and Distributed Learning (15 articles), followed by Computers and Education (13), IEEE Transactions on Learning Technologies (9), and IEEE Access (8). Proceedings also play an important role in the field of MOOCs user feedback (Proceedings of the Fourth and Third ACM Conference on Learning). Among all the sources, Computers and Education has the highest citations in the dataset (526), and it also has a high H index (9), which indicates its relatively high academic influence. Most journals belong to education or computer science discipline, but cross-disciplinary journal (eg., IEEE Access) can also be a choice to publish articles related to MOOCs user feedback.

4.2 Co-citation analysis

Co-citation analysis is a science mapping technique which has been used to reveal knowledge foundations in a field of study [13]. This technique can spot the most influential publications based on the citations they received and find clusters in references. Table 3 shows the 10 most cited references on MOOCs user feedback. The most cited article focused on a MOOC in edX and it analyzed students' use of resources by time. It also produced an in-depth picture of students, including their background, capabilities, and persistence [25]. The paper by Kizilcec, Piech and Schneider ranked second. It developed a classification method that identifies users' engagement in MOOCs, which can help to provide research and design directions [26]. The study by Hew and Cheung ranked third.

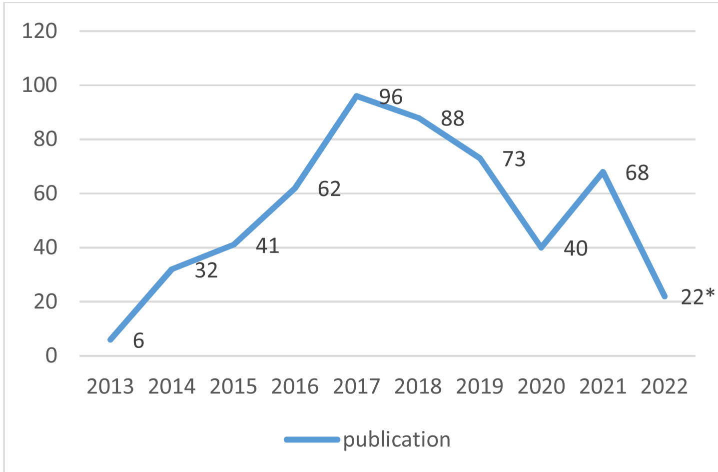

Figure 1: Publications by year (*Data for 2022 is for the first five months)

Table 1: Most contributing countries and institutions

Country	Publications	Institution	Publications
USA	242	Central China Normal University	21
China	180	Pennsylvania State University	18
UK	94	Purdue University	13
Spain	56	University of Southampton	13
India	41	University of Leeds	12
France	40	University of Valladolid	12
Germany	40	National University of Singapore	10
Australia	38	University of Pittsburgh	10
Netherlands	30	Indian Institutes of Technology	9
Canada	24	Delft University of Technology	8

Table 2: Most relevant sources

Source	Publications	Citations	H index
International Review of Research in Open and Distributed Learning	15	475	10
Computers and Education	13	526	9
IEEE Transactions on Learning Technologies	9	104	4
IEEE Access	8	34	4
Proceedings of the Fourth (2017) ACM Conference on Learning	8	21	4
Proceedings of The Third (2016) ACM Conference on Learning	7	85	5
Computer Applications in Engineering Education	6	27	5
Interactive Learning Environments	6	48	3
The Sixth International Learning Analytics and Knowledge Conference	6	72	5
Online Learning	6	48	3

Table 3: Most cited references

Title	Author(s)	Source	Citations	Cluster
Studying Learning in the Worldwide Classroom Research into edX's First MOOC	Breslow et al. (2013)	Research and Practice in Assessment	65	1
Deconstructing disengagement: analyzing learner subpopulations in massive open online courses	Kizilcec, Piech & Schneider (2013)	Proceedings of the third international conference on learning analytics and knowledge	55	1
Students' and instructors' use of massive open online courses (MOOCs): Motivations and challenges	Hew & Cheung (2014)	Educational research review	40	1
Learning about Social Learning in MOOCs: From Statistical Analysis to Generative Model	Brinton et al. (2014)	IEEE transactions on Learning Technologies	37	2
Engaging with massive online courses	Anderson et al. (2014)	Proceedings of the 23rd international conference on World wide web	35	2
MOOCs: A systematic study of the published literature 2008-2012	Liyanagunawardena, Adams & Williams (2013)	International Review of Research in Open and Distributed Learning	34	1
Instructional quality of Massive Open Online Courses (MOOCs)	Margaryan, Bianco & Littlejohn (2015)	Computers and Education	33	1
Communication patterns in massively open online courses	Gillani & Eynon (2014)	The Internet and Higher Education	31	2
Initial trends in enrolment and completion of massive open online courses	Jordan (2014)	International Review of Research in Open and Distributed Learning	29	1
Making Sense of MOOCs: Musings in a Maze of Myth, Paradox and Possibility	Daniel (2012)	Journal of interactive Media in education	28	1

The aim of this paper was to explore the motivations for students and instructors to use MOOCs [27]. The above-mentioned papers all belong to cluster 1, and they cover the definition, design, and assessment of MOOCs.

For articles in cluster 2, Brinton et al. investigated two issues related to MOOC discussion forums: sharp decline of participation over time and information overload [28]. Anderson et al. divided students' behavior of MOOCs engagement into five different categories. They designed a system of badges to help shift patterns of student engagement, especially for behavior in MOOCs discussion forums [29]. Gillani and Eynon studied students' communication patterns in MOOC discussion forums, and their findings revealed the background and behavior of participants [30]. Cluster 2 mainly focuses on MOOCs discussion forum and students' interactions.

4.3 Co-word analysis

Unlike co-citation analysis that focuses on cited publications, co-word analysis is based on the actual contents of the articles. The words or contents often come from the articles' titles, abstracts, and author keywords [13]. Words that usually appear together will be assigned to one thematic cluster. Chang, Huang and Lin proposed that co-word analysis can be used as a supplement to enrich the results of co-citation analysis, and it can also help researchers to find trend topics for future study [31]. Table 4 shows the results of keywords clustering generated by Bibliometrix R. General words such as "MOOC", "Education", and "Learning" were excluded, because it is difficult to assign them into any one cluster. BC (Betweenness centrality) in Table 4 is a measurement to detect the amount of influence for a keyword. The 10 most cited publications in each cluster can be regarded as representatives to demonstrate the research focus.

Cluster 1 is the largest cluster, and the most important keywords in this cluster are "Online learning" and "Instructional design". Papers in this cluster are aimed at developing instructional design strategies to improve MOOCs performance based on user feedback. For example, in this cluster, the paper by Elizondo-Garcia, Schunn and Gallardo examined the relationship between quality of feedback and peer-feedback pedagogical design [32]. Cluster 2 is mostly related to "Learning analytics", which means collecting, analyzing, and reporting learners' data to understand and optimize learning and the environments. Some highly cited publications in this cluster have made user feedback a source for learning analytics. For example, Lau et al. applied learning analytics model at four levels: global, series, video, and feedback for evaluation of a video-based lecture series [33]. Cluster 3 mainly focused on analyzing data provided by MOOC discussion forums. Crossley et al. combined click-stream data and students' words in discussion forum to predict students' MOOC completion, and the result showed an accuracy of 78% [34]. The most important topics in cluster 4 are "Educational data mining" and "Sentiment analysis". Studies in this cluster adopted data mining techniques to better understand user feedback. Onan used machine learning, ensemble learning, and deep learning methods for sentiment analysis based on 66,000

Table 4: Keywords in each cluster

Cluster 1		Cluster 2		Cluster 3	
Keyword	BC	Keyword	BC	Keyword	BC
Online learning	50.06	Learning analytics	83.82	Discussion forum	18.60
Instructional design	4.90	Feedback	2.85	Social network analysis	0.26
Blended learning	2.60	Self-regulated learning	0.46	Machine learning	2.25
Higher education	0.14	Deep learning	0.08	Content analysis	1.02
Assessment	0.16	Future learn	0.63	Natural language processing	1.10
Flipped classroom	0			Social interaction	0.07
MOOC design	0				
Cluster 4		Cluster 5			
Keyword	BC	Keyword	BC		
Sentiment analysis	36.59	Peer assessment	10.52		
Educational data mining	48.54	Motivation	7.96		
Electronic learning	0.89	Formative assessment	3.99		
Computer aided instruction	0.33	Self-directed learning	3.68		
Text mining	0	Student engagement	0.11		
		Peer feedback	0		

MOOC reviews, and the performance of different sentiment classification methods was reported and compared [35]. The focal point of cluster 5 is "Peer assessment", which offers students opportunities to critique and provide feedback on each other's work. Publications in cluster 5 studied the effect and improvement of peer assessment in MOOCs. For example, Staubitz et al. analyzed the importance of peer assessment in MOOCs environment. They also presented a peer assessment workflow concept to help enhancement of MOOC peer assessment process [36]. To summarize the 5 clusters, existing literature has covered different types of user feedback (discussion forum, peer assessment), methods of analyzing user feedback (learning analytics, sentiment analysis, educational data mining), and the aim of learning user feedback (instructional design).

Co-word analysis can also identify the trending topics according to their occurrence frequency among all the collected publications by year (Figure 2). After removing some general words, the key points in early stage (2014-2018) included "MOOC design", "evaluation", and "peer assessment". During this period, MOOC peer assessment was regarded as an important source to gain feedback information, which assisted in improving MOOCs design. From 2018 to 2020, "discussion forum" indicated that people started to explore new sources for user feedback. The ways to deal with feedback data were "learning analytics", "content analysis", and "educational data mining". With the development of technology, articles are getting more technical after 2020. Some advanced techniques derived from computer science field have been widely used in MOOCs user feedback study, such as "machine learning", "deep learning", "text mining" and "sentiment analysis". These techniques can reduce the manual workload and help researchers extract the topics and emotions from user feedback text.

Based on co-word analysis results in Table 4 and Figure 2, this study proposed several directions for future research. First, Figure 2 shows that there was a burst of publications using machine learning and other related techniques after 2020. Considering the dramatic progress and wide application of machine learning in the past few years, future research can dig deeper into this area. Current studies applying machine learning in MOOCs user feedback mostly focused on topic modeling and sentiment analysis, but there are many other promising directions, for example, using machine learning to detect fake reviews [37]. Second, researchers can gain user feedback from sources which has not been well studied. For example, feedback in social media like Twitter and Facebook can also influence students' behavior [38]. The last direction is to learn different feedback components. Existing publications mainly studied the feedback text, but other components like star rating (indicating student satisfaction by stars from 1–5), are also worth pursuing [7].

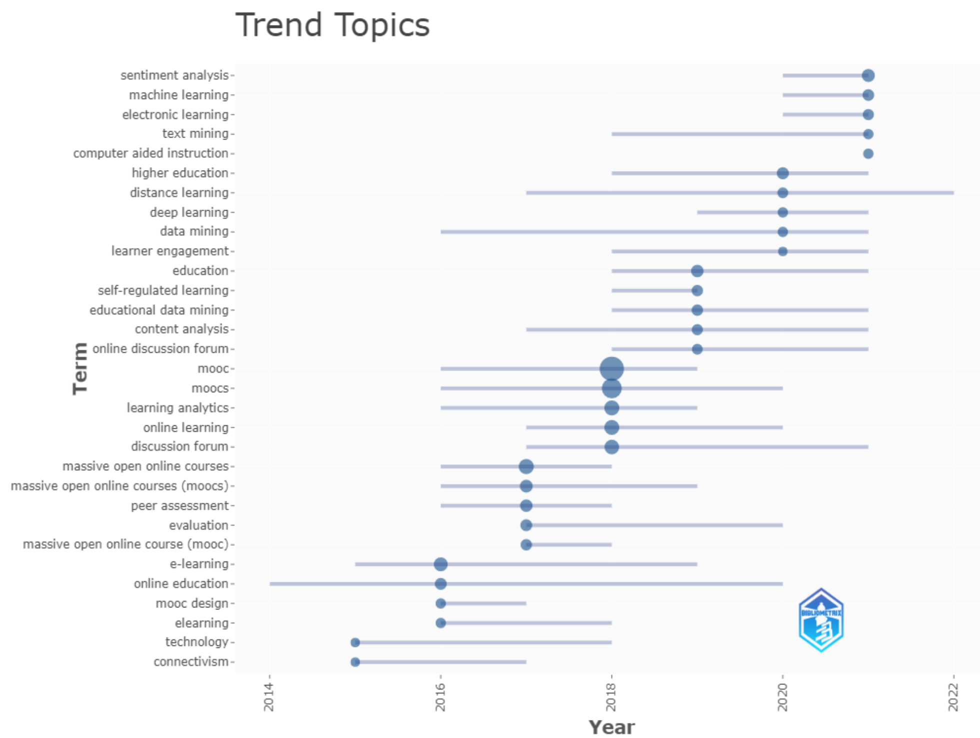

Figure 2: Trend topics

5 CONCLUSION AND DISCUSSION

This study explored the intellectual structure of MOOCs user feedback by using bibliometric analysis and systematic analysis techniques. The results of performance analysis showed a rising trend of publications between 2013 and 2017, and the number of publications remained a high level after 2017. Many of the top 10 contributing countries and institutions came from US, China, and Europe, and majority of publication sources belonged to the education or computer science discipline. Co-citation analysis presented the knowledge foundations, which can be divided into 2 clusters. One was the definition, design, and assessment of MOOCs. The other focused on MOOCs discussion forum and students' interactions. Finally, this study used co-word analysis to identify keywords and trend topics. The keywords can be grouped into 5 sets: courses design and feedback, learning analytics, MOOC discussion forums, educational data mining and sentiment analysis, and peer assessment in MOOCs, which covered different types of user feedback, methods of analyzing user feedback, and the aim of learning user feedback. The suggestions for future research are further application of machine learning, collecting user feedback from different sources, and investigating more components of user feedback.

We have contributed to existing research in two ways. On one hand, this study presented a knowledge map in MOOCs research from the perspective of user feedback, which is a supplement to existing publications concentrating on the whole MOOC field. On the other hand, this study combined systematic review with bibliometric analysis techniques. Bibliometric analysis allowed researchers to investigate a large number of publications, and systematic analysis assisted in gaining a deeper insight for existing literature.

This study has some limitations. First, the data source was limited to WOS. Future research can use other sources, like Scopus, or merge records gained form different databases. Second, the search criteria may not cover all the publications related to MOOCs user feedback. For example, research that adopted social media mining for MOOC-related tweets was not included in the search. Finally, to construct a more detailed knowledge map, further qualitative analysis is needed to summarize more aspects about prior studies, such as research purpose, research methodology, data collection methods, and data analysis tools.

REFERENCES

[1] Mishra, A., & Satish, S. M. (2016). eWOM: Extant research review and future research avenues. Vikalpa, 41(3), 222-233.
[2] Jiménez, F. R., & Mendoza, N. A. (2013). Too popular to ignore: The influence of online reviews on purchase intentions of search and experience products. Journal of Interactive Marketing, 27(3), 226-235.
[3] Calheiros, A. C., Moro, S., & Rita, P. (2017). Sentiment classification of consumer-generated online reviews using topic modeling. Journal of Hospitality Marketing and Management, 26(7), 675-693.
[4] White, M. A. (1983). Synthesis of research on electronic learning. Educational Leadership, 40(8), 13-15.
[5] Dodson, M., Kitburi, K., and Berge, Z. (2015). Possibilities for MOOCs in corporate training and development. Performance Improvement, 54(10), 14–21.
[6] Weng, J., Gan, W., Ding, G., Tian, Z., Gao, Y., & Qiu, J. (2020). SESM: Emotional social semantic and time series analysis of learners' comments. In 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC) (pp. 4134-4139). IEEE.
[7] Hew, K. F., Hu, X., Qiao, C., & Tang, Y. (2020). What predicts student satisfaction with MOOCs: A gradient boosting trees supervised machine learning and sentiment analysis approach. Computers and Education, 145, 103724.

[8] Ramesh, A., Goldwasser, D., Huang, B., Daumé III, H., & Getoor, L. (2014). Understanding MOOC discussion forums using seeded LDA. In Proceedings of the ninth workshop on innovative use of NLP for building educational applications (pp. 28-33).
[9] Broadus, R. N. (1987). Toward a definition of "bibliometrics". Scientometrics, 12(5), 373-379.
[10] Zupic, I., & Čater, T. (2015). Bibliometric methods in management and organization. Organizational research methods, 18(3), 429-472.
[11] Xu, X., Chen, X., Jia, F., Brown, S., Gong, Y., & Xu, Y. (2018). Supply chain finance: A systematic literature review and bibliometric analysis. International Journal of Production Economics, 204, 160-173.
[12] Li, X., Ma, E., & Qu, H. (2017). Knowledge mapping of hospitality research− A visual analysis using CiteSpace. International Journal of Hospitality Management, 60, 77-93.
[13] Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. Journal of Business Research, 133, 285-296.
[14] Liyanagunawardena, T. R., Adams, A. A., & Williams, S. A. (2013). MOOCs: A systematic study of the published literature 2008-2012. International Review of Research in Open and Distributed Learning, 14(3), 202-227.
[15] Veletsianos, G., & Shepherdson, P. (2016). A systematic analysis and synthesis of the empirical MOOC literature published in 2013–2015. International Review of Research in Open and Distributed Learning, 17(2), 198-221.
[16] Zhu, M., Sari, A., & Lee, M. M. (2018). A systematic review of research methods and topics of the empirical MOOC literature (2014–2016). The Internet and Higher Education, 37, 31-39.
[17] Wahid, R., Ahmi, A., & Alam, A. S. A. (2020). Growth and collaboration in massive open online courses: A bibliometric analysis. International Review of Research in Open and Distributed Learning, 21(4), 292-322.
[18] Zheng, X., Zhang, J., & Yang, X. (2019). Visual analysis of MOOC research using CiteSpace from 2012 to 2018. In 2019 International Joint Conference on Information, Media and Engineering (IJCIME) (pp. 119-124). IEEE.
[19] Roca, J. C., and Gagné, M. (2008). Understanding e-learning continuance intention in the workplace: A selfdetermination theory perspective. Computers in Human Behavior, 24(4), 1585-1604.
[20] Guo, P. J., Kim, J., and Rubin, R. (2014). How video production affects student engagement: An empirical study of MOOC videos. Proceedings of the first ACM conference on Learning@ scale conference, pp. 41-50.
[21] Bote-Lorenzo, M. L., and Gómez-Sánchez, E. (2017). Predicting the decrease of engagement indicators in a MOOC. Proceedings of the Seventh international learning analytics & knowledge conference, pp. 143-147.
[22] Wang, B., Pan, S. Y., Ke, R. Y., Wang, K., & Wei, Y. M. (2014). An overview of climate change vulnerability: a bibliometric analysis based on Web of Science database. Natural hazards, 74(3), 1649-1666.
[23] Tunger, D., & Eulerich, M. (2018). Bibliometric analysis of corporate governance research in German-speaking countries: applying bibliometrics to business research using a custom-made database. Scientometrics, 117(3), 2041-2059.
[24] Donthu, N., Kumar, S., Pandey, N., Pandey, N., & Mishra, A. (2021). Mapping the electronic word-of-mouth (eWOM) research: A systematic review and bibliometric analysis. Journal of Business Research, 135, 758-773.
[25] Breslow, L., Pritchard, D. E., DeBoer, J., Stump, G. S., Ho, A. D., & Seaton, D. T. (2013). Studying learning in the worldwide classroom research into edX's first MOOC. Research & Practice in Assessment, 8, 13-25.
[26] Kizilcec, R. F., Piech, C., & Schneider, E. (2013). Deconstructing disengagement: analyzing learner subpopulations in massive open online courses. In Proceedings of the third international conference on learning analytics and knowledge (pp. 170-179).
[27] Hew, K. F., & Cheung, W. S. (2014). Students' and instructors' use of massive open online courses (MOOCs): Motivations and challenges. Educational research review, 12, 45-58.
[28] Brinton, C. G., Chiang, M., Jain, S., Lam, H., Liu, Z., & Wong, F. M. F. (2014). Learning about social learning in MOOCs: From statistical analysis to generative model. IEEE transactions on Learning Technologies, 7(4), 346-359.
[29] Anderson, A., Huttenlocher, D., Kleinberg, J., & Leskovec, J. (2014). Engaging with massive online courses. In Proceedings of the 23rd international conference on World wide web (pp. 687-698).
[30] Gillani, N., & Eynon, R. (2014). Communication patterns in massively open online courses. The Internet and Higher Education, 23, 18-26.
[31] Chang, Y. W., Huang, M. H., & Lin, C. W. (2015). Evolution of research subjects in library and information science based on keyword, bibliographical coupling, and co-citation analyses. Scientometrics, 105(3), 2071-2087.
[32] Elizondo-Garcia, J., Schunn, C., & Gallardo, K. (2019). Quality of Peer Feedback in Relation to Instructional Design: A Comparative Study in Energy and Sustainability MOOCs. International Journal of Instruction, 12(1), 1025-1040.
[33] Lau, K. V., Farooque, P., Leydon, G., Schwartz, M. L., Sadler, R. M., & Moeller, J. J. (2018). Using learning analytics to evaluate a video-based lecture series. Medical teacher, 40(1), 91-98.
[34] Crossley, S., Paquette, L., Dascalu, M., McNamara, D. S., & Baker, R. S. (2016). Combining click-stream data with NLP tools to better understand MOOC completion. In Proceedings of the sixth international conference on learning analytics & knowledge (pp. 6-14).
[35] Onan, A. (2021). Sentiment analysis on massive open online course evaluations: a text mining and deep learning approach. Computer Applications in Engineering Education, 29(3), 572-589.
[36] Staubitz, T., Petrick, D., Bauer, M., Renz, J., & Meinel, C. (2016). Improving the peer assessment experience on MOOC platforms. In Proceedings of the third (2016) ACM conference on Learning@ Scale (pp. 389-398).
[37] Wu, Y., Ngai, E. W., Wu, P., & Wu, C. (2020). Fake online reviews: Literature review, synthesis, and directions for future research. Decision Support Systems, 132, 113280.
[38] Liu, M., Kang, J., McKelroy, E., Harron, J., & Liu, S. (2016). Investigating Students' Interactions with Discussion Forums, Facebook, and Twitter in a MOOC and their Perceptions. In Revolutionizing Modern Education through Meaningful E-Learning Implementation (pp. 18-41). IGI Global.